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EUROSYSTEM

APRIL 2007

RISK MEASUREMENT AND SYSTEMIC RISK

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FOURTH JOINT CENTRAL BANK RESEARCH CONFERENCE 8-9 NOVEMBER 2005

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ISBN 978-92-899-0048-5 (print)
ISBN 978-92-899-0049-2 (online)

Preface

The Fourth Joint Central Bank Research Conference on Risk Measurement and Systemic Risk took place at the European Central Bank in Frankfurt on 8 and 9 November 2005. The conference was hosted by the ECB in cooperation with the Bank of Japan and the Board of Governors of the Federal Reserve System, under the auspices of the Committee on the Global Financial System (CGFS).[1] The three earlier conferences were hosted by the Federal Reserve Board, the Bank of Japan, and the Bank for International Settlements in 1995, 1998 and 2002, respectively.

Staff from the Bank of Japan (Tokiko Shimizu), the Federal Reserve Board (Mark Carey and William English), the Bank for International Settlements (Ingo Fender) and the European Central Bank (Philipp Hartmann) were the principal organisers of the conference. Important contributions to the successful organisation of the event were also made by Reint Gropp and Roberto Perli, Sabine Wiedemann, Suzanne Heinrich, Werner Breun, Martin Scheicher, Jose-Luis Peydro-Alcalde, Elmar Häring, Peter Claisse, and Jane Vergel. Reint Gropp edited the present volume with the help of Martin Scheicher, and staff from the ECB's Official Publications and Library Division helped prepare it for publication.

This volume contains papers that either were presented or interpret presentations at the conference. In a few cases substitute papers were accepted in place of the original contribution made at the conference. Authors retain their copyright. The following chapter summarising the conference was prepared by Reint Gropp and Martin Scheicher.

One of the main goals of the conference was to bring together the business, research and policy communities to foster active exchange on issues related to risk measurement and systemic risk. The organisers wish to express their appreciation to all those who agreed to attend the conference, be it as paper presenters, session chairs, discussants or participants in the open discussion. The conference's 18 papers, grouped in six sessions, were selected from 148 submissions. In order to foster interaction, session chairs were drawn from the central bank community, while a mixture of academics and central bankers served as discussants. The policy panel was composed of a mix of very senior policymakers and leading practitioners in the field drawn from the private sector.

These arrangements worked well in terms of promoting the exchange of ideas. Authors had the opportunity to present their research to a relatively senior audience of policymakers and risk management professionals. In turn, these practitioners offered their views on various issues of practical relevance, providing a valuable perspective on current findings and possible guidance for future research. We hope that the tradition that was initiated by the first Joint Central Bank Research Conference on Risk Measurement and Systemic risk more than ten years ago, and which was continued by this conference, will continue to stimulate interesting research and discussions in these important areas.

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[1] The Committee on the Global Financial System (CGFS) is a central Bank committee established by the Governors of the G10 central banks. It monitors and examines broad issues relating to financial markets and systems, with a view to elaborating appropriate policy recommendations to support the central banks in the fulfilment of their monetary and financial stability responsibilities. In carrying out these tasks, the Committee places particular emphasis on assisting the Governors in recognising, analysing and responding to threats to the stability of financial markets and the global financial system. The CGFS is chaired by Donald L. Kohn, Vice Chairman of the Board of Governors of the Federal Reserve System.

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RISK MEASUREMENT AND SYSTEMIC RISK: A SUMMARY

1. Overview

Financial innovation, liberalisation and development, by completing markets and improving risk sharing opportunities, should be good news for financial stability. However, some policy makers have voiced concerns that these changes may also generate new challenges and, indeed, new risks. For instance, the consolidation process in the banking system has yielded larger, better diversified financial institutions that have the resources and know-how to apply the latest risk management techniques. However, consolidation has also resulted in the emergence of a relatively limited number of large and complex financial institutions, which play a pivotal role for many financial markets and may require increasingly sophisticated supervision. Second, the emergence of hedge funds broadens investment opportunities for institutional and individual investors, and may have increased liquidity in some markets. At the same time, the behaviour of highly leveraged and weakly regulated or unregulated institutions, such as hedge funds, may differ significantly from those of banks. Some of the key factors influencing the behaviour of hedge funds are a high degree of opacity, leverage, targeting absolute returns, and trading in less liquid markets. Finally, credit derivatives have facilitated the transfer of credit risk, which used to be very difficult and costly. As the risk profiles of most banks are dominated by their credit exposures, credit derivatives offer the potential to have profound effects on the banking system in particular. In parallel, they offer new investment opportunities to new classes of institutions and investors, who differ significantly from banks, tend to be unregulated, and whose characteristics and expertise may have changed profoundly over time.

The initial empirical evidence on whether financial innovation increases or reduces risks to financial stability is encouraging. Since the market turmoil in 1997 and 1998, the global financial system has weathered a number of sizable shocks, including turbulence triggered by the downgrades of Ford and GM in the spring of 2005, the default of Argentina, and the discovery of large accounting irregularities at some major US and European firms. In addition, the terrorist attacks on September 11, 2001, had the potential for generating sustained financial instability, which did not materialise. Furthermore, financial markets and institutions had to deal with the large and widespread correction of stock prices from March 2000 onwards. Overall, the global financial system absorbed these shocks without significant adverse effects on market functioning.

This recent resilience may give policy makers cause for comfort. However, some observers have argued that financial innovation has changed the characteristics of financial fragility, potentially reducing the frequency of crises, but increasing their severity, if they do happen. Further, the problems may have shifted towards risks where policy makers may have relatively little experience, such as herding, mis-pricing of risk, the allocation of new risks outside the banking system, and the interaction of financial innovation with market participants' incentives.

The potential for increased systemic risk may be particularly related to combinations of the structural trends. For example, hedge funds' increasing use of credit risk transfer (CRT) instruments raises two specific concerns. First, banks that purchase protection need to be mindful not only of residual risks that can follow both from the contractual terms and the enforceability of CRT instruments, but also of risks to the counterparty that is providing protection. Second, the CRT market is very concentrated as only a small number of major banks possess the know-how and technology to be fully active in this sophisticated market. This high degree of concentration inevitably brings about potentially significant counterparty risk concentrations. As hedge funds typically use comparatively high leverage, their possible impact on markets can be quite sizeable. Additionally, the provision of liquidity and risk bearing capacity can become quite difficult in times of crises.

Against this background, the aim of this conference was to provide a comprehensive analysis of current developments in risk measurement and systemic risk with a particular emphasis on the effect of new financial instruments and non-bank financial institutions. Some of the major themes in the conference were advances in risk modelling, the measurement of systemic risk, contagion effects, and the impact of credit derivatives on the financial system. The conference papers highlight a number of potential new challenges for policymakers concerned with financial stability. They include how to monitor risks outside the banking sector, an enhanced emphasis on sophisticated indicators of financial sector resilience, how to design appropriate stress tests, the appropriate policy response to a rapid drying up of liquidity in key markets, and the extent to which the regulatory framework is sufficiently equipped to deal with the new environment. The conference included researchers from the academic community as well as from central banks and the private sector.

In his opening remarks, **Ottmar Issing** outlined some major economic implications of the recent financial innovations, in particular in the context of conducting monetary policy. He argued that the overall effect on economic performance should be positive. As regards the conduct of monetary policy, there is no robust evidence. However given the current developments it seems quite likely that the monetary transmission mechanism is changing in the direction of stronger wealth effects. The impact of credit derivatives on the financial system was also at the centre of the discussion in the **policy panel**. **Lucas Papademos** discussed a number of open policy issues in the debate on the impact of the CRT markets. In particular, he focused on the transfer of risk from banks to less regulated entities and the transfer to less informed market participants. He closed by outlining some specific challenges such as the role of rating agencies, the crucial impact of market liquidity and the reduced information content of balance sheets. **Eiji Hirano** focused on the policy implications of the development of credit derivatives and structured finance from the perspective of the Japanese financial system. He outlined the development of the CRT market in Japan and also discussed challenges in analysing banking system risk in the new financial environment. **Roger Ferguson** argued that policymakers can best balance these goals by expending the effort needed to understand financial innovations as they emerge and by avoiding overregulation that may stifle valuable innovations. In his view, the desired strategy is a middle ground in which markets are allowed to work and develop, and in which policymakers work hard to understand new developments and to help market participants see the need for improvements where appropriate.

The three central bankers' perspectives were complemented by those of two practioners from the banking industry. **Mark Alix** and **Sean Kavanagh** discussed the impact of credit risk transfer on their banks' business strategies and risk management practices. According to their banks' experience, structured finance has doubtlessly improved the ability to manage credit risks. They argued that the widespread use of credit portfolio management tools together with CRT markets has profoundly affected the functioning of banks' credit departments. Indeed Sean Kavanagh emphasised that Deutsche Bank is now routinely able to sell first loss tranches in the market. In sum, there is evidence that the traditional strategy of granting and holding loans has been (or is in the process of being) replaced by an approach where banks originate the loans and then transfer the risks to other market participants.

2. Non-bank financial institutions and systemic risk

The first session focussed on the interlinkages in the financial sector that may result in the transmission of shocks from one financial intermediary to others. All three papers attempt to empirically or theoretically model financial structures that may be prone to interdependencies and the spread of adverse shocks. The papers then characterise the strength of these links and derive some policy consequences.

The first paper of the session, "Systemic risk and hedge funds" by **Chan, Getmansky-Sherman, Haas and Lo**, examines the potential systemic risk implications of the hedge fund industry. The authors develop a number of new risk measures for hedge fund investments and apply them to individual and aggregate hedge fund return data. These measures include exposure to liquidity risk, factor models for hedge fund and banking sector indices, the estimation of hedge fund liquidation probabilities, and aggregate measures of volatility and distress based on regime-switching models. The authors find that the recent massive inflows into the hedge fund industry have reduced hedge fund returns, increased illiquidity, changed correlations of returns across asset classes and increased mean and median liquidation probabilities for hedge funds in 2004. The paper also suggests that a number of smaller banks may be significantly exposed to these risks and larger banks are exposed through proprietary trading activities, credit arrangements, structured products, and prime brokerage services.

The other two papers in the session were theoretical, taking two different perspectives on how shocks may spread through the financial system. **Charkravorti and Lall** argue that managerial incentive schemes of fund managers may result in contagion even in the absence of asymmetric information. Furthermore, managerial compensation schemes may result in asset prices deviating from fundamentals over extended period of time, even in the presence of fund managers compensated based on the absolute return of their portfolio. The paper provides support to the view that while financial market development may have improved the allocation of risks in financial markets, fundamental characteristics of financial intermediaries may now make economies more vulnerable to financial sector turmoil. This point was recently also underlined in R. Rajan's 2005 paper presented at the Jackson Hole conference. In **Brusco and Castiglionesi**, the source of contagion is more traditional, namely moral hazard arising from liquidity co-insurance. In their model banks are protected by limited liability and therefore may engage in excessive risk taking. In the model it is optimal to address this problem by imposing capital requirements. Interestingly, in their model a perfectly connected interbank deposit structure is more conducive to crises than an imperfectly connected deposit structure. This result is in sharp contrast to that of Allen and Gale (2000).

3. Liquidity risk and contagion

The measurement of the interdependence among the various participants of the financial system is a key step in analysing financial stability. The second session studied direct linkages among financial institutions as well as those that run through the systems providing the financial infrastructure.

The first paper of this session by **Bech and Garratt** shows how the financial system can become illiquid following wide-scale disruptions. The key drivers in this model are operational problems and changes in behaviour by participants. The authors use game-theoretic approaches to model the interbank payment system and outline cases where central bank intervention might be required to re-establish the socially efficient equilibrium. The paper also explores how the network topology of the underlying payment flow among banks affects the resiliency of coordination. In addition, the paper provides a theoretical framework to analyze the effects of events such as September 11, 2001. In a related approach, **Devriese and Mitchell** study the potential impact on securities settlement systems (SSSs) of a major market disruption caused by the default of the largest member. A multi-period, multi-security model with intraday credit is used to simulate direct and second-round settlement failures triggered by the default, as well as the dynamics of settlement failures arising from a lag in settlement relative to the date of trades. The paper finds that central bank liquidity support to SSSs cannot eliminate settlement failures due to major market disruptions. Whereas a broad program of securities borrowing and lending might help, it is precisely during periods of market disruption that participants will be least willing to lend securities.

In contrast, the third paper applies an empirical perspective to contagion. **Iyer and Peydró-Alcaldez** study interbank contagion from the perspective of real transactions. The paper uses a unique dataset from India to identify the interbank commitments in order to test contagion in the banking system of an idiosyncratic shock --caused due to a fraud in one of the banks. The results provide strong evidence in favour of financial linkages as an important mechanism for contagion and may also have some implications for policy formulation.

4. Credit risk transfer and trading in credit markets

Research on new developments in credit markets has taken a variety of approaches, ranging from asset pricing analysis to market functioning and more general analysis of the impact of CRT on the financial system. Together with the policy panel the three papers in this session try to capture the variety of issues in this important financial stability topic.

The first paper looks at the determinants of the market price of credit risk. Specifically, **Zhang, Zhou and Zhu** explore relationships between observed equity returns and credit spreads in the credit default swap (CDS) market. They use a novel approach to identify the realized jumps of individual equities from high frequency data. Empirical results suggest that volatility risk alone predicts 50 percent of the variation in CDS spreads, while jump risk alone forecasts 19 percent. The pricing effects of volatility and jump measures vary consistently across investment-grade and high-yield entities. The estimated nonlinear effects of volatility and jumps are in line with the model-implied relationships between equity returns and credit spreads. This paper's conclusions are therefore the opposite of Collin-Dufresne et al. (2001) who documented a 'puzzle' in bond-based credit spreads.

Information asymmetries and the potential for insider trading has been seen as a potential threat to orderly market functioning. The second paper of this session, **Acharya and Johnson** empirically study insider trading in the credit derivatives market. Using news reflected in the stock market as a benchmark for public information, they report evidence of significant incremental information revelation in the CDS market under circumstances consistent with the use of non-public information by informed banks. Specifically, the information revelation occurs only for negative credit news and for entities that subsequently experience adverse shocks. Moreover the degree of advance information revelation increases with the number of banks that have lending/monitoring relationships with a given firm, and this effect is robust to controls for non-informational trading. The authors find no evidence, however, that the degree of asymmetric information adversely affects prices or liquidity in either the equity or credit markets. If anything, with regard to liquidity, the reverse appears to be true.

The literature on credit markets has found evidence of market frictions both within the corporate bond market and between the cash market and the credit derivatives market. In this context, **Levin, Perli and Zakrajsek** construct an empirical measure of market frictions in the credit market based on the difference between the CDS premium and the spread on corporate bonds equal. A potential divergence indicates that significant market frictions are present, preventing investors' from arbitraging away what in effect are opportunities to earn a risk-free profit. The authors find that the causes of market frictions can be both systematic and firm- or bond-specific, with the idiosyncratic causes accounting for the dominant part.

5. Systemic risk across countries

The market turbulence around the collapse of LTCM in 1998 has strengthened central banks' efforts to measure systemic risk in order to be ready to provide risk-mitigation measures in periods of market turbulence. The literature offers a variety of approaches to the analysis of systemic risk and this session includes two papers dealing with banks and one paper with a more abstract perspective.

Hartmann, Straetmans, and de Vries derive indicators of the severity and structure of banking system risk from asymptotic interdependencies between banks' equity prices. Using data for the United States and the euro area, they also compare banking system stability between the two largest economies in the world. The results suggest that estimated extreme spillover risk in the US is higher than in the euro area, mainly as cross-border risks are still relatively mild in Europe. In contrast, extreme systematic risk is very similar on both sides of the Atlantic. Moreover, the evidence suggests that both forms of systemic risk have increased during the 1990s. Using a unique dataset, **Bartram, Brown and Hund** develop three distinct methods to quantify the risk of a systemic failure in the global banking system. They examine a sample of 334 banks (representing 80% of global bank equity) in 28 countries around 6 global financial crises and show that these crises did not create large probabilities of global financial system failure. More precise point estimates of the likelihood of systemic failure are obtained from structural models. These estimates provide further evidence that systemic risk is limited even during major financial crises such as the Asian crisis. The largest values are obtained for the Russian crisis and September 11.

The last paper in this session chooses a different perspective on systemic risk. **Taketa** studies the implications of the presence of large speculators during a contagious currency crisis. The model shows that the presence of the large speculator makes countries more vulnerable to crises, but mitigates contagion of crises across countries. The model presents policy implications as to financial disclosure by and the size of speculators, such as hedge funds. First, financial disclosure by speculators eliminates contagion, but may make countries more vulnerable to crises. Second, regulating the size of speculators (e.g., constraining hedge funds' leverage and thereby limiting their short-selling) makes countries less vulnerable to crises, but makes contagion more severe.

6. Risk measurement and market dynamics

The introduction of Value at Risk (VaR) models in the 1990s represents a major step in the evolution of risk management practices. Since 1998, the Basle Committee has allowed banks to seek supervisory approval for setting capital requirements for market risks based on their internal models. Hence, banks as well as supervisors have focused considerable efforts on studying the performance of these internal risk models. In this session, three papers approach this topic from quite diverse angles.

Baba and Nishioka evaluate the role of TIBOR/LIBOR, i.e. the "Japan spread,"' as an indicator of bank credit risk and investigate the interdependence of bank credit risk in money markets within and across borders since the 1990s. They find that observed risk premia constructed from TIBOR/LIBOR contain global and currency factors, which explain most of the variance of the risk premia. Furthermore, the correlations of the same bank groups' risk premia between the yen banks' risk premiums in the same currency market are very high. Finally they also document that the fundamental prices account for only a small portion of the total variance of risk premia.

Hanson, Pesaran and Schuermann consider a simple model of credit risk and derive the limit distribution of losses under different assumptions regarding the structure of systematic and idiosyncratic risks and the nature of firm heterogeneity. Their results document a rich and complex interaction between the underlying model parameters and the resulting loss distributions. By means of theoretical as well as empirical analysis, the authors show that after controlling for expected losses neglecting parameter heterogeneity leads to overestimation of risk. These results have considerable implications for banks' internal credit risk models, in particular they imply that careful specification of the firm-specific parameters is required.

Berkowitz, Christoffersen and Pelletier focus on market risk modelling. They present new evidence on disaggregated profit and loss and VaR forecasts obtained from a major bank. The dataset includes daily profit and loss figures generated by four separate business lines within the bank. All four business lines are involved in securities trading, and each is observed daily for a period of at least two years. Given this rich dataset, the paper provides an integrated, unifying framework for assessing the accuracy of VaR forecasts.

7. Stress testing and financial stability policies

The last session of the conference focused on central banks' methodologies for analysing potentials signs of fragility in the financial system. Stress-testing has been widely applied by banks since the early 1990s and regulators currently require stress-tests for monitoring market as well as credit risks in banks' portfolios. The aim of these methodologies is to provide a bank-wide evaluation of its risk bearing capacity. In parallel, central banks have developed 'macro' stress-testing to measure the fragility of entire financial systems. This session focused on aggregate stress testing as well as on specific indicators for financial stability.

Drehmann, Patton and Sorensen explore the impact of possible non-linearities on aggregate credit risk in a vector autoregression framework. By using aggregate data on corporate credit in the UK they investigate the non-linear transmission of macroeconomic shocks to the aggregate corporate default probability. They document that non-linearities matter for the level and shape of impulse response functions of credit risk following small as well as large shocks to systematic risk factors. Furthermore, ignoring estimation uncertainty in stress tests can lead to a substantial underestimation of credit risk, particularly in extreme conditions. **Jacobson, Linde and Roszbach** empirically study interactions between real activity and the financial stance. Using aggregate data the authors examine a number of candidate measures of the financial stance of the economy. The authors find strong evidence for substantial spillover effects on aggregate activity from their preferred measure. Given this result, the authors use a large micro-data set for corporate firms to develop a macro–micro model of the interaction between the financial and real economies. This approach implies that the impulse responses of a given aggregate shock will depend on the portfolio structure of firms at any given point in time.

Finally, **Nelson and Perli** provide a comprehensive discussion of some of the financial stability indicators available for central bank monitoring. Drawing on data from the US financial system, they study not only the equity and Treasury markets but also credit markets. Furthermore, they analyse the information content of indicators for the condition of systemically important banks. Among other findings they show that recent financial innovations allow market observers to construct refined measures of systemic risk.

PART 1

OPENING REMARKS, CONCLUDING REMARKS AND DINNER ADDRESS

OPENING REMARKS

OTMAR ISSING

MEMBER OF THE EXECUTIVE BOARD OF THE EUROPEAN CENTRAL BANK

Ladies and gentlemen,

It is my pleasure to welcome you this morning to the Fourth Joint Central Bank Research Conference on Risk Measurement and Systemic Risk.

Today I will talk about some recent financial innovations and their implications for monetary policy.

By financial innovation, I mean the emergence of novel financial instruments, new financial services and new forms of organisation in financial intermediation. To be successful, financial innovation must increase financial market completeness, allowing better risk sharing and, more generally, improving the services for the participants of the financial system.

In view of this definition, I will not talk about my favourite recent financial innovation the euro but about securitisation, structured finance, credit derivatives and hedge funds. After describing each of these innovations, I will analyse their impact on the economy. Finally, I will briefly discuss the potential implications for the conduct of monetary policy.

I. Recent innovations in financial systems[1]

As regards financial instruments, in recent years, we have seen the wide expansion of products to transfer risk such as loan securitisations, collateralised debt obligations and credit default swaps. As far as financial institutions are concerned, we have witnessed the rapid expansion of hedge funds. Quite interestingly, as we will see, these recent financial innovations are closely related.

Securitisation is the process of creating and issuing securities backed by a pool of assets. Securitisation may involve the actual transfer of loans off the financial intermediary s balance sheet or, alternatively, the transfer by the bank of the credit risk through the use of credit derivatives for example, through credit default swaps

[1] See the ECB s Financial Stability Review (December, 2004, and June, 2005) and its publication Credit risk transfer by EU banks: activities, risks and risk management (May, 2004), as well as Garbaravicius and Dierick (2005).

(CDS), whereby the bank buys protection in case a credit event occurs such as the bankruptcy of the debtor. The notional amount of credit derivatives outstanding globally is higher than 5 trillion US dollars. Although the market has been rapidly expanding, it is useful to put its size into perspective: the total volume of credit derivatives still represents less than 5% of all derivatives outstanding.

Structured finance, broadly defined, refers to the repackaging of cash flows that can transform the risk, return and liquidity characteristics of financial portfolios. A collateralised debt obligation (CDO) is a debt security issued by a Special Purpose Vehicle and backed by corporate loan or bond portfolios. A synthetic CDO has similar features, but the underlying securities are CDS, which have been repackaged into a reference portfolio. Typically, several classes (or tranches) of securities with different degrees of seniority are issued to investors. The most junior is called equity, the next tranche is called mezzanine, and the senior tranche can achieve a triple-A rating, as is indeed the case for 80% of the structured finance market in Europe. Just to give you an idea of the exponential growth of this market in Europe: the number of deals in CDOs more than doubled between 2003 and 2004, with a total gross protection sold of more than 300 billion.

Who participates in these markets? While all of these instruments would have permitted the transfer of risk out of the banking sector, the bulk of the activity in credit risk transfer markets has still continued to take place between banks. Yet some important changes have taken place in the structure of counterparts over recent years. The global insurance industry, which has been an active protection seller in credit derivatives instruments, began to pull out of the market in 2003. Taking their place, hedge funds have become very important participants in the market. Since hedge funds are not regulated, relatively little is known about their activities. Rough estimates suggest that hedge funds may trade as much as 20-30% of the overall credit derivatives volume. Although there is no common definition of what constitutes a hedge fund, it can be described as a fund which can freely use various active investment strategies to maximise the profits of investors. Typically, the fees of fund managers are related to the absolute performance of the fund in question and managers often even commit their own money. Although hedge funds typically target very rich individuals and institutional investors, they have recently also become increasingly available to retail investors due to the development of funds investing in hedge funds and structured financial instruments with hedge fund-linked performance.

II. Implications for the economy

By separating the origination and funding of credit from the allocation of the credit risk, securitisation, structured finance and credit derivatives facilitate the transfer of risk across different agents in the economy. Furthermore, the tradability of CRT instruments permits an allocation of risks to the agents most willing to bear them. Recently, hedge funds have developed a particular appetite for them. Moreover, through their expansion to retail investors, households have indirectly absorbed part of this risk. As a consequence, the broader dispersion of risk across different financial intermediaries and households may have improved risk sharing. Besides, since wider access to credit risk insurance enables banks to reduce their vulnerability to idiosyncratic or industry-specific credit risk shocks, these recent financial innovations may well have enhanced financial stability.

Both market and funding liquidity are also enhanced by these recent financial innovations. For instance, through securitisation, a bank can obtain liquidity to provide new loans. Insofar as the growing presence of hedge funds in CRT markets contributes to its deepening and widening as a result of the increase in market liquidity, hedge funds facilitate securitisation by banks. In turn, this reduces banks riskiness, strengthening their funding liquidity capacity, i.e. banks have the ability to lend to more profitable projects. Consequently, the supply of credit may be less dependent on conditions affecting banks funding ability, which in turn allows the economy to sustain higher investment and growth.

By accessing the market for credit risk, banks are able to sell some loans to the market where relations are conducted at arm s length. This not only allows banks to lend more (and generate more non-financial investment) but also to specialise more in the risks in which they have a comparative advantage i.e. those risks that arm s length markets are not particularly good at dealing with. All of this improves both the efficiency of the financial system and economic growth.[2]

[2] See for instance Rajan (2005).

Financial innovation through the increase of arm s length finance may also have affected bank-firm lending relationship. By relationship lending I mean that, through repeated contact, banks and their customers build up agreements on terms of credit, implying for instance secured access to credit lines at pre-set prices. The bank acquires expertise about the credit-worthiness of its customer by keeping close contact with the management of the firm. For instance, the bankers who sit on the board of many European firms can gain insider information on these firms. The implication of this close link may be that the bank provides the firm with easier access to liquidity, especially in times of tight supply of funds. In consequence, through the increase in arm s length finance, it is possible that the liquidity insurance provided by banks may be reduced for some firms. In addition, it may be more difficult for these firms to renegotiate their debt in times of distress i.e. it is more difficult for very distressed firms to renegotiate their debt with the market (arm s length finance) than to renegotiate it with the bank that they have a close relationship with. Both the reduction of liquidity insurance and the difficulty in renegotiating debt may reinforce declines in investment during downturns.

More arm s length finance and lower relationship lending may thus increase the volatility of the business cycle. This potential risk should be viewed against the potential benefits that credit risk transfer instruments apart from improving the possibilities of risk sharing may improve the ability of financial intermediaries to elastically offset tight credit supply in downturns. I will come back later to this point.

All this means that, from a theoretical perspective, the swift development of credit risk transfer instruments over the last years could increase or decrease the general riskiness of banks. The net effect is therefore an empirical question. As a matter of fact, Raghuram Rajan, the Economic Counselor and Director of Research at the IMF, argued in his contribution to the last Jackson Hole conference that the evolution of these instruments may not have reduced the riskiness of individual banks.[3] Actually, risk developments seem to vary across different countries and over time. He advances, however, the hypothesis that the incentives of managers in market-oriented forms of finance is likely to lead to increased forms of risk taking in terms of small probability extreme forms of risk, known as tail risk . Available evidence is actually consistent

[3] See also Gropp (2004).

with somewhat increased multivariate tail risks among major banks in the euro area and the United States.[4] The policy panel which Mr. Papademos will chair this afternoon will address the financial stability implications in detail.

Overall, these recent financial developments increase the importance of arm s length finance, improve the possibilities of risk sharing and augment both funding and market liquidity. The better performance of the financial system facilitates greater possibilities of financing for households and firms. Consequently, these financial innovations may be beneficial for the overall performance of the economy and thereby support growth.

III. Implications for monetary policy

The implications of financial innovations for the transmission mechanism are not straightforward. One reason is that they touch on more than one channel through which monetary policy operates. Another reason is that financial innovations may have ambiguous effects on the strength of the transmission mechanism.

On the one hand, the recent financial innovations have made financial systems more developed. In particular, market and funding liquidity creation is enhanced by these innovations. Suppose, for instance, that the central bank were to increase interest rates. Since the cost of funds would be higher, bank loans should decrease. Banks could nowadays, however, obtain liquidity through more securitisation. Notice the increasing importance of hedge funds as a source of liquidity in CRT markets. This access to liquidity partially insulates banks from the direct effects of monetary policy. In fact, there is evidence that securitisation has reduced the effect of funding shocks on banks credit supply. Hence, securitisation may have weakened the link from bank funding conditions to credit supply in the aggregate, thereby partially mitigating the real effects of monetary policy.[5]

On the other hand, more arm s length finance can weaken the liquidity insurance provided by banks to their customers through relationship lending. That is, relationship lending implies that, as a tendency, a bank insulates its customers from

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[4] See Hartmann et al. (2005).
[5] See Estrella (2002) and Loutskina and Strahan (2005).

liquidity or interest rate shocks. In case of a drop in its cash flow, for example, a firm can draw on a credit line that has been previously negotiated. Likewise, bank lending rates will not necessarily be adjusted in line with market interest rates. While firms that have access to these risk-sharing schemes can be expected to pay some form of an insurance premium to the bank, their decisions on investment, employment and production should be less sensitive to financial shocks. In consequence, through the weakening of the liquidity insurance provided by banks, more arm s length finance may strengthen the real effects of monetary policy.

Furthermore, loans which will be securitised tend to have interest rates that are more closely tied to market interest rates.[6] By arbitrage in capital markets, securitised corporate loans ought to have similar interest rates than other securities of similar risk. Thus, a change in market interest rates should also change the rate on loans that will be securitised. As a result, with securitisation, the influence of monetary policy on corporate loan rates may as well depend on its ability to affect market interest rates, and not only on its direct ability to influence the cost and availability of funds to banks. As a consequence, more arm s length finance may shorten the legs in monetary transmission.

We have seen how the interest rate and the credit channels of the transmission mechanism are affected. In addition, the wealth channel of the transmission mechanism is also affected by securitisation and the spreading of hedge funds. As I mentioned earlier, non-financial firms and households nowadays bear more systematic risks. For instance, households have higher levels of debt and participate more (directly and indirectly) in the stock market. Hence, an increase of interest rates through the reduction of the value of debt and equity nowadays has stronger real effects. In consequence, recent financial innovations are likely to increase the importance of wealth effects for the conduct of monetary policy.

All in all, recent financial innovations may have changed the strength of monetary transmission. Furthermore, since arm s length finance has increased and financial markets react quickly the speed of monetary policy may have increased.

[6] See Sellon (2002).

Now let me turn to the implications for the ECB s monetary policy strategy. Earlier this year at Jackson Hole, Raghuram Rajan pointed out that: somewhat *obviously*, one can no longer just examine the state of the banking system and its exposure to credit to reach conclusions about aggregate credit creation, let alone the stability of the system. [7] At the ECB, we do not only consider monetary and credit aggregates. We take institutional factors and financial innovations into account in our two-pillar strategy. However, money and credit aggregates remain very relevant. For instance, empirical evidence suggests that monetary and/or credit aggregates are important indicators for financial and price stability over the medium term.

Let me explain these issues in more detail. The emergence of new financial products may lead economic agents to substitute money with other types of assets, potentially affecting the information content of those assets and the demand for money. This could potentially have destabilising effects on money demand. The ECB s monetary policy strategy is designed in such a way that monetary policy decisions can take account of the consequences of financial innovation. The ECB carefully analyses monetary developments and their information content for price stability. In addition, by cross-checking the information from monetary developments with that of a wide range of non-monetary economic variables, monetary policy is made robust against the possible effects of financial innovation on money demand. As demonstrated in several recent papers, extraordinary increases in asset prices have typically been accompanied by strong monetary and/or credit growth. This empirical relationship suggests that monetary and/or credit aggregates can be important indicators of the possible emergence of asset price bubbles , and thus are crucial to any central banks approach to maintaining macroeconomic and price stability over the medium term.[8]

IV. Conclusion

Overall, securitisation and the spreading of hedge funds may improve the efficiency of the financial system, foster liquidity creation and increase the capacity of risk sharing in the economy. In turn, this may increase investment and allow the economy

[7] See Rajan (2005).
[8] See for instance Detken and Smets (2004).

to sustain higher growth. Furthermore, though a better financial system facilitates the operation of monetary policy, some financial developments may change the way in which the economy reacts to it, or may affect the information content of the indicators that central banks regularly monitor. The ECB s monetary policy strategy is well designed to deal with these challenges.

I thank you for your attention and I hope you enjoy the coming two days at the ECB.

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DINNER SPEECH

ANDRÉ ICARD

DEPUTY GENERAL MANAGER OF THE BANK FOR INTERNATIONAL SETTLEMENTS

Introduction

I would like to begin by expressing my gratitude for being given the opportunity to address this impressive group of academics, risk management professionals and central bankers.

* * *

I am sincerely glad to be here, as the topic of this conference – "Risk measurement and systemic risk" – is of special interest to me, for at least two reasons: first, as the BIS's Chief Risk Officer (CRO), issues related to risk measurement are very much a part of my day-to-day activities. Fortunately, or unfortunately, running an effective risk control unit can be a "boring" exercise. In fact, the more successful the unit, the less you have to worry about, and the more "boring" your life can be. But, all in all, if I had to choose between comfort and excitement in this kind of business, no doubt I would much prefer to confine myself to interpreting the results of stress test scenarios, rather than having to deal with live situations.

Second, as a former member of the committee now named CGFS (Committee on the Global Financial System), the focus on systemic risk issues has been part of my professional career, from the Latin American crisis in the mid-1980s to the episodes of financial instability that we have experienced most recently.

That is why, using my two roles at the BIS as a starting point, I will organise my speech tonight as a story of two perspectives: (1) The *CRO's view* on the importance of risk management for the day-to-day operations of the BIS as a bank; and (2) a *central banker's view* on the changing nature of the concept of systemic risk.

The CRO's view: the role of risk measurement and management

It may come as a surprise to some of you that the BIS not only bears the title "bank" in its name, but actually is a bank – although a very specialised one. Indeed, with a balance sheet of SDR 180bn (the equivalent of EUR 210bn, as of end-March 2005), the BIS offers a wide range of financial services to assist central banks and official monetary authorities in the management of their foreign reserves.

How is risk measurement and management important for the BIS?

The BIS aims to offer its central bank customers two key things: the "safety and liquidity" of their deposits and the reliability of the BIS's services – even in times of crisis. By design, it is thus a "conservative" investor, avoiding many of the risks that other banks take. This implies that, for lack of involvement in trading some of the more complex instruments used by private sector institutions, demand for highly sophisticated risk measurement and management tools is perhaps somewhat less pronounced than elsewhere. Still, like any other financial institution, the BIS has to balance the opportunities and complexities created by financial innovation with best practice standards, customers' demands for diversified services and shareholders' preference for prudence. Hence, there is a need for constant monitoring of market developments, counterparty assessments, and the subsequent determination of any adjustments to the bank's overall exposure to credit, liquidity and market as well as operational risks. In other words, there is a need for quantitative approaches, such as value-at-risk based models and stress tests, to measure and effectively control risk, appropriately embedded into an overall risk management framework. Indeed, we find it useful to discipline ourselves by having the communication channels and internal controls in place that are so essential in fostering a risk management culture within an organisation.

* * *

Let me note that all this is very much standard procedure across the financial world. But "best practice" has evolved substantially over the last 10-15 years. One issue that is of particular concern for the BIS and, in fact, regularly consumes quite a bit of my own attention is the trade-off between credit quality and concentration risk considerations. To control this risk, we have a series of limits in place, which are derived from the BIS's own internal credit analysis. Among other things, this analysis utilises a Merton-type model and credit default swap spreads in looking for market signals on credit quality. This, again, is very much standard. However, given the aim of providing our clients with "safety and liquidity", our policies result in the vast majority of the bank's assets being invested with high-quality sovereigns or financial institutions rated A or above. In addition, the number of counterparties big enough to accommodate our business needs is very limited, especially in the domain of OTC derivatives. As this limits the number of eligible investments and counterparties, the BIS runs significant credit risk and business volume concentrations. In fact, the resulting triangularity between credit quality, liquidity and concentration is exacerbated not only by the growth of our own business volume, but also by the continuing merger activity among issuers and counterparties. As most of you will agree, a situation like this requires careful monitoring and management of the resulting risks; and models alone, though helpful, do not guarantee that we get such a trade-off right. Furthermore, the use of collateral can help mitigate the counterparty risk posed by positions in OTC derivatives, but leaves open a significant part of the risk involved.

Still, sound risk measurement is an indispensable tool for providing decision-makers with the quantitative information needed to better understand the inherent risks of alternative decisions and to underpin otherwise qualitative judgments.

On this basis, I think it is fair to say that financial research has materially influenced the way business is done at the BIS, as is generally the case in the financial sector. It has done so not only by pushing financial innovation and expanding the range of instruments and tools available for trading and risk management, but also by strongly influencing the character of regulatory and policy initiatives. Basel II, quite obviously, is the key example in this regard.

Even abstracting from Basel II, however, I think it fair to argue that advances in risk measurement have enabled market participants, including the BIS, to better differentiate among different types of risk, "slice and dice" them, and spread these risks more widely and in ways that are likely to better align risk exposures and the actual risk-bearing capacities of those who assume these risks. Not for no reason, therefore, is better risk measurement credited with having helped to enhance the resilience of the global financial system in the face of the many challenges encountered in recent years.

Yet, the notion of "systemic risk" and the nature of the challenges posed in safeguarding financial stability have themselves been subject to change over time – indeed, the pursuit of this stability seems akin to "shooting at a moving target". Let me address this topic next.

The central banker's view: the changing nature of systemic risk

Drawing on my experience, I would now like to spend some time going through parts of the evolution of the "systemic risk" concept. In other words: what are the questions that have occupied us over the past two decades or so?

* * *

In the mid-1980s, a more or less explicit assumption behind the concept of systemic risk was that systemic disturbances would essentially arise and spread within the banking sector. Progressively, however, the attention shifted away from bank lending, ie dependencies on common risk factors, and interdependencies between banks, to also include banks' reliance on financial markets and market infrastructure, such as payment and settlement systems.

While there have certainly been earlier crisis episodes, a defining event was the Latin American debt crisis of 1982-83. Simply speaking, this crisis was about large and growing bank exposures to a relatively narrow set of sovereign borrowers that had accumulated increasingly unsustainable external debt positions. Much has been written about whether or not the amount and concentration of banks' exposures as well as their maturity profile was known before the crisis actually erupted. For the purpose of this speech, it suffices to say that the CGFS (then called the Euro-currency Standing Committee) actively helped – even before the crisis – to quantify the growing external indebtedness of the crisis countries. Indeed, the BIS banking statistics have been in the public domain since end-1975 and the growing exposures were there for everyone to see. Yet, this didn't help to avoid the crisis – but that is another story.[1]

What I would like to emphasise on this occasion is merely that concerns at the time of the Latin American crisis mostly rested on international banks' joint exposures to particular borrowers. However, after the Latin American crisis, attention shifted, first in reaction to the growth in interest and foreign exchange derivatives markets and the increasing involvement of international banks in capital market activities. The CGFS's so-called "Cross Report" (1986) put some emphasis on risks associated with off-balance sheet as well as securities market exposures. A few years later (1990), another central bank report, which bears Alexandre Lamfalussy's name, placed the focus on interbank exposures and the idea that netting can reduce the size of credit and liquidity positions incurred by market participants – which, in turn, should help to contain systemic risk. At the same time, however, it was recognised that netting may also obscure exposure levels and that multilateral netting may concentrate risks, while raising legal enforceability issues – possibly increasing the likelihood of multiple failures.

* * *

But the story didn't end there: financial and technological innovation have continued to foster the growth of risk transfer markets, such as derivatives and structured products, while deregulation has helped to further increase the growth of cross-border activity and the entry of new market participants. As a result, financial systems overall have become more competitive, less bank-based and more market-based. Indeed, when comparing the 1982-83 Latin American crisis to the 1994-95 "tequila crisis", the debtors had not fundamentally changed, but instruments and lenders had. Loans had been replaced by bond securities, while the creditors were no longer exclusively banks, but more generally bondholders. In the case of the Asian crisis (1997) then, banks – though local ones – again took centre stage, this time as

1 See the BIS's 1982 Annual Report for more detail. An "eye witness" account of this and three other financial crises, as well as lessons for crisis prevention and management, can be found in Lamfalussy, *Financial crises in emerging markets: an essay on financial globalisation and fragility*, 2000.

borrowers in the international debt market and lenders to an excessively leveraged corporate sector.

The consensus view, therefore, is that systemic disturbances are now more likely than in the past to erupt outside the international banking system and to spread through market linkages rather than lending relationships. LTCM is the most prominent example of how this might happen. Indeed, the Russian crisis of 1998, which is so closely linked to the LTCM episode, also marked a new experience in that a "regional event" on the periphery spread through global bond, credit and equity markets.

The concept of systemic risk has thus been broadened along several dimensions: (1) it has come to explicitly include non-banks along with banks; (2) the concept has moved beyond traditional lending to include all sorts of financial activities and resulting exposures, including exposures to operational and reputational risks; while (3) the focus is now firmly on interdependencies between market participants as well as their exposures to common risk factors, including institutions' reliance on core parts of market infrastructure.

The last point is of some importance, as a relatively small number of institutions has become key to the integrity and smooth functioning of quite a number of markets. As these players combine various forms of intermediation activities, on and off balance sheet, it is conceivable that problems in one of these activity areas could affect the activity of other parts of the firm, and thus spread across various markets. Idiosyncratic shocks to key bank or non-bank institutions, particularly when coinciding with *systematic* factors, could thus become *systemic*. Indeed, the concentration phenomenon that I identified in the first part of my talk as a feature of the BIS's risk exposure reappears here as a potential concern about the system's "plumbing".

Let me give you one example: the recent troubles at Refco, an important futures broker. The dust has not yet settled, making an in-depth analysis difficult. However, it seems that the discovery of a serious case of accounting-related fraud at one of its subsidiaries, while relatively minor in absolute terms, has in practice led to the collapse of that company.

While big, Refco was probably not big enough to matter in any systemic sense, and its crucial futures brokerage continued to be operational. But the events surrounding its demise offer a taste of how the proverbial "flap of a butterfly's wing" could cause repercussions throughout the financial system by affecting parts of the market infrastructure. What if a bigger broker with more of a presence in OTC instruments had been hit by the same event? At the risk of overemphasising the point, I find it relatively easy to imagine that cases involving bigger institutions with more complex net positions would have much broader implications.

The role of research

In closing, let me briefly answer one last question: how is all this related to research and, hence, this conference?

Structural change, though a good thing in general, also means uncertainty. While there is agreement that most of the structural developments observed since the first Latin American crisis have in fact been efficiency- and stability-enhancing, the increasing interaction of markets and institutions has also meant that the financial system has become more complex. This complexity, in turn, has resulted in more uncertainty as to the origin and nature of shocks to that system and how these will actually play out.

This is where research can help. Again, there are two dimensions. The first relates to the need to better understand the interactions between different market participants as well as the implied interaction of idiosyncratic and systematic risks in the event of shocks.

The second dimension is closely related and calls for research to help in improving practical risk measurement solutions – at both the individual firm and system levels. A key challenge in both cases is to operationalise any findings for the use of policymakers, regulators and practitioners.

There is, thus, plenty of scope for research to continue contributing to ongoing policy discussions, and it is on this note that I now formally end the first day of this conference.

CLOSING REMARKS

LUCREZIA REICHLIN

DIRECTOR GENERAL RESEARCH
OF THE EUROPEAN CENTRAL BANK

Ladies and Gentlemen,

It is my great pleasure to address you after two intense conference days here at the ECB.

I know that after two days of a very intense conference you must be exhausted by now, so I will be very brief.

I will organize my remarks in three parts.

In the first part, I would like to review a little bit the history and tradition of this conference.

In the second part I will discuss some issues in areas that are a little bit closer to my own current research interests, namely issues relevant for monetary policy and macroeconomics.

And last, I would like to look ahead a bit and see what comes next.

1. The tradition of the Risk Measurement and Systemic Risk conference

The Joint Central Bank Research Conference on Risk Measurement and Systemic Risk (RMSR) under the auspices of the G-10 Committee on the Global Financial System, the former Euro-currency Standing Committee, has now a decade of history.

The first edition was hosted in 1995 by the Federal Reserve Board in Washington, DC. It featured papers on credit risk, market volatility and co-movements, trading techniques, market risk management models and systemic risk in the banking sector.

At the time, Federal Reserve Chairman Alan Greenspan deplored the widespread use of thin-tailed distributions in the measurement of portfolio risk and in the assessment of overall banking system risk. He said that improving the characterization of the distribution of extreme values is of paramount concern . I am happy to say that not only we here in DG Research of the ECB, but also other researchers and policy institutions have made progress in using extreme-value theory to analyse the events we care most about from the perspective of financial stability. More generally, it seems that the themes of RMSR 1 have remained important over the years and they still constitute core areas of interest in the later editions of the conference.

In 1998 the Bank of Japan hosted Risk Measurement and Systemic Risk in Tokyo. This was actually the first time that we , which meant at the time staff of the European Monetary Institute (the predecessor of the ECB), actively participated in it. This second edition focused very much on systemic risk in banking and payment systems, stress scenarios in financial markets   memories of LTCM must have been fresh at the time , market microstructure studies of financial instability and central bank policy responses to systemic risk.

 Issue 3 took place in 2002 at the Bank for International Settlements in Basel. It was the first time that the ECB acted as a co-organiser of RMSR , only three years after the introduction of the euro and immediately after the circulation of euro banknotes and coins in the euro area.

At the time liquidity was very high on the research agenda. At the conference it was particularly debated whether liquidity dries up during financial crises, making them deeper and more widespread, and through which mechanisms that could happen. Clearly, this phenomenon is a major concern also today. For example, on the days after the terrorist attack of 11 September 2001 it was of crucial importance that the Eurosystem was able to provide US dollar liquidity to European banks with the help of a swap arrangement with the Federal Reserve Bank of New York.

We at the ECB here are very pleased to have been able to host the fourth edition of the conference now. Collaborating with the Federal Reserve Board, the Bank of Japan and the CGFS Secretariat we have tried to stick to its tradition, while gearing the program towards research and policy issues of highest relevance at the present time.

We identified the pricing, trading and transfer of credit risk, particularly through so-called structured products, as an area that deserves particular attention. It is more for you than for me to judge whether the conference has been successful in providing you with new and interesting insights in this regard.

2. Financial stability, monetary policy and the macroeconomy

This brings me to the second part of my remarks, which will refer to the last session we saw today. It is the session that is closest to the question how monetary policy and financial stability interact. I firmly believe that this is a key issue, but we are still in a learning process to understand very basic questions in this regard. We in the ECB pay increasing attention to financial sector issues in general and the link of financial stability and monetary policy in particular. And if I may say, Otmar Issing and Lucas Papademos who addressed you before are certainly key drivers of this process.

The paper by Bill Nelson and Roberto Perli on Selected Indicators of Financial Stability presents a number of key market-based indicators of financial stability that need to be monitored closely, both for the purposes of maintaining price and financial stability.

This is a good illustration of what central banks should look at when monitoring financial systems. Given the new developments in financial markets that this conference has discussed, central banks will be well advised in deriving also new indicators for monitoring financial systems. These could provide useful information in addition to the one contained in traditional bank credit and monetary indicators.

Market participants closely monitor these measures as well. Following the evolution of these measures, therefore, helps to understand how large institutional investors assess financial risks. This may also help policy makers in communicating with market participants.

I have been particularly struck by the finding that almost a fifth of the downward trend in US ten-year government yields can be explained by hedging strategies of large players in the mortgage-backed securities (MBS) market.

The presence of spillovers is a feature that has received some attention, but this is indeed a high figure!

In general, what are spillovers telling us about monetary policy? How much do they explain of the break in the relationship between short and long term interest rates, which has been called by the Federal Reserve Chairman the interest rate conundrum? As it has been stressed by the work of Hyun Shin and others, in standard models for monetary policy financial markets play a passive role. They are far-sighted but essentially passive. This might not be a good representation of the world, and I am definitely more convinced of this after two days at this Conference. Is the break in the term structure a symptom of financial market activism and what does this tell us about the effectiveness of monetary policy? Food for thought for research and for another conference!

The other two papers of the Section focus on the relation between credit risk and macroeconomic variables. This is a more standard subject for monetary policy, but the papers bring interesting insights which lead to new questions.

The paper by Mathias Drehmann, Andrew Patton and Steffen Sorensen on Corporate Defaults and Large Macroeconomic Shocks puts the emphasis on non-linearities and large monetary policy shocks. The main point of the paper is that standard linear macro models tend to over-estimate the impact of small monetary policy shocks on credit risk and under-estimate the effect of large shocks.

This result provides a new perspective on the recent monetary policy debate on the value of gradual policies and interest rate smoothing. Small gradual changes in policy may be less destabilising. Distinguishing between standard and extreme shocks is a very useful idea and I hope that future research on other countries will shed further light on these asymmetric effects.

In Exploring Interactions between Real Activity and the Financial Stance Tor Jacobson, Jesper Linde and Kaspar Rozbach study interaction and feedbacks between firms balance sheets and the macroeconomy. This is a nice paper, which exploits information from a rich panel data set that covers firm balance-sheets for almost all Swedish incorporated companies. The paper makes points which are important both for understanding the role of the credit channel in monetary policy and the interaction between financial stability and monetary policy.

Their findings suggest that the response to a given monetary policy shock depends on the portfolio structure of firms and that monetary policy is more effective during recessions than during booms.

Here I have some questions and suggestions for further research. The credit channel for monetary policy identified by this paper would suggest that the effect of monetary policy is amplified with respect to the conventional interest rate effect. This points to greater effectiveness of monetary policy, whereas the observation I made before on the weakened link between short and long rates suggests lack of effectiveness via the term structure channel. How do we quantify the relative importance of these different effects? This is a key question for the understanding of the monetary transmission mechanism.

According to the authors, the amplification of monetary policy is at work especially during recessions. Since there is only one in their sample this conjecture requires further empirical research with longer data series.

I would encourage research that uses event study methodologies to analyse what happens during recessions. Recessions are indeed very informative events to understand the role of large shocks for both financial fragility and the propagation of monetary policy. Unfortunately, there are only few of them! (I am of course joking here.)

Let me now get to the third part of my remarks.

3. Next steps

What are the next steps?

Let me emphasise again that research on Risk Measurement and Systemic Risk remains important for central banks. Central banks manage risks on their balance sheets from foreign exchange portfolios as well as domestic assets and liabilities. Even when they have no direct supervisory responsibility, as the case here at the European Central Bank, they have to have a good understanding of risks in financial institutions, which include the reliability of their risk management practices.

More generally, central banks need to have a deep understanding of vulnerabilities in banking, in particular credit risk, and other parts of the financial system that could lead to a systemic crisis. The ECB s Financial Stability Review, whose second edition will come out next month, is an important tool in this context. Last, as I was trying to argue in the previous part of my remarks, central bankers need to know how monetary policy interacts with financial stability.

This is why we in the ECB will continue conducting research on Risk Measurement and Systemic Risk in order to support financial stability monitoring and effective policies. This is also why I very much hope that in three years from now we will see a fifth edition of RMSR and that it will raise as much interest as the one held here in Frankfurt, as suggested by the 170 participants who attended over the last two days.

My last remark relates to another good tradition of RMSR . In all previous editions a little volume has been produced displaying or summarising the conference contributions. The organisers from the Fed, the BoJ, the CGFS secretariat and the ECB will contact all authors in the next few weeks to explore whether and in which format this tradition should be continued. Meanwhile, all papers will be available on the internet.

So, let me thank you all again for participating and actively contributing to this exciting conference. Good bye and have a safe trip home.

PART 2

POLICY PANEL

THE POLICY IMPLICATIONS OF CREDIT DERIVATIVES AND STRUCTURED FINANCE: SOME ISSUES TO BE RESOLVED

LUCAS PAPADEMOS

VICE-PRESIDENT OF THE EUROPEAN CENTRAL BANK

Ladies and gentlemen,

Welcome to our panel discussion this afternoon. I would like to extend a special welcome to the members of the panel. We are particularly pleased to have brought together such a distinguished and diverse group of speakers, who come from the private as well as the public sector. In my introductory remarks, I will first briefly summarise the current state of our knowledge concerning the impact of credit derivatives on the financial system. Then I will point to, and briefly discuss, a number of issues where our understanding is less than perfect.

I. Background to the CRT debate

Let me start with a few general observations regarding the market for credit risk transfer (CRT) instruments. Despite considerable structural change in the financial system, the risk profile of the banking system is still dominated by its credit exposure. Institutions build up exposure to credit risk not only through their lending activities, but also through their position-taking in the corporate bond market or through transactions in over-the-counter markets, where banks also face the risk of the counterparty defaulting.

In the past, the transfer of credit risk was very difficult and costly. The introduction of credit derivatives less than ten years ago can therefore be seen as a major structural improvement because it has made credit risk tradable. Since this fundamental risk category can now be bought and sold like other financial risks, such as interest rate risk, banks can hedge and diversify most of their positions which are exposed to credit risk. The existence of a properly functioning market for credit risk has enabled banks to improve their pricing and also their management of this risk category. The CRT market has been a major financial innovation in recent years; it has developed at a very fast pace over a relatively short period of time and is already offering significant benefits to banks and institutional investors.

Market participants particularly value the benefits resulting from the ability to transfer risks and reduce risk concentrations. In addition, CRT activity also contributes to more liquid markets for credit risk generally. According to a report by the Joint Forum,[1] CRT activity is also fostering some significant long-term changes in the approach taken by credit market participants. For example, the pricing of credit risk for large investment-grade borrowers is increasingly based on an assessment of the marginal risk contribution to a portfolio of credit exposures, as opposed to a pure "stand-alone" assessment. While a similar approach has been applied to stock markets for a long time, credit markets' progress in this direction will undoubtedly have beneficial effects on their functioning.

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[1] Basel Committee on Banking Supervision (2005), "Credit Risk Transfer", report of the Joint Forum, Basel, BIS.

The ECB (in cooperation with the ESCB Banking Supervision Committee)[2] has also published a report on this topic which examines the activities of EU banks in CRT markets on the basis of the most comprehensive survey undertaken by EU supervisors and central banks on the use of CRT instruments. The ECB report presents a tentatively positive overall assessment of trends in the CRT market, arguing that the improved ability of banks and other financial institutions to diversify and hedge their credit risks is helping the financial system to become more efficient and stable.

Nevertheless, the report also identifies the need for improvement in areas such as transparency and risk management practice. More generally, our analysis has frequently highlighted a number of issues where our knowledge of the functioning of this market and its impact on systemic risk is rather limited. I will now focus on those issues, not least in order to provide some material and "food for thought" for our panel discussion. I believe there are at least three interrelated questions to which we have not yet found satisfactory answers.

II. Some open issues in the CRT debate

First: *What are the consequences of the (at least partial) transfer of credit risk from regulated to less regulated, or unregulated, entities?*

The first area where we should extend our knowledge relates to the opacity of the credit risk transfer markets. Here, a particular challenge arises from the growing role of "alternative investors" in the new market. There are concerns that credit risk is being reallocated (more and more) to unregulated market participants who are not subject to sufficient disclosure requirements. Empirical evidence on system-wide risk allocation is still sketchy. Hence, we lack reliable information on the potential distribution of "hidden risks".

With regard to this issue, we can draw some lessons from the first major and real "stress test" of the CRT market, which we witnessed earlier this year. There is some evidence that the downgrading of the credit ratings of GM and Ford to below investment-grade levels in May 2005 had an adverse impact on markets for credit derivatives. In particular, the two downgrades caused abrupt and unexpected changes in the relationships between the prices of a number of assets, forcing many investors, particularly hedge funds, to rebalance their portfolios in order to adjust their hedges and reduce their risk exposures. These transactions reduced liquidity in a number of market segments. As many hedge fund investors had similar positions, the concealed concentration of these positions magnified the selling pressure.

In this context, it may be useful to emphasise that credit risk transfer by means of credit derivatives or securitisation transactions does not always eliminate the entire credit risk from the protection seller's

[2] European Central Bank (2004), Credit risk transfer by EU banks: activities, risks and risk management.

portfolio. For instance, in most collateralised debt obligation (CDO) transactions, the equity or "first-loss" component remains with the issuer and serves as the first level of protection against defaults in the underlying assets in the pool. Another example of an incomplete risk transfer stems from single-name products such as credit default swaps. In this case, the underlying default risk is certainly transferred, but in exchange the protection buyer acquires exposure to counterparty risk. These two examples show that credit risk transfer also entails risk transformation.

The second question that must be addressed is: *To what extent are risks being transferred from better-informed to less-informed market participants? And what are the implications of this?*

Credit markets are, in general, characterised by asymmetry in the information available to banks and their creditors. In the CRT market specifically, there is an asymmetric distribution of information between those who evaluate risk and those who bear it. The role of rating agencies in structured finance is therefore crucial, as they provide an external risk assessment on many transactions, such as collateralised debt obligations.

A report published earlier this year[3] by the Committee on the Global Financial System has voiced considerable concern about the role of rating agencies in the credit risk transfer market. In particular, it argues that ratings may provide an incomplete description of the risks incurred in structured finance. If structured finance investors rely too much on ratings, they may unintentionally become too strongly exposed to unexpected losses, as the rating agencies mainly consider only the expected losses in transactions. In this context, due diligence is a key requirement for investors. Those willing to invest in structured finance should not only rely on rating information, but rather develop the necessary know-how for their independent risk analysis.

Hence, in order to mitigate this concern, we need to expand our knowledge on the information available to investors in credit derivatives or structured finance instruments. In particular, the new instruments require prudent valuation and risk-management practices, as they may entail significant risks for un-sophisticated market participants.

The third, and final, question we must answer is: *What are the consequences of CRT for financial stability monitoring?*

In my view, CRT presents a number of interrelated challenges for financial stability monitoring. First, we need to draw the appropriate conclusions from the fact that the information content of notional values is quite limited. Currently, banks' CRT exposure is mainly reported as the nominal value of their positions. However, in order to analyse an institution's exposure, it is crucial for central banks to try to collect information, at least about the rating or expected loss of a specific collateralised debt obligation tranche.

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[3] Committee on the Global Financial System (2005), "The role of ratings in structured finance: issues and implications", Working Group Report No 23.

Second, there are significant concerns about the reduced information content of the balance sheets of the new holders of credit risk. For instance, more detailed information on the insurance sector's exposures may be required. For central banks' monitoring of financial stability, these two uncertainties certainly complicate a comprehensive analysis of systemic risk in the financial system.

Third, the importance of monitoring market liquidity is also increasing. Given the pivotal role of these new markets, their orderly and uninterrupted functioning is crucial for the financial system as a whole. This is also one of the lessons learned from the downgrades in May 2005 which I have already mentioned. Compared with other risk categories, we know relatively little about liquidity risk, both from an academic as well as a policy angle.

Unless we can expand our knowledge in these areas, it may not be possible to draw definite conclusions about the overall impact of credit derivatives or structured finance instruments on the stability of the financial system. Keeping these three questions in mind, I hope that we can have a lively and informative discussion.

Thank you for your attention.

POLICY IMPLICATIONS OF THE DEVELOPMENT OF CREDIT DERIVATIVES AND STRUCTURED FINANCE

EIJI HIRANO

1. Introduction

It is a great pleasure for me to speak at this distinguished conference. The development of credit derivatives and structured finance markets is probably the most important development in international financial markets over the last decade, and it has wide implications on policy including our thinking on systemic risk.

Hearing a lot of arguments today, I am impressed, stimulated and overwhelmed by the enthusiasm of the participants. Frankly speaking, I take great comfort from the questions from the floor, which clearly point to the need for our further efforts in filling the gap between model implications, the true state of the markets, and possible policy challenges.

Today, I will first illustrate our experiences so far in the Japanese credit derivatives and structured finance markets, comparing them with the global markets. I will then raise some policy issues, which we could discuss in this session. Before going any further, I should note that any views expressed are my own and do not necessarily represent those of the Bank of Japan.

2. Development of the Japanese credit derivatives and structured finance markets

In order to understand the significance of developments in the Japanese markets, it is useful to review quickly what is happening in the global market.

As you know, the global credit derivatives and structured finance markets have recently seen remarkable growth. According to a market survey by ISDA, which is often cited, outstanding amounts of credit default swaps in notional terms jumped from 0.6 trillion dollars in the first half of 2001 to 12.4 trillion dollars in the first half of 2005.

Furthermore, there has been a change in how risks are transferred between market participants. According to the Credit Derivatives Report published by the British Bankers Association, the market share of hedge funds as sellers of credit protection has trebled from 5% in 2001 to 15%

in 2003. The same Report shows another interesting development. In 2001, credit derivatives were traded mainly because banks had to adjust their exposure to credit risk in the light of individual credit lines and capital adequacy regulations. Trades motivated as such overwhelmed trades for product structuring and hedging. In just two years, in 2003, the opposite occurred: product structuring became far more important than adjusting credit exposure at the margins.

We can identify three stages in this development process.

In the first stage, the markets emerged out of necessity. Banks had to control risk exposures associated with assets such as bank loans, and began to use these products. Accordingly, banks originated credit derivatives and structured finance products, and the growth of the markets was broadly constrained by the size of the credit exposure that banks had on their balance sheets.

In the second stage, the markets grew in both size and scope. Increasingly, products for trading and investment purposes became more important. No longer was it regarded necessary for an originator to have an underlying credit exposure. Market participants became increasingly diversified.

In the last few years, the markets seem to have entered a new stage. The dramatic acceleration in the pace of expansion is only part of the story. Today, market participants do not always have exposure to specific credits when they originate credit derivatives and structured products. In other words, trading is increasingly becoming concept-led rather than credit-led. Products such as single-tranche CDOs and tranched index CDS are developed in order to meet newly developed trading strategies of market participants. As a result, the global aggregate gross outstanding positions in credit derivatives and structured finance have outgrown by far the referenced credit exposures. Obviously, the progress in information technology and financial engineering has driven such transformation and expansion. Cyclical factors may also have contributed to accelerating the expansion. The worldwide monetary easing may have encouraged market participants to dip their toes into the newly developed credit markets, as they searched for extra returns to compensate for the decline in returns on traditional credit products.

In comparison to this development in the global credit markets, the Japanese markets for credit derivatives and structured products are still in their infancy. For instance, outstanding notional amounts of credit default swaps in the Japanese market total only 51 billion dollars, less than 0.5% of the global markets.

The Japanese markets were born out of necessity as with much of the global markets. The type of credit exposure, however, was a little different. As the financial crisis hit Japan in 1997 and 98, Japanese banks had to restructure their credit exposures in order to survive. They were forced to liquidate distressed loans quickly and on a massive scale. A secondary market for these assets quickly emerged. Necessity was indeed the mother of invention. In addition, the corporate bond markets also expanded as an alternative credit channel to bank loans. These developments provided the Japanese credit markets with an opportunity to deepen and expand.

The liquidation of distressed assets was a backward-looking exercise, but helped Japan to establish the basic infrastructure of credit markets, for example, the legal and tax basis for the assignment and transfer of credit exposures. It also encouraged banks and other financial intermediaries to break out of their traditional business models and encouraged them to test new markets, such as credit derivatives, structured finance, and syndicated loans.

On this foundation, the Japanese credit markets are now following a clear uptrend. For the last few years, we have seen positive signs suggesting that Japan s credit markets are growing out of their infant stage. Global players of credit markets, such as hedge funds, have started to trade Japanese credits in credit derivatives markets. As a result, Japan s credit markets, left local for a long time, have increasingly become interconnected with the global markets.

This raises an interesting question. Can the Japanese market run before it has even learned to walk? Theoretically, the markets for trading credit provide tools for transferring risks to those who can best bear those risks. As a result, it is politically correct to say that markets should be able to keep on functioning even in the face of a downward credit cycle. On the other hand, a credit down-cycle tends to reveal new weaknesses in the system. Let me return to our episode in the bubble era.

In a bubble, positive outlook forms a strong feedback loop. Speculation fuels more speculation. Even the most prudent person is afflicted by hubris. During the Japanese bubble of the late 80s, Japanese banks began to expand their loan assets. They thought that larger assets would bring them higher profits. The borrowers were speculators in real estate, mainly non-banks, real estate developers, construction companies and retailers. As more banks lent against real estate collateral, real estate prices climbed, and banks could lend even more against enhanced collateral value. We are all familiar with what happened next when this cycle reversed, and I will not repeat it here.

We can obviously draw many lessons from these episodes. In the context of this conference, I would like to make two observations.

One is the importance of accurately measuring risks, in other words, setting prices consistent with fundamental economic value. Unless risks are priced correctly, they cannot be traded and assumed in a way that makes economic sense. The economic law of gravity will come back with a vengeance if risks are systematically mispriced. We should have paused for thought when we heard that we could buy the whole of the United States by selling all the land in metropolitan Tokyo.

The other point is the importance of good corporate governance. Even if you measure the risks correctly, you need a mechanism to ensure that traders are not entering into mispriced trades. I do not intend to elaborate on this, but during the bubble years, the behavior of Japanese banks was less than prudent.

The two lessons I have just mentioned accurate measurement of risks and good corporate governance are, in fact, elements of sound risk management. Are we confident that these elements are firmly established in the context of the markets for credits? Credits are extremely granular and fraught with event risks, therefore, we face a greater challenge in their pricing. After all, how can we objectively price the risk of the CFO or the CEO cooking the books, and the mitigating effects of Sarbanes-Oxley? At the same time, further development of credit markets, driven by credit derivatives, should enhance market discipline and enhance corporate governance. Nevertheless, we should also be aware that sound internal controls often lag behind the rapid expansion of markets.

As I said earlier, Japan s credit markets are likely to follow a growth pattern as shown in the global markets. This implies that Japan is going to share the common issues, both good and bad, with the global markets. Our job at the Bank of Japan is to ensure that Japanese market participants can begin running as soon as they have learned to walk.

3. Paradigm shifts in credit markets, and evolution of systemic risk

The current global credit markets can be characterized by three keywords: conceptualized, globally connected, and highly liquid. All three are interlinked. The expansion of the markets owes much to the increasing emphasis on conceptual, or standardized, products. The conceptual financial products make it easier for overseas institutions to enter local credit markets. One can trade credit exposure with certain standardized characteristics without learning the nuances of the local markets. As a result, local markets are more strongly connected to each other. A large market thus created with diverse participants should contribute to greater market liquidity.

Such an evolution in the credit markets poses a new challenge to today s global financial markets, particularly in view of systemic risk. The deeper and more liquid markets with more diverse market participants will contribute to enhancing market efficiency under normal conditions. Markets will also be more resilient.

Furthermore, the changes may have positive influences on the traditional source of systemic risk, i.e., a bank s insolvency or illiquidity. As credit is increasingly traded and thus priced in the market, it becomes practical and perhaps appropriate to mark a portfolio of bank loans to market. This will facilitate the earlier identification of insolvent banks. In addition, since it also becomes easier to raise cash against the traditionally illiquid portfolio, banks will be less prone to liquidity problems.

However, we must also be aware of the potential vulnerabilities once stress reaches a threshold.

There are issues arising from the conceptualized nature of the products. Since products are standardized, discrepancies or errors between the products and referenced credits are inevitable. In times of stress, such differences can create destructive dynamics, as market participants scramble to fill the gaps. Another issue is the diverse market participation that is facilitated by conceptualized products. No longer are banks the sole originator of credit exposures. This increasingly makes it difficult to locate any weak links in the financial system. The presence of non-regulated market participants will reduce visibility for authorities. For example, is the system more robust if a hedge fund writes default protection on a corporation about to go under?

Increased global linkages present us with more challenges. When risk materializes in one part of the global markets, it may quickly be transmitted to other parts of the global markets through the linkages. I heard many good arguments on this aspect today. Diverse participation may result in channels of transmission previously unknown to us. The ease with which conceptualized products are traded may result in extremely quick transmission.

Market liquidity may also be ephemeral and hide problems underneath. Theoretically, high liquidity strengthens an efficient price discovery function of the markets and it is desirable. However, if it is only a reflection of crowded trades, it can easily vanish at the first sign of stress.

In order to meet these challenges, central banks will have to review how they monitor the markets, and develop channels to exchange information across borders. We should do that, though we know that central banks may be systematically behind the market, as Dr. Issing alluded this morning. We will also have to develop our thinking on elements of market structure that will enhance resilience. Another issue is to understand pricing practices prevailing in the market, and developing the expertise to evaluate their soundness and robustness. To this end, we need more research. This conference provides us with valuable clues for our future research and opportunities to exchange issues among central banks and practitioners from all over the world.

For researchers, a set of enriched price information, which we can obtain today, can be an extremely valuable source of food for thought. I am encouraged to see so many insightful results presented in this conference. Among them, in Session VI, Dr. Nelson and Dr. Peril presented several indexes constructed from market data including CDS spreads. These indexes are monitored by the FRB, and this offers one example of a practical application of the price data to the monitoring of the markets. All three researches presented in Session III also use CDS spread data to examine information contained in the credit market data. The Bank of Japan is also interested in finding timely indicators of credit conditions. Likewise, in Section V, my colleague, Dr. Baba investigated whether the TIBOR-LIBOR spread can be a reliable credit index for Japanese banks.

In order to fulfill my duty of initiating the discussions in this session, let me conclude by outlining three broad sets of questions which we could explore today.

i) What are the key features of today s credit markets? I have referred to three: conceptualized, globally connected, and highly liquid. Are there any other features we should consider?
ii) What are the implications of the key features on systemic risk? How should we adjust our understanding of systemic risk?
iii) If the nature of systemic risk is changing, what should be our responses?

Thank you very much for your attention.

FINANCIAL REGULATION: SEEKING THE MIDDLE WAY

REMARKS BY

ROGER W. FERGUSON, JR.

I am pleased to participate in the panel discussion at this Fourth Joint Central Bank Research Conference. As I will make clear, I think conferences of this sort, by contributing to our understanding of financial innovations, can play a critical role in policymakers decisions. Financial innovations have been coming at a rapid pace in recent years; new financial products have been introduced and are expanding rapidly, and new institutions have taken on prominent roles in key financial markets. Financial technologies have improved as well and have the potential to contribute to the efficiency and resilience of financial markets. However, with new products and institutions comes the potential for new risks to financial stability. As a result, we policymakers are likely to be torn. On the one hand, we may want to encourage welfare-improving innovations by limiting the extent of regulation. On the other hand, because of possible systemic concerns, some policymakers may want to regulate innovative instruments and institutions even as they are developing. In my view, policymakers can best balance these goals by expending the effort needed to understand financial innovations as they emerge and by avoiding overregulation that may stifle valuable innovations.

When I talk about financial innovations, I have in mind several types of developments. A far-reaching set of innovations--and the focus of this panel--is the development and increasing popularity of products for the transfer of credit risk. Prominent among such innovations are credit derivatives, asset-backed securities, and secondary-market trading of syndicated loans. Another important development has been the rapid growth of the hedge fund industry, about which we learned a lot this morning, and its expanded role in the financial system. On the retail side, we have seen a proliferation of new lending products in the United States, including home-equity lines of credit, interest-only and even negative-amortization mortgages, and subprime mortgages and consumer loans.

Today, I will discuss the potential benefits and drawbacks associated with new products and institutions and a middle way that regulators might pursue as these new products and institutions emerge.

Benefits and Drawbacks

Financial innovations hold the promise of improved efficiency and increased overall economic welfare. For example, new products and markets can open the door to new investment opportunities for a variety of market participants. And improved risk-measurement and risk-management technologies can contribute to an improved allocation of risk as risk is shifted to those more willing and able to bear it.

Financial innovations also have the potential to boost financial stability. Risk-transfer mechanisms can not only better allocate risk but also reduce its concentration. Improved efficiencies and increased competition may result in substantially lower trading costs and may consequently improve liquidity in many markets. Better liquidity, which is instrumental to faster and more accurate price discovery and therefore to more-informative prices, can also be brought about by an increased presence of new institutions in new or existing markets. The entry of those new institutions into new markets can, so long as the institutions prove resilient, increase the availability of funds to borrowers in times of stress and may thus reduce the likelihood of credit crunches.

Although financial innovations have the capacity to improve economic welfare overall, it is natural for policymakers to worry that innovations may have unexpected and undesirable side effects and may even represent new sources of systemic risk. For example, policymakers may be concerned about unexpected price dynamics or problems in infrastructure or operations. Market participants estimate how prices and investment flows are likely to behave for new instruments, but their understanding becomes more detailed and more accurate only as behavior under a variety of economic conditions is observed, and the development of that understanding obviously takes time. Under turbulent conditions, or when new information causes market participants to question their own investment strategies, their behavior may change rapidly, leading to rapid price changes that may seem outsized relative to changes in economic fundamentals. That was briefly the case recently in the market for synthetic collateralized debt obligations. Market participants did not anticipate the sharp decline in implied default correlations that followed the downgrades of Ford and General Motors debt. Prices moved quite a bit for a short time as portfolios were rebalanced, but spillovers to other markets were limited, and market volatility subsequently eased.

Problems with the infrastructure or operations that support an innovation--including the underlying legal documentation and accounting--are also likely to be revealed only over time, as exemplified by the technical difficulties with restructuring clauses in credit default swaps that became apparent a few years ago. In that case, default events and related payoffs sometimes did not occur as expected, and so actual exposures differed from those investors had intended. The result was a change in the value of existing contracts and a period of market adjustment as new restructuring clauses were developed and implemented.

Of course, we should not want to prevent rapid price changes or changes in investment flows, as such changes may be appropriate as new information about fundamentals emerges. And the occurrence of glitches in new markets and institutions need not reflect policy failures or provide evidence that an innovation is undesirable. Preventing all such occurrences would probably require us to stop all innovation. But neither is it desirable that growing pains in one market or at a few institutions spill over so strongly that the financial system as a whole could be destabilized.

A Middle Way in Regulation

Policymakers have a range of strategies available for dealing with innovation. At one extreme, in theory we could take a completely hands-off approach, allowing new financial markets and instruments to develop without restrictions and indeed without any scrutiny, trusting private market participants to do everything necessary for stability and efficiency. At the other extreme, policymakers theoretically might be quite heavy-handed, either imposing regulations on virtually every market and instrument to stop any innovations that, in their judgment, could cause harm or, conversely, actively fostering or subsidizing innovations seen as desirable.

Obviously, these are extreme positions, and I do not know of any practicing policymaker who seriously wants to pursue either extreme course. Today I wish to argue for a middle ground in which markets are allowed to work and develop and in which policymakers work hard to understand new developments and to help market participants see the need for improvements where appropriate. In my view, regulations should be imposed only when market participants do not have the incentive or the capability to effectively manage the risks created by financial innovation. For example, explicit or implicit subsidies of some institutions could limit market discipline of their risk-taking, leading to a concentration of risk so large that even the most sophisticated institutions would find it next to impossible to manage the risk under stressful circumstances. Or policymakers may be concerned that some potential parties to innovative contracts, especially in the retail arena, are insufficiently knowledgeable to understand or manage the associated risks. I believe such instances are rare. Making a case for early regulatory intervention is particularly difficult when the private parties involved in an innovation are sophisticated because, in many cases, they will be the first to recognize possible problems and will have strong incentives to fix them and also to protect themselves against fraud or unfair dealing.

So how should policymakers proceed down this middle path? First of all, we need to learn--we need to understand and evaluate the innovations that are taking place in financial markets. This process should include information sharing with other authorities, including those in other nations, in order to benefit from the experiences in other markets and regions. The resulting improved understanding is often enough to prepare policymakers to deal with any breakdowns that do occur and to avoid having the breakdowns turn into systemic problems. The U.S. response to the century date change is an example from a different context that fits into this category. In that case, policymakers worked hard to understand the complex practical issues and to share that knowledge with financial firms. Those firms independently evaluated the risks they faced and took appropriate action to manage them effectively.

Improved understanding may also ease concerns about potential risks. For example, in light of the effects of financial consolidation on the number of firms acting as dealers in the market for dollar interest rate options, the Federal Reserve became concerned about possible risks to the functioning of that market. These concerns included questions about the adequacy of risk management at the remaining dealers and about the possible effects that problems at one of those dealers could have on its counterparties and market liquidity. However, further investigation by Federal Reserve staff suggested that market participants were generally managing their market and counterparty risks effectively and that those hedging risk in the options market would not unduly suffer from a temporary disruption in liquidity. Our wariness about concentration in this market has not disappeared as a result of our improved understanding, but it has diminished. In general, improved knowledge about financial innovations may prevent the imposition of unwarranted restrictions and is surely a precursor to intelligent regulation in the event it is warranted.

A second step for policymakers walking the middle path should be to ensure that market participants have the proper incentives and the information they need to protect themselves from any problems related to new products, markets, or institutions; by so doing, policymakers can perhaps mitigate those problems. Policymakers should insist that regulated firms effectively manage the risks associated with new activities and markets, thereby fostering effective market discipline of risk-taking, including risk-taking by unregulated firms. Such an insistence generally does not require new regulation but rather is an application of existing regulation in a potentially new context. One of the lessons of the difficulties at Long-Term Capital Management (LTCM) was that the hedge fund had been able to achieve very high levels of leverage because some regulated counterparties had not appropriately managed their counterparty risk exposures. Subsequently, both banks and supervisors had to reassess what such management entailed. Clearly, supervisors should strongly encourage institutions to know their risk posture and to be able to control it and react appropriately as circumstances change. Policymakers should insist on similarly high risk-management standards for regulated financial institutions that provide retail products. As a case in point, bank supervisors in the United States recently issued guidance about the management of risks related to home-equity lines of credit. This guidance did not involve new regulation of these instruments but rather reminded institutions offering such products that they have an obligation to manage the resulting risks appropriately.

A pervasive lack of awareness about the risks embedded in new financial products certainly increases the likelihood that users of those products may face difficulties and that those difficulties may become systemic. One way policymakers can help prevent this possibility from happening is by supporting increased transparency and disclosure. Although counterparties in wholesale markets should generally be expected to demand and obtain the information they need to evaluate their risks, policymakers can no doubt help establish high standards. In the case of retail transactions, support for efforts to foster the basic financial literacy of households is a useful complement to efforts to promote appropriate disclosure. The more consumers are equipped to interpret disclosures, the more effective those disclosures are likely to be.

A third feature of the moderate approach I am trying to chart is an active dialogue between policymakers and market participants. In my view, policymakers should serve as a voice for the development of infrastructure and sensible standards and practices. Ideally such steps would be taken by market participants of their own volition, but sometimes informal interventions by policymakers can help foster cooperative efforts by market participants. For example, partly in reaction to the report of the second Counterparty Risk Management Policy Group, the Federal Reserve Bank of New York recently hosted a meeting with representatives of major participants in the credit default swap market, as well as with their domestic and international supervisors, to discuss a range of issues, including market practices with regard to assignments of trades and operational issues associated with confirmation backlogs. The result was an industry commitment to take concrete steps to address issues of concern.

A fourth dimension of my proposed middle path is the ongoing monitoring of key markets and institutions. Policymakers should be aware of any emerging stresses in the financial system, including those related to new instruments and institutions. Indeed, some central banks have created financial stability staff groups to oversee such monitoring and, in some cases, to publish regular financial stability reports. In the event that such monitoring suggests that the operations of some institutions or markets are under significant strain and, importantly, that the resulting pressures on businesses and households could have a material adverse effect on the real economy, the central bank may want to respond by adjusting the stance of monetary policy.

Finally, financial innovations may on occasion warrant new regulations because financial institutions either cannot or will not manage the associated risks appropriately. Indeed, regulation should be seen as part of the broader infrastructure that supports both financial stability and innovation, and like other more traditional infrastructure, regulatory regimes have to keep up. For example, developments in financial markets and advances in the ability of banks to measure and manage their risks have increasingly made the existing capital regulation of the largest banks, the 1988 Basel Accord, look antiquated. Basel II is a more flexible framework than Basel I and is intended to better permit capital regulation to keep up with financial market innovations in the future.

To conclude, I wish to emphasize that policymakers should have a bias toward trusting financial markets to manage the introduction of new products and the development of new institutions smoothly and without undue stress to the financial system. However, we cannot take such an outcome for granted: Financial firms may not consider the effects of their decisions on the stability of other firms or on the broader financial markets, and some may lack the incentives and ability to learn about and manage the risks induced by financial innovations. In such cases, policymakers may need to work with markets and their participants, and on occasion regulate them, to achieve the desired outcomes. However, policymakers should, wherever possible, avoid premature regulation that could stifle innovation. I would note that a significant number of substantial shocks to financial markets have occurred in recent years--including, for example, the difficulties at Long-Term Capital Management and the unexpected and massive fraud at some high-profile companies--and yet the broader effects on the real economy have ultimately been quite small. Our financial markets are flexible and resilient, and they can absorb shocks surprisingly well. As a result, most risks caused by new developments in financial markets should be manageable without heavy-handed regulation. This meeting is a good example of what my middle course suggests we should be doing: working hard to understand innovations and their possible implications. Alertness and knowledge on the part of policymakers would go a long way toward ensuring that our positive recent track record will carry on amid what I am sure will continue to be a rapidly changing financial landscape.

PART 3

PAPERS

SESSION I

NON-BANK FINANCIAL INSTITUTION AND SYSTEMIC RISK

SYSTEMIC RISK AND HEDGE FUNDS

NICHOLAS CHAN, MILA GETMANSKY, SHANE M. HAAS, AND ANDREW W. LO

The term "systemic risk" is commonly used to describe the possibility of a series of correlated defaults among financial institutions - typically banks - that occurs over a short period of time, often caused by a single major event. A classic example is a banking panic in which large groups of depositors decide to withdraw their funds simultaneously, creating a run on bank assets that can ultimately lead to multiple bank failures. Banking panics were not uncommon in the U.S. during the nineteenth and early twentieth centuries, culminating in the 1930-1933 period with an average of 2,000 bank failures per year during these years according to Mishkin (1997), and which prompted the Glass-Steagall Act of 1933 and the establishment of the Federal Deposit Insurance Corporation (FDIC) in 1934.

Although today banking panics are virtually non-existent thanks to the FDIC and related central banking policies, systemic risk exposures have taken shape in other forms. With the repeal in 1999 of the Glass-Steagall Act, many banks have now become broad-based financial institutions engaging in the full spectrum of financial services including retail banking, underwriting, investment banking, brokerage services, asset management, venture capital, and proprietary trading. Accordingly, the risk exposures of such institutions have become considerably more complex and interdependent, especially in the face of globalization and the recent wave of consolidations in the banking and financial services sectors.

In particular, innovations in the banking industry have coincided with the rapid growth of hedge funds, unregulated and opaque investment partnerships that engage in a variety of active investment strategies, often yielding double-digit returns and commensurate risks.

Currently estimated at over $1 trillion in size, the hedge fund industry has a symbiotic relationship with the banking sector, providing an attractive outlet for bank capital, investment management services for banking clients, and fees for brokerage services, credit, and other banking functions. Moreover, many banks now operate proprietary trading units which are organized much like hedge funds. As a result, the risk exposures of the hedge-fund industry may have a material impact on the banking sector, resulting in new sources of systemic risks. And although many hedge funds engage in hedged strategies, where market swings are partially or completely offset through strategically balanced long and short positions in various securities, such funds often have other risk exposures such as volatility risk, credit risk, and liquidity risk. Moreover, many hedge funds are not hedged at all, and also use leverage to enhance their returns and, consequently, their risks.

In this paper, we attempt to quantify the potential impact of hedge funds on systemic risk by developing a number of new risk measures for hedge-fund investments and applying them to individual and aggregate hedge-fund returns data. We argue that the risk/reward profile for most alternative investments differ in important ways from more traditional investments, and such differences may have potentially important implications for systemic risk, as we experienced during the aftermath of the default of Russian government debt in August 1998 when Long Term Capital Management and many other hedge funds suffered catastrophic losses over the course of a few weeks, creating significant stress on the global financial system and a number of substantial financial institutions. Two major themes emerged from that set of events: the importance of liquidity and leverage, and the capriciousness of correlations among instruments and portfolios that are supposedly uncorrelated. These are the two main themes of this study, and both are intimately related to the dynamic nature of hedge-fund investment strategies and risk exposures.

The new risk measures we consider in this paper are: illiquidity risk exposure, nonlinear factor models for hedge-fund and banking-sector indexes, logistic regression analysis of hedge-fund liquidation probabililties, and aggregate measures of volatility and distress based on regime-switching models. Readers interested in the methodology and derivations for illiquidity risk exposure, should read Lo (2001, 2002) and Getmansky, Lo and Makarov (2004), for hedge-fund liquidation probabilities analysis, should consult

Getmansky (2004) and Getmansky, Lo and Mei (2004), and for regime-switching approach applied to hedge funds, should consider Billio, Getmansky and Pelizzon (2006).

In this paper, we find that massive fund inflows into the hedge fund industry have had a material impact on hedge-fund returns and risks in recent years, as evidenced by changes in correlations, reduced performance, increased illiquidity as measured by the weighted autocorrelation, and increased mean and median liquidation probabilities for hedge funds in 2004.

We also find that the banking sector is exposed to hedge-fund risks, especially smaller institutions, but the largest banks are also exposed through proprietary trading activities, credit arrangements and structured products, and prime brokerage services.

The risks facing hedge funds are nonlinear and more complex than those facing traditional asset classes. Because of the dynamic nature of hedge-fund investment strategies, and the impact of fund flows on leverage and performance, hedge-fund risk models require more sophisticated analytics, and more sophisticated users.

The sum of our regime-switching models' high-volatility or low-mean state probabilities is one proxy for the aggregate level of distress in the hedge-fund sector. Recent measurements suggest that we may be entering a challenging period. This, coupled with the recent uptrend in the weighted autocorrelation, and the increased mean and median liquidation probabilities for hedge funds in 2004 from our logit model implies that systemic risk is increasing.

We hasten to qualify our tentative conclusions by emphasizing the speculative nature of these inferences, and hope that our analysis spurs additional research and data collection to refine both the analytics and the empirical measurement of systemic risk in the hedge-fund industry.

SUMMARY OF MANAGERIAL INCENTIVES AND FINANCIAL CONTAGION

BY SUJIT CHAKRAVORTI AND SUBIR LALL*

The phenomenon of financial contagion has achieved considerable attention in both academic and policy circles in recent years. The *tequila* crisis of 1994-95, the Asian crisis of 1997, the Russian default and the collapse of Long Term Capital Management in 1998, the boom and bust related to the Internet bubble in the late 1990s, the response of international markets in the immediate aftermath of September 11, and the run-up to the Argentine debt default in late 2001, all were accompanied by the transmission of financial market volatility across borders. In the case of emerging markets, the prices of assets of countries which were not related through direct macroeconomic links (e.g. trade channels, linked exchange rates, or vulnerability to similar commodity prices) showed comovements in excess of what could be explained through traditional macroeconomic linkages.

The theoretical literature on financial contagion has tried to identify the possible channels of contagion, including the herding behavior of investors, the transmission of panic, and automated risk management procedures. Chari and Kehoe (2003) construct a model to explain outflows of capital based on herding behavior of investors. Calvo and Mendoza (2000) suggest that information regarding investments in a portfolio may be expensive and investors may choose to "optimally" mimic market portfolios. There are several models that consider investor portfolio rebalancings as a source of contagion (Goldstein and Pauzner, 2004, Kodres and Pritsker, 2002, Kyle and Xiong, 2001, Schinasi and Smith, 1999).

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Our article best fits in the theoretical literature on contagion where the reallocation of assets by investors is not necessarily based on market fundamentals. Calvo and Reinhart (1996) distinguish between fundamentals-based contagion and "true" contagion where channels of potential interconnection are not present (also see Kaminsky and Reinhart, 2000). Contagion is defined as the propagation of a shock to another country's asset when there are no fundamental linkages between the country hit by the shock and the other countries, and the comovement of asset prices across borders is based on the behavior of global investors.

We extend the literature by considering the case where investors optimally rebalance their portfolios based on an idiosyncratic shock to one market that may potentially result in contagion. Unlike the previous literature, the focus is on the managerial incentives of fund managers and their role in dampening or exacerbating contagion. Fund managers are often restricted in the amount that they can invest in emerging markets. In addition, they may also be compensated on the relative return on the portfolio to the emerging market index.

The benchmarking of portfolio performance for institutional investors such as mutual fund managers, insurance and pension funds, dedicated fund managers and other 'real money" investors is a prominent institutional feature of portfolio management. Since modern portfolio theory suggests that an optimal portfolio is one that mimics the market in a passive portfolio, it is natural that active managers be compensated for outperforming the market. In other words, their compensation is linked to the performance of a portfolio that is long the actual portfolio and short the benchmark. This compensation system is the most common way to solve the agency problem between fund managers and the investors whose funds they intermediate, given the costs of monitoring.

The market distortions and arbitrage opportunities created by investors benchmarked to a portfolio can, in many cases, be eroded by hedge funds who have a much more flexible investment strategy and a different compensation mechanism. Hedge fund managers' compensation system are linked to the absolute returns their portfolios generate. This is in response to the relative sophistication and high net worth of their investors, and the flexibility hedge fund managers enjoy in their portfolio strategy choices, making the appropriate choice of a benchmark difficult if not impossible. The agency problems between hedge fund managers and sophisticated investors with typically higher tolerance for risk take on a different dimension, and absolute return benchmarks are as a result more common.

We analyze the phenomenon of contagion by showing that the institutional structure of markets can play a significant role in creating market architectures that may lead to contagion. In particular, the incentives fund managers face can lead to contagion even in a market with no asymmetric information, when the market is dominated by certain classes of institutional investors—a key feature both of emerging debt markets as well as major equity markets. The different compensation mechanisms of different classes of fund managers, themselves an outcome of optimal principal-agent relationships between fund managers and their clients, are a root cause of deviations of asset prices from what may be the efficient market outcome. This also suggests that asset prices may continue to significantly deviate from underlying "fundamentals" and the behavior of fund managers is optimally guided not just by the fundamentals, but by their expected compensations for taking on risky positions.

We construct a theoretical model with two types of fund managers—dedicated and opportunistic along with local noise traders. Dedicated managers are compensated based on deviations from an emerging market index and are not allowed to borrow cash or short any asset. Opportunistic managers are compensated based on the absolute return on their portfolio and are allowed to short any asset and borrow cash.

We find the following results. First, the optimal weights for each asset for each type of investor are derived. We find that dedicated investors tend to rebalance their portfolios towards the index when asset volatility or their risk aversion increases. We also find that opportunistic managers decrease the amount of leverage in response to increased asset volatility or increase in risk aversion. Second, we derive equilibrium expected asset returns and prices. We find that a demand shock in one asset affects the expected price of the other asset. Specifically, the relative contribution of one type of trader to contagion depends on underlying market condition.

We find that given the domination of markets by distinct types of portfolio managers, who are distinguished by their mandates and compensation mechanisms, the optimal responses of these investor classes to the same information set and market conditions vary considerably. While groups of investors behave in well-defined ways in response to shocks, we find that the impact on equilibrium market prices and fund managers' rebalancing of their portfolio weights is based on the type of shock and the relative sizes of the two fund manager classes, and the initial conditions in the market.

A key conclusion that emerges is that managerial compensation systems are a key source of distortions in financial markets, and may be the source for long-term deviations of prices from the so-called fundamentals. This also leads to the conclusion that the opportunity to arbitrage away such deviations may be limited for long periods of time, and markets may be over- or undervalued and be perceived as such for extended periods.

We focus on some key points which are consistent with market practitioners' experience in the comovement of asset prices and its link with the investor base. While common external factors are also shown to have an impact on two emerging market assets, pure contagion arising from noise trading in one country spilling over to another country not linked through macroeconomic fundamentals is an outcome of the optimal behavior of international investors. In sum, we conclude that fund managers' compensation and investment systems bear in them the seeds of contagion arising from "technical" factors, and do not eliminate all sources of contagion even in the presence of full information.

Our model provides analytical support for the view that while financial development may have reduced risks in markets, fundamental characteristics of financial intermediaries may now make economies more vulnerable to financial sector turmoil, under some conditions, than in the past (Rajan, 2005). This framework could be applied to other markets dominated by institutional investors, such as markets within one country. For example, the interaction between high-yield fund managers and broader fixed income managers, and between equity managers and comingled stock and bond fund managers, could shed further light on the comovement of seemingly unrelated equity prices or high yield bonds, and their interaction with broader bond market prices.

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LIQUIDITY COINSURANCE, MORAL HAZARD AND FINANCIAL CONTAGION[#]

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Abstract

We study the propagation of financial crises between regions characterized by moral hazard problems. The source of the problem is that banks are protected by limited liability and may engage in excessive risk taking. The regions are affected by negatively correlated liquidity shocks, so that liquidity coinsurance is Pareto improving. The moral hazard problem can be solved if banks are sufficiently capitalized. Under autarky, a limited investment is needed to achieve optimality, so that a limited amount of capital is sufficient to prevent risk-taking. With interbank deposits the optimal investment increases, and capital becomes insufficient to prevent excessive risk-taking. Thus bankruptcy occurs with positive probability and the crises spread to other regions via the financial linkages. Opening the financial markets is nevertheless Pareto improving; consumers benefit from liquidity coinsurance, although they pay the cost of excessive risk-taking. Finally, we show that in this framework a completely connected deposit structure is more conducive to financial crises than an incompletely connected structure.

JEL Classification: G21.
Keywords: Moral Hazard, Liquidity Coinsurance, Contagion.

Journal of Finance, forthcoming

[#] We would like to thank Michele Boldrin, Giovanni Cespa, Ignacio Peña, Margarita Samartín, Georges Siotis, Branko Urosevic and seminar participants at Universitat Autònoma de Barcelona, XII Foro de Finanzas, Universidad Carlos III and the CFS Conference at Goethe University Frankfurt for useful comments. The usual disclaimer applies.

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SESSION 2

LIQUIDITY RISK AND CONTAGION

THE INTERBANK PAYMENT SYSTEM FOLLOWING WIDE-SCALE DISRUPTIONS

MORTEN L. BECH[1]

At the apex of the financial system is a network of interrelated financial markets by which domestic and international financial institutions allocate capital and manage their risk exposures. Critical to the smooth functioning of these markets are a number of financial infrastructures that facilitate clearing and settlement. The events of September 11, 2001 underscored both the resiliency and the vulnerabilities of these financial infrastructures to wide-scale disruptions.[2] Any interruption in the normal operations of these infrastructures may seriously impact not only the financial system, but also the economy as a whole. Currently, the financial industry and regulators are devoting considerable resources to strengthening the resiliency of the U.S. financial system (see House of Representatives (2004)).

Despite the importance of financial infrastructures, little research is available on how they operate following disruptions. One segment of the literature focuses on simulating the default of a major participant and evaluating the effects on other institutions (Humphrey (1986), Angelini et al. (1996) and Devriese and Mitchell (2006)). Another segment presents detailed case studies on the responses of the U.S. financial system to shocks such as the 1987 stock market crash and the attacks of September 11, 2001 (Bernanke (1990), McAndrews and Potter (2002) and Lacker (2004)).

The interbank payment system is primus inter pares among financial infrastructures. Wide-scale disruptions may not only present operational challenges for participants in the interbank payment system, but they may also induce participants to

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[2] The Interagency Paper on Sound Practices to Strengthen the Resilience of the U.S. Financial System issued by the Board of Governors of the Federal Reserve System, the Securities and Exchange commission and the Office of the Comptroller of the Currency defines a wide-scale disruption as an event that causes a severe disruption or destruction of transportation, telecommunication, power, or other critical infrastructure components across a metropolitan or other geographical area and the adjacent communities that are economically integrated with it, or that results in wide-scale evacuation or inaccessibility of the population within normal commuting range of the disruption's origin.

change their behavior in terms of how they conduct business. The actions of participants have the potential to either mitigate or augment the adverse effects. Hence, understanding how participants react when faced with operational adversity will assist operators and regulators in designing countermeasures, devising policy, and providing emergency assistance, if necessary.

The Federal Reserve's Fedwire Funds Service® (Fedwire) is the primary interbank payment system in the United States.[3] Fedwire continued to operate on September 11, 2001, but the Federal Reserve had to intervene to by extending the operating hours and providing emergency liquidity. The massive damage to property and communications systems in lower Manhattan made it more difficult, and in some cases impossible, for many banks to complete transactions with one another. The inability of some banks to process payments also disrupted the "payments coordination" by which banks use incoming payments to fund their own transfers to other banks. Once some banks began to experience shortages of incoming payments, they became more reluctant to release their outgoing payments. In effect, banks were experiencing liquidity shortages and subsequently creating liquidity shortages for other banks. The Federal Reserve recognized this trend and counteracted the liquidity shortages by opening the discount window and performing open market operations in unprecedented amounts throughout during the week following the attacks. The participants' opening account balances with the Federal Reserve peaked at more than $120 billion compared to approximately $15 billion on a normal day. Moreover, the Federal Reserve waived the overdraft fees normally charged to participants. On September 14, daylight overdrafts peaked at $150 billion, more than 60 percent higher than usual (see Ferguson (2003)).

In our paper "Illiquidity in the Interbank Payment System following Wide-scale Disruptions," we provide a theoretical framework to analyze the behavioral effects

[3] Fedwire is a Real -time Gross Settlement (RTGS) system where payments are settled individually and with instant finality in real-time. Over 9,500 participants use Fedwire to send or receive time critical and/or large-value payments on behalf of corporate and individual clients, settle positions with other financial institutions stemming from other payment systems, clearing arrangements or securities settlement, submit federal tax payments and buy and sell Federal Reserve funds. In the second quarter of 2005, the average daily number of payments was 527,000 and the average value transferred was around $2.0 trillion per day.

observed in Fedwire following 9/11. In Bech and Garratt (2003), we advocate interpreting Fedwire participants' payment decisions as a stag hunt coordination game. In this game there are two Nash equilibria; one involves the early settlement of payments, and the other involves the late settlement of payments. Early settlement implies lower settlement costs but is risky in the sense that the cost incurred by a participant depends on the actions of other participants. A failure of participants to coordinate on early settlement implies additional funding costs for participants that settle early. McAndrews and Potter (2002) find evidence that there was a breakdown in (and later a reemergence) of coordinated payments after the 9/11 attacks. We shed light on why coordination on early settlement occurs in normal times and how operational difficulties for participants in Fedwire are likely to effect equilibrium selection. We are able to characterize circumstances under which the system will converge to early (versus late) payment equilibrium.

We argue that the ability of banks in Fedwire to maintain payment coordination following a wide-scale disruption depends critically on a number of different factors. First of all, continued payment coordination between banks depends on the size of the disruption. A disruption that affects a large part of the United States or that hits a key geographical area is more likely to result in the breakdown of payment coordination, as more banks will experience operational difficulties. Secondly, it also depends on the cost of liquidity relative to the cost of postponing payments. The cheaper the liquidity, the more likely it is that banks will be able to maintain coordination. The Federal Reserve's response to the tragic events of September 11, 2001 by providing an unprecedented amount of liquidity to the system at virtually zero cost aimed to discourage banks from holding back payments. Thirdly, we argue that the banking structure can affect the smooth functioning of the payment system after a wide-scale disruption and that a bank can be considered "too big to fail" in a new, interesting way. We show that the resiliency of a large bank could be important not only because of its share of the payment flow, but also because of its interconnectivity with other banks. Fourthly, we show that the Federal Reserve can play a critical role in avoiding coordination failures by advocating patience among large banks and encouraging them to continue with timely processing of payments following a disruption to small banks. If the Federal Reserve can persuade the large banks to be patient and thereby allowing smaller banks to resume timely processing following a disruption, then more drastic measures, such as injecting liquidity and eliminating overdraft fees, might not be required to restore coordination. This is an instance where moral suasion can be effective.

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LIQUIDITY RISK IN SECURITIES SETTLEMENT*

JOHAN DEVRIESE, JANET MITCHELL

Abstract

This paper studies the potential impact on securities settlement systems (SSSs) of a major market disruption, caused by the default of the largest player. A multi-period, multi-security model with intraday credit is used to simulate direct and second-round settlement failures triggered by the default, as well as the dynamics of settlement failures, arising from a lag in settlement relative to the date of trades. The effects of the defaulter's net trade position, the numbers of securities and participants in the market, and participants' trading behavior are also analyzed.

We show that in SSSs – contrary to payment systems – large and persistent settlement failures are possible even when ample liquidity is provided. Central bank liquidity support to SSSs thus cannot eliminate settlement failures due to major market disruptions. This is due to the fact that securities transactions involve a cash leg and a securities leg, and liquidity can affect only the cash side of a transaction. Whereas a broad program of securities borrowing and lending might help, it is precisely during periods of market disruption that participants will be least willing to lend securities.

Settlement failures can continue to occur beyond the period corresponding to the lag in settlement. This is due to the fact that, upon observation of a default, market participants must form expectations about the impact of the default, and these expectations affect current trading behavior. If, ex post, fewer of the previous trades settle than expected, new settlement failures will occur. This result has interesting implications for financial stability. On the one hand, conservative reactions by market participants to a default – for example by limiting the volume of trades – can result in a more rapid return of the settlement system to a normal level of efficiency. On the other hand, limitation of trading by market participants can reduce market liquidity, which may have a negative impact on financial stability.

Keywords: Securities settlement, liquidity risk, contagion;
JEL-classification numbers: G20, G28

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Journal of Banking and Finance, Vol. 30 (2006): 1807-1834.

CONTAGION VIA INTERBANK MARKETS: A SURVEY

JOSE-LUIS PEYDRO-ALCALDE

The idea that interbank markets can act like a double-edged sword is widely acknowledged. On the one hand, interbank markets play a very important role for the provision of liquidity among banks, for the disciplining and monitoring of banks, and for the conduct of monetary policy (Meulendyke, 1998; Hartmann et al., 2001; Cocco et al., 2004). On the other hand, if a bank fails, the interbank market could transmit the shock (contagion) thereby increasing the likelihood of a banking crisis (systemic risk). Given the economic importance of interbank markets and, the huge economic costs associated with banking crises (Friedman and Schwartz, 1963; Bernanke, 1983; Calomiris and Mason, 2003b; Dell'Ariccia et al., 2005), understanding the role of the interbank market in transmission of shocks is of utmost importance.[1]

The failure of a large bank raises the risk of contagion to the rest of the banking system. There is contagion if the failure of a bank causes a significant negative externality to other banks.[2] The three types of contagion that may arise (Gorton and Winton, 2002, pp. 85-87; De Bandt and Hartmann, 2002, pp. 251-256; Allen and Gale, 2000) are the following: The first type is financial contagion due to interbank linkages. The failure of a bank leads to a loss in value for its creditor banks which hold interbank claims in the failed bank. Furthermore, the loss for the creditor banks may increase due to the (over)reaction of their depositors and other creditors (i.e., a considerable reduction of liquidity) (see e.g., Allen and Gale, 2000; Freixas et al. 2000; Dasgupta, 2004; Iyer and Peydró-Alcalde, 2005).[3] The second type of contagion is "information" based. The failure of a bank could lead depositors and creditors to update their beliefs about the likelihood of failure of other banks with similar characteristics as the failed bank (Chen, 1999, Acharya and Yorulmazer, 2005). Finally, the third type is "pure"

[1] Hoggarth et al. (2002) find that, for banking crises, direct resolution costs are approximately 5% of GDP, and cumulative output losses incurred during crisis periods are found to be roughly 15%-20% of annual GDP. Furthermore, they find that output losses incurred during crises in developed countries are as high, or higher, on average, than those in emerging market economies.

[2] For a very similar definition of contagion, see Kaminsky and Reinhart (2000). For an excellent survey on bank contagion, see Kaufman (1994).

[3] In Rochet and Tirole (1996), a bank failure signals to the rest of the banking system that monitoring has not been effective, in turn increasing the probability of systemic risk. In Aghion et al. (2000), a bank failure signals an aggregate liquidity shortage. In Diamond and Rajan (2005), the failure of a bank causes a negative externality through the reduction of available liquidity. In Cifuentes et al. (2005), the sale of assets by a distressed bank creates a negative externality through the reduction of the market price for assets. See Flannery (1996) for a model with adverse selection and contagion, and Brusco and Castiglionesi (2005) for a model with moral hazard and contagion. Leitner (2005) presents a model in which contagion is optimal in order to ensure provision of liquidity.

contagion. In this case, the contagion is purely random and has no relation either with interbank linkages or with information commonalities. This taxonomy of contagion builds on the theoretical literature of bank runs, i.e. information and fundamental based theory of bank runs (Chari and Jaganathan, 1988; Jacklin and Bhattacharya, 1988; and Allen and Gale, 1998) versus the sunspot-based theory of bank runs (Diamond and Dybvig, 1983).[4]

The fear of contagion was present when Continental Illinois Bank failed in 1984. Continental Illinois was at that time the seventh biggest US bank with 2300 banks having exposures with it. Continental Illinois was bailed-out.[5] The statement issued by the U.S. Comptroller of Currency C.T. Conover, justifying the bailout of Continental Illinois Bank, aptly summarizes these concerns.[6] In his testimony before the Congress, he asserted that: "Had Continental failed and been treated in a way in which depositors and creditors were not made whole, we could very well have seen a national, if not an international financial crisis, the dimensions of which were difficult to imagine. None of us wanted to find out." The Chairman at the Fed at the time of the bailout, Paul Volcker said: "As if we had not stepped in, the ultimate domino effect that so many people have feared for so long, would have occurred and wiped out the Western financial system."[7] The fear of contagion and systemic risk when an important bank fails is a general concern. For instance, three quarters of the 104 bank failures considered by Goodhart & Schoenmaker (1995) involved a bailout: "it has been revealed preference of the monetary authorities in *all* developed countries to rescue those large banks whose failure *might* lead to a contagious, systemic failure."[8]

Among the different types of contagion, financial contagion due to interbank linkages has most often been posited as a great threat for the stability of the banking system. Yet empirical work on the transmission of a crisis due to interbank linkages is scant. The main problem that has hampered empirical work is the lack of interbank data during a crisis.

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[4] See also Bhattacharya and Gale (1987) and Bhattacharya and Fulghieri (1994) on the role of the interbank market to cope with bank specific liquidity shocks.
[5] See Kaufman (1994).
[6] See U.S. Congress, House of Representatives, Subcommittee on Financial Institutions Supervision, Regulation and Insurance, Inquiry into Continental Illinois Corp. and Continental Illinois National Bank (98-111), (98th Congress 2nd session, 1984).
[7] For this reference, see Degryse and Nguyen, 2004.
[8] See the excellent survey on contagion through interbank markets by Upper (2006).

Most of the existing empirical studies on contagion focus primarily on measuring equity returns around large failures. These papers test whether all banks experience negative abnormal returns, or whether negative returns are limited to banks with similar characteristics to the failed banks. Aharony and Swary (1983) study the market reaction to the three biggest US bank failures prior to Continental Illinois. Swary (1986) and Jayanti and Whyte (1996) examine the market effect of the failure of Continental Illinois. Aharony and Swary (1996) study the market reaction in the context of five large bank failures that occurred in the Southwest region of the U.S. during the mid-1980s. These papers find that surviving banks are most affected if they have portfolio characteristics similar to the failing institution. This, they argue, is evidence of "information" based contagion. More recently, Gropp et al. (2005) use the tail properties of distance to default to study contagion risk in Europe; they find that contagion risk in Europe is important. Hartmann et al. (2005) study tail risk in major banks in the Euro Area and United States; they find that multivariate tail risks among major banks have recently increased.

There is an alternative stream of literature that studies the possibility of financial contagion due to interbank linkages via simulations.[9] Humphrey (1986) uses data from the Clearing House Interbank Payments System (CHIPS) to simulate the impact of a settlement failure of a major participant in the payment system. He shows that this failure could lead to a significant level of further settlement failures. Upper and Worms (2004) study financial contagion due to interbank exposures in the German interbank market. Through a simulation, they find that the failure of a single bank could lead to the breakdown of 15% of the banking system. In contrast, Furfine (2003) uses exposure data on interbank federal funds to simulate the risk of financial contagion and finds it to be negligible.[10] Elsinger et al. (2003) use detailed data from the Austrian interbank market and study the possibility of contagious failures due to an idiosyncratic shock. In their simulations, they find the probability to be low.[11] While the

[9] See the excellent survey by Upper (2006).

[10] Furfine (2002) studies the federal funds market during the LTCM and Russian crises; he finds that risk premiums on overnight lending were largely unaffected and lending volumes increased.

[11] Although the probability of contagious default is low, there are cases in which up to 75% of the defaults are due to contagion.

above papers explore the issue of financial contagion due to interbank exposures, they do not capture the endogenous response of depositors and creditors during a crisis.[12]

Another related strand of empirical literature investigates depositor runs on banks during a crisis. This literature explores whether depositors run randomly across banks or run on banks based on fundamentals (i.e., a test between the sunspot-based theory of bank runs by Diamond and Dybvig, 1983, versus the information-based theory of bank runs by Chari and Jaganatthan, 1988, Jacklin and Bhattacharya, 1988 and Allen and Gale, 1998). Schumacher (2000) studies depositor behaviour in Argentina following the Tequila Shock, and finds that depositors primarily concentrate their runs on fundamentally weak banks. Martinez Peria and Schmukler (2000) also find evidence of depositor discipline in Argentina, Mexico and Chile. Calomiris and Mason (1997) look at the Chicago Banking Panic of 1932, and investigate whether solvent banks fail during the crisis. They find that banks that fail during the panic are ex-ante weak banks. They also provide some evidence in support of interbank cooperation helping prevent failures of solvent banks. Gorton (1988) studies the banking panics during the U.S. National Banking Era (1865-1914). He finds them not random events but products of revisions in the perceived risk of the banking system based on the arrival of new information. Our paper adds to this literature by studying depositor runs, not only through fundamental characteristics of banks, but also through financial linkages of banks with other banks.

Iyer and Peydró-Alcalde (2006) use a unique dataset from India, which allows them to identify the interbank linkages, in conjunction with an idiosyncratic shock caused by the failure of a large co-operative bank due to a fraud to test contagion in the banking system. The fact that the cause of the failure was a fraud (and there were no other frauds) allows them to abstract away (to a great deal) from information based contagion. In consequence, the shock provides them with a natural experiment to cleanly test the risk of financial contagion due to interbank linkages versus pure contagion. First, they find that a bank with higher level of exposure to the failed bank experiences higher depositor runs. Second, a bank with higher fraction of its deposits held by other banks experiences considerably higher depositor runs

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[12] See also Sheldon and Maurer (1998), Blavarg and Patrick Nimander (2002), Cifuentes (2003), Müller (2003), Lelyveld and Liedorp (2004), Wells (2004), Degryse and Nguyen (2005), Mistrulli (2005), Amundsen and Arnt (2005), and Lubloy (2005).

provided its exposure to the failed bank is sufficiently high. Furthermore, as the exposure to the failed bank increases, the runs stemming from higher fraction of deposits held by other banks drastically increase. Finally, they find that media reports have destabilizing effects on runs. The most important contribution of their paper is the following: they use a natural experiment caused by a large bank failure due to a fraud –in conjunction with precise data on interbank exposures– to cleanly test for financial contagion due to interbank linkages. Existing studies on financial contagion due to interbank linkages have been limited to simulations due to lack of actual failure events. Furthermore, papers that test for contagion using an actual failure do not address the issue of financial contagion due to lack of data on interbank linkages. Their paper bridges this void and highlights the risk of contagion due to depositor behaviour, which is one of the prime concerns of the theoretical literature. In consequence, they are able to test the hypothesis of financial contagion due to interbank linkages against the hypothesis of pure contagion, in turn providing some directions for policy-making.

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SESSION 3

CREDIT RISK TRANSFER AND TRADING IN CREDIT MARKETS

EXPLAINING CREDIT DEFAULT SWAP SPREADS WITH THE EQUITY VOLATILITY AND JUMP RISKS OF INDIVIDUAL FIRMS

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HAO ZHOU[2]
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Abstract:
A structural model with stochastic volatility and jumps implies specific relationships between observed equity returns and credit spreads. This paper explores such effects in the credit default swap (CDS) market. We use a novel approach to identify the realized jumps of individual equities from high frequency data. Our empirical results suggest that volatility risk alone predicts 50 percent of the variation in CDS spreads, while jump risk alone forecasts 19 percent. After controlling for credit ratings, macroeconomic conditions, and firms' balance sheet information, we can explain 77 percent of the total variation. Moreover, the pricing effects of volatility and jump measures vary consistently across investment-grade and high-yield entities. The estimated nonlinear effects of volatility and jumps are in line with the model-implied relationships between equity returns and credit spreads.

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INSIDER TRADING IN CREDIT DERIVATIVES

VIRAL V. ACHARYA AND TIMOTHY C. JOHNSON

Abstract

Insider trading in the credit derivatives market has become a significant concern for regulators and participants. This paper attempts to quantify the problem. Using news reflected in the stock market as a benchmark for public information, we report evidence of significant incremental information revelation in the credit default swap (CDS) market under circumstances consistent with the use of non-public information by informed banks. Specifically, the information revelation occurs only for negative credit news and for entities that subsequently experience adverse shocks. Moreover the degree of advance information revelation increases with the number of banks that have lending/monitoring relations with a given firm, and this effect is robust to controls for non-informational trade. We find no evidence, however, that the degree of asymmetric information adversely affects prices or liquidity in either the equity or credit markets. If anything, with regard to liquidity, the reverse appears to be true.

Keywords: adverse selection, bank relationships, credit derivatives.

JEL CLASSIFICATIONS: G12, G13, G14, G20, D8

‘‘[B]anks must not use private knowledge about corporate clients to trade instruments such as credit default swaps (CDS), says a report [by] the International Swaps and Derivatives Association and the Loan Market Association...[M]any banks and institutions are trading CDS instruments in the same companies they finance - sometimes because they want to reduce the risks to their own balance sheets.” (Financial Times, April 25, 2005 - ‘Banks warned on insider trading threat posed by market for credit derivatives’)

FRICTIONS IN THE MARKETS FOR CORPORATE DEBT AND CREDIT DERIVATIVES

ANDREW LEVIN, ROBERTO PERLI, AND EGON ZAKRAJŠEK

Abstract. We construct an empirical measure of market frictions in the corporate market based on the difference between the credit default swap spread and the corporate bond spread (referred to as the basis) for a large number of firms in a new, large dataset that we construct. Under fairly standard assumptions, the two spreads should be equal; if they diverge, we argue that significant market frictions are present that prevent investors from arbitraging away what in effect are opportunities to earn a risk-free profit. We find that the causes of market frictions can be both systematic and firm- or bond-specific, with the idiosyncratic causes accounting for the dominant part of the variation in the basis.

1. Introduction

The smooth functioning of financial markets is crucial for the health of the whole financial system and for the well-being of the economy in general. This paper is an empirical study of how various types of macroeconomic and firm-specific conditions and events may be related to frictions that interfere with the smooth functioning of the U.S. market for corporate debt. Because market frictions are inherently difficult to observe—especially in over-the-counter markets, where order flow data is not readily available—we argue that a reasonable proxy for those frictions can be constructed in terms of investors' ability to take advantage of apparent arbitrage opportunities between two related securities. In our case, the two securities are a corporate bond and a credit default swap (CDS) referenced to the bond's issuer.

Arbitrage opportunities between bonds and CDSs cannot exist if there are no impediments to the efficient functioning of the corporate cash and derivatives markets, as market participants' trades would tend to make them disappear quickly. Conversely, a market where seeming arbitrage opportunities persist is, almost by definition, not functioning smoothly; in our view, the extent of market frictions will be more pronounced the larger and the

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The opinions expressed here are those of the authors and not those of the Board of Governors of the Federal Reserve System.

The authors would like to thank Bill English, Bill Nelson, Reint Gropp, and participants to the Fourth Joint Central Bank Research Conference on Risk Measurement and Systemic Risk for helpful comments and suggestions. Arshia Burney, Andrew Marder, and Andrea Surratt provided excellent research assistance.

longer-lasting those opportunities are. Of course, if arbitrage opportunities persist, they are not real opportunities; we call market frictions anything that prevents investors from taking advantage of those opportunities.[1]

An intuitive measure of the presence of arbitrage opportunities across corporate markets is given by the "basis," the difference between CDS and bond spreads. As has been pointed out by Duffie (1999) and reiterated by several authors, the basis should be zero under ideal conditions.[2] If the CDS spread was higher than the bond spread for a certain reference entity, investors seeking credit protection could recreate a cheaper CDS by shorting a par, floating-rate corporate bond issued by the reference entity and buying a par, floating-rate risk-free bond of the same maturity with the proceeds. Analogously, if the bond spread was higher than the CDS spread, investors wishing to take on credit risk could buy a par corporate floater and short a par risk-free floater, thereby earning a higher spread than by selling protection in the CDS market.[3]

Ideal conditions, however, do not always prevail in the markets, either because of market imperfections or because of the particular real-world characteristics of both corporate bonds and CDS contracts. While there are technical factors that may affect the basis, such as different tax treatment of cash and derivative instruments, fixed- vs. floating-rate coupons for corporate bonds, etc., those technical factors are generally not believed to account for large and persistence deviations of the basis from its natural value of zero. For example, Duffie and Liu (1999) show that the fact that most corporate bonds pay a fixed rather than a floating coupon can account for, at most, a few basis points difference in their yield, depending on the shape of the yield curve. We find that the basis moves over time and across firms by substantially larger amounts.

Various aspects of the behavior of the basis have recently attracted attention of a number of authors.[4] Blanco *et al.* (2005) test the theoretical equivalence of CDS and bond spreads for a sample of 33 U.S. and European firms from January 2001 to June 2002. Although they find that the basis

[1]We implicitly include in our definition a variety of sources of frictions. For example, transaction costs, agency problems, information asymmetries, liquidity, and contract specifications are just a few of the underlying factors that might cause discrepancies in pricing between the two markets. In sections 4 and 5 below we attempt to measure some of them. Others, however, are not so easily quantified, but are still captured, we believe, by our general definition.

[2]The theoretical properties of the basis are discussed in detail by, among others, Beinstein (2005), Bomfim (2005), Duffie and Singleton (2004), and O'Kane and McAdie (2001).

[3]As has been pointed out by Beinstein (2005), investors in the CDS market typically can earn swap rates as their "risk-free" rates. Swaps have thus become the risk-free instrument of choice, even though they are not completely risk-free. Our own analysis of the basis in section 3, as well as the studies of Blanco *et al.* (2005), Houweling and Vorst (2005), and Zhu (2004) confirm this fact.

[4]For a comprehensive review of the literature, at both a theoretical and empirical level, see Meng and Gwilym (2005).

is, on average, close to zero, they also report that the basis for a few firms exhibits persistent deviations from zero. They attribute these deviations to imperfections in CDS contract specifications and to measurement error. In addition, they find that frequent short-run deviations of the basis from zero are consistent with CDS leading cash instruments in the price discovery process. Houweling and Vorst (2005) assemble a dataset with a larger number of firms, though spanning an earlier time period (from May 1999 to January 2001). They find a small positive basis for investment-grade firms, but a much larger one for speculative-grade firms. Moreover, CDS spreads in their sample conform more closely to the spreads predicted by a reduced-form model than to the actual bond spreads, a likely reflection of the nascent CDS market. Zhu (2004) reports a small positive average basis for a sample of 24 reference entities from January 1999 to December 2002. He also finds that the basis can deviate significantly from zero and, like Blanco *et al.* (2005), he concludes that this is because price adjustments in the CDS market often occur before adjustments in the bond market. Similar results concerning the differences in the timing of price adjustment were obtained by Hull *et al.* (2003), Longstaff *et al.* (2004), and Norden and Weber (2004). A different aspect of frictions in the credit markets is studied by Acharya and Johnson (2005). They find evidence of significant incremental information revelation in the CDS market under circumstances consistent with the use of non-public information by informed banks; the information revelation appears to occur only for negative credit news and for entities that subsequently experience adverse shocks. They find no evidence, however, that the degree of asymmetric information adversely affects prices or liquidity in either the equity or credit markets.

We contribute to this growing literature by constructing a new dataset containing daily bond and CDS spreads, as well as other firm- and bond-specific variables, for a large number of firms over a long period of time. The scope of these data allows us to take a deeper look into the nature and some possible determinants of the basis and thus of frictions in the corporate market.

Our findings can be summarized in four stylized facts. First, the average basis, over time and across different bonds, is essentially zero. Thus, in the aggregate, corporate debt markets appear to be relatively frictionless. Second, there are systematic and persistent deviations over time in the aggregate basis. This suggest a significant degree of comovement among the bases of different bonds, a likely reflection of common factors or shocks that induce different responses in the CDS and bond market. Third, the dispersion of individual-specific average bases across bonds is considerable. And fourth, the persistence of deviations of the basis *from its mean* is relatively small (about two weeks). These last two facts indicate that bases that are significantly different from zero are common and that their deviations from *zero* are highly persistent. Therefore, there must be other bond- or firm-specific factors that induce frictions in the corporate market, in addition to the aggregate factors that affect all bases. Indeed, we find that bond-specific effects account for a substantially larger portion—about seven times as large—of the variation in the bases than do aggregate effects.

We are able to identify a number of factors that account for substantial fractions of the movements in both the aggregate and bond-specific basis. At the aggregate level, macroeconomic and financial variables such as uncertainty about the future path of interest rates, the slope of the yield curve, liquidity conditions in the derivative and cash market, and proxies for liquidity preferences all have a significant impact on the basis. Indeed, these factors account for as much as 75 percent of the variation in the investment-grade aggregate basis and about 55 percent of the variation in the speculative-grade aggregate basis. At the level of individual securities, we find that factors such as bond maturity, coupon size, price volatility, credit rating migrations, along with issuer implied volatility, recovery rates, and CDS liquidity proxies, account for about 35 percent of the idiosyncratic variation in the basis and for about 65 percent of its cross-sectional standard deviation. Those same factors, however, appear to be largely unrelated to the variation of the persistence of individual bases away from their mean.

The remainder of the paper is organized as follows: section 2 describes the data; section 3 presents some statistics about the basis, both over time and across firms; section 4 relates the time-series behavior of the mean basis to several macroeconomic and financial variables; in section 5 we study the cross-sectional behavior of the basis; and section 6 concludes.

2. Data Description

Our analysis utilizes a large bond-level panel at the daily frequency, constructed by merging information from following four data sources: (1) Merrill Lynch corporate bond dataset; (2) Moody's DRS dataset; (3) Markit CDS dataset; and (4) Bloomberg implied volatility dataset. We now describe each source of data in turn.

2.1. **The Merrill Lynch Corporate Bond Dataset.** The Merrill Lynch (ML henceforth) dataset contains daily information on a large number of corporate long-term debt obligations. Typically, details such as CUSIP, maturity, effective yield, and par and market values are listed for bonds issued by a given corporation.[5] The ML dataset includes only rated bonds that have at least one year remaining to maturity, a fixed coupon schedule, and exceed a certain threshold.[6] We performed an additional level of filtering and eliminated all bonds not denominated in U.S. dollars and all bonds issued by non-U.S. firms. Finally, we dropped securities with non-standard features, such as embedded options, sinking-fund provisions, etc.

[5]At the firm level, the database lists the credit rating of the issuer, the currency in which the bond is issued, the market where it is issued, the nationality of the issuer, etc.

[6]Investment-grade bonds must have at least $150 million outstanding, while speculative-grade bonds must have at least $100 million outstanding.

For each of the remaining bonds, we computed the daily spread to swaps by subtracting from the bond yield an estimated swap yield with the maturity equal to the remaining maturity of the bond.[7] Our final dataset spans the time period from January 2, 2001, to September 1, 2005, and contains 10,974 different bonds, issued by 2,737 different entities.[8]

2.2. **The Moody's DRS Dataset.** From the information contained in the ML dataset it is generally not possible to separate senior unsecured bonds from other types of corporate obligations. Because the ISDA rules that govern most CDS contracts specify that only senior unsecured debt can be delivered to the protection-buyer in case of default of a reference entity, it is crucial to use only senior unsecured securities when calculating the basis. To identify the relevant securities, we used the Moody's DRS database, which contains detailed information on the characteristics of a large number of corporate bonds, including their seniority, coupon frequency, as well as whether or not they are backed by collateral. We used this information to select only senior unsecured bonds that pay semi-annual coupons. Out of 10,974 bonds in the original ML dataset, 7,005 of them met these requirements.

2.3. **The Markit Credit Default Swaps Dataset.** The Markit dataset contains spreads on credit default swaps of maturities between 6 months and 30 years referenced to individual institutions, as well as information on the reference entities, such as their credit rating, industry sector, region of operation, etc. On any given day, Markit collects quotes from 13 CDS dealers and from a number of customers that provide their own quotes.[9] The quotes are daily and represent an average of the midpoint between the bid and the ask quote provided by the different contributors.

Markit applies several filters to the data to eliminate outliers and stale quotes. Furthermore, if a reference entity does not have quotes from at least three different sources on a certain day for a certain maturity, no data are reported. Because our focus in on the U.S. market, we eliminated from the Markit dataset all non-U.S. reference entities, as well as quotes for CDS contracts written on U.S. entities but denominated in currencies other than U.S. dollars. We also restrict our attention to the MR, or "modified restructuring," clause, which reportedly is the most widely used in the U.S.[10]

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[7]Most CDS investors can earn swap rates as their "risk-free" rate (see Beinstein, 2005). Blanco *et al.* (2005) and Houweling and Vorst (2005), among others, confirm empirically that the theoretical relationship between bond and CDS spreads holds much more closely if swap rates are used as risk-free rates instead of Treasury rates. We estimated the daily swap curve using the modification of the Nelson-Siegel method due to Svensson (1997).

[8]The total number of issuers includes subsidiaries. For example, General Motors and GMAC count as two different issuers.

[9]The 13 dealers are ABN Amro, Bank of America, Citigroup, CSFB, Deutsche Bank, Dresdner KW, Goldman Sachs, JP Morgan Chase, Lehman Brothers, Merrill Lynch, Morgan Stanley, TD Securities, and UBS.

[10]The current ISDA documentation specifies that CDS contracts can be written according to four different restructuring clauses: "cum restructuring," or CR, whereby any

TABLE 1. Number of CDS data at stated maturities in the Markit dataset

Maturity (years)	Observations	Percentage
0.5	1,469,219	34.2
1	3,281,698	76.4
2	3,028,986	70.6
3	3,531,031	82.2
5	3,880,358	90.4
7	3,239,238	75.4
10	3,120,663	72.7
15	1,908,048	44.4
20	1,973,203	46.0
30	1,234,397	28.7
Memo: 4,295,962 observations in the Markit CDS dataset		

Our CDS data starts on January 2, 2001, when Markit provided data on 78 North American companies for at least one CDS maturity under the MR restructuring clause. Over time, that number of contracts has increased dramatically, with 1,110 contracts available as of the end of our sample, September 1, 2005.[11] Not every firm has CDS quotes on every day after it was first included in the dataset. As reported in table 1, there is a noticeable drop-off in quote availability for maturities of six months and greater than ten years. Accordingly, we retain only quotes for maturities between one and ten years. The dataset confirms the often-reported fact that the five-year maturity is the most popular, as 90 percent of all observations in the dataset have a quote at that maturity.

2.4. **The Bloomberg Implied Volatility Dataset.** From Bloomberg, we collected daily time series of equity implied volatility data on 842 publicly traded U.S. firms that have equity options traded on their stock. The implied volatility is computed from at-the-money options as the average between the call and the put implied volatilities. As was the case for the CDS data, the number of firms in the panel increases significantly over time.

restructuring event is treated as a default, and the protection buyer is allowed to deliver bonds of any maturity to the protection seller upon default or restructuring; "ex restructuring," or XR, under which no restructuring event is considered a default; "modified restructuring," which considers certain types of restructuring as a default event, but limits the maturity of the debt that can be delivered in the case of restructuring; and "modified modified restructuring," or MM, which imposes different limits on the bonds that can be delivered upon restructuring.

[11]As was the case for the ML dataset, the number of reference entities includes parent companies as well as subsidiaries.

2.5. **Our Dataset.** We merged the individual datasets described above by firm and day to obtain a single dataset which consists of data on senior-unsecured bonds that pay semi-annual coupons, CDS contracts with maturities between one and ten years, and implied volatilities. We require that each firm has at least 30 (possibly nonconsecutive) observations. That is, firm i is included in the panel on day t only if bond, implied volatility, and at least some CDS data are all non missing. The resulting dataset, albeit considerably smaller than the individual component datasets, is still fairly large: It includes 1,290 bonds issued by 306 different firms for a maximum of 1,163 days. The median bond is in the panel for 471 days, while the median firm tenure is 541 days. The minimum number of days that both a bond and a firm are in the panel is 30 (our self-imposed lower limit), while the longest tenure is 1,159 days for bonds and 1,163 days for firms.

3. Computation and Description of the Basis

We can use our merged dataset to compute a measure of the difference between the CDS spread and the corporate spread, which we refer to as the *basis*, and to analyze its determinants, both in the cross-sectional and time series dimensions. In this section we first describe how we compute the basis—which, given the richness of our dataset, we are able to do for each bond, rather than for each firm—and we present some of its basic properties.

The first problem that we face when trying to compute the basis is that CDS and bonds are, in general, not available at matching maturities on any given day and for any given firm. Most papers in the literature focus exclusively on the five-year maturity, which is widely reported as being the most actively traded in the U.S. CDS market. Authors typically select only bonds that have a maturity near five years, and subtract the spread of those bonds from the CDS spread to compute the five-year basis. If we did that, however, we would significantly reduce the number of bonds that is available for our analysis. As noted in table 1 above, with the development of the CDS market, investors have become increasingly willing to trade contracts of various other maturities, and dealers have become likewise willing to provide quotes outside the five-year range.[12] We do not thus limit ourselves to just one maturity, but we rather exploit the full contents of our dataset.

[12]It may be the case that not all CDS quotes reported by Markit are actual market quotes. Some may be derived from other information available on a certain firm at a certain date; for example, if a quote for, say, the three-year maturity is missing for the MR restructuring clause but is available for the CR clause, Markit may adjust the CR quote down appropriately and report it as an MR quote. Markit reports that there doesn't seem to be a significant difference in the number of imputed quotes across maturities: quotes at the five-year maturity quotes are just as likely to be imputed as any other maturity. Therefore, concentrating on the five-year maturity would not eliminate this potential problem. Note finally that many bond yields are typically matrix-priced as well, and thus suffer from the same problem. Merrill Lynch, like most other data providers, does not include a field that indicates whether the quotes are actually observed or matrix-priced.

Even if we are willing to use all maturities in our dataset—at least those between one and ten years, given Table 1—we still face the problem that bonds and CDS do not have the exact same maturity, except by coincidence. We could tackle this problem in two ways: one would be to use the bond yields to estimate a yield curve for each firm on each day and then interpolate bond yields at the exact CDS maturities. While feasible, this approach requires us to estimate yield curves with a number of bonds that is often very small. Since CDS data are more regularly available at most maturities between one and ten years, we prefer instead to use the CDS spreads to estimate daily credit curves for each firm in the dataset, and read off of them a CDS spread of the exact maturity of any bond the firms may have outstanding.

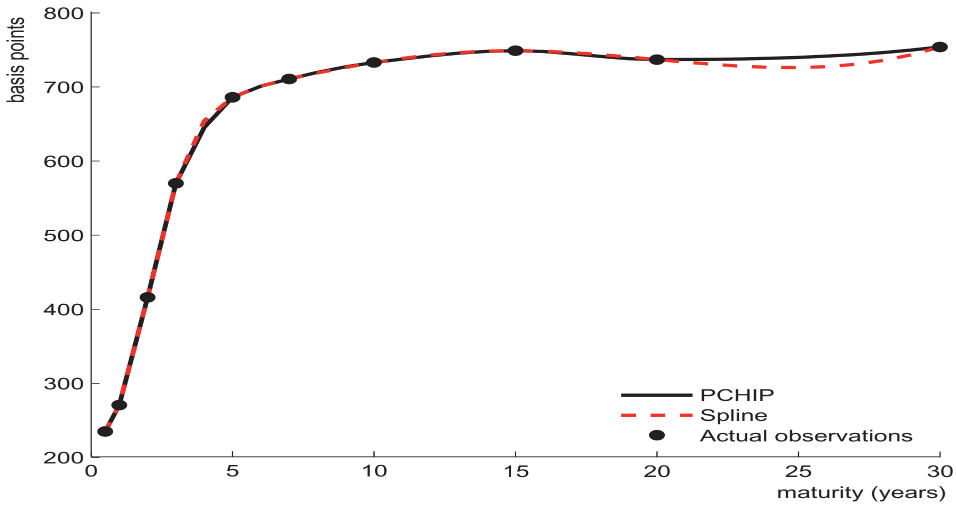
In the following we will use the subscript i to denote a firm, the subscript t to denote time, and the subscript k to denote a bond. To fit a CDS curve for firm i on day t we use a Piecewise Cubic Hermite Interpolating Polynomial (PCHIP) algorithm. That algorithm, which is similar to a spline and is readily available in Matlab, can be set up to fit a curve through various points subject to the condition that the curve passes exactly through the given points. Our curves, thus, never depart from the observed CDS spreads. The algorithm is convenient because it preserves monotonicity in the data and because, at points where the data have a local extremum, so does the interpolated curve. This implies that PCHIP does not introduce artificial oscillations between one point and the next, as a spline algorithm may do. Figure 1 illustrates this point: The thirty-year CDS spread for GM on September 1, 2005 was higher than the twenty-year spread; accordingly, the PCHIP curve slopes up throughout the twenty- to thirty year interval, unlike the spline curve, which is U-shaped over that time interval. Both algorithms produce interpolating curves with a continuous first derivative; the PCHIP algorithm, unlike the spline algorithm, produces curves for which the second derivative need not be continuous at the observed points. Except in cases like the one in the figure, however, PCHIP produces results very similar to a cubic spline.

In order to be able to interpolate a CDS curve, we need to impose some restrictions on our data. First, as already mentioned, we restrict the CDS maturities from which we interpolate a curve to the one- to ten-year range; second, we interpolate a curve only if the CDS spreads at the one- and ten-year maturities are not missing; and third, we require that no more than two spreads at intermediate maturities be missing. We proceed to estimate a credit curve for every firm and every day for which those conditions are satisfied.

Once we have estimated the credit curves, we can easily compute the basis for all bonds in our sample:

$$b_{itk}(m) = s_{it}(m) - c_{itk}(m), \qquad (1)$$

FIGURE 1. General Motors CDS curve on September 1, 2005



where $s_{it}(m)$ is the CDS spread of maturity m for firm i at date t, and $c_{itk}(m)$ is the corresponding spread for bond k issued by firm i. Note that on days when one firm has more than one bond in the ML dataset, our merged dataset contains more than one basis for that firm.

Given that CDS maturities do not exactly match bond maturities, the arbitrage between the two instruments is not perfect in general. However, given the availability of CDS at many different maturities, investors that wished to take advantage of price discrepancies between the two instruments would, in most cases, have access to CDS with maturities that are no more than one year away from the maturity of a bond issued by a certain reference entity. In perfectly frictionless markets, thus, we would expect most (even though not quite all) of the price discrepancies to quickly disappear. Note that this arbitrage argument would remain the same if we had confined our analysis to the five-year maturity, as most authors that have done so have used bond maturities of between four and six years—i.e., one year on either side of the CDS maturity—in their analysis.

Table 2 summarizes the basis across different groups of firms. Overall, and as found by other authors, the basis is very small: just -2 basis points on average, with the median virtually at zero. For investment-grade firms, the basis is very close to zero, both in mean and in median, independently of the credit rating; this confirms the results obtained by other authors with much smaller datasets (see Blanco *et al.* , 2005, Houweling and Vorst, 2005, and Zhu, 2004). While most of the existing literature finds a small but positive basis, the mean for all investment-grade firms in our sample is about -4 basis points; this indicates that, on average, the CDS spread for those firms has been below their bond spread. That result, however, appears to be driven entirely by small firms: If we eliminate from the sample firms

TABLE 2. Basis statistics

	N. Obs.	Mean	Median	St. Dev.	IQR	Skew
All firms	**606,286**	**-2.32**	**-0.35**	**32.17**	**31.33**	**0.14**
Investment-grade	**485,016**	**-3.99**	**-0.53**	**28.18**	**29.05**	**-0.37**
>$1bn outstanding	355,448	-0.39	2.28	25.13	24.52	-0.86
30 largest	206,866	4.00	4.79	23.76	27.11	-0.46
AAA	4,204	3.85	4.97	10.47	30.23	-0.88
AA	22,939	-1.20	3.87	21.91	19.58	-1.64
A	167,345	-0.87	3.59	23.57	23.08	-1.27
BBB	290,528	-6.11	-3.72	29.63	31.43	-0.13
Speculative-grade	**121,270**	**6.02**	**1.11**	**46.41**	**55.27**	**0.35**
30 largest	97,787	9.43	3.01	42.40	49.16	0.34
BB	89,536	-3.57	-4.63	38.87	42.64	0.36
B	29,677	26.01	28.44	53.23	74.01	0.20
CCC	4,057	24.88	28.35	63.90	105.01	0.13

that have bonds outstanding (as reported by Merrill Lynch) for less than $1 billion, the average basis turns out to be almost exactly zero. The difference between large and small firms is further evidenced if we look at just the thirty firms in the sample with the largest amount of bonds outstanding—a sample which is more comparable to those used by the above-mentioned authors. For those firms, the mean and median basis are both positive, at about 4 basis points. Note finally that, independently of size and credit rating, the distributions of the investment-grade basis, even for just the largest firms, are all significantly skewed to the left, as is also evident from figures 2 and 3.

To visually assess the effect of not limiting our analysis to the five-year maturity, figure 2 plots the distribution of the basis computed from five-year CDS and bonds—the top panel—and from one- to ten-year CDS and bonds—the bottom panel. Both methods produce very similar distributions; in both cases, as was to be expected, the investment-grade basis distribution is much more concentrated than the speculative-grade distribution, and appears to have a negative skew. Even if we break down the one- to ten-year basis distribution into subsets that span two years of maturities each, the distributions remain very similar. Figure 3 plots the investment-grade—the top panel—and the speculative-grade basis distributions—the bottom panel—at different maturity ranges. As is clear from the figure, the investment-grade distributions are all almost identical to each other; the two- to four-year speculative-grade basis distribution is slightly more dispersed than the remaining three distributions, and is shifted a touch to the left. Overall, based

FIGURE 2. Distribution of the basis across time and reference entities

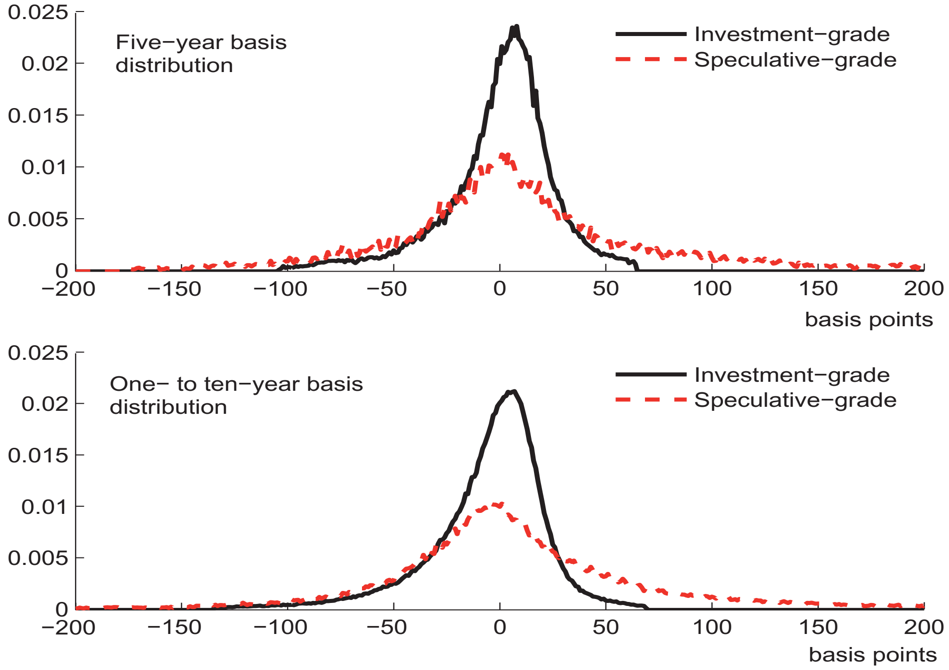
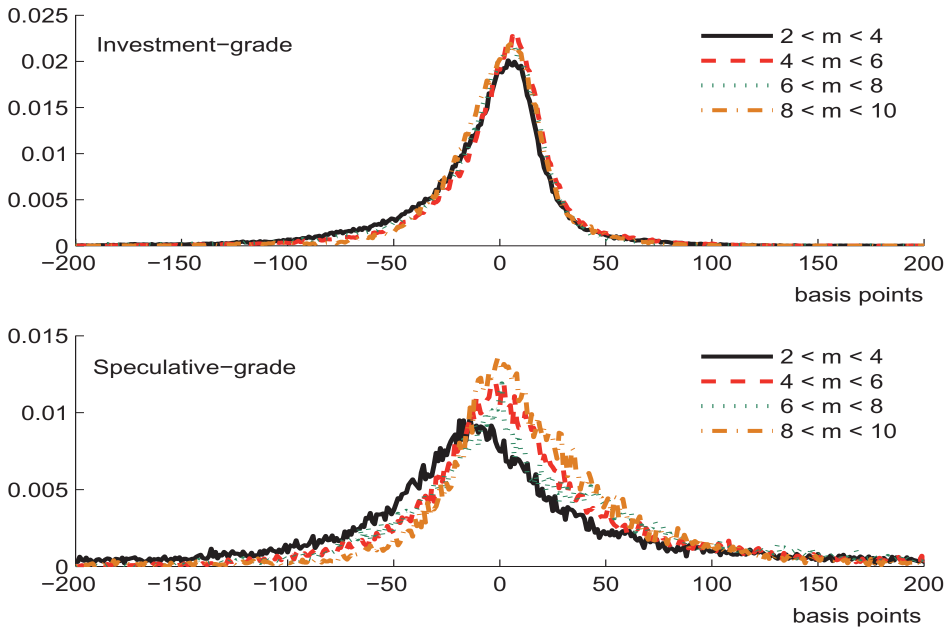


FIGURE 3. Distribution of the basis for different maturities across time and reference entities



on the casual observation of the figures, there does not appear to be a systematic relationship between maturity and basis in our dataset, a further confirmation that we do not introduce any spurious bias by working with all maturities. We will conduct a more rigorous analysis on this point later.

The picture is somewhat different for speculative-grade firms. For those, the basis is, on average, still fairly small, at 6 basis points; the median is even lower, at 1 basis point. The amount of outstanding bonds does not appear to make a major difference, as the thirty largest firms have mean and median bases that are only a bit larger than those of the whole sample. The differences across credit ratings, however, are remarkable. While the mean and the median for BB-rated firms are actually negative and comparable to those of investment-grade firms, the same statistics for firms rated B and CCC are much higher.[13] While the number of observations for firms at the lower end of the credit spectrum is comparatively small, a large basis appears to be a stable property for those firms. We also note that the speculative-grade distribution is skewed in the opposite direction as the investment-grade distribution, again as is evident from figures 2 and 3. The positive skewness holds for all sub-investment-grade ratings.

To impose some structure to our analysis, we specify the following simple model to describe the basis:

$$b_{kt} = \alpha_k + \beta_t + \varepsilon_{kt}, \qquad (2)$$

where α_k indicates an effect specific to bond k (issued by firm i), and β_t indicates a time-specific, or aggregate, effect. The residual ε_{kt} captures anything else that has an effect on the basis b_{kt}.[14]

The first three rows of Table 3 contain an analysis of the variance of the basis that is explained by equation (2). Overall, bond-specific and aggregate effects explain about 44 percent of the variance of the basis. The majority of that explanatory power is accounted for by bond-specific effects, while aggregate effects represent only about 4 percent of the total variation. The presence of both effects is highly significant.

It is conceivable that there may be some differences in either the bond-specific or aggregate effects (or both) depending on whether a bond is rated as investment-grade or as speculative-grade. We explore this possibility in the remaining rows of the table. First, in the middle rows, we interact the aggregate term β_t with a dummy variable that takes on the value one for bonds that are rated speculative-grade and zero otherwise. Distinguishing between classes of firms raises the percentage of the variance explained by the aggregate component by about one-third, although that fraction is still small at 6 percent. When we interact the firm-specific effect with out rating

[13]There are no firms rated lower than CCC in the Markit dataset that have CDS traded in their name.

[14]Since we use all available maturities between one and ten years to compute the basis, we drop the m in equation 1.

Table 3. Analysis of variance for the basis

	Pct. of Variance	F Value	Prob > F
α_k	40.39	341.05	0
β_t	4.04	37.78	0
Model	44.43	197.20	0
α_k	40.39	341.05	0
β_t·rating	6.22	30.60	0
Model	46.61	146.90	0
α_k·rating	42.02	347.73	0
β_t·rating	6.08	30.72	0
Model	48.10	151.00	0

indicator as well, the fraction of the variance explained by α_k rises modestly. Overall, we conclude that our simple model in equation 2 can explain about half of the variation in the data, and that, while aggregate effects are clearly visible and significant, bond-specific effects are predominant.

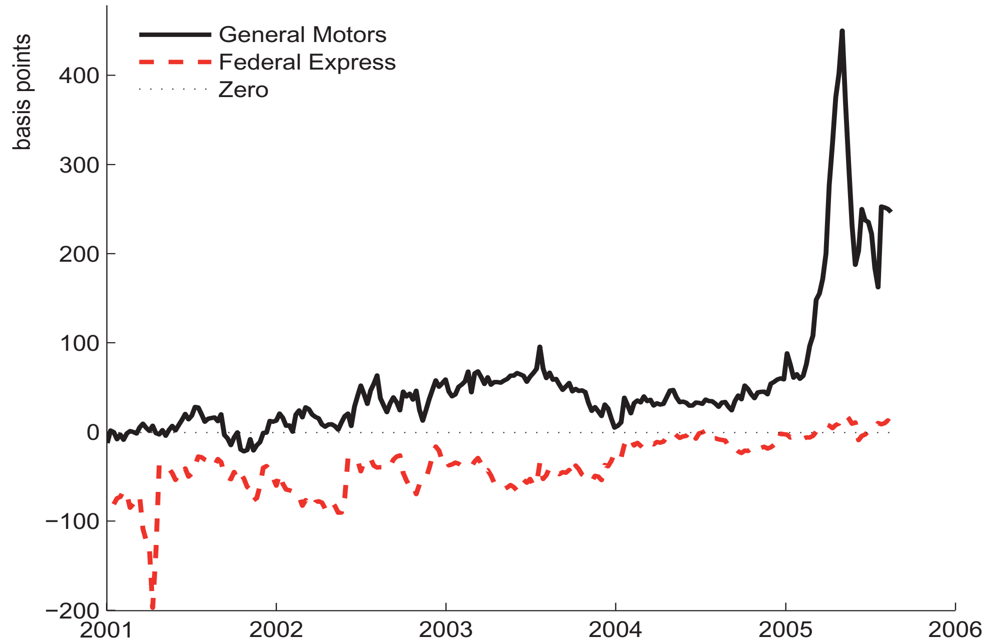
The results in tables 2 and 3 indicate that, even if the basis is, on average, close to zero for investment-grade and the best of the speculative-grade firms, it is not, in general, near zero for all firms all the time. In fact, the basis distributions are quite dispersed, with interquartile ranges of 29 and 55 basis points for investment-grade and speculative-grade firms, respectively. Moreover, the bond-specific means (the α_k) are also far from concentrated. Indeed, for a number of firms, the basis appears to be substantially different from zero for long consecutive periods of time. As an example, figure 4 shows a time series of the basis for two large firms: For General Motors, the basis was mostly positive over our sample period and rose to extreme levels (in excess of 400 basis points) in the spring of 2005, following the notorious difficulties at the firm that resulted in its debt being downgraded to junk status. Conversely, the basis for Federal Express has been negative for most of the sample period and became close to zero only starting in 2004.[15]

It is also instructive to look at a plot of the aggregate basis over time across our whole sample of firms. As shown in figure 5, β_t for both investment-grade and speculative-grade firms fluctuate noticeably over time and are relatively highly correlated—the correlation coefficient is 0.61 at a weekly frequency.[16] Indeed, several turning points can be easily identified, such as the summer of 2002, when investors were skittish about defaults and corporate malfeasance; mid-2003, when interest rates backed up fast after

[15]We chose these two firms for purely illustrative purposes, as their bases are so significantly different from zero for such long periods of time.

[16]We plot weekly time series to highlight the cyclical properties of the bases and to eliminate some of the high-frequency noise that is present in the data.

FIGURE 4. Weekly time series of the basis for two individual firms



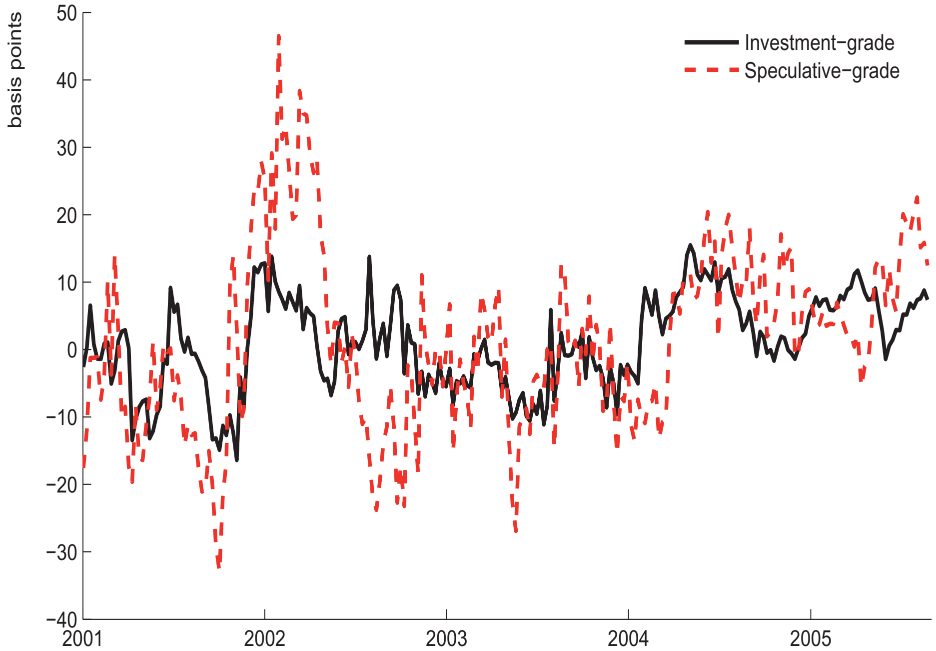
investors realized that the Federal Open Market Committee would not ease monetary policy any further; the spring of 2004, when investors realized that monetary policy tightening was about to begin; and the spring of 2005, when credit quality problems at the large U.S. automobile manufacturers roiled the credit markets.

This anecdotal evidence that the aggregate basis moves at times that are linked to specific events may be a sign that indeed there may be variables or events that affect investors' ability to take advantage of arbitrage opportunities, and thus the functioning of the corporate market. Similarly, the fact that different bonds may have such widely different bases at any given point in time may reflect individual bond characteristics as well as firm-specific circumstances that may make it easier or more problematic to exploit the seeming arbitrage opportunities. In the next sections we will separately analyze the two components of the basis and we will investigate what variables correlate with them significantly.

4. THE AGGREGATE COMPONENT OF THE BASIS

The heuristic description of the two previous figures suggest that there may be aggregate factors that drive a wedge between the CDS and the corporate bond market. For example, it may be the case that liquidity preferences, policy expectations, interest rate movements, and possibly other macroeconomic conditions affect the two markets differently, and therefore

FIGURE 5. Time series of the basis (weekly medians across reference entities)



induce the bases of all firms to move together. In this section we study which aggregate variables correlate well over time with our measure of the mean basis across all bonds in the sample. Our strategy is simply to regress the mean basis on a set of explanatory variables, as in:

$$\beta_t = aX_t + u_t, \tag{3}$$

where X_t is a matrix containing a number of potential explanatory financial variables. To determine what exactly those variables may be, we follow the existing literature and our intuition.

There are a number of well-understood reasons why the basis may not be zero at all times. Some of those are technical in nature, others have more economic and financial meaning. Below, we briefly discuss some of them and our proposed way of accounting for their effect.

4.1. **Fixed-rate vs. floating-rate bonds.** One first obvious departure from the standard arbitrage argument that leads to the theoretical equivalence of bond and CDS spreads is that there are very few, if any, floating-rate corporate or risk-free bonds. Duffie and Liu (1999) estimate that the difference in spread between a fixed-rate and a floating-rate bond of the same characteristics is very small, of the order of a few basis points at most, and depends on the slope of the yield curve. They show that, if the yield curve is upward sloping, floating spreads should be slightly higher than fixed spreads. This suggests that the basis should be positively related to the slope of the yield curve, although the effect should be very small. It seems unlikely, thus, that the paucity of floaters could account for the relatively sizable swings in the aggregate basis over time (see figure 5).

4.2. **The slope of the yield curve.** There may be a more important reason why the slope of the term structure could lead to variations in the basis. The total cost of shorting a bond is inversely related to the steepness of the yield curve: An investor who is short a bond needs to first obtain the bond in the repo market by lending cash to the owner of the bond, and, under normal circumstances, is compensated for that loan at a short-term rate (often an overnight rate) called the repo rate. [17] The investor also has to pay the bond coupons, or accrued interest if the shorting period does not span a coupon date. The flatter (or the more inverted) the yield curve, the cheaper it will thus be to short a bond, because the negative cash flow induced by the accrued interest is offset by the repo rate received from the bond owner. This argument, like the one above, leads us to expect a positive relationship between the slope of the yield curve and the basis, as the total cost of shorting a corporate bond would be higher the steeper the curve is.[18]

4.3. **Liquidity conditions.** Market liquidity should also play an important role in determining the basis. A commonly-used measure of liquidity in either market would be the bid-ask spread; however, we do not have access to that data. Instead, Markit provides us with the number of five-year CDS quote providers for each firm on any given day; we assume that the CDS market is more liquid when that number is high, both across firms and over time. We use the average number of quotes across firms on any given day. Zhu, in a panel setting, finds that high liquidity in the CDS market tends to lead to a higher basis. While he finds the result somewhat puzzling, we tend to view it as consistent with market participants preferring the CDS market to the cash market, especially when credit quality deteriorates. Accordingly, we expect that this variable enters with a positive sign in our regressions.

A similar argument can be made for liquidity in the bond market. Again, we do not have bid-ask spread data, so we use gross bond issuance as a proxy for liquidity. On the one hand, few corporations will attempt issuing debt at times when the market is illiquid; on the other hand, a high amount of issuance usually leads to high trading activities, as dealers place the bonds

[17] At times the bond may be in such a high demand in the repo market that investors are willing to lend funds to the owners of the bond at a below-market rate; that rate is called a repo-special rate. Duffie (1999) shows that, if a bond is "on special" in the repo market, the basis will be theoretically positive by the difference between the repo rate and the special rate.

[18] Note that, since swaps are the risk-free instrument of choice for investors in the CDS market, there is no need for those investors to short a risk-free bond: They may just enter into a pay-fix swap instead.

and investors perhaps need to make room for them in their portfolios. We would expect that high issuance would lead to a tightening of the basis.

Besides liquidity conditions in specific markets, there may be situations that induce investors to prefer to allocate their funds to generally very liquid markets, such as the U.S. Treasury market. While we do not attempt here to characterize what the causes of such liquidity preferences might be, we proxy that behavior with the liquidity premium that investors are willing to pay to hold on-the-run Treasury securities over off-the-run securities of (roughly) the same maturity. In particular, we use the spread between the first off-the-run and the on-the-run ten-year Treasury security. Ideally, at times of strong preference for safe, liquid assets, investors should shy away equally from the CDS and the corporate bond market; if it is true that it is easier to move in and out of the CDS market than the bond market, however, we should find that a high liquidity premium leads to a positive basis.

A different measure of broad market liquidity conditions is given by the swap spread over Treasury securities. Grinblatt (2002) argues that swap spreads are accounted for by differences in liquidity conditions between Treasury securities and short-term eurodollar deposits. Apedjinou (2003) finds empirically that liquidity conditions are a more important determinant of swap spreads than credit conditions, especially in more recent years. We include the five-year swap spread among our explanatory variables, and expect its coefficient to be positive, just like the coefficient for the on-the-run premium.

4.4. **Counterparty credit risk.** If investors in the CDS market, especially protection buyers, are concerned that their counterpart in the trade might default at the same time that the reference entity defaults, they may demand to pay a lower spread for credit protection. Since the cash market is not affected by counterparty credit risk, this would tend to lower the basis, everything else equal (see, for example, O'Kane and McAdie, 2001). As attested by various surveys (see Bank for International Settlements, 2005, among several others), most counterparts to CDS trades are large dealers. We thus proxy counterparty credit risk with the CDS spread of the major dealers in the market, and we would expect a negative sign for the coefficient of that variable in our regressions.

4.5. **Macroeconomic uncertainty.** The term "macroeconomic uncertainty" is typically used broadly to denote the possibility that economic conditions may take on any of a variety of different states in the more or less immediate future. A finer parsing of different uncertainties is also possible. For example, if market participants are concerned about the economy entering a recession, equity implied volatility is likely to increase, but uncertainty about the direction of short-term interest rates may very well decline, as investors anticipate an easing of monetary policy on the part of the central bank. Similarly, at times of overall good economic conditions, equity implied volatility may be generally low, but short- and long-term interest rate implied volatility may be elevated due to a potentially broad range of monetary policy choices available to the central bank. Accordingly, we use three different measures of uncertainty in our regressions: equity implied volatility, to measure sentiment about broad macroeconomic conditions; three-month eurodollar implied volatility, to measure uncertainty about monetary policy choices; and ten-year Treasury yield implied volatility, to measure concerns about the evolution of long-term interest rates induced, for example, by inflation or other types of risks.

Uncertainty, especially as measured by equity implied volatility (Blanco *et al.* , 2005) or realized volatility (Zhang *et al.* , 2005) has been found to be related to both the CDS and the bond spread. We do not have an a priori opinion as to the direction in which our three proxies may affect the basis, or even if at all. It may indeed be possible that implied volatilities affect the two markets equally, and thus that the aggregate basis is insensitive to market uncertainty. To the extent that we find significant coefficients on any of those variables, we would be led to conclude that one of the two markets seems to react more to the specific type of risk represented by the particular implied volatility.

4.6. **Other.** The presence of cheapest-to-deliver (CTD) options in the CDS market is induced by the restructuring clause used in a specific contract. The problem arises because, while at default all bonds issued by the reference entity should have the same price (the recovery value), upon restructuring that equivalence may not hold, and near-term bonds may be valued significantly more than longer-term bonds.[19] According to the revised ISDA rules governing CDS trading, only bonds within a relatively narrow window can be delivered to the protection-seller in case of debt restructuring on the part of a reference entity. For example, according to the MR restructuring clause to which our data refer, a protection buyer can deliver to the protection seller a bond with a maturity of no more than thirty months longer than the maturity of the CDS contract upon the occurrence of a restructuring event. The CTD option should introduce an extra element of risk for the protection-seller, and thus should lead to a positive basis, everything else equal; the revised ISDA rules should have significantly reduced the value of the option, however. We do not have any proxy for this option at this stage, and we suspect the overall effect should be fairly small. In future research, we plan to test that conjecture by comparing the basis computed under the MR clause to the basis that results from no-restructuring (XR) CDS.

Synthetic CDO issuance appears to be an important source of imbalances in the CDS and cash markets. Cash collateralized debt obligations, or CDO, are securities backed by pools of corporate bonds or loans. Synthetic CDO, on the other hand, reference a portfolio of credit default swaps, rather than

[19]Bomfim (2005) describes the famous case of the Conseco restructuring which led to the revised ISDA rules.

a portfolio of cash assets. Both types of CDO divide the risk of loss of the underlying portfolio into tranches based on seniority: equity, mezzanine, senior, and super-senior. Losses in the reference portfolio will be absorbed first by the equity tranche, and then by the other tranches in order. As pointed out by Gibson (2004), buyers of a certain synthetic CDO tranche gain exposure to credit risk, effectively selling credit protection to the issuer. The issuer, in turn, typically hedges its position by selling protection on the portfolio in the form of single-name CDS to other investors. Assuming that the CDO buyers do not hedge their positions but rather seek exposure to a portfolio of credit risk, as appears to be the case, CDO issuance creates an (arguably temporary) excess supply of CDS in the market, driving CDS spreads below corporate spreads, everything else being equal. According to Calamaro and Tierney (2004), synthetic CDO issuance has very recently grown in importance as a reason of negative observed CDS-bond basis. We plan to investigate this channel of divergence between CDS and cash spreads in future research.

4.7. **Results.** We include in our analysis as many of the variables discussed above as we can. Specifically, our matrix X_t in equation (3) contains: the slope of the yield curve; a transformation of the average number of dealers providing CDS quotes on any given week (a proxy for CDS market liquidity); [20] gross weekly bond issuance (a proxy for bond market liquidity); the Treasury liquidity premium and the swap spread over Treasuries (as proxies for investors' preference for liquid assets); the average CDS spread of major CDS dealers (as a proxy for counterparty credit risk); implied volatilities for ten-year the Treasury yield; three-month eurodollar rate, and the S&P 500 index (as proxies for market uncertainty); and the weekly returns on the S&P 500 (intended to proxy general perceptions about economic conditions).

The results of our regressions are reported in table 4 for investment-grade and speculative-grade credits separately. Several facts are worth mentioning. First, the behavior of interest rates appears to be an important determinant of the basis. As predicted, and consistent with what other authors have found, the slope of the yield curve is positively related to the basis. The effect is stronger for speculative-grade credits; since shorting high-yield bonds is arguably more problematic than shorting investment-grade bonds, we view this as reflecting more the difficulty of obtaining corporate bonds, especially speculative-grade ones, in the repo market than the lack of floating-rate corporate bonds in the market.

All liquidity variables have the expected sign and are highly significant for investment-grade credits, except for the Treasury liquidity premium.

[20] Since the average number of reporting dealers has grown steadily over our sample period, including the variable in levels would have the implication of assuming that the basis may grow without limits in absolute value. We construct our measure as $l_{CDS} = 1 - exp(-\gamma N_{dealers})$, where $N_{dealers}$ is the average number of CDS dealers. We estimate the parameter γ jointly with the other parameters using nonlinear least squares.

TABLE 4. Time series regressions: investment-grade.

Variable	Investment-grade	Speculative-grade
Constant	-0.717***	-0.423**
	(0.063)	(0.018)
Yield Curve Slope	0.035***	0.049**
	(0.008)	(0.002)
No. of CDS contribs.	62.351***	33.818**
	(4.467)	(14.514)
Bond Issuance	-0.196**	-0.692
	(0.081)	(0.492)
Liquidity Premium	0.078	1.422***
	(0.170)	(0.322)
Swap Spread 5yrs	0.521***	-0.027
	(0.051)	(0.140)
CDS Dealers Spread	0.067	-0.247
	(0.054)	(0.173)
10yr Rate Implied Vol.	-0.876**	-0.300
	(0.396)	(0.887)
3mo ED Implied Vol.	-0.908	12.781***
	(1.316)	(3.990)
SP500 Implied Vol.	-0.259*	-1.069***
	(0.160)	(0.404)
R^2	0.733	0.839

T statistics in parenthesis. *** denotes significance at the 1 percent level or better; ** and * denote significance at the 5 and 10 percent levels, respectively.

We interpret these findings as a sign that, at times of strong preference for liquidity, investors may find it easier to exit the CDS market than to exit the corporate bond market, thereby pushing CDS spreads higher. Conversely, at times when liquidity preferences are not a factor, investors may be more inclined to acquire corporate cash assets. In agreement with Zhu (2004), we find that a high number of CDS quote providers also tends to correlate with a higher basis. Since the number of quote providers has grown over time, this finding may be a sign that, as liquidity in the CDS market has improved, CDS have become the instrument of choice to trade credit risk. Also as expected (and different from what Zhou, 2004, finds), high bond issuance tends to lower the basis. The results are broadly similar for speculative grades, except that bond issuance and swap spread are not significant, while the Treasury liquidity premium is.

A third fact worth mentioning is that the conjecture that counterparty credit risk would tend to decrease the basis is not supported by our data.

TABLE 5. The persistence of the aggregate bases.

	Unconditional		Conditional	
	$\bar{\rho}$	$\bar{h}$	$\bar{\rho}\|X$	$\bar{h}\|X$
Investment-grade	0.909	7.250	0.577	1.259
Speculative-grade	0.845	4.108	0.691	1.872

The coefficient on the CDS spread of large dealers is statistically insignificant for both investment-grade and speculative-grade credits, and has the wrong sign (positive) for the former. It could be that, precisely because the vast majority of CDS trades have a large dealer as a counterpart, counterparty credit risk is not of great concern to investors. In other words, the credit quality of those dealers has remained excellent throughout our sample period, and its variation may not have been enough to produce a noticeable effect on the basis.

Uncertainty about macroeconomic conditions—as proxied by the S&P 500 implied volatility—has a negative effect on the basis. The volatility of the ten-year Treasury yield has a similar effect, but is significant only in the investment-grade case. These negative signs indicate that, at times of heightened macroeconomic uncertainty, the bond market tends to sell off at a faster pace than the CDS market. Interestingly, uncertainty about the monetary policy path, as proxied by the implied volatility on the three-month eurodollar rate, has a positive and highly significant effect on the speculative-grade basis.

Finally, we note that the R^2 are fairly high for both sets of firms, and especially so for investment-grade firms, indicating that our set of explanatory variables captured most of the aggregate variation in the basis.

The persistence of deviations of the aggregate bases away from their means is also interesting, since it gives a sense of how fast the aggregate bases tend to return to zero, and thus how fast market frictions induced by systematic effects tend to disappear. One way to study persistence is to simply look at the estimated autoregressive coefficient of the investment-grade and speculative-grade bases; another would be to examine the estimated autoregressive coefficient conditional on the explanatory variables contained in the matrix X. Table 5 contains those estimates. We find it useful to transform the correlation coefficients into half lives, which are measures of the time it takes a process with a certain autocorrelation coefficient to return half way to its mean upon displacement. In particular, we define the unconditional half life h as:

$$h = \frac{\log(0.5)}{\log(\bar{\rho})} \tag{4}$$

and the conditional half life analogously. Unconditionally, the estimated autocorrelation coefficients are fairly high. As a consequence, it takes more than 7 weeks for the investment-grade basis to return to its mean; the speculative-grade basis takes instead more than four weeks. Conditionally on our explanatory variables, however, the half lives are much shorter, with both of them under two weeks.[21] We view this as a further confirmation that we capture the most relevant aggregate factors that induce wedges between the CDS and cash market.

5. The bond-specific component of the Basis

As we discussed in section 3, credit default swap spreads tend to be systematically higher or lower than bond spreads for long periods of time for a number of bonds. In this section, we study possible factors that may concur to determine the average level of the basis across bonds and firms. Our dataset contains several variables that are either bond-specific or firm-specific that could potentially be informative as to why idiosyncratic types of frictions may prevail between the two markets. Bond-specific variables include maturity, credit rating, the size of the issuance, and price; firm-specific variables include the recovery rate as estimated by the contributors to the Markit dataset, the number of contributors that provide CDS quotes at the five-year maturity, the firm's equity implied volatility, and the sector in which the firm operates.

All of the variables mentioned above, which include measures of liquidity and distress, as well as purely technical factors, could potentially play a role in determining whether it could be possible or cost-effective to arbitrage away any differences between CDS and bond spreads. For example, the availability of corporate bonds in the repo market, and therefore the possibility of shorting them, may depend on the size of the outstanding bond issue. Poor liquidity in the CDS market may result in high transaction costs that may compromise investors' ability to take advantage of arbitrage opportunities. High firm-specific implied volatilities may be a sign that firms are experiencing difficulties that may create imbalances in the relative demand and supply for their securities. Finally, there may be bond-specific factors that, while not immediately obvious, may still play a role in determining the presence and the extent of market frictions.

Our list of firm- or bond-specific variables could be useful in explaining not just the behavior of the average basis across time, but also of several other properties of the basis. For example, we believe that understanding some of the factors that may help account for the dispersion of the basis across firms is equally important from the perspective of understanding frictions in the corporate market. And so is understanding the factors that may affect the persistence of deviations of each bond's basis around its mean, as well

[21] Note that, when adding a lagged basis term to equation 3, the signs and the significance of the coefficients reported in table 4 do not change.

as around the aggregate basis β_t. Our strategy is to run a series of cross-sectional regressions using the explanatory variables mentioned above. Our regressions are of the type:

$$\begin{aligned}\alpha_k &= a_1 Z_k + \epsilon_k \\ \sigma_k &= a_2 Z_k + \epsilon_k \\ h_k &= a_3 Z_k + \epsilon_k\end{aligned}$$

$$\phi_k = a_4 Z_k + \epsilon_k$$

where α_k denotes the bond-specific effects estimated in section 3, σ_k denotes their volatility over time, h_k is the estimated half-life of the basis deviations, and ϕ represents the "beta" of each individual basis.

Specifically,

$$h_k = \frac{\log(0.5)}{\log(\hat{\rho}_k)}, \tag{5}$$

where $\hat{\rho}_k$ is the estimate of the first-order autoregressive coefficient of each individual basis obtained from $b_{kt} = \mu_k + \rho_k b_{kt-1} + e_{kt}$. Similarly, ϕ_k, our measure of the basis "beta," is obtained from a series of regressions of the type:

$$b_{kt} = \mu_k + \phi_k \beta_t + e_{kt} \tag{6}$$

Our explanatory variables are grouped in the matrix Z_k as time averages of the variables listed at the beginning of the section,

The results are reported in tables 6 (for the average and standard deviation of the basis), and 7 (for the half-life and the "beta." From the R^2 it is clear that our variables are more effective at explaining the variation in α_k than its level, while they do not do a particularly good job at explaining either the half-life or the "beta."

For the typical firm, it seems that bond size has a positive effect on the basis, everything else equal; in other words, large bonds tend to have a higher basis than smaller bonds in our dataset. While this may seem counterintuitive, we speculate that it may reflect the difficulty of shorting bonds with a large amount outstanding, perhaps because those bonds are held by large investors who have no interest in making them available in the repo market. Consistent with this interpretation, the basis for large bonds is less dispersed around its mean. The fact that, on average, bonds of long maturity also seem to have a larger basis may also be consistent with our previous interpretation, as long bonds tend to be larger in size and may be held by "steady money" investors.

An alternative interpretation could be that holders of the largest bonds tend to resort more to the CDS market to buy protection, and are willing to pay for it. This interpretation may be partially supported by the fact that bond size and maturity also tend to significantly reduce the time the basis takes to return to its mean once it is displaced. It could be that, once the

TABLE 6. Cross-sectional regressions: basis mean and standard deviation.

Variable	α_k	σ_k
Average Maturity	5.872***	-0.005
	(1.225)	(0.517)
(Average Maturity)^2	-0.343***	-0.067
	(0.108)	(0.045)
Bond size (log)	7.905***	-1.583***
	(1.074)	(0.385)
Coupon	-3.083***	1.886***
	(0.443)	(0.198)
Implied Vol. (avg.)	0.285***	0.167***
	(0.092)	(0.033)
Implied Vol. (std.)	-0.173	0.186
	(0.215)	(0.128)
Recovery (avg.)	-1.291***	0.126**
	(0.181)	(0.063)
Credit Spread Vol.	-0.006	0.051***
	(0.014)	(0.014)
High Yield	9.800***	5.877***
	(2.041)	(0.923)
No. of Downgrades	3.183***	1.228*
	(1.109)	(0.634)
No. of Upgrades	0.777	-0.556
	(1.322)	(0.648)
No. of CDS contributors (avg.)	-0.596***	-0.043
	(0.184)	(0.056)
Sector Dummies	***	***
	F=5.571	F=3.63
R^2	0.344	0.646

T statistics in parenthesis. *** denotes significance at the 1 percent level or better; ** and * denote significance at the 5 and 10 percent levels, respectively.

reasons for concern disappear, investors in those bonds are quick to shed protection in the CDS market, thereby returning the basis to its normal level.

Bonds that have been downgraded often also tend to have a higher and more dispersed basis on average, and so do bonds that belong (or have

TABLE 7. Cross-sectional regressions: basis half-life and "beta."

Variable	h_k	ϕ_k
Average Maturity	0.487	0.155*
	(0.407)	(0.083)
(Average Maturity)^2	-0.072**	-0.009
	(0.034)	(0.007)
Bond size (log)	-1.628***	-0.012
	(0.318)	(0.074)
Coupon	0.918***	0.098***
	(0.128)	(0.032)
Implied Vol. (avg.)	-0.089***	0.002
	(0.019)	(0.006)
Implied Vol. (std.)	0.185***	-0.034**
	(0.058)	(0.017)
Recovery (avg.)	0.118***	0.015
	(0.038)	(0.010)
Credit Spread Vol.	-0.007*	0.001
	(0.004)	(0.001)
High Yield	-1.321**	-0.196
	(0.622)	(0.128)
No. of Downgrades	1.122**	0.105
	(0.563)	(0.109)
No. of Upgrades	0.760	-0.121
	(0.999)	(0.083)
No. of CDS contributors (avg.)	0.127**	-0.005
	(0.056)	(0.010)
Sector Dummies	***	***
	F=4.833	F=3.63
R^2	0.105	0.039

T statistics in parenthesis. *** denotes significance at the 1 percent level or better; ** and * denote significance at the 5 and 10 percent levels, respectively.

belonged for at least one day) to the high-yield universe.[22] In agreement with common intuition, bonds that have been downgraded the most also tend to have longer half lives; high-yield bonds that have not been subject to many rating changes, however, have shorter half lives, everything else equal.

[22]Our high-yield indicator takes on the value of one if a bond has ever been rated below BBB, and zero otherwise. We do not separate bonds into investment-grade and speculative-grade categories because those categories are not the same over time.

Bonds whose issuer has a high average implied volatility over our sample tend to have higher and more volatile bases. This could again reflect the fact that investors find it easy to seek and obtain protection in the CDS market for firms that are riskier than other or that are perceived as being in distress for prolonged periods of time. The deviations of the basis away from the mean for those high-volatility firms, however, tend to be shorter, perhaps because the bond market does not take much longer to react.[23] In somewhat of a puzzle, the volatility of implied volatility does not seem to have an effect on either the level or the standard deviation of the average basis. We interpret the volatility of implied volatility as an indicator that a firm has undergone periods of stress while its bonds were in our sample, and thus we would expect its basis to be, on average, higher than normal if it is true that investors prefer the CDS market at times of stress.[24] We also note that a high volatility of volatility significantly lengthens the half life of the basis, and reduces ϕ_k (indeed, it is one of the few factors that enters significantly in the basis "beta" in equation 6).

High CDS liquidity, as proxied by the number of dealers willing to provide CDS quotes in the Markit dataset, tends to lower the basis, on average. Admittedly, this is not a perfect measure of liquidity, as at any given time there may be many dealers willing to provide quotes with extremely high bid-ask spreads, or many of those dealers may be providing very expensive quotes to protection seekers. Still, we find our result interesting, because it may point to poor liquidity conditions in the CDS market as a cause for high, positive bases. Also, the negative sign of the liquidity coefficient in the cross-sectional regressions is in contrast with the positive sign the corresponding coefficient has in the time series regressions. We are investigating this point further and we will report more results in future versions of the paper.

Finally, we note that high recovery rates tend to reduce the basis, as do bonds with large coupons. Intuitively, while the coupon effect may be technical in nature, the higher the recovery rate, the lower the credit risk that investors face, and thus the less incentives investors will have to seek pricey protection in the CDS market. The sector that a firm belongs to also appears to be significant in determining the level, dispersion, persistence, and "beta" of the average bond-specific basis. This may be because firms in certain sectors are more likely to experience common shocks.

6. Conclusions

We proposed to quantify the degree of corporate market functioning by the extent to which seeming arbitrage opportunities remain persistently unexploited. We defined those arbitrage opportunities in term of the basis,

[23] Both Blanco *et al.* (2005) and Zhu (1994) find that the CDS market leads the cash market in the price discovery process.

[24] Our interpretation is consistent with the GM experience plotted in figure 4: GM's basis surges in the spring of 2005 when the firm's credit quality deteriorated fast and its implied volatility spiked.

the difference between the CDS and corporate bond spread. We find that a large fraction of the variation in the basis across a large sample of bonds and firms is idiosyncratic in nature and reflects factors that are specific to a particular bond or firm.

Aggregate macroeconomic and financial variables account for a smaller, though certainly not negligible, fraction of the total variation in the basis. A large portion of the aggregate variation can be explained by variables related to liquidity conditions and liquidity preferences, as well as to the shape of the yield curve and the uncertainty about future economic and financial conditions.

In future research we plan to expand our analysis to the study of market frictions in a panel setting, where bond- and firm-specific variables are allowed to have a different effect on the basis over time. In a related, event-study type of project we are also working to understand the effects of aggregate and idyiosincratic shocks on the basis. We plan to proxy aggregate shocks with macroeconomic and monetary policy surprises, while we define firm-specific shocks in terms of the discrepancy between actual and expected earnings releases. We believe that those shocks may be yet another source of frictions in the corporate market, and some preliminary results support that belief.

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SESSION 4

SYSTEMIC RISK ACROSS COUNTRIES

BANKING SYSTEM STABILITY A CROSS-ATLANTIC PERSPECTIVE[1]

BY PHILIPP HARTMANN[2], STEFAN STRAETMANS[3] AND CASPER DE VRIES[4]

1 Paper prepared for the NBER project on "Risks of Financial Institutions". We benefited from suggestions and criticism by many participants in the project, in particular by the organizers Mark Carey (also involving Dean Amel and Allen Berger) and Rene Stulz, by our discussant Tony Saunders and by Patrick de Fontnouvelle, Gary Gorton, Andy Lo, Jim O'Brien and Eric Rosengren. Furthermore, we are grateful for comments we received at the 2004 European Finance Association Meetings in Maastricht, in particular by our discussant Marco da Rin and by Christian Upper, at the 2004 Ottobeuren seminar in economics, notably the thoughts of our discussant Ernst Baltensberger, of Friedrich Heinemann and of Gerhard Illing, as well as at seminars of the Max Planck Institute for Research on Collective Goods, the Federal Reserve Bank of St. Louis, the ECB and the University of Frankfurt. Gabe de Bondt and David Marques Ibanez supported us enormously in finding yield spread data, Lieven Baele and Richard Stehle kindly made us aware of pitfalls in Datastream equity data. Very helpful research assistance by Sandrine Corvoisier, Peter Galos and Marco Lo Duca as well as editorial support by Sabine Wiedemann are gratefully acknowledged. Any views expressed only reflect those of the authors and should not be interpreted as the ones of the ECB or the Eurosystem.

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Abstract

This paper derives indicators of the severity and structure of banking system risk from asymptotic interdependencies between banks' equity prices. We use new tools available from multivariate extreme value theory to estimate individual banks' exposure to each other ("contagion risk") and to systematic risk. By applying structural break tests to those measures we study whether capital markets indicate changes in the importance of systemic risk over time. Using data for the United States and the euro area, we can also compare banking system stability between the two largest economies in the world. For Europe we assess the relative importance of cross-border bank spillovers as compared to domestic bank spillovers. The results suggest, inter alia, that systemic risk in the US is higher than in the euro area, mainly as cross-border risks are still relatively mild in Europe. On both sides of the Atlantic systemic risk has increased during the 1990s.

Key words and phrases: Banking, Systemic Risk, Asymptotic Dependence, Multivariate Extreme Value Theory, Structural Change Tests

JEL classification: G21, G28, G29, G12, C49

Reprinted from M. Carey and R. Stulz (eds., 2006), Risks of Financial Institutions (Chicago University Press and National Bureau of Economic Research), pages 133 - 188, with kind permission of the Chicago University Press and the NBER.

Non-technical summary

A particularly important sector for the stability of financial systems is the banking sector. Banking sectors in major economies such as the United States and the euro area have been subject to considerable structural changes. For example, the US (and Europe) have experienced substantial banking consolidation since the 1990s and the emergence of large and complex institutions. The establishment of the conditions for the single market for financial services in the EU in conjunction with the EMU has led to progressing banking integration. These structural changes have made the monitoring of banking system stability even more complex. In Europe, for example, issues are raised about how to pursue macroprudential surveillance in a context of national banking supervision.

For all these reasons the present paper presents a new approach how to assess banking system risk, whether it is domestic or cross-border. This approach is based on new techniques available from multivariate extreme value theory, a statistical approach to assess the joint occurrence of very rare events, such as severe banking problems. More precisely, as measures of systemic risk we estimate semi-parametrically the probability of crashes in bank stocks, conditional on crashes of other bank stocks or of the market factor. The data cover the 50 most important banks in the US and in the euro area between 1992 and 2004. We estimate the amount of systemic risk in the euro area and in the US, and compare it across the Atlantic. We also compare domestic risk to cross-border risk and, finally, we test for structural change in systemic risk over time.

Our results suggest that the risk of multivariate extreme spillovers between US banks is higher than between European banks. Hence, despite the fact that available balance-sheet data show higher interbank exposures in the euro area, the US banking system seems to be more prone to contagion risk. Second, the lower spillover risk among European banks is mainly related to relatively weak cross-border linkages. Domestic linkages in France, Germany and Italy, for example, are of the same order as domestic US linkages. One interpretation of this result is that further banking integration in Europe could lead to higher cross-border contagion risk in the future, with the more integrated US banking system providing a benchmark. Third, cross-border spillover probabilities tend to be smaller than domestic spillover probabilities, but only for a few countries this difference is statistically significant. For example, among the banks from a number of larger countries – such as France, Germany, the Netherlands and Spain – extreme cross-border linkages are statistically indistinguishable from domestic linkages. In contrast, the effects of banks from these larger countries on the main banks from some smaller countries – including particularly Finland and Greece,

and sometimes also Ireland or Portugal – tend to be significantly weaker than the effects on their domestic banks. Hence, those smaller countries located further away from the center of Europe seem to be more insulated from European cross-border contagion.

Fourth, the effects of macro shocks on banking systems are similar in the euro area and the US, and they illustrate the relevance of aggregate risks for banking system stability. While stock market indices perform well as indicators of aggregate risk, we find that high-yield bond spreads capture extreme systematic risk for banks relatively poorly, both in Europe and the US. Fifth, structural stability tests for our indicators suggest that systemic risk, both in the form of interbank spillovers and in the form of aggregate risk, has increased in Europe and in the US. Our tests detect the break points during the second half of the 1990s, but graphical illustrations of our extreme dependence measures show that this was the result of developments spread out over time. In particular in Europe the process was very gradual, in line with what one would expect during a slowly advancing financial integration process. Interestingly, the introduction of the euro in January 1999 seems to have had a reductionary or no effect on banking system risk in the euro area. This may be explained by the possibility that stronger cross-border crisis transmission channels through a common money market could be offset by better risk sharing and the better ability of a deeper market to absorb shocks.

1. Introduction

A particularly important sector for the stability of financial systems is the banking sector. Banks play a central role in the money creation process and in the payment system. Moreover, bank credit is an important factor in the financing of investment and growth. Faltering banking systems have been associated with hyperinflations and depressions in economic history. Hence, to preserve monetary and financial stability central banks and supervisory authorities have a special interest in assessing banking system stability.

This is a particularly complex task in very large economies with highly developed financial systems, such as the United States and the euro area. Moreover, structural changes in the financial systems of both these economies make it particularly important to track risks over time. In Europe, gradually integrating financial systems under a common currency increase the relationships between banks across borders. This development raises the question how banking systems should be monitored in a context where banking supervision − in contrast to monetary policy − remains a national responsibility. In the US, tremendous consolidation as well as the removal of regulatory barriers to universal and cross-state banking has led to the emergence of large and complex banking organizations (LCBOs), whose activities and interconnections are particularly difficult to follow. For all these reasons we present a new approach how to assess banking system risk in this paper and apply it to the euro area and the US.

A complication in assessing banking system stability is that, in contrast to other elements of the financial system, such as securities values, interbank relationships that can be at the origin of bank contagion phenomena or the values of and correlations between loan portfolios are particularly hard to measure and monitor.[1] Hence, a large part of the published banking stability literature has resorted to more indirect market indicators. In particular, spillovers in bank equity prices have been used for this purpose.[2] Pioneered by Aharony and Swary (1983) and Swary (1986) a series of papers have applied the event

[1]Even central banks and supervisory authorities usually do not have continuous information about interbank exposures. For the Swedish example of a central bank monitoring interbank exposures at a quarterly frequency, see Blavarg and Nimander (2002).

[2]The choice of bank equity prices for measuring banking system risk may be motivated by Merton's (1974) option-theoretic framework toward default. The latter approach has become the cornerstone of a large body of approaches for quantifying credit risk and modeling credit rating migrations, including J.P. Morgan's CreditMetrics (1999).

study methodology to the effects of specific bank failures or bad news for certain banks on other banks' stock prices (see, e.g., also Wall and Petersen, 1990; Docking, Hirschey and Jones, 1997; Slovin, Sushka and Polonchek, 1999). In another series of papers various regression approaches are used in order to link abnormal bank stock returns to asset-side risks, including those related to aggregate shocks (see, e.g., Cornell and Shaphiro, 1986; Smirlock and Kaufold, 1987; Musumeci and Sinkey, 1990; or Kho, Lee and Stulz, 2000). De Nicolo and Kwast (2002) relate changes in correlations between bank stock prices over time to banking consolidation. Gropp and Moerman (2004) measure conditional co-movements of large abnormal bank stock returns and of equity-derived distances to default. Gropp and Vesala (2004) apply an ordered logit approach to estimate the effect of shocks in distances to default for some banks on other banks' distances to default.[3]

Some authors point out that most banking crises have been related to macroeconomic fluctuations rather than to prevalent contagion. Gorton (1988) provides ample historical evidence for the US, Gonzalez-Hermosillo, Pazarbasioglu and Billings (1997) also find related evidence

[3]Other market indicators used in the literature to assess bank contagion include bank debt risk premia (see, in particular, Saunders (1986) and Cooperman, Lee and Wolfe (1992)).

A number of approaches that do not rely on market indicators have also been developed in the literature. Grossman (1993) and Hasan and Dwyer (1994) measure autocorrelation of bank failures after controlling for macroeconomic fundamentals during various episodes of US banking history. Saunders and Wilson (1996) study deposit withdrawals of failing and non-failing banks during the Great Depression. Calomiris and Mason (1997) look at deposit withdrawals during the 1932 banking panic and ask whether also ex ante healthy banks failed as a consequence of them. Calomiris and Mason (2000) estimate the survival time of banks during the Great Depression, with explanatory variables including national and regional macro fundamentals, dummies for well known panics and the level of deposits in the same county (contagion effect).

A recent central banking literature attempts to assess the importance of contagion risk by simulating chains of failures from (incomplete and mostly confidential) national information about interbank exposures. See, e.g., Furfine (2003), Elsinger, Lehar and Summer (2002), Upper and Worms (2004), Degryse and Nguyen (2004), Lelyveld and Liedorp (2004) or Mistrulli (2005).

Chen (1999), Allen and Gale (2000) and Freixas, Parigi and Rochet (2002) develop the theoretical foundations of bank contagion.

for the Mexican crisis of 1994-1995 and Demirgüc-Kunt and Detragiache (1998) add substantial further support for this hypothesis using a large multi-country panel dataset.[4]

The new approach for assessing banking system risk presented in this paper also employs equity prices. It is based on extreme value theory (EVT) and allows us to estimate the probabilities of spillovers between banks, their vulnerability to aggregate shocks and changes in those risks over time. More precisely, we want to make three main contributions compared to the previous literature. First, we use the novel multivariate extreme value techniques applied by Hartmann, Straetmans and de Vries (2003a/b and 2004) and Poon, Rockinger and Tawn (2004) to estimate the strength of banking system risks. In particular, we distinguish conditional "co-crash" probabilities between banks from crash probabilities conditional on aggregate shocks. While EVT - both univariate and multivariate - has been applied to general stock indices before, it has not yet been used to assess the extreme dependence between bank stock returns with the aim to measure banking system risk. Second, we cover both euro area countries and the United States to compare banking system stability internationally. We are not aware of any other study that tries to compare systemic risk between these major economies. Third, we apply the test of structural stability for tail indexes by Quintos, Fan and Phillips (2001) to the multivariate case of extreme linkages and assess changes in banking system stability over time with it. Again, whereas a few earlier papers addressed the changing correlations between bank stock returns, none focused on the extreme interdependence we are interested in in the present paper.

The idea behind our approach is as follows. We assume that bank stocks are efficiently priced, in that they reflect all publicly available information about (i) individual banks' asset and liability side risks and (ii) relationships between different banks' risks (be it through correlations of their loan portfolios, interbank lending or other channels). We identify a critical situation of a bank with a dramatic slump of its stock price. We identify the risk of a problem in one or several banks spilling over to other banks ("contagion risk") with extreme negative co-movements between individual bank stocks (similar to the conditional co-crash probability in our earlier stock, bond and currency papers). In addition, we identify the risk of banking system destabilization through aggregate shocks with the help of the "tail-β" proposed

[4] Hellwig (1994) argues that the observed vulnerability of banks to macroeconomic shocks may be explained by the fact that deposit contracts are not conditional on aggregate risk. Chen (1999) models, inter alia, how macro shocks and contagion can reinforce each other in the banking system.

by Straetmans, Verschoor and Wolf (2003). The tail-β is measured by conditioning our co-crash probability on a general stock index (or another measure of systematic risk) rather than on individual banks' stock prices. Therefore, in some respects it reflects the tail equivalent to standard asset pricing models. In this paper we further extend the analysis of tail-β by also using high-yield bond spreads as measures of aggregate risk. Based on the estimated individual co-crash probabilities and tail-βs, we can then test for the equality of banking system risk between the US and the euro area and for changes in systemic risk over time.

Our work is also related to an active literature examining which phenomena constitute financial contagion and how they can be identified empirically. In our reading, the main criteria proposed so far to identify contagion are that (i) a problem at a financial institution adversely affects other financial institutions or that a decline in an asset price leads to declines in other asset prices; (ii) the relationships between failures or asset price declines must be different from those observed in normal times (regular "interdependence"); (iii) the relationships are in excess of what can be explained by economic fundamentals; (iv) the events constituting contagion are negative "extremes", such as full-blown institution failures or market crashes, so that they correspond to crisis situations; (v) the relationships are the result of propagations over time rather than being caused by the simultaneous effects of common shocks.

Most empirical approaches proposed in the recent literature how to measure contagion capture the first criterion (i), but this is where the agreement usually ends. Authors differ in their view which of the other criteria (ii) through (v) are essential for contagion. Forbes and Rigobon (2002) stress statistically significant changes in correlations over time as a contagion indicator and illustrate how they emerge among emerging country equity markets. Shiller (1989), Pindyck and Rotemberg (1993) and Bekaert, Harvey and Ng (forthcoming) emphasize "excess co-movements" between stock markets and stock prices, beyond what is explained in various forms of regressions by dividends, macroeconomic fundamentals or asset pricing "factors". Eichengreen, Rose and Wyplosz (1996) estimate probit models to examine whether the occurrence of a balance-of-payments crisis in one country increases the probability of a balance-of-payments crisis in other countries, conditional on macroeconomic country fundamentals. Bae, Karolyi and Stulz (2003) propose the logit regression model to estimate probabilities that several stock markets experience large negative returns, given that a smaller number of stock markets experience large negative returns, conditional on interest and exchange rates. Longin and Solnik (2001) are among the first to apply bivariate EVT to estimate extreme equity market correlations, also assuming the logistic distribution. Hartmann et al. (2003a/b, 2004) stress that market co-movements far out in the tails ("asymptotic dependence") may be very different from regular dependence in multivariate distributions and that such crisis behavior may not have the same parametric form in different markets. Based on a different branch of EVT, they estimate semi-parametrically for stocks, bonds and currencies the likelihood of widespread market crashes conditional on contemporaneous and lagged other market crashes. The reason why we particularly focus on criterion (iv) is that it allows us to concentrate on events that are severe enough to be basically always of a concern for policy. Other criteria are also interesting and have their own justifications, but more regular propagations or changes in them are not necessarily a concern for policies that aim at the stability of financial systems.[5]

The data we use in this work are daily bank stock excess returns in euro area countries and the United States between April 1992 and February 2004. For each area or country we choose 25 banks based on the criteria of balance-sheet size and involvement in interbank lending. So, our sample represents the systemically most relevant financial institutions, but neglects a large number of smaller banks. During our sample period several of the banks selected faced failure-like situations and also global markets passed several episodes of stress. All in all, we have about 3,100 observations per bank.

Our results suggest that the risk of multivariate extreme spillovers between US banks is higher than between European banks. Hence, despite the fact that available balance-sheet data show higher interbank exposures in the euro area, the US banking system seems to be more prone to contagion risk. Second, the lower spillover risk among European banks is mainly related to relatively weak cross-border linkages. Domestic linkages in France, Germany and Italy, for example, are of the same order as domestic US linkages. One interpretation of this result is that further banking integration in Europe could lead to higher cross-border contagion risk in the future, with the more integrated US banking system providing a benchmark. Third, cross-border spillover probabilities tend to be smaller than domestic spillover probabilities, but only for a few countries this difference is statistically significant.

[5]Less extreme spillovers might still indicate some form of microeconomic inefficiencies but not necessarily widespread destabilization.

De Bandt and Hartmann (2000) provide a more complete survey of the market and banking contagion literature. Pritsker (2001) discusses different channels of contagion.

For example, among the banks from a number of larger countries – such as France, Germany, the Netherlands and Spain – extreme cross-border linkages are statistically indistinguishable from domestic linkages. In contrast, the effects of banks from these larger countries on the main banks from some smaller countries – including particularly Finland and Greece, and sometimes also Ireland or Portugal – tend to be significantly weaker than the effects on their domestic banks. Hence, those smaller countries located further away from the center of Europe seem to be more insulated from European cross-border contagion.

Fourth, the effects of macro shocks emphasized by the estimated tail-βs are similar for the euro area and the US, and they illustrate the relevance of aggregate risks for banking system stability. While stock market indices perform well as indicators of aggregate risk, we find that high-yield bond spreads capture extreme systematic risk for banks relatively poorly, both in Europe and the US. Fifth, structural stability tests for our indicators suggest that systemic risk, both in the form of interbank spillovers and in the form of aggregate risk, has increased in Europe and in the US. Our tests detect the break points during the second half of the 1990s, but graphical illustrations of our extreme dependence measures show that this was the result of developments spread out over time. In particular in Europe the process was very gradual, in line with what one would expect during a slowly advancing financial integration process. Interestingly, the introduction of the euro in January 1999 seems to have had a reductionary or no effect on banking system risk in the euro area. This may be explained by the possibility that stronger cross-border crisis transmission channels through a common money market could be offset by better risk sharing and the better ability of a deeper market to absorb shocks.

The paper is structured as follows. The next section describes our theoretical indicators of banking system stability, distinguishing the multivariate spillover or contagion measure from the aggregate tail-β measure for stock returns. Section 3 outlines the estimation procedures for both measures; and section 4 presents two tests, one looking at the stability of spillover and systematic risk over time and the other looking at the stability of both measures across countries and continents (cross-sectional stability). Section 5 summarizes the data set we employ, in particular how we selected the banks covered, provides some standard statistics for the individual bank and index returns, and gives some information about the occurrence of negative extremes for individual banks and the related events.

Section 6 then presents the empirical results on extreme bank spillover risks. For both the euro area and the US we estimate the overall multivariate extreme dependence in the banking sector and we test whether one is larger than the other. Moreover, for Europe we assess whether domestic spillover risk is stronger or weaker than cross-border risk. Section 7 turns to the empirical results for aggregate banking system risk on both continents. We estimate individual tail-βs for European banks and for US banks. We also aggregate those βs and test for the equality of them in the euro area and the US. Section 8 then asks the question whether on any of the two continents the risk of interbank spillovers or the vulnerability of the banking system to aggregate shocks has changed over time. The final section concludes. We have five appendices. The first one (appendix A) discusses small sample properties of estimators and tests. Appendix B lists the banks in our sample and the abbreviations used for them across the paper. Appendix C presents some balance-sheet information characterizing the systemic relevance of banks. Appendix D contains the standard statistics for our return data and for yield spreads. Finally, appendix E discusses the role of volatility clustering for extreme dependence in bank stock returns.

2. Indicators of banking system stability

Our indicators of banking system stability are based on extreme stock price movements. They are constructed as conditional probabilities, conditioning single or multiple bank stock price "crashes" on other banks' stock price crashes or on crashes of the market portfolio. Extreme co-movements, as measured by multivariate conditional probabilities between individual banks' stock returns, are meant to capture the risk of contagion from one bank to another. Extreme co-movements between individual banks' stock returns and the returns of a general stock market index or another measure of non-diversifiable risk (the so-called "tail-β") are used to assess the risk of banking system instability through aggregate shocks. The two forms of banking system instability are theoretically distinct, but in practice they may sometimes interact. Both have been extensively referred to in the theoretical and empirical banking literature. In what follows we describe them in more precise terms.

2.1. **Multivariate extreme spillovers: A measure of bank contagion risk.** Let us start with the measure of multivariate extreme bank spillovers. The measure can be expressed in terms of marginal (univariate) and joint (multivariate) exceedance probabilities. Consider an N-dimensional banking system, i.e., a set of N banks from, e.g., the same country or continent. Denote the log first differences of the price changes in bank stocks minus the risk-free interest rate by the random variables X_i $(i = 1, \cdots, N)$. Thus, X_i describes a bank i's excess return. We adopt the convention to take the negative of stock returns, so that we can define all used formulae in terms of upper tail returns. The crisis levels or extreme quantiles Q_i $(i = 1, \cdots, N)$ are chosen such that the tail probabilities are equalized across banks, i.e.,

$$P\{X_1 > Q_1\} = \cdots = P\{X_i > Q_i\} = \cdots = P\{X_N > Q_N\} = p\ .$$

With the significance level in common, crisis levels Q_i will generally not be equal across banks, because the marginal distribution functions $P\{X_i > Q_i\} = 1 - F_i(Q_i)$ are bank specific. The crisis levels can be interpreted as "barriers" that will on average only be broken once in $1/p$ time periods, i.e., p^{-1} days if the data frequency is daily.[6] Suppose now that we want to measure the propagation of severe problems through the European and US banking sectors by calculating the probability of joint collapse in an arbitrarily large set of N bank stocks, conditional on the collapse of a subset $L < N$ banks:

$$(2.1) \qquad \begin{aligned} P_{N|L} &= P\left\{\bigcap_{i=1}^{N} X_i > Q_i(p) \,\middle|\, \bigcap_{j=1}^{L} X_j > Q_j(p)\right\} \\ &= \frac{P\left\{\bigcap_{i=1}^{N} X_i > Q_i(p)\right\}}{P\left\{\bigcap_{j=1}^{L} X_j > Q_j(p)\right\}}\ . \end{aligned}$$

Clearly, the right-hand side immediately follows from the definition of conditional probability. With independence the measure reduces to p^{N-L}. This provides a benchmark against which the dependent cases are to be judged.

Equation (2.1) is very flexible in terms of the conditioning set on the right-hand side. For example, the conditioning banks do not necessarily have to be a subset of the bank set on the left-hand side. Moreover, the conditioning random variables could also be others than just bank stock prices.[7]

[6] Notice that the set of banks in a given country can be thought of as a "portfolio" for which the supervisory authority is responsible. From a risk management point of view a common significance level makes the different portfolio positions comparable in terms of their downside risk. Moreover, we argue later on that our bivariate and multivariate probability measures that use the common tail probability as an input will solely reflect dependence information.

[7] In Hartmann, Straetmans and de Vries (2003b) we applied an analogous measure to assess the systemic breadth of currency crises.

2.2. **Tail-βs: A measure of aggregate banking system risk.** Our second measure of banking system risk is from a methodological point of view a bivariate "variant" of (2.1), in which $N = 1$ and the conditioning set is limited to extreme downturns of the market portfolio or another indicator of aggregate risk ($L = 1$).[8] This tail-β measure is inspired by portfolio theory and has been used before by Straetmans et al. (2003) to examine the intraday effects of the September 11 catastrophe on US stocks. Let M be the excess return on the market portfolio (e.g. using a stock market index) and let p be the common tail probability, then this measure can be written as:

$$\begin{aligned} P\left\{X_k > Q_k\left(p\right)|X_M > Q_M\left(p\right)\right\} &= \frac{P\left\{X_k > Q_k\left(p\right), X_M > Q_M\left(p\right)\right\}}{P\left\{X_M > Q_M\left(p\right)\right\}} \\ &= \frac{P\left\{X_k > Q_k\left(p\right), X_M > Q_M\left(p\right)\right\}}{p}. \end{aligned} \tag{2.2}$$

The measure captures how likely it is that an individual bank's value declines dramatically, if there is an extreme negative systematic shock. Analogous to the multivariate spillover probability (2.1), the tail-β (2.2) reduces to $p^2/p = p$ under the benchmark of independence. We extend the analysis of extreme aggregate risk in this paper by also experimenting with high-yield bond spreads as a measure X_M of systematic shocks.[9]

3. Estimation of the indicators

The joint probabilities in (2.1) and (2.2) have to be estimated. Within the framework of a parametric probability law, the calculation of the proposed multivariate probability measures is straightforward, because one can estimate the distributional parameters by, e.g., maximum likelihood techniques. However, if one makes the wrong distributional assumptions, the linkage estimates may be severely biased due to misspecification. As there is no clear evidence that all stock returns follow the same distribution – even less so for the crisis situations we are interested in here –, we want to avoid very specific assumptions for bank stock returns. Therefore, we implement the semi-parametric EVT approach proposed by Ledford and Tawn (1996; see also Draisma et al., 2001, and Poon et al., 2004, for recent applications). Loosely

[8] Technically, it is also possible to derive and estimate this measure for $N > 1$, but we do not do this in the present paper.

[9] In the present paper we limit ourselves to these two measures of banking system risk. In future research, the approach could be extended by also including further economic variables in the conditioning set, such as interest rates or exchange rates.

speaking, their approach consists of generalizing some "best practice" in univariate extreme value analysis – based on the generalized Pareto law behavior of the minima and maxima of the relevant distributions for financial market returns – to the bivariate case. So, they derive the tail probabilities that occur in measures (2.1) and (2.2) for the bivariate case. We go a step further by applying their approach to the multivariate case.

Before going ahead with applying the Ledford-Tawn approach to our two measures of banking system stability, it is important to stress that the dependence between two random variables and the shape of the marginal distributions are unrelated concepts. To extract the dependence, given by the copula function, it is convenient to transform the data and remove any possible influences of marginal aspects on the joint tail probabilities. One can transform the different original excess returns to ones with a common marginal distribution (see, e.g., Ledford and Tawn, 1996, and Draisma et al., 2001). After such a transformation, differences in joint tail probabilities across banking systems (e.g., Europe versus the US) can be solely attributed to differences in the tail dependence structure of the extremes. This is different, e.g., from correlation-based measures that are still influenced by the differences in marginal distribution shapes.

In this spirit we transform the bank stock excess returns $(X_1, \cdots, X_i, \cdots, X_N)$ to unit Pareto marginals:

$$\widetilde{X}_i = \frac{1}{1 - F_i\left(X_i\right)},\ i = 1, \cdots, N,$$

with $F_i(\cdot)$ representing the marginal cumulative distribution function (cdf) for X_i. However, since the marginal cdfs are unknown, we have to replace them with their empirical counterparts. For each X_i this leads (with a small modification to prevent division by 0) to:

$$\widetilde{X}_i = \frac{n+1}{n+1-R_{X_i}},\ i = 1, \cdots, N, \tag{3.1}$$

where $R_{X_i} = rank(X_{il}, l = 1, \cdots, n)$. Using this variable transform, we can rewrite the joint tail probability that occurs in (2.1) and (2.2):

$$P\left\{\bigcap_{i=1}^{N} X_i > Q_i(p)\right\} = P\left\{\bigcap_{i=1}^{N} \widetilde{X}_i > q\right\},$$

where $q = 1/p$.[10] The multivariate estimation problem can now be reduced to estimating a univariate exceedance probability for the cross-sectional minimum of the N bank excess return series, i.e., it is always true that:

$$(3.2) \qquad P\left\{\bigcap\nolimits_{i=1}^{N} \widetilde{X}_i > q\right\} = P\left\{\min_{i=1}^{N}\left(\widetilde{X}_i\right) > q\right\} = P\left\{\widetilde{X}_{\min} > q\right\} \ .$$

The marginal tail probability at the right-hand side can now be calculated, provided the following additional assumption on the univariate tail behavior of $\widetilde{X}_{\min}$ is made. Ledford and Tawn (1996) argue that the bivariate dependence structure is a regular varying function under fairly general conditions.[11] Peng (1999) and Draisma et al. (2001) give sufficient conditions and further motivation. Therefore, we assume that the auxiliary variable $\widetilde{X}_{\min}$ has a regularly varying tail. Notice, however, that in contrast to Ledford and Tawn (1996) we often consider more than two dimensions.[12]

Assuming that $\widetilde{X}_{\min}$ exhibits heavy tails with tail index α, then the regular variation assumption for the auxiliary variables implies that the univariate probability in (3.2) exhibits a tail descent of the Pareto type:

$$(3.3) \qquad P\left\{\widetilde{X}_{\min} > q\right\} \approx \ell(q)q^{-\alpha} \ , \ \alpha \geq 1 \ ,$$

with q large (p small) and where $\ell(q)$ is a slowly varying function (i.e., $\lim_{q\to\infty} \ell(xq)/\ell(q) = 1$ for all fixed $x > 0$). We can now distinguish the

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[10] The multivariate probability stays invariant under the variable transformation $(X_1, \cdots, X_i, \cdots, X_N) \to \left(\widetilde{X}_1, \cdots, \widetilde{X}_i, \cdots, \widetilde{X}_N\right)$, because the determinant of the Jacobian matrix can be shown to be equal to 1.

[11] A function $F(x)$ is said to have a regularly varying left tail if

$$\lim_{u\to\infty} F(-ux)/F(-u) = x^{-\alpha}$$

for any $x > 0$ and tail index $\alpha > 0$.

[12] Equation (3.2) requires a common quantile q. This can, however, be easily generalized to the case where q differs across the marginals. Assume that we both allow the quantiles of the original distribution function Q_1 and Q_2 and the corresponding marginal probabilities p_1 and p_2 to be different from each other. For the bivariate case this would imply, for example, that

$$P\left\{X_1 > Q_1(p_1), X_2 > Q_2(p_2)\right\} = P\left\{\widetilde{X}_1 > q_1, \widetilde{X}_2 > q_2\right\} \ ,$$

with $q_i = 1/p_i$ $(i = 1, 2)$. By multiplying $\widetilde{X}_2$ with q_1/q_2 the above joint probability again reduces to a probability with a common quantile q_1 and we are back to the framework described above, where the loading variable $\widetilde{X}_{\min}$ can be calculated.

two cases in which the $\widetilde{X}_i$ are *asymptotically dependent* and asymptotically independent. In the former case $\alpha = 1$ and

$$\lim_{q\to\infty} \frac{P\left\{\widetilde{X}_{\min} > q\right\}}{P\left\{\widetilde{X}_{\max} > q\right\}} > 0 \ ,$$

with $P\left\{\widetilde{X}_{\max} > q\right\} = P\left\{\max_{i=1}^{N}\left(\widetilde{X}_i\right) > q\right\}$. Examples of asymptotically dependent random variables include, e.g., the multivariate Student-T distribution. For *asymptotic independence* of the random variables $\alpha > 1$, and we have that

$$\lim_{q\to\infty} \frac{P\left\{\widetilde{X}_{\min} > q\right\}}{P\left\{\widetilde{X}_{\max} > q\right\}} = 0 \ . \tag{3.4}$$

An example of this case is the bivariate standard normal distribution with correlation coefficient ρ. For this distribution $\alpha = 2/(1+\rho)$ and the limit (3.4) applies. When the normal random variables are independent ($\rho = 0$), one immediately obtains that $\alpha = 2$. In general, whenever the $\widetilde{X}_i$ are fully independent in the N-dimensional space, $\alpha = N$ and $P\left\{\widetilde{X}_{\min} > q\right\} = p^N$. But the reverse is not true, i.e., there are joint N-dimensional distributions with non-zero pairwise correlation that nevertheless have $\alpha = N$. The Morgenstern distribution constitutes an example of this tail behavior. (A bivariate version is employed in a Monte Carlo exercise in appendix A.1.)

The steps (3.1), (3.2) and (3.3) show that the estimation of multivariate probabilities can be reduced to a univariate estimation problem that is well known. Univariate tail probabilities for fat-tailed random variables – like the one in (3.2) – can be estimated by using the semi-parametric probability estimator from De Haan et al. (1994):

$$\widehat{P}\left\{\widetilde{X}_{\min} > q\right\} = \frac{m}{n}\left(\frac{C_{n-m,n}}{q}\right)^{\alpha} , \tag{3.5}$$

where the "tail cut-off point" $C_{n-m,n}$ is the $(n-m)$-th ascending order statistic from the cross-sectional minimum series $\widetilde{X}_{\min}$. The estimator (3.5) basically extends the empirical distribution function of $\widetilde{X}_{\min}$ outside the domain of the sample by means of its asymptotic Pareto tail from (3.3). An intuitive derivation of the estimator is provided in Danielsson and de Vries (1997). The tail probability estimator is conditional upon the tail index α and a choice of the threshold parameter m.

To estimate α we use the popular Hill (1975) estimator for the index of regular variation:

$$\widehat{\eta} = \frac{1}{m}\sum_{j=0}^{m-1} \ln\left(\frac{C_{n-j,n}}{C_{n-m,n}}\right) = \frac{1}{\widehat{\alpha}}, \tag{3.6}$$

where $\widehat{\eta}$ is the estimate of our parameter of tail dependence and m is the number of higher order extremes that enter the estimation. The higher $\widehat{\eta}$, and given the slowly varying function $\ell(s)$, the more dependent are the components $\left(\widetilde{X}_1, \cdots, \widetilde{X}_i, \cdots, \widetilde{X}_N\right)$ from (3.2) far out in their joint tail. Following from the discussion above, for asymptotic dependence our tail dependence parameter $\eta = 1$ and for asymptotic independence $\eta = 1/N$. Draisma et al. (2001) derive asymptotic normality of $\sqrt{m}\left(\frac{\widehat{\eta}}{\eta} - 1\right)$ under fairly general conditions.[13] The asymptotic normality will prove convenient for the tests implemented later on. Further details on the Hill estimator can be found in Jansen and De Vries (1991), for example, and in the monograph by Embrechts, Klüppelberg and Mikosch (1997).

The optimal choice of the threshold parameter m is a point of concern in the extreme value theory literature. Goldie and Smith (1987) suggest to select the nuisance parameter m so as to minimize the asymptotic mean-squared error. A widely used heuristic procedure plots the tail estimator as a function of m and selects m in a region where $\widehat{\eta}$ is stable. Double bootstrap techniques based upon this idea have been developed recently (see, e.g., Danielsson et al., 2001), but these are only advisable for sample sizes that are larger than the ones we have available for this paper. For simplicity and in accordance with the minimization criterion of Goldie and Smith (1987), we select $m = \kappa n^{\gamma}$ with $\gamma = 2/3$, sample size n and where κ is derived from the widely used Hill plot method.[14] We provide in appendix A.1 a discussion of the properties of our tail dependence parameter η in small samples.

[13] For discussions of alternative estimators and proper convergence behavior, see e.g. Draisma et al. (2001), Peng (1999), and Beirlandt and Vandewalle (2002).

[14] Minimizing the asymptotic mean-squared error for the Hill estimator by balancing bias and variance renders a nonlinear selection rule like the one above. For convenience, we impose the parameter restriction $\gamma = 2/3$. While simplifying, it can be shown to hold for a wide variety of distribution functions (see Hall, 1990). Moreover, establishing stable and accurate estimates of γ is notoriously difficult (see, e.g., Gomes et al., 2002, for a recent example). κ is calibrated by means of the heuristic Hill plot method. Once a value of m^* is selected in a horizontal range of $\widehat{\eta} = \widehat{\eta}\,(m)$, the scale factor immediately follows from $\kappa = m^*/n^{2/3}$.

4. Hypothesis testing

In this section we introduce some tests that can be used to assess various hypotheses regarding the evolution and structure of systemic risk in the banking system. The first one allows to test for the structural stability of the amount of risk found with our two indicators. The second test allows us to compare the systemic risk across countries and continents.

4.1. **Time variation.** The multivariate linkage estimator (2.1) and its bivariate counterpart in (2.2) were presented so far assuming stationarity of tail behavior over time. From a policy perspective, however, it is important to know whether systemic risk in the banking system – either in terms of contagion risk (2.1) or in terms of extreme systematic risk (2.2) – has changed over time. As the discussion of the Ledford and Tawn approach toward estimating (2.1) or (2.2) has shown, the structural (in)stability of systemic risk will critically depend on whether the tail dependence parameter η is constant or not. We study the occurrence of upward and downward swings in η with a recently developed structural stability test for the Hill statistic (3.6).

Quintos, Fan and Phillips (2001) present a number of tests for identifying single unknown breaks in the estimated tail index $\widehat{\alpha}$. As our estimation approach allows to map the multivariate dependence problem into a univariate estimation problem, we can choose from them the best test procedures for our tail dependence parameter η. Balancing the prevention of type I and type II errors we opt for the *recursive* test from Quintos et al. Let t denote the endpoint of a sub-sample of size $w_t < n$. The recursive estimator for η is calculated from (3.6) for sub-samples $[1;t] \subset [1;n]$:

$$\widehat{\eta}_t = \frac{1}{m_t} \sum_{j=0}^{m_t - 1} \ln \left(\frac{X_{t-j,t}}{X_{t-m_t,t}} \right), \tag{4.1}$$

with $m_t = \kappa t^{2/3}$.

The value of the recursive test statistic equals the supremum of the following time series:

$$Y_n^2(t) = \left(\frac{t m_t}{n} \right) \left(\frac{\widehat{\eta}_n}{\widehat{\eta}_t} - 1 \right)^2 . \tag{4.2}$$

Expression (4.2) compares the recursive value of the estimated tail parameter (3.6) to its full sample counterpart $\widehat{\eta}_n$. The null hypothesis of interest is that the tail dependence parameter does not exhibit any temporal changes. More specifically, let η_t be the dependence in the left tail of X. The null hypothesis of constancy then takes the form

$$H_0 : \eta_{[nr]} = \eta, \quad \forall r \in R_\varepsilon \ = [\varepsilon; 1 - \varepsilon] \subset [0; 1] \,, \tag{4.3}$$

with $[nr]$ representing the integer value of nr. Without prior knowledge about the direction of a break, one is interested in testing the null against the two-sided alternative hypothesis $H_A : \eta_{[nr]} \neq \eta$. For practical reasons the above test is calculated over compact subsets of $[0; 1]$, i.e., t equals the integer part of nr for $r \in R_\varepsilon = [\varepsilon; 1 - \varepsilon]$ and for small $\varepsilon > 0$. Sets like R_ε are often used in the construction of parameter constancy tests (see, e.g., Andrews, 1993).[15] In line with Quandt's (1960) pioneering work on endogenous breakpoint determination in linear time series models, the candidate break date r can be selected as the maximum value of the test statistic (4.2), because at this point in time the constancy hypothesis is most likely to be violated.

Asymptotic critical values can be derived for the sup-value of 4.2, but if the data are temporally dependent the test sequence Y_n^2 needs to be scaled in order to guarantee convergence to the same limiting distribution function as in the case of absence of temporal dependence. It is well known that financial returns exhibit nonlinear dependencies like, e.g., ARCH effects (volatility clustering). It is likely that the loading variable $\widetilde{X}_{\min}$, previously defined as the cross-sectional minimum of the bank stock returns (transformed using their proper empirical distribution function), partly inherits these nonlinearities. The nonlinear dependence implies that the asymptotic variance of the Hill estimator $1/\widehat{\eta}$ is $\frac{s^2}{\eta^2}$, with s some scaling factor. If the scaling factor differs from 1 (presence of temporal dependence), the asymptotic critical values of the test statistic will depend on the scaling. Quintos et al. suggest to pre-multiply the test statistic with the inverse of the scaling factor in order to let it converge to the same critical values as in the i.i.d. case. However, their scaling estimator is based upon the ARCH assumption for univariate time series. As we do not want to make very specific assumptions on the precise structure of the nonlinear dependence in the marginals, we apply a block bootstrap to the asymptotic variance

[15] The restricted choice of r implies that $\varepsilon n \leq t \leq (1 - \varepsilon)\, n$. When the lower bound would be violated the recursive estimates might become too unstable and inefficient because of too small sub-sample sizes. On the other hand, the test will never find a break for t equal or very close to n, because the test value (4.2) is close to zero in that latter case. Thus, for computational efficieny one might stop calculating the tests beyond the upper bound of $(1 - \varepsilon)\, n < n$. In line with Andrews, we search for breaks in the $[0.15n; 0.85n]$ subset of the total sample.

of the Hill statistic $1/\widehat{\eta}$ and thus the scaling factor s.[16] Following Hall, Horowitz and Jing (1995), the optimal block length is set equal to $n^{1/3}$. One now selects r for the recursive test such that $Y_n^2(t)$ – appropriately scaled – is maximal:

$$\Omega_{r \in R_\tau} = \sup \widehat{s}^{-1} Y_n^2(t), \tag{4.4}$$

with $\widehat{s}$ the estimate of the scaling factor. The null of parameter constancy is rejected if the sup-value exceeds the asymptotic critical values.

Quintos et al. provide a Monte Carlo study that shows convincingly the very good small sample power, size and bias properties of the recursive break test. Only in the case of a decrease of extreme tail dependence under the alternative hypothesis ($\eta_1 > \eta_2$) they detect less acceptable power properties. We solve this problem by executing the recursive test both in a "forward" version and a "backward" version. The forward version calculates η_t in calender time, and the backward version in reverse calender time. If a downward break in η occurs and the forward test does not pick it up, then the backward test corrects for this. Appendix A.2 provides a further Monte Carlo study of the small-sample properties of the recursive structural break test.

4.2. **Cross-sectional variation.** Apart from testing whether systemic banking risk is stable over time, we would also like to know whether cross-sectional differences between various groups of banks or different banking systems, say between the US and Europe or between different European countries, are statistically and economically significant. The asymptotic normality of tail dependence coefficient estimates $\widehat{\eta}$ referred to above enables some straightforward hypothesis testing. A test for the equality of tail dependence parameters between, e.g., Europe and the United States can thus be based on the following T-statistic:

$$T = \frac{\widehat{\eta}_1 - \widehat{\eta}_2}{s.e.\left(\widehat{\eta}_1 - \widehat{\eta}_2\right)}, \tag{4.5}$$

which converges to a standard normal distribution in large samples.[17] In the empirical applications below the asymptotic standard error in the test's denominator (4.5) is estimated using a block bootstrap with 1,000 replications. Again following Hall et al. (1995), we set the optimal block length equal to $n^{1/3}$. Similar to the structural stability

[16]The scale is estimated by $s = \widehat{\eta} m \widehat{\sigma}^2 (1/\widehat{\eta})$ with $\widehat{\sigma}^2$ the block bootstrapped variance of the Hill statistic.

[17]One can safely assume that T comes sufficiently close to normality for empirical sample sizes as the one used in this paper (see, e.g., Hall, 1982, or Embrechts et al., 1997).

test above, we opt for bootstrapping in blocks because of the nonlinear dependencies that might be present in the return data.

5. Data and descriptive statistics

We collected daily stock price data (total return indexes including dividends) for 25 euro area banks and 25 US banks. Excess returns are constructed by taking log first differences and deducting 3-month LIBOR rates (adjusted linearly to derive daily from annual rates). They are expressed in local currency, so that they do not vary directly with exchange rates. The market risk factor or aggregate shocks to the euro area and US banking systems are proxied by several measures with an eye toward some sensitivity analysis. First, we employ a general stock index and the banking sector sub-index for the euro area and the US, respectively. Second, we use the spread between below-investment-grade and treasury bond yields for each of these economies. Finally, we use a global stock index and the global banking sector sub-index.

All series, except one, start on 2 April 1992 and end on 27 February 2004, rendering 3,106 return observations per bank. The euro area high-yield bond spread is only available from 1 January 1998 onwards, yielding 1,497 observations. All series are downloaded from Datastream, whose source for high-yield bond spreads is Merrill Lynch.[18] The stock indices are the total return indices calculated by the data provider.

The following sub-section provides detailed information about how the 50 banks were chosen, based on balance sheet items for European and US banks. The subsequent section discusses the return data in greater depth, referring to the typical host of standard descriptive statistics.

5.1. **Bank selection and balance sheet information.** The time dimension of this dataset was very much constrained by the unavailability of longer stock price series for European banks. Before the 1990s fewer large European banks were privately quoted on stock exchanges and also many banks disappeared as a consequence of mergers. Ten out of 12 euro area countries have banks in our sample. There is no Austrian bank, as we could not construct a long enough stock price series for any of the two largest banks from this country. We deliberately excluded banks from Luxembourg, as they are considerably smaller than the larger banks from all other euro area countries. Roughly in proportion to the sizes of their economies in terms of GDP and the sizes of their

[18] See de Bondt and Marques (2004) for an in-depth discussion of high-yield bond spreads.

banking systems in terms of assets, we have 6 banks from Germany, 4 banks from France, 4 banks from Italy, 3 banks from Spain, 2 banks each from the Netherlands and from Belgium and one bank from Finland, Greece, Ireland and Portugal, respectively. Appendix B contains the full list of banks, the abbreviations used in the tables and their country of origin.

Apart from the above constraints, banks were chosen on the basis of two main criteria: First, their size (as measured mainly by assets and deposits) and, second, their involvement in interbank lending (as measured by interbank loans, amounts due to and due from other banks and total money market funding). The necessary balance-sheet information was taken from Bureau van Dijk's Bankscope database (considering end of year values between 1992 and 2003). For the United States, the choice of banks was double-checked on the basis of the Federal Reserve Bank of Chicago commercial bank and bank holding company databases.

We used this balance-sheet information to identify the "systemically most important" banks across all the twelve years. By using several criteria, naturally some choices had to be made. This is illustrated in appendix C, which reports data for one size (total assets) and one interbank trading ("due from banks") measure, all expressed in US dollars. Table C.2 displays the assets of all 25 US banks over the sample period, by declining order of average size. The corresponding table for "due from banks" is C.4. It turns out that the most important US bank according to the latter criterion is State Street, although in terms of assets it only comes at number 13. Similar phenomena can also be observed for other "clearing banks", such as Northern Trust (5th by interbank linkages and only 24th by assets), Bank of New York and Mellon, whose sizes are relatively poor indicators for their role in interbank relationships. We were particularly careful to have these banks that are most active in clearing and settlement in our sample. The justification for this is that failures of one or several main clearing banks may constitute a particularly severe source of contagion risk, even though they may not be very large compared to other players.[19] Interestingly, as one can see by comparing tables C.1 and C.3 size and interbank activity are much more aligned for euro area banks.

Moreover, by comparing table C.1 with table C.2 we can see that the banks chosen for the euro area and the ones chosen for the US

[19]For example, the failure of Continental Illinois in 1983-84 and the computer problem of Bank of New York in 1985 raised major concerns and were accompanied by public action in order to prevent those incidents from spreading through the banking system.

are of comparable size, even though the aggregate balance sheet of the euro area banks is overall larger than the US aggregate. The same similarity, however, does not apply to the "due from banks" measure of interbank relations, which is significantly larger in Europe than in the US (see tables C.3 and C.4). The larger interbank relationships in Europe compared to the US is an interesting finding in itself, which – to our knowledge – has not been emphasized in the literature on banking system risk before.[20] It will be interesting to verify below whether this aggregate information from balance sheets is informative about the relative importance of systemic risk in the euro area as compared to the US banking system. In particular, does the greater amount of interbank lending in Europe translate into larger systemic risk?

5.2. **Descriptive statistics for stock returns and yield spreads.** Appendix D presents the typical host of standard descriptive statistics for our 50 bank stock return series and three of the factors capturing aggregate risk (the banking sector indices, the general stock indices and the yield spread). Tables D.1 and D.2 report on the left-hand side mean excess returns, standard deviations, skew and kurtosis as well as on the right-hand side correlations between the individual bank stock returns and the three aggregate risk factors for the euro area and the United States, respectively. Mean returns are basically zero, as one would expect, whereas standard deviations of returns tend to be around 2. Naturally, the volatility of the two stock indices is significantly lower than the one of the individual bank stocks. While there are little signs of skew, except for the troubled bank Banesto (see next sub-section for details) that shows some right skew, the high kurtosis signals that most series are leptokurtic.

As regards the correlations between bank stocks and aggregate risk factors, they are pretty high for the two stock indices, as could have been expected. Many correlation coefficients (though not all) reach levels of the order of 0.6 or higher, and plausibly the banking sector sub-index tends to be slightly more related to the individual stocks than the general stock market index. The picture is different for correlations between individual stock returns and the high-yield bond spread. First of all, correlation coefficients tend to be very low, varying between 0 and 0.05 in absolute value. Moreover, many of the US correlations have the "wrong" sign (a small positive correlation coefficient). This

[20]As we were concerend about differences in reporting conventions or standards across the Atlantic, we discussed the difference with the data provider. No evidence of mistakes or different standards came out of this discussion.

provides first evidence that the high-yield bond spread might not be a good predictor of aggregate banking system risk.

We complete the discussion of standard return statistics with the correlation matrices of individual bank stock returns. Table D.3 shows the correlation matrix for the euro area. Euro area bank returns seem to be generally positively correlated, with correlation coefficients varying between 0.05 and 0.77. For the US, table D.4 provides a similar picture, although correlation coefficients appear to be more uniform (varying only between 0.32 and 0.66) and on average slightly higher.

For the purpose of the present paper, we are particularly interested in extreme negative returns. The left-hand sides of tables 1 and 2 report the three largest negative excess returns (in absolute value) for all the banks in the sample and for the two banking sector stock indices. Starting with Europe, the largest stock price decline in the sample (a massive daily collapse of 85%) happens for Banesto (Banco Espanol de Credito) in February 1994. Around that time, this Spanish bank faced major difficulties and was rescued by an initial public intervention in December 1993. Another bank in major difficulties during our sample period is Berliner Bankgesellschaft from Germany. This is reflected in two consecutive stock price "crashes" of 38% and 27% during the summer of 2001. Ultimately, also this bank was saved by the federal state of Berlin. As regards the United States, the largest daily stock price slump happens to Unionbancal Corporation. The market value of this troubled Californian bank declined in June 2000 by as much as 36%, as a consequence of credit quality problems. The next most significant corrections of just above 20% occur for Comerica Inc. and AmSouth Bancorporation.[21] These examples illustrate that we have a number of individual bank crises in the sample.

Extreme negative returns of stock indices are obviously smaller than the ones for individual banks. In contrast to the stock returns, the high-yield bond spreads reported at the bottom of tables 1 and 2 are maxima, as extreme positive values indicate a situation of high risk. One can see that in times of stress non-investment grade corporate debt can trade at yields more than 10% above government debt.

There is also some first evidence of clustering in extreme bank stock declines, as many of them happen around a number of well-known crisis

[21]As we work with individual return data from Datastream, we screened our dataset for the problems described in Ince and Porter (2004). As one could probably expect for the relatively large banks and developed countries we are looking at, we did not find any signs of erroneous returns. For example, tables 1 and 2 suggest that stock splits or re-denominations did not artificially generate any huge returns.

episodes. For example, a significant number European and US-based banks faced record downward corrections around the end of the summer 1998. This is the infamous episode related to the Long Term Capital Management (LTCM) collapse (and perhaps also to the Russian default). Another similar episode, very much limited to US banks, happened in spring and summer 2000, potentially related to the burst of the technology bubble. Interestingly, record bank stock crashes around 11 September 2001 – the time of the New York terrorist attack – are registered for a number of European banks, but not for US banks.[22] Finally, some American and European banks were hit significantly by the onset of the Asian crisis in fall 1997. These examples illustrate, first, that our sample covers a number of stress situations in global and national markets.[23] Second, they also indicate the relevance of systematic shocks for banking stability, which motivates our tail-β indicator.

As mentioned already above, many series indicate a high kurtosis, which might be caused by the fat tail property of bank stock returns. To address this issue more systematically, we report in tables 1 and 2 the estimated tail indexes $\widehat{\alpha}$ for individual banks and for the stock indices. It turns out that the tail indexes vary around 3, which is in line with the evidence presented in Jansen and De Vries (1991), further illustrating the non-normality of bank stock returns and the non-existence of higher-order moments.[24] If anything, the tails of a number of European banks seem to be slightly fatter (smaller α) than

[22]The less extreme reactions of US bank stocks may, however, also have to do with a four-day suspension of trading at the New York stock exchange.

[23]The presence of single and aggregate crisis situations in our sample is reassuring, as the interest of our paper is financial stability. At the same time, however, we would like to note that extreme-value methods do not require the presence of individual or aggregate failures in the sample. In contrast to fully non-parametric and parametric approaches, our semi-parametric approach allows to estimate reliably extremal behavior even beyond the sample boundaries.

A related issue is whether the absence of some banks from our sample, due to their failure or their merger with other banks, could imply sample selection bias. First of all, outright bank failures tend to be rare, so that related selection bias should be quite limited. A more intricate issue is banking consolidation. If mergers lead to the exlusion of relatively similar, highly connected banks, then a downward bias in measured systemic risk might occur. If they lead to the exclusion of different and little connected banks, then the amount of systemic risk in our sample should not be biased. As efficient mergers would often require the diversification of business, we might conclude that the overall room for sample selection bias in our sample is relatively contained.

[24]The non-normality of stock returns in general is a well-known fact in financial economics since at least the fundamental work by Mandelbrot (1963). For a related

the ones of US banks. In addition to the larger interbank lending in Europe referred to above, this observation raises again the issue whether systemic risk on this side of the Atlantic is more pronounced than on the other. Another observation is that the yield spreads have much thinner tails than stock index returns.

The right-hand sides of tables 1 and 2 show the estimated quantiles for all the banks, when assuming a common percentile (or crash probability). In this paper, we experiment with percentiles p between 0.02% and 0.05% (explicitly reporting results for the latter), as for these values the implied crisis levels tend to be close to or slightly beyond the historical extremes (see left-hand side). In other words, there cannot be any doubt about the fact that the phenomona considered constitute critical situations for banks. In terms of sensitivity analysis, all our qualitative results reported below are robust to varying the crash probability p within this range. Finally, as was to be expected, the extreme quantiles implied by the common crash probability p exhibit some variation across banks.

6. Bank contagion risk

In this section we report the results from our multivariate bank spillover measure. We are trying to answer two main sets of questions. 1) How large is bank contagion risk in euro area countries? And, in particular, what do our stock market indicators suggest about the relative importance of the risk of domestic spillovers between banks as compared to the risk of cross-border spillovers? Answers to the latter question are particularly important for macroprudential surveillance and for the ongoing debate about supervisory co-operation and the structure of supervisory authorities in Europe. 2) What do our indicators say about the relative size of bank contagion risk when comparing the euro area with the United States? Is one banking system more at risk than the other? The former set of questions is addressed in sub-section 6.1 and the latter in sub-section 6.2. In the present section we still abstract from extreme systematic risk for the euro area and US banking system, as this is addressed in the following section (section 7). For expositional reasons, we also abstract here from changes of spillover risk over time, which are addressed in section 8.

6.1. **Euro area.** In order to assess the exposure of euro area banks to each other, as derived from their extreme stock price co-movements, we

discussion of non-normality and the difficulty of parametric distributions to accurately capture the behavior of large bank stock returns for a wider cross-section of European banks, see Gropp and Moerman (2004).

report in table 3 the estimation results for our measure (2.1). To keep the amount of information manageable, we do not show the extreme dependence parameters η that enter in the estimation of (2.1) and we only display the spillovers to the largest banks of the countries listed on the left-hand side. We calculate the co-crash probabilities conditional on the second (column $\widehat{P}_1$), second and third (column $\widehat{P}_2$), second, third and fourth (column $\widehat{P}_3$) and so on largest banks from Germany (upper panel), from Spain (upper middle panel), from Italy (lower middle panel) and from France (lower panel). All probabilities refer to the crisis levels (extreme quantiles) reported in table 1 for $p = 0.05\%$.

For example, the value 22.4% in the row "Germany" and the column "$\widehat{P}_1$" in the upper panel, refers to the probability that Deutsche Bank (the largest German bank) faces an extreme spillover from HypoVereinsbank (the second largest German bank). Going a few cells down, the value 11.2% describes the probability that Banco Santander Central Hispano (the largest Spanish bank) faces an extreme spillover from HypoVereinsbank. The difference between these two values would suggest that the likelihood of cross-border contagion could only be half of the likelihood of domestic contagion. When going through the table more systematically (in particular through the columns for more than one conditioning bank crash), it turns out that cross-border contagion risk is generally estimated to be smaller than domestic contagion risk in the euro area banking system, indeed. To pick just another example, the probability that the largest French bank (BNP Paribas) faces an extreme stock price slump given that the second (Crédit Agricole) and third largest French bank (Société Générale) have experienced one is a non-negligible 35.9% (see column $\widehat{P}_2$, upper middle panel, row France). The same probability for the largest Italian bank (Banca Intesa) is 7.5.% (see column $\widehat{P}_2$, upper middle panel, row Italy). The probabilities in the first row of each panel are very often higher than the probabilities in the rows underneath.

There are also some exceptions, in particular among the bivariate probabilities reflecting linkages between two large banks (column $\widehat{P}_1$). This is not too surprising, as the largest players will have more extensive international operations, implying more scope for cross-border contagion. In particular, ABN AMRO – the largest Dutch bank – is more affected by problems of HypoVereinsbank than Deutsche Bank (26.5%>22.4%). Actually, the linkages between Dutch and German banks tend to be among the largest cross-border linkages in our sample. Other important cross-border linkages exist between the top banks of France, Germany and the Netherlands and the top Spanish bank. Moreover, as in the case of BNP Paribas, Crédit Agricole and Société Générale, the largest institutions of a country must not always be very strongly interlinked in the home market. As a consequence, the French panel shows that ABN AMRO and Fortis – the largest Belgian bank – are more exposed to the second and third largest French bank than is BNP Paribas. The fact that Belgian and Dutch banks are associated with the largest cross-border spillover risks is also intuitive, since the banking sectors of these countries are dominated by a small number of very large international financial conglomerates. Also the results of Degryse and Nguyen (2004) and van Lelyveld and Liedorp (2004) suggest their special exposure to cross-border risk.

Another observation from table 3 is that the main Finnish and Greek banks, located in two countries next to the outside "border" of the euro area, tend to be least affected by problems of large banks from other euro area countries. Something similar, but to a lesser extent, can be observed for Ireland and, with exceptions, for Portugal. Apparently, smaller banking systems located more in the periphery of the euro area are more insulated from foreign spillovers than larger systems in the center. Overall, the level of spillover risk seems to be economically relevant, both domestically and across borders, in particular when more than one large bank face a stock price crash. Contagion risk for single crashes tends, however, to be markedly lower.

An interesting exception is Italy. While being a larger core country in the euro area, it is much less affected by problems in French, German or Spanish banks than other core countries. This is also consistent with the findings of Mistrulli (2005). In addition, spillovers from the largest Italian banks to other main banking systems in Europe seem also quite limited. One explanation for this phenomenon could be the low penetration of the Italian banking system from abroad and the limited number of acquisitions by Italian banks in other European countries.[25]

The test results in table 4 show whether the differences between domestic and cross-country contagion risk are statistically significant or not. Rows and columns refer to the same banks as in table 3, but the cells now show T-statistics of the cross-sectional test described in sub-section 4.2. The null hypothesis is that domestic spillovers equal

[25] This must, however, not remain like this, as the recent acquisition of HypoVereinsbank by UniCredito suggests.

cross-border spillovers.[26] The test statistics partly qualify the interpretation of some of the contagion probabilities in table 3. Extreme cross-border linkages between Belgian, Dutch, French, German and Spanish banks are not (statistically) significantly different from domestic linkages within the major countries. In contrast, for Finland and Greece the null hypothesis is rejected in all cases. Moreover, the same happens in many cases for Ireland and Portugal. So, severe problems of larger French, German, Italian and Spanish banks may create similar problems for other large banks at home or in other central euro area countries, but often would do much less so for the largest banks of those smaller countries close to the outside "border" of the euro area. Hence, for the latter countries the tests of table 4 confirm the impression from the estimations in table 3.

The T-tests also confirm the special situation of Italy among the larger euro area countries. In many cases the exposure of Italian banks to foreign problems is significantly lower than domestic exposures in the other main countries. In addition, the greater exposure of ABN AMRO to Crédit Agricole (cross-border) than BNP Paribas to Crédit Agricole (domestic) is statistically significant at the 1% level. And, similarly, the greater exposure of Fortis to Crédit Agricole (cross-border) than BNP Paribas to Crédit Agricole (domestic) is significant at the 10% level.

The probabilities in table 3 allow one to derive a relationship between the likelihood of a bank crash as a function of the number of other banks crashing. In our previous paper on currencies, we have denoted this relationship between the probability of crises and the number of conditioning events as "contamination function" (see Hartmann, et al., 2003, figures 1 to 7). Bae et al. (2003) speak in their international equity market contagion paper of "co-exceedance response curves". Gropp and Vesala (2004) apply the latter concept to European banks. While the results in table 3 suggest that most contamination functions in European banking are monotonously increasing (as for currencies), at least over certain ranges of conditioning events, there are also some

[26]The T-statistics result from comparing cross-border η-values with domestic η-values (ceteris paribus the number of conditioning banks), as used for the spillover probabilities of table 3. The estimation of tail dependence parameters η have been described in equation (3.6). For example, the T-statistic in row Netherlands and column T_1 in table 4 results from testing whether the η-value for the largest Dutch bank (ABN AMRO) with respect to the second largest German bank (HypoVereinsbank) significantly differs from the domestic η-value of the largest German bank (Deutsche Bank) with respect to the second largest German bank (HypoVereinsbank).

exceptions. Witness, for example, the exposure of Banco Commercial Portugues (the largest Portuguese bank) to problems of German banks. Going from $\widehat{P}_4$ to $\widehat{P}_5$ implies a reduction in the crash probability of BCP.

One potential explanation for this phenomenon is "flight to quality", "flight to safety" or "competitive effects". Some banks may benefit from the troubles at other banks, as e.g. depositors withdraw their funds from the bad banks to put them in good banks. Such behavior has been referred to by Kaufman (1988) in relation to US banking history, and Saunders and Wilson (1996) provided some evidence for it during two years of the Great Depression. For a more recent time period, Slovin, Sushka and Polonchek (1999) find regional "competitive effects" in response to dividend reduction and regulatory action announcements. Non-monotonicity of contamination functions might also occur for the curse of dimensionality, as very few observations may enter the joint failure area for more than two banks.

The finding of statistically similar spillover risk between major euro area banks within and between some large countries could be important for surveillance of the banking system and supervisory policies. One explanation for it may be the strong involvement of those banks in the unsecured euro interbank market. As these large players interact directly with each other, and in large amounts, one channel of contagion risk could be the exposures resulting from such trading. For example, Gropp and Vesala (2004) find interbank exposures at the country level to be a variable explaining part of spillovers in default risk between European banks. One implication of the similarity of domestic and cross-border spillover risks for some countries is that macroprudential surveillance and banking supervision need to have a cross-border dimension in the euro area. This is currently happening through the Eurosystem monitoring banking developments, through the application of the home-country principle (the home supervisor considers domestic and foreign operations of a bank), through the existence of various bilateral memoranda of understanding between supervisory authorities, through multilateral "colleges" of supervisors for specific groups and now also through the newly established "Lamfalussy Committees" in banking. The results could provide some arguments in favor of an increasing European-wide component in macroprudential surveillance and supervisory structures over time.

It is also interesting to see that in some smaller and less central countries in the area cross-border risk is more contained. This could suggest that even the larger players from those countries are still less interlinked with the larger players from the bigger countries. The existence of significant differences in the degree of cross-border risks between different groups of European countries could make the development of homogenous supervisory structures more complicated.

Overall, one could perhaps conclude that the results so far suggest that the still relatively limited cross-border integration of banking in the euro area does not seem to eliminate any contagion risk among the larger players from some key countries to levels that are so low that they can be simply ignored. This conclusion is also consistent with Degryse and Nguyen (2004) and Lelyveld and Liedorp (2004), whose analyses of interbank exposures suggest that risks from abroad may be larger than domestic risks in the Belgian and Dutch banking systems. One explanation for the relevance of cross-border bank risks could be that while bank mergers have been mainly national and traditional loan and deposit business of banks are only to a very limited extent expanding across national borders (see, e.g., the recent evidence provided in Hartmann, Maddaloni and Manganelli; 2003, figures 10 and 11), much of the wholesale business of these large players happens in international markets that are highly interlinked.

6.2. **Cross-Atlantic comparison.** Our final step to examine interbank spillovers consists of comparing them between the euro area and US banking systems. To do so, we calculate for each system the tail dependence parameter η that governs the estimate of the multivariate contagion risk measure (2.1). Notice that for each continent η_{US} and η_{EA} are derived from all the extreme stock return linkages (bilateral and multilateral) between the respective $N = 25$ banks, following the estimation procedure described in section 3.

As indicated in table 5, we obtain $\widehat{\eta}_{US} = 0.39$ and $\widehat{\eta}_{EA} = 0.17$. The evidence thus suggests that overall contagion risk in the US banking system is higher than contagion risk among euro area banks (about two times).[27] Moreover, knowing that for the case of independence $\eta = 1/N = 0.04$, the amount of multivariate linkage is of economically relevant magnitude. The $\widehat{P}$ values in the table describe the probability that all 25 banks in the euro area or the US crash, given that any of them crashes. These probabilities illustrate that overall systemic risk related to the crash of a single bank is extremely low. Of course, multivariate contagion risk increases for multiple bank crashes.

[27] Strictly speaking, this and related statements below make the plausible assumption that the dependence structure is sufficiently similar on both sides of the Atlantic for the slowly varying function $\ell(q)$ in 3.1 not to have a large impact on relative probabilities.

Is this difference between the US and the euro area statistically significant? We apply the cross-sectional stability test (4.5) described in sub-section 4.2, with the following null hypothesis:

$$H_0 : \eta_{US} = \eta_{EA} \ .$$

It turns out that the T-statistic reaches T=7.25. In other words, our indicators and tests suggest that the difference in systemic spillover risk between the US and the euro area is statistically significant, way beyond the 1% confidence level.

One explanation could be that in a much more integrated banking system, such as the one of the United States, area-wide systemic risk is higher, as banking business is much more interconnected. We examine this hypothesis by also estimating the multivariate contagion risk for individual European countries. If the explanation above was true, then overall systemic spillover risk should not be lower within France, Germany or Italy than it is in the US.[28] The bottom part of table 5 shows that this is actually the case. Overall domestic spillover risk in France and Germany is about the same as in the US; in Italy it is even larger than in the US (see also figure 1 in sub-section 8.1). Our cross-sectional test cannot reject parameter equality between France and the US or between Germany and the US, but it rejects it between Italy and the US (as Italy is even more risky). In other words, the lower overall spillover risk in Europe is explained by the quite weak extreme cross-border linkages.

Having said all this, we need to note that there is some structural instability in the extreme dependence of bank stock returns on both sides of the Atlantic. As we will discuss in depth in section 8 below, the risk of spillovers has quite generally increased in the course of our sample period. We will, however, also show that all our conclusions here are robust to taking structural instability into account. The only caveat we have to keep in mind is that the probabilities in table 3 represent averages across the whole sample period, so that they tend to overestimate the risk of spillovers at the start of the sample and underestimate it towards the end of the sample.

Looking ahead, the analysis in the present section suggests that – as the European banking system integrates further over time – it could become more similar to the US system in terms of contagion risk. In other words, the ongoing and gradual integration process should be

[28]We thank Christian Upper for suggesting this exercise to us.

accompanied by appropriate changes in macroprudential surveillance and supervisory structures.

7. Aggregate banking system risk

Next we turn to the analysis based on our measure of extreme systematic risk. We are interested in assessing to which extent individual banks and banking systems are vulnerable to an aggregate shock, as captured by an extreme downturn of the market risk factor or an extreme upturn of high-yield bond spreads. Across this section we assume stability of estimated tail-βs over time. The same caveat applies as in the previous section, as structural breaks of extreme systematic banking system risk are only considered in section 8.

The results are summarized in tables 6 and 7 for the euro area and the US, respectively, and for all measures of aggregate risk listed in sub-section 5.2. The different stock indices capture market risk, as in traditional asset pricing theory. The high-yield bond spread is also "tested" as a measure of aggregate risk. For example, Gertler and Lown (1999) have shown that it can be a good predictor of the business cycle, at least in the US, and fluctuations in economic activity are the most important determinant of banks' asset quality. Some might also regard high-yield spreads as a particularly suitable indicator for crisis situations.

The upper part of the tables report tail-βs for individual banks. To take an example, the value 12.1 in the row "IRBAN" and column "stock index" of table 6 means that a very large downturn in the general euro area stock index is usually associated with a 12% probability that Allied Irish Banks, a top Irish bank, faces an extreme stock price decline. The value 30.2 in row "BNPPAR" and column "stock index" suggests that the same probability for the largest French bank is substantially higher. Going more systematically up and down the columns as well as right and left in the rows, one can see (i) that tail-βs can be quite different across banks, both in Europe and in the US, and (ii) that the relative sizes of tail-βs seem to be quite similar for different measures of aggregate risk. For example, a number of banks from some more peripheral and smaller euro area countries or smaller banks from large euro area countries can have quite low tail-βs. One interpretation of this result is that the more local business of the latter banks exposes them less to aggregate euro area risk. Similar cases can be found for the US in table 7. For example, some players focussing on regional or local retail business, such as e.g. a savings&loans association like

Washington Mutual, have relatively low tail-βs (in this specific case 3% for the US stock index as aggregate risk factor). In contrast, large and geographically broad banks – such as Deutsche Bank, BNP Paribas, Citigroup or JP Morgan Chase – exhibit larger tail-βs, as they are much more diversified.

The bottom of tables 6 and 7 report the means and standard deviations of tail-βs across the 25 banks for each continent. Overall, tail-βs in Europe and in the US are of similar order of magnitude, although the US βs tend to be slightly less variable (except for yield spreads). We can use a cross-sectional T-test to compare aggregate banking risk across the Atlantic. Table 8 shows the average extreme dependence parameters $\overline{\eta}$ derived from the individual η parameters governing the tail-βs of the 25 banks on each continent. It also shows the T-values for a test with the following null hypothesis:

$$H_0 : \overline{\eta}_{US} = \overline{\eta}_{EA} \ .$$

The equality of extreme dependence between stock returns and the market risk factor in Europe and the United States cannot be rejected.

When turning to extreme systematic risk associated with high-yield bond spreads (see the right-hand side of tables 6 and 7), the results are somewhat different. Most importantly, tail-βs for spreads are extremely small. Extreme positive levels of spreads on average do not seem to be associated with a high likelihood of banking problems. Quite the contrary, the probabilities are almost zero. This also confirms the simple correlation analysis reported in sub-section 5.2 and appendix D.

Accordingly, the tail dependence parameters $\overline{\eta}$ for spreads in table 8 are much smaller than the ones for stock indices. And note that the mean dependence parameters for yield spreads are all estimated to be quite close to the level associated with asymptotic independence for this two-dimensional measure, $\eta_{indep} = 1/N = 0.5$. Then it does not come as a surprise that the T-tests show that – as for the market risk factor – the level of extreme aggregate risk in the US and in the euro area is statistically indistinguishable.

We conclude from this that high-yield bond spreads are not very informative about extreme aggregate banking system risk on both sides of the Atlantic. This finding could mean, for example, that credit spreads are a less good predictor of business cycle fluctuations – in particular of severe ones – than previously thought. It could also mean that the banks in our sample hold only a very limited amount of loans from borrowers that are rated below investment grade. Still, future research could address whether they have at least some incremental explanatory value for banking problems when other variables are controlled for as well.

8. Has systemic risk increased?

A crucial issue for macroprudential surveillance and supervisory policies is whether banking system risks change over time. In particular, it would be important to know whether they may have increased lately. Therefore, we apply in the present section our multivariate application of the structural stability test by Quintos, Fan and Phillips (2001; see sub-section 4.2) to the estimators of multivariate spillovers and systematic risk (sub-sections 8.1 and 8.2, respectively).

8.1. **Time variation of bank contagion risk.** We apply the recursive structural stability test described in equations (4.1), (4.2) and (4.4) to the extreme tail dependence parameters η that govern the spillover probabilities reported in table 3. The null hypothesis of constancy of η for the cases in the table is given by (4.3). The test results are reported in table 9, with the different cases structured in the same way as in tables 3 and 4.

Each entry first shows the endogenously estimated break point, if any, and then the value of the test statistic in parentheses. It turns out that the forward version of the recursive test discovers a significant upward break in spillover risk in almost every case, be it a domestic linkage or a cross-border linkage. For spillovers conditioned on German, Italian and Spanish banks almost all increases in risk occur some time during the year 1997. If crashes of French banks are the conditioning events, breaks tend to occur somewhat later, most often around the year 2000. While there have been economic events in the vicinity of the break point times found by the test that could have contributed to increases in spillover risks (e.g. the Asian financial crisis or the end of the technology boom), we would not pay too much attention to the exact dates. The reason is that further evidence presented below suggests that changes in risk exhibit a fairly gradual patterns, so that just singling out the most important break point could be misleading.

These results suggest that there was also an increase in system-wide spillover risks. We examine this question in table 10. We first calculate the 25-dimensional (N=25) tail dependence parameter values that span the whole US block $\widehat{\eta}_{US}$ and the whole euro area block $\widehat{\eta}_{EA}$ (as in subsection 6.2, table 5) and test for structural change. The same we do for Germany (N=6), France (N=4) and Italy (N=4), separately. The null is again like in (4.3). The table shows on the left-hand side break points and test statistics for the full sample; in the middle of table 10 estimated sub-sample values for the different ηs are reported. Finally, the right-hand side of the table also displays the results of two further structural stability tests, limited to the second half of the sample after the first endogenous break. The first test is another Quintos et al. endogenous stability test, and the second an exogenous stability test (T_{EMU}), in which the break point is chosen to be 1 January 1999, the start of Economic and Monetary Union in Europe.

The tests indicate a significant upward break in euro area systemic risk around mid 1996 (test value 4.9) and in US systemic risk at the end of 1995 (test value 18.5). These breaks are both slightly earlier than the lower-dimensional ones in table 9.[29] $\widehat{\eta}_{US}$ increases from 0.20 to 0.41 and $\widehat{\eta}_{EA}$ from 0.13 to 0.20. Gropp and Vesala (2004) also find an increase in bank spillover risk in Europe, using a different methodology, but they impose the break point at the time of the introduction of the euro. For France, Germany and Italy, our test also indicates strong domestic upward breaks, but in addition France and Germany experience a (weaker) downward break (as indicated by the backward version of the test). In sum, we detect a significant increase of multivariate spillover risk both in the euro area and in the US banking system. Both systems seem to be more vulnerable to contagion risk today than they have been in the early 1990s, the US even more so than the euro area.

The increase of spillover risk found for the US is consistent with the findings of de Nicolo and Kwast (2002), who detect an upward trend of regular correlations between US large and complex banking organizations (LCBOs) during the period 1988 to 1999 and interpret it as a sign of increasing systemic risk.[30] The authors estimate that part of the increase is likely to be related to consolidation among LCBOs. The timing of structural change in de Nicolo and Kwast's paper is not exactly the same as in ours but quite similar, as they find most correlation changes during 1996 and perhaps 1997. Mistrulli (2005)

[29]Quintos et al. (2001) report critical values in the table of their appendix A (p. 662), which are reproduced in the notes to our tables 9 and 10.

One explanation for the earlier increase in fully systemic risk could be that the (many) cases not covered in table 9 have earlier breaks than the ones shown.

[30]Within the group of about 22 LCBOs, however, most of the increase in correlations is concentrated among the less complex banks.

argues that some increase in domestic contagion risk in the Italian banking sector has been caused by new interbank lending structures that emerged from consolidation. And the risk seems to pick up around 1997, similar to our break points. Hence, banking consolidation may be one important explanation for a higher contagion risk *within* the countries dicussed. It is, however, a less likely explanation for the increase in η for the euro area banking system as a whole. The reason is that cross-border bank mergers are still relatively rare in Europe (see, e.g., Hartmann et al., 2003, figure 10).

In order to get a better view of the evolution of multivariate contagion risk over time, we plot in figure 1 the recursive estimates of η for the euro area, the US, France, Germany and Italy. In addition to unfiltered results (solid lines), we also display results for GARCH-filtered return data (dotted lines). For the reasons given in appendix E, however, we mainly focus on the unfiltered results. Comparing the two upper panels of the figure, we can see the smaller and gradual character of the increase in spillover risk in the euro area. Notice the consistency of this evolution with a slowly advancing integration process. Multivariate risk in the US starts at a higher level and begins to rise later but at a much faster pace. The lower panels of the figure confirm the results discussed in sub-section 6.2, in so far as general spillover risk within France, Germany and Italy is higher than in the euro area as a whole and, on average, of a similar order of magnitude as within the United States. (The results are qualitatively the same for filtered data, although the strength of changes is sometimes muted.[31]) All these findings are consistent with the hypothesis advanced in section 6 that banks are more exposed to each other within a country than across borders. So far, this even remains true in the euro area, which shares a common currency and a common interbank market.

Figure 2 shows then the recursive statistics of the cross-sectional tests comparing US multivariate spillover risk with euro area, French, German and Italian spillover risk. We would like to learn from this whether the similarities and differences in multivariate risk across those banking systems established in section 6 generally hold across our sample period. Each panel exhibits the difference in η between the first country (always the US) and the second area or country. The straight dashed lines describe two standard deviation confidence intervals. So, when a solid curve moves out of a confidence interval, then the test rejects

[31] A similar phenomenon for general stock market data has already been observed by Poon et al. (2004).

the equality of multivariate tail dependence parameters between the two countries. If a curve is above the confidence interval, then the first country is more susceptible to contagion. In the opposite case, the second country is the more risky one. We can immediately confirm from the upper left-hand chart in figure 2 that the US is more risky than the euro area, except for the very start of the sample. The lower right-hand chart illustrates that Italy is more risky than the US.

Finally, we turn to the results of the two structural stability tests for the second half of the sample on the right of table 10. Interestingly enough, the endogenous test (backward version) finds a second break point for the euro area in January 1999 reducing η (test value 3.2 compared to a critical value of 2.6 for a significant change at the 1% level). In other words, it indicates that multivariate contagion risk decreased in parallel with the introduction of the euro. As we are concerned about the validity of the asymptotic properties of the Quintos et al. test when it is applied in a sequential way, we also conduct an exogenous stability test for which we impose 1 January 1999 as the break point. This test exploits the asymptotic normality of the tail dependence parameter, as in the case of cross-sectional differences discussed earlier. It confirms that there is some decline in η_{EA} at the time of the euro changeover, but this decline is not statistically significant (test value 1.4 compared to a critical value of 1.9 for a significant change at the 5% level).

While it is often assumed that the introduction of the euro with a common money market should have led to an increase in contagion risk in the euro area, our results do not provide any evidence of that actually happening. On the contrary, if anything there was a slight decrease of multivariate extreme dependence between all euro area banks. One explanation for such a development would be as follows. Whereas the introduction of a single currency with a common (and fully integrated) money market could increase the interbank linkages between banks across borders, and thereby the risk of contagion, on the other hand the much larger and more liquid money market as well as the wider access to different contingent claims under a single currency could also increase the money market's resilience against shocks and improve risk sharing. If the latter effects dominate the former, then the banking system could well become less prone to extreme spillovers.

As for the three larger euro area countries, Germany experiences a similar reduction in risk as the area as a whole. But in this case the reduction is also statistically significant for the exogenous break test, at least at the 10% level. France and Italy also have some further breaks. While statistically significant, they do not happen in the vicinity of the euro changeover. The United States banking system faces a further increase in multivariate spillover risk at the end of 1997.

We close this sub-section with a word of caution. While the evidence supporting increases in multivariate extreme dependencies among banks in both the euro area and the United States seems statistically relatively strong, we should not forget that our sample period extends "only" over 12 years. This means, first, that we cover only a small number of economic cycles.[32] Since there was a relatively long upturn during the 1990s, there may be a risk that this had an impact on extreme bank stock return dependence. More generally, similar to correlation extreme dependence can oscillate over time. Obviously, we cannot know whether there was already a period of higher extreme linkages between banks before our sample starts or whether the high linkages observed towards the end of our sample will come down again in the future.

8.2. **Time variation of aggregate banking system risk.** Now we apply the structural stability test to extreme systematic risk in banking systems. More precisely, we study whether the bivariate extreme dependence parameters η that enter our estimates of tail-βs have changed between 1992 and 2004. Table 11 reports the results for each euro area bank in our sample and table 12 for each US bank. Each table shows for the respective banks the estimated break points, if any, with test values in parentheses. Tests are performed for all aggregate risk measures on which we condition the tail-βs.

The general result is that extreme systematic risk has increased over time. In other words, both the euro area and the US banking system seem to be more exposed to aggregate shocks today than they were in the early 1990s. We further illustrate this at the system-wide level in figure 3, which gives us a better insight into the time evolution of extreme systematic risk. The lines in the two panels refer to averages of ηs across the 25 euro area and 25 US banks, respectively. We choose the general local stock indices as aggregate risk factors, but the picture is unchanged for other stock indices. Similar to figure 1 above for interbank spillover risk, the η-values entering the figure are calculated recursively. One can see that the increase in aggregate banking system risk

[32]Following the NBER and CEPR business cycle dating programs, we cover at most two full cycles; see http://www.nber.org/cycles.html and http://www.cepr.org/data/Dating/.

is also economically significant, both in the euro area and in the US.[33] While results corrected for time-varying volatility (GARCH-filtered returns) are somewhat more muted, qualitatively they are unchanged. Moreover, the similarity of extreme aggregate banking system risk in the euro area and the US established in section 7 seems to be valid for the entire sample period.

Table 11 locates the timing of most European break points for the stock indices around 1997 and for some cases in 1996. In the US they happen somewhat earlier, with many breaks in 1996 (table 12). For Europe the timing is roughly in line with, but not identical to interbank spillover risks (see the previous sub-section), for the US the tail-β breaks happen somewhat later than the contagion breaks. Similar to the spillover risks discussed earlier, the time evolution visible in figure 3, however, suggests that not too much importance should be given to the exact break dates.

We do not report the pre- and post-break tail-β and η values in the tables in order to save space and since figure 3 provided already a good general impression.[34] We just mention that economically relevant changes apply also to some of the most important players, such as the largest US banks (Citigroup and JP Morgan Chase). The βs of important clearing banks, such as Bank of New York, State Street or Northern Trust, changed as well, sometimes by even more than the former. The main US clearers have also some of the statistically most significant breaks (table 12). Similarly significant changes can also be observed for the euro area.

Both in Europe and in the US there are also breaks in tail-βs for yield spreads. They happen, however, with surprising regularity in 2000, the time of the burst of the technology bubble. In any case, given the very low extreme systematic risk associated with yield spreads, not too much importance should be given to this result. Finally, the same words of caution about business cycles and time-varying co-movements should be kept in mind as for the previous sub-section.

[33]Notice that these results are different from the ones by de Nicolo and Kwast (2002) using standard market model βs among US LCBOs. They do not identify any increase of the impact of the general market index on LCBO stock returns between 1992 and 1999. They only observe an increase of the impact of a special sectoral LCBO index in late 1992/early 1993, conditional on the general market index.

[34]They are available from the authors on request.

9. Conclusions

In this paper we made a new attempt to assess banking system risk, by applying recent multivariate extreme-value estimators and tests to excess returns of the major banks in the euro area and the United States. We distinguish two types of measures, one capturing extreme spillovers among banks ("contagion risk") and another capturing the exposure of banks to extreme systematic shocks (which we denote as tail-β). We compare the importance of those forms of systemic risk across countries and over time.

Our results suggest that bank spillover risk in the euro area seems to be significantly lower than in the US. As domestic linkages in the euro area are comparable to extreme linkages among US banks, this finding seems to be related to weak cross-border linkages in Europe. For example, the largest banks of some smaller countries at the periphery of the area seem to be more protected from cross-border contagion risk than some of the major European banks originating from some central European countries. Extreme systematic risk for banks seems to be roughly comparable across the Atlantic. In contrast to stock indices, high-yield bond spreads in general do not seem to be very informative about aggregate banking risks. Structural stability tests for both our banking system risk indicators suggest a general increase in systemic risk taking place over the second half of the 1990s, both in Europe and the US. We do not find, however, that the introduction of the euro had any adverse effect on cross-border banking risks, quite the contrary. Overall, the increase of risk in the euro area as a whole seems to have happened extremely gradually, as one would expect from the slow integration of traditional banking business. For the US it may be noteworthy that some of the strongest increases in extreme systematic risk seem to be concentrated among the largest players and the main clearing banks.

Our results provide some interesting perspectives on the ongoing debate on financial stability policies in Europe. For example, the benchmark of the US seems to indicate that cross-border risks may further increase in the future, as banking business becomes better integrated. At the same time, it should be recognized that the direction of this process is not unique to Europe. And in addition, our twelve-year sample period includes one long economic cycle that may have overemphasized commonality in banking risks. Keeping these caveats in mind, the results in this paper underline the importance of macroprudential surveillance that takes a cross-border perspective, in particular in Europe. They also encourage further thinking about the best institutional structures for supervision in a European banking system that slowly overcomes the barriers imposed by national and economic borders. While important steps have already been taken in this regard, if one thinks for example of the newly established Lamfalussy Committees in banking, it is nevertheless important to prepare for a future that may be different from the status quo.

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TABLE 1. Historical minima, tail indexes and quantile estimates for excess stock returns of euro area banks

Bank	|Extreme negative returns| in %			$\widehat{\alpha}$	$\widehat{Q}(p)$ in %	
	$X_{1,n}$ (date)	$X_{2,n}$ (date)	$X_{3,n}$ (date)		$p = 0.05\%$	$p = 0.02\%$
DEUTSCHE	12.4 (09/11/01)	12.0 (03/09/00)	10.1 (09/19/01)	3.3	13.8	18.2
HYPO	17.3 (10/23/02)	14.3 (09/30/02)	11.5 (09/11/01)	3.1	17.9	24.0
DRESDNER	11.1 (10/28/97)	9.9 (07/22/02)	9.7 (03/09/00)	3.2	16.1	21.5
COMMERZ	13.3 (09/11/01)	13.1 (09/20/01)	13.1 (10/23/02)	2.9	15.9	21.9
BGBERLIN	37.9 (08/30/01)	27.0 (09/10/01)	17.1 (01/17/94)	2.4	23.4	34.2
DEPFA	16.5 (11/29/00)	10.4 (10/08/98)	10.3 (07/23/02)	3.2	13.4	17.6
BNPPAR	12.5 (09/30/98)	11.2 (09/30/02)	11.0 (10/04/02)	3.0	15.4	20.8
CA	19.6 (11/19/01)	12.4 (07/12/01)	10.5 (09/12/02)	2.4	13.3	19.4
SGENERAL	12.5 (09/10/98)	11.6 (09/30/02)	10.4 (07/19/02)	2.7	17.1	23.6
NATEXIS	13.6 (10/08/97)	10.8 (09/25/96)	10.6 (03/25/94)	3.6	9.6	12.3
INTESA	12.7 (11/07/94)	12.2 (09/20/01)	11.6 (10/28/97)	3.9	13.7	17.4
UNICREDIT	10.9 (07/20/92)	10.3 (09/10/98)	9.9 (10/21/92)	3.6	12.9	16.7
PAOLO	9.9 (12/04/00)	9.7 (09/10/98)	9.5 (09/20/01)	3.5	13.3	17.3
CAPITA	18.2 (03/07/00)	12.0 (10/01/98)	11.5 (06/20/94)	3.3	16.7	24.6
SANTANDER	15.9 (10/01/98)	12.8 (01/13/99)	11.4 (07/30/02)	3.0	15.8	21.4
BILBAO	14.5 (01/13/99)	11.8 (09/10/98)	10.7 (09/24/92)	2.6	17.4	24.8
BANESP	84.8 (02/02/94)	18.9 (11/27/02)	15.5 (08/28/98)	2.2	20.1	30.6
ING	16.1 (10/15/01)	14.0 (10/02/98)	13.9 (09/11/01)	2.4	23.4	34.4
ABNAMRO	12.6 (09/14/01)	11.9 (09/11/01)	11.3 (09/30/02)	2.5	19.6	28.3
FORTIS	11.0 (08/01/02)	10.6 (09/30/02)	10.6 (09/11/01)	3.1	14.6	19.7
ALMANIJ	8.7 (11/26/99)	8.0 (04/30/92)	6.2 (08/01/02)	3.8	9.7	12.4
ALPHA	9.4 (04/27/98)	9.4 (09/09/93)	9.1 (01/13/99)	3.1	14.4	19.3
BCP	17.1 (10/23/02)	9.9 (02/25/03)	9.1 (04/16/99)	2.5	13.8	19.8
SAMPO	20.7 (08/17/92)	18.3 (12/21/92)	15.6 (08/26/92)	2.6	23.8	33.7
IRBAN	18.2 (02/06/02)	10.3 (10/08/98)	10.1 (10/28/97)	2.9	12.7	17.4
BANK INDEX	6.9 (09/11/01)	6.7 (10/01/98)	6.3 (09/10/98)	2.5	11.2	16.1
STOCK INDEX	6.3 (09/11/01)	5.3 (10/28/97)	5.0 (09/14/01)	3.2	7.7	10.2
YIELD SPREAD	16.6 (10/02/01)	16.5 (10/03/01)	16.3 (10/01/01)	9.1	22.3	24.7

Note: Returns and quantiles are reported in absolute values and therefore positive. $X_{1,n}$,$X_{2,n}$ and $X_{3,n}$ are the three smallest daily excess returns in the sample for each bank or each index. The last line describes the largest values (maxima) for high-yield bond spreads. Dates in parentheses are denoted XX/YY/ZZ, where XX=month, YY=day and ZZ=year. $\widehat{\alpha}$ is the tail index, estimated with the method by Hill (1975). $\widehat{Q}(p)$ is the estimated quantile (crisis level) for each bank, as implied by the estimated tail index and the assumed percentile (crisis probability). The quantiles are calculated for two percentiles p that correspond to an in-sample quantile ($p = 0.05\%$) and an out-of-sample quantile ($p = 0.02\%$). Data are from 2 April 1992 to 27 February 2004. The source of raw data is Datastream.

TABLE 2. Historical minima, tail indexes and quantile estimates for excess stock returns of US banks

Bank	|Extreme negative returns| in %			$\widehat{\alpha}$	$\widehat{Q}(p)$ in %	
	$X_{1,n}$ (date)	$X_{2,n}$ (date)	$X_{3,n}$ (date)		$p = 0.05\%$	$p = 0.02\%$
CITIG	17.1 (07/23/02)	11.7 (07/22/02)	11.5 (10/27/97)	3.3	13.7	18.0
JP MORGAN	20.0 (07/23/02)	10.8 (09/03/98)	10.1 (09/13/00)	3.7	12.9	16.6
BAMERICA	11.6 (10/14/98)	10.7 (10/27/03)	9.1 (06/16/00)	3.6	12.0	15.5
WACHOVIA	9.2 (11/14/00)	9.1 (05/25/99)	9.0 (01/27/99)	3.5	10.9	14.1
FARGO	9.2 (06/16/00)	7.5 (06/08/98)	7.3 (04/14/00)	3.7	9.6	12.3
BONE	25.8 (08/25/99)	11.4 (11/10/99)	9.5 (10/27/97)	3.0	13.5	18.4
WASHING	11.7 (10/17/01)	10.3 (09/04/98)	9.3 (12/09/03)	3.5	12.7	16.5
FLEET	11.2 (07/16/02)	10.2 (02/21/95)	8.0 (07/23/02)	3.7	11.7	15.0
BNYORK	16.9 (12/18/02)	13.9 (07/16/01)	11.1 (10/03/02)	3.4	12.6	16.5
SSTREET	19.7 (04/14/93)	12.1 (03/21/03)	11.9 (10/12/00)	3.0	14.8	20.0
NTRUST	10.6 (10/03/02)	9.1 (04/14/00)	8.5 (05/25/00)	3.5	11.8	15.4
MELLON	13.0 (10/27/97)	10.6 (01/22/03)	9.8 (03/08/96)	3.3	12.7	16.7
BCORP	17.4 (10/05/01)	15.9 (06/30/92)	10.7 (10/04/00)	2.9	14.4	19.8
CITYCO	9.5 (04/14/00)	8.2 (10/27/97)	7.7 (02/04/00)	3.1	11.3	15.2
PNC	16.1 (07/18/02)	10.3 (10/17/02)	9.8 (01/29/02)	3.4	10.9	14.3
KEYCO	8.9 (08/31/98)	8.3 (03/07/00)	8.2 (06/30/00)	3.4	11.4	14.9
SOTRUST	10.6 (04/26/93)	10.3 (01/03/00)	9.7 (03/17/00)	3.1	12.0	16.2
COMERICA	22.7 (10/02/02)	9.1 (04/17/01)	9.1 (04/14/00)	3.4	10.7	14.0
UNIONBANK	36.4 (06/16/00)	15.5 (03/17/00)	10.9 (12/15/00)	3.0	15.1	20.6
AMSOUTH	20.9 (09/22/00)	15.0 (06/01/99)	6.9 (01/10/00)	3.5	9.4	12.2
HUNTING	18.3 (09/29/00)	10.4 (01/18/01)	10.0 (08/31/98)	3.1	13.2	17.8
BBT	8.2 (01/21/03)	7.2 (06/15/00)	7.0 (04/14/00)	3.4	10.1	13.2
53BANCO	8.5 (11/15/02)	7.3 (01/14/99)	7.0 (04/14/00)	3.8	9.6	12.3
SUTRUST	10.2 (07/20/98)	9.5 (04/14/00)	8.9 (06/16/00)	3.2	10.6	14.2
REGIONS	11.2 (12/15/03)	9.1 (08/31/98)	8.5 (06/15/00)	3.5	10.2	13.2
BANK INDEX	7.0 (04/14/00)	6.8 (07/23/02)	6.7 (10/27/97)	3.4	9.1	12.0
STOCK INDEX	7.0 (08/31/98)	6.8 (04/14/00)	6.8 (10/27/97)	3.7	6.3	8.0
YIELD SPREAD	10.8 (10/10/02)	10.7 (10/09/02)	10.7 (10/11/02)	15.8	12.1	12.9

Note: Returns and quantiles are reported in absolute values and therefore positive. $X_{1,n}$,$X_{2,n}$ and $X_{3,n}$ are the three smallest daily excess returns in the sample for each bank or each index. The last line describes the largest values (maxima) for high-yield bond spreads. Dates in parentheses are denoted XX/YY/ZZ, where XX=month, YY=day and ZZ=year. $\widehat{\alpha}$ is the tail index, estimated with the method by Hill (1975). $\widehat{Q}(p)$ is the estimated quantile (crisis level) for each bank, as implied by the estimated tail index and the assumed percentile (crisis probability). The quantiles are calculated for two percentiles p that correspond to an in-sample quantile ($p = 0.05\%$) and an out-of-sample quantile ($p = 0.02\%$). Data are from 2 April 1992 to 27 February 2004. The source of raw data is Datastream.

TABLE 3. Domestic versus cross-border extreme spillover risk among euro area banks: Estimations

Largest bank	$\widehat{P}_1$	$\widehat{P}_2$	$\widehat{P}_3$	$\widehat{P}_4$	$\widehat{P}_5$
	Conditioning banks: German				
Germany	22.4	65.1	74.3	72.7	55.4
Netherlands	26.5	54.1	70.1	43.0	34.2
France	8.2	25.2	35.8	31.0	16.2
Spain	11.2	17.4	24.2	44.1	40.3
Italy	7.5	13.6	12.9	7.5	10.8
Belgium	16.1	44.2	42.6	28.5	9.2
Ireland	4.0	5.5	5.4	24.7	16.5
Portugal	7.7	13.6	21.7	25.1	18.0
Finland	0.9	1.7	2.3	4.0	4.5
Greece	0.9	1.4	1.3	1.3	2.1
	Conditioning banks: French				
France	2.9	35.9	76.6		
Germany	3.1	23.9	69.5		
Netherlands	8.2	48.7	71.8		
Italy	1.5	7.5	13.1		
Spain	3.3	27.4	70.1		
Belgium	6.7	38.0	56.3		
Ireland	1.0	1.8	6.9		
Portugal	2.5	6.5	26.5		
Finland	0.0	0.2	0.7		
Greece	0.2	0.3	0.6		
	Conditioning banks: Italian				
Italy	9.6	16.4	16.6		
Germany	5.1	12.4	18.8		
Netherlands	7.2	16.1	18.0		
Spain	4.6	11.7	14.6		
France	5.2	7.3	8.6		
Belgium	4.7	12.0	11.4		
Ireland	1.6	2.6	5.1		
Portugal	1.8	2.5	3.3		
Finland	1.9	3.2	2.5		
Greece	0.8	0.8	0.7		
	Conditioning banks: Spanish				
Spain	45.4	31.6			
Germany	22.4	13.9			
Netherlands	26.5	15.6			
France	25.8	21.6			
Italy	8.3	9.0			
Belgium	13.7	5.6			
Ireland	4.1	3.3			
Portugal	6.2	6.5			
Finland	1.1	1.4			
Greece	1.7	1.1			

Note: The table reports estimated extreme spillover probabilities between banks, as defined in (2.1). Each column $\widehat{P}_j$ shows the spillover probabilities for the largest bank of the country mentioned on the left-hand side conditional on a set of banks j from either the same country or other countries. The number of conditioning banks varies from 1 to 5 for Germany (top panel), 1 to 3 for France (upper middle panel), 1 to 3 for Italy (lower middle panel) and 1 to 2 for Spain (bottom panel). For example, the $\widehat{P}_2$ column contains probabilities for a stock market crash of the largest bank in each country, conditional on crashes of the 2nd and 3rd largest bank in Germany, France, Italy or Spain. All probabilities are estimated with the extension of the approach by Ledford and Tawn (1996) described in section 3 and reported in %. Univariate crash probabilities (crisis levels) are set to $p = 0.05\%$.

Table 4. Domestic versus cross-border extreme spillover risk among euro area banks: Tests

Largest bank	T_1	T_2	T_3	T_4	T_5
	Conditioning banks: German				
Netherlands	-1.01	0.00	-0.50	0.66	0.59
France	1.61	1.58	1.20	0.83	1.52
Spain	0.98	**2.51	**2.19	0.50	0.21
Italy	1.56	***2.58	***3.10	***2.59	*1.91
Belgium	0.12	0.26	0.83	0.98	*1.86
Ireland	**2.08	**-2.15	***3.78	1.36	1.51
Portugal	1.28	**2.49	*1.90	0.91	1.17
Finland	***3.93	***4.82	***4.32	***3.09	***2.62
Greece	***3.61	***4.47	***4.44	***3.28	***2.66
	Conditioning banks: French				
Germany	-0.31	0.86	-0.39		
Netherlands	**-2.50	-1.11	-0.75		
Spain	-0.24	0.48	0.08		
Italy	1.03	***2.75	*1.92		
Belgium	*-1.85	-0.51	0.37		
Ireland	1.32	***3.20	***2.58		
Portugal	0.11	**2.36	1.04		
Finland	***3.56	***3.96	***3.93		
Greece	**2.56	***3.73	***3.65		
	Conditioning banks: Italian				
Germany	1.11	0.42	-0.09		
Netherlands	0.41	-0.17	-0.56		
Spain	1.33	0.45	-0.01		
France	0.96	1.27	-0.09		
Belgium	1.01	0.31	-0.36		
Ireland	**2.50	**2.52	1.46		
Portugal	***2.70	**2.57	**2.07		
Finland	**2.33	**2.10	**2.16		
Greece	***3.90	***3.59	***3.34		
	Conditioning banks: Spanish				
Germany	1.41	1.04			
Netherlands	0.89	1.00			
France	0.68	0.31			
Italy	***2.83	1.51			
Belgium	*1.83	*1.91			
Ireland	***4.21	***3.00			
Portugal	***3.47	**2.05			
Finland	***5.40	***3.92			
Greece	***4.58	***3.39			

Note: The table reports the statistics for the cross sectional test (4.5). Within each panel the degree of extreme domestic spillover risk is compared with the degree of extreme cross-border spillover risk for a given fixed number of conditioning banks. So, each T-statistic describes whether the differences between domestic and cross-border values of η that entered the estimations in table 3 are statistically significant. For example, in the top panel the test statistic in the row "Netherlands" and the column T_1 indicates whether the difference between the η for the spillover probability between ABN AMRO and HypoVereinsbank and the η between Deutsche Bank and HypoVereinsbank is statistically signifcant. The null hypothesis is that the respective two ηs are equal. Insignificant T-statistics imply that the domestic and cross-border spillover risks are indistinguishable. A significant rejection with positive sign implies that cross-border spillover risk is statistically smaller than its domestic counterpart; and a rejection with negative sign implies that cross-border risk is larger than domestic risk. The critical values of the test are 1.65, 1.96 and 2.58 for the 10%, 5% and 1% levels, respectively. Asterisks *, ** and *** indicate rejections of the null hypothesis at 10%, 5% and 1% significance.

Table 5. Multivariate extreme spillover risk among euro area and US banks

Country/Area		Estimations		Cross-sectional
		$\widehat{\eta}$	$\widehat{P}$	test T
United States	(N=25)	0.39	2.8E-4	$H_0 : \eta_{US} = \eta_{EA}$
Euro area	(N=25)	0.17	6.7E-15	$T = 7.25$
Germany	(N=6)	0.42	1.5E-3	
France	(N=4)	0.48	1.4E-2	
Italy	(N=4)	0.62	0.6	

Note: The table reports in the column $\widehat{\eta}$ the coefficient that governs the multivariate extreme tail dependence for all the banks of the countries/areas detailed on the left-hand side. In the column $\widehat{P}$ it shows the probabililty that all banks of a specific country/area crash given that one of them crashes. Both statistics are estimates of system-wide extreme spillover risks. Univariate crash probabilities (crisis levels) are set to $p = 0.05\%$. The right-hand column describes the cross-sectional test (4.5) for the whole US and euro area banking systems. A positive (negative) test statistic indicates that the US (euro area) η is larger than the euro area (US) η. The critical values of the test are 1.65, 1.96 and 2.58 for the 10%, 5% and 1% levels, respectively. Note that η values for countries/areas with different numbers of banks may not be comparable.

TABLE 6. Extreme systematic risk (tail-βs) of euro area banks

Bank	Aggregate risk factor				
	Bank index	Stock index	Global bank	Global stock	Yield spread
DEUTSCHE	51.1	35.0	25.6	13.0	3.8E-5
HYPO	22.3	20.8	9.3	5.5	0.1
DRESDNER	37.9	27.7	19.1	11.6	0.3
COMMERZ	39.5	30.8	15.2	13.9	0.2
BGBERLIN	2.8	1.6	0.8	0.7	0.8
DEPFA	6.2	7.3	3.0	2.9	3.4E-2
BNPPAR	42.1	30.2	23.2	13.2	2.7E-2
CA	9.2	6.7	1.6	2.0	0.4
SGENERAL	45.8	30.0	22.7	16.0	6.9E-2
NATEXIS	1.8	1.9	2.2	1.7	9.1E-3
INTESA	19.1	11.2	7.2	5.9	0.4
UNICREDIT	14.5	9.5	10.5	5.0	0.3
PAOLO	36.7	28.5	15.2	10.2	0.3
CAPITA	16.5	9.3	9.4	6.4	0.3
SANTANDER	36.4	33.4	17.4	14.5	0.6
BILBAO	41.6	31.1	20.4	13.4	0.6
BANESP	2.6	1.2	1.4	0.6	2.7E-3
ING	61.7	46.0	23.1	14.1	0.5
ABNAMRO	50.3	46.3	23.7	13.9	0.2
FORTIS	48.5	36.3	11.8	10.9	0.1
ALMANIJ	11.9	11.1	7.4	4.5	0.2
ALPHA	3.7	4.1	1.5	1.2	8.0E-3
BCP	17.0	11.9	9.3	7.5	0.3
SAMPO	2.7	2.2	3.4	1.4	2.1E-2
IRBAN	13.9	12.1	6.9	4.6	0.1
average	25.4	19.4	11.6	7.8	0.2
st. dev.	18.8	14.5	8.3	5.3	0.2

Note: The table exhibits the estimates of extreme systematic risk (2.2) (tail-βs) for individual euro area banks and for the euro area banking system as a whole. The entries show the probability that a given bank crashes given that a market indicator of aggregate risk crashes (or in the case of the yield spread booms). Results are reported for five different aggregate risk factors: The euro area banking sector sub-index, the euro area stock index, the world banking sector sub-index, the world stock index and the euro area high-yield bond spread. Data for the euro area yield spread are only available from 1998 to 2004. All probabilities are estimated with the extension of the approach by Ledford and Tawn (1996) described in section 3 and reported in %. Univariate crash probabilities (crisis levels) are set to $p = 0.05\%$. The average and the standard deviation at the bottom of the table are calculated over the 25 individual tail-βs in the upper rows, respectively.

Table 7. Extreme systematic risk (tail-βs) of US banks

Bank	Aggregate risk factor				
	Bank index	Stock index	Global bank	Global stock	Yield spread
CITIG	41.1	26.5	16.5	17.4	0.3
JPMORGAN	39.4	18.0	15.2	16.4	1.3
BOA	37.7	12.4	6.4	7.1	0.2
WACHO	27.2	9.6	8.6	9.3	0.5
FARGO	17.1	7.1	4.5	3.8	2.4E-2
BONEC	31.0	14.0	9.7	10.0	0.4
WASHMU	9.5	2.8	4.7	1.8	0.1
FLEET	38.8	13.1	10.6	10.1	0.6
BNYORK	25.2	12.9	10.9	11.3	1.0
STATEST	26.8	19.0	10.9	18.3	1.0
NOTRUST	26.7	17.4	12.0	10.0	0.9
MELLON	29.4	16.4	10.6	10.4	0.8
USBANC	19.6	6.6	7.8	4.8	0.3
CITYCO	32.3	8.9	7.4	6.7	0.2
PNC	25.8	12.7	10.2	8.9	0.3
KEYCO	24.9	8.4	6.1	6.1	0.2
SUNTRUST	32.0	11.7	8.9	7.8	0.3
COMERICA	24.0	13.5	7.1	7.1	0.5
UNIONBAN	11.2	3.9	5.9	3.8	0.1
AMSOUTH	15.1	7.5	8.7	6.4	0.3
HUNTING	17.5	7.0	8.3	6.0	0.1
BBT	19.9	6.6	5.3	5.4	0.2
53BANCO	21.7	8.6	4.9	3.6	0.2
SOTRUST	33.3	7.3	6.8	4.4	0.3
RFCORP	26.5	11.6	8.4	7.8	0.2
average	26.2	11.3	8.6	8.2	0.4
st. dev.	8.5	4.4	3.0	4.2	0.3

Note: The table exhibits the estimates of extreme systematic risk (2.2) (tail-βs) for individual US banks and for the US banking system as a whole. The entries show the probability that a given bank crashes given that a market indicator of aggregate risk crashes (or in the case of the yield spread booms). Results are reported for five different aggregate risk factors: The US banking sector sub-index, the US stock index, the world banking sector sub-index, the world stock index and the US high-yield bond spread. All probabilities are estimated with the extension of the approach by Ledford and Tawn (1996) described in section 3 and reported in %. Univariate crash probabilities (crisis levels) are set to $p = 0.05\%$. The average and the standard deviation at the bottom of the table are calculated over the 25 individual tail-βs in the upper rows, respectively.

TABLE 8. Comparisons of extreme systematic risk across different banking systems

	Aggregate risk factor				
Banking system	Bank index	Stock index	Global bank	Global stock	Yield spread
$\overline{\eta}_{US}$	0.87	0.79	0.78	0.77	0.55
$\overline{\eta}_{EA}$	0.86	0.83	0.80	0.76	0.53
$\overline{\eta}_{FR}$	0.85	0.82	0.79	0.76	0.50
$\overline{\eta}_{GE}$	0.86	0.84	0.80	0.76	0.53
$\overline{\eta}_{IT}$	0.88	0.83	0.82	0.78	0.57
Null hypothesis					
$\overline{\eta}_{US} = \overline{\eta}_{EA}$	0.19	-0.94	-0.44	0.21	0.30
$\overline{\eta}_{US} = \overline{\eta}_{FR}$	0.34	-0.59	-0.32	0.14	1.18
$\overline{\eta}_{US} = \overline{\eta}_{GE}$	0.20	-1.05	-0.47	0.30	0.48
$\overline{\eta}_{US} = \overline{\eta}_{IT}$	-0.08	-0.63	-0.81	-0.16	-0.48

Note: the table exhibits the average tail dependence parameters η that govern the tail-β estimates reported in tables 6 and 7 for the US, euro area, French, German and Italian banking system (upper panel) and the statistics of tests examining differences in extreme systematic risk between the US and euro area banking systems (lower panel). Each $\overline{\eta}$ is calculated as the mean of tail-β dependence parameters across all the banks in our sample for the respective country/area. The tests are applications of the cross-sectional test (4.5). The null hypothesis is that extreme systematic risk in the US banking system is the same as in the other banking systems. A positive (negative) test statistic indicates that extreme systematic risk in the US banking system (in the respective euro area banking system) is larger than in the respective euro area (US) banking system. The critical values of the test are 1.65, 1.96 and 2.58 for the 10%, 5% and 1% levels, respectively. All results are reported for the five different aggregate risk factors: The euro area/US banking sector sub-index, the euro area/US stock index, the world banking sector sub-index, the world stock index and the euro area/US high-yield bond spread. Univariate crash probabilities (crisis levels) are set to $p = 0.05\%$.

Table 9. Domestic and cross-border extreme spillover risk among euro area banks: Time variation

Largest bank	$\widehat{\eta}_1$	$\widehat{\eta}_2$	$\widehat{\eta}_3$	$\widehat{\eta}_4$	$\widehat{\eta}_5$
	Conditioning banks: German				
Germany	3/31/97 (43.5)	8/1/97 (62.0)	4/2/97 (38.4)	8/15/97 (7.2)	7/23/97 (17.3)
Netherlands	3/31/97 (81.1)	4/2/97 (77.9)	4/2/97 (66.2)	8/21/97 (16.9)	4/2/97 (7.3)
France	7/23/97 (25.6)	8/1/97 (37.5)	9/9/97 (41.2)	7/23/97 (19.3)	8/15/97 (8.4)
Spain	7/21/97 (68.8)	5/27/97 (39.7)	5/29/97 (55.9)	7/23/97 (18.9)	8/14/97 (5.5)
Italy	7/21/97 (49.2)	9/9/97 (46.2)	9/9/97 (41.4)	8/21/97 (20.2)	8/21/97 (9.3)
Belgium	8/21/97 (62.2)	4/2/97 (50.1)	3/27/97 (56.7)	7/23/97 (25.9)	6/12/98 (6.9)
Ireland	8/20/97 (43.0)	10/16/97 (24.3)	8/15/97 (21.9)	8/14/97 (11.3)	8/15/97 (4.7)
Portugal	9/9/97 (27.5)	1/14/94 (37.1)	1/25/94 (50.1)	7/23/97 (23.2)	7/23/97 (7.5)
Finland	10/16/97 (30.5)	10/16/97 (26.3)	5/23/94 (37.2)	8/22/97 (23.6)	7/23/97 (9.6)
Greece	3/27/97 (64.0)	3/27/97 (58.8)	4/2/97 (47.8)	3/27/97 (18.8)	8/15/97 (7.4)
	Conditioning banks: French				
France	2/15/02 (25.3)	9/19/00 (32.8)	6/17/94 (22.5)		
Germany	10/9/00 (52.6)	11/21/00 (36.3)	5/21/96 (4.4)		
Netherlands	10/10/00 (54.4)	9/20/00 (44.9)	10/22/97 (39.0)		
Italy	1/11/02 (20.1)	1/31/01 (37.8)	10/22/97 (32.5)		
Spain	10/10/00 (34.3)	9/19/00 (40.6)	10/13/97 (32.1)		
Belgium	9/1/00 (47.7)	11/27/01 (52.4)	6/9/98 (40.8)		
Ireland	9/20/00 (13.8)	11/21/00 (19.4)	12/7/01 (12.2)		
Portugal	1/25/02 (24.8)	1/29/02 (30.4)	10/22/97 (20.4)		
Finland	4/14/00 (6.1)	5/31/94 (26.0)	11/4/96 (27.5)		
Greece	6/11/98 (15.5)	2/28/97 (32.5)	2/28/97 (19.2)		
	Conditioning banks: Italian				
Italy	9/30/97 (5.4)	9/25/ 97 (9.0)	9/30/97 (3.6)		
Germany	7/25/97 (23.9)	7/25/97 (31.7)	10/8/97 (18.8)		
Netherlands	10/7/97 (16.6)	8/1/97 (27.7)	8/7/97 (18.7)		
Spain	6/27/97 (7.6)	7/14/97 (19.9)	9/9/97 (12.1)		
France	10/8/97 (9.9)	10/22/97 (8.3)	9/9/97 (7.9)		
Belgium	7/31/97 (25.8)	8/1/97 (44.8)	10/8/97 (30.2)		
Ireland	8/22/97 (4.9)	10/8/97 (7.0)	8/7/97 (6.7)		
Portugal	8/1/97 (9.1)	8/1/97 (18.2)	8/7/97 (13.6)		
Finland	-	7/25/97 (8.5)	10/24/97 (5.9)		
Greece	9/9/97 (15.3)	10/17/97 (19.2)	8/15/97 (13.4)		
	Conditioning banks: Spanish				
Spain	7/16/97 (33.1)	7/16/97 (4.0)			
Germany	3/17/97 (88.0)	5/21/97 (9.0)			
Netherlands	7/21/97 (39.0)	7/3/97 (7.3)			
France	10/22/97 (34.6)	5/27/97 (5.4)			
Italy	7/28/97 (33.2)	6/18/97 (3.8)			
Belgium	7/17/97 (47.7)	2/25/97 (12.4)			
Ireland	7/16/97 (22.7)	-			
Portugal	6/16/97 (42.7)	3/31/97 (12.8)			
Finland	10/24/97 (21.3)	7/23/97 (3.9)			
Greece	6/2/97 (37.9)	3/27/97 (12.4)			

Note: The table reports the results of tests examining the structural stability of the extreme spillover risks documented in table 3. This is done by testing for the constancy of the η tail dependence parameters (null hypothesis) that govern the spillover probabilities in table 3. Applying the recursive test (4.1) through (4.4) by Quintos et al. (2001), each cell shows the endogenously found break date and the test value in parentheses. Dates are denoted XX/YY/ZZ, where XX=month, YY=day and ZZ=year. The critical values of the test are 1.46, 1.78 and 2.54 for the 10%, 5% and 1% levels, respectively. A test value exceeding these numbers implies an increase in extreme dependence over time. The absence of a break over the sample period is marked with a dash.

Table 10. Multivariate extreme spillover risk among euro area and US banks: Time variation

Country/Area		Full sample break test	Sub-sample estimates		Second sub-sample break tests	
			$\widehat{\eta}_1$	$\widehat{\eta}_2$	Endogenous	Exogenous
United States	(N=25)	11/22/95 (18.5)	0.20	0.41	3/11/97 (2.2)	n.a.
Euro area	(N=25)	12/5/96 (4.9)	0.13	0.20	(B) 1/18/99 (3.2)	(1.4)
Germany	(N=6)	7/23/97 (17.6)	0.24	0.52	-	(1.9)
		(B) 4/2/97 (2.1)			(B) 1/22/99 (3.9)	
France	(N=4)	6/17/94 (21.9)	0.19	0.52	12/7/01 (12.8)	(-3.0)
		(B) 5/21/96 (4.3)			(B) 2/24/97 (3.0)	
Italy	(N=4)	09/30/97 (3.4)	0.45	0.72	(B) 4/11/03 (2.2)	(2.1)

Note: The table reports tests and estimations assessing time variation in the multivariate spillover probabilities of table 5. The column on the left displays estimated break dates and values from the recursive Quintos et al. (2001) test (4.1) through (4.4) applied to the η parameter governing the extreme tail dependence of the banks located in the countries/areas displayed on the extreme left. Dates are denoted XX/YY/ZZ, where XX=month, YY=day and ZZ=year. The forward recursive version of the test is used, unless marked otherwise. (B) marks the backward recursive version of the test. The critical values of the test are 1.46, 1.78 and 2.54 for the 10%, 5% and 1% levels, respectively. The middle columns show pre- and post-break estimates for η. The columns on the right display two tests that assess the occurrence of further breaks in the second half of the sample. The first one is the same as the one on the left-hand side. The second one is a simple differences-in-means test based on (4.5). The exogenous break point is chosen to be 1/1/99, the time of the introduction of the euro. Critical values for this test are 1.65, 1.96 and 2.58 for the 10%, 5% and 1% significance levels. Note that η values for countries/areas with different numbers of banks may not be comparable.

FIGURE 1. Evolution of multivariate extreme spillover risk among euro area and US banks

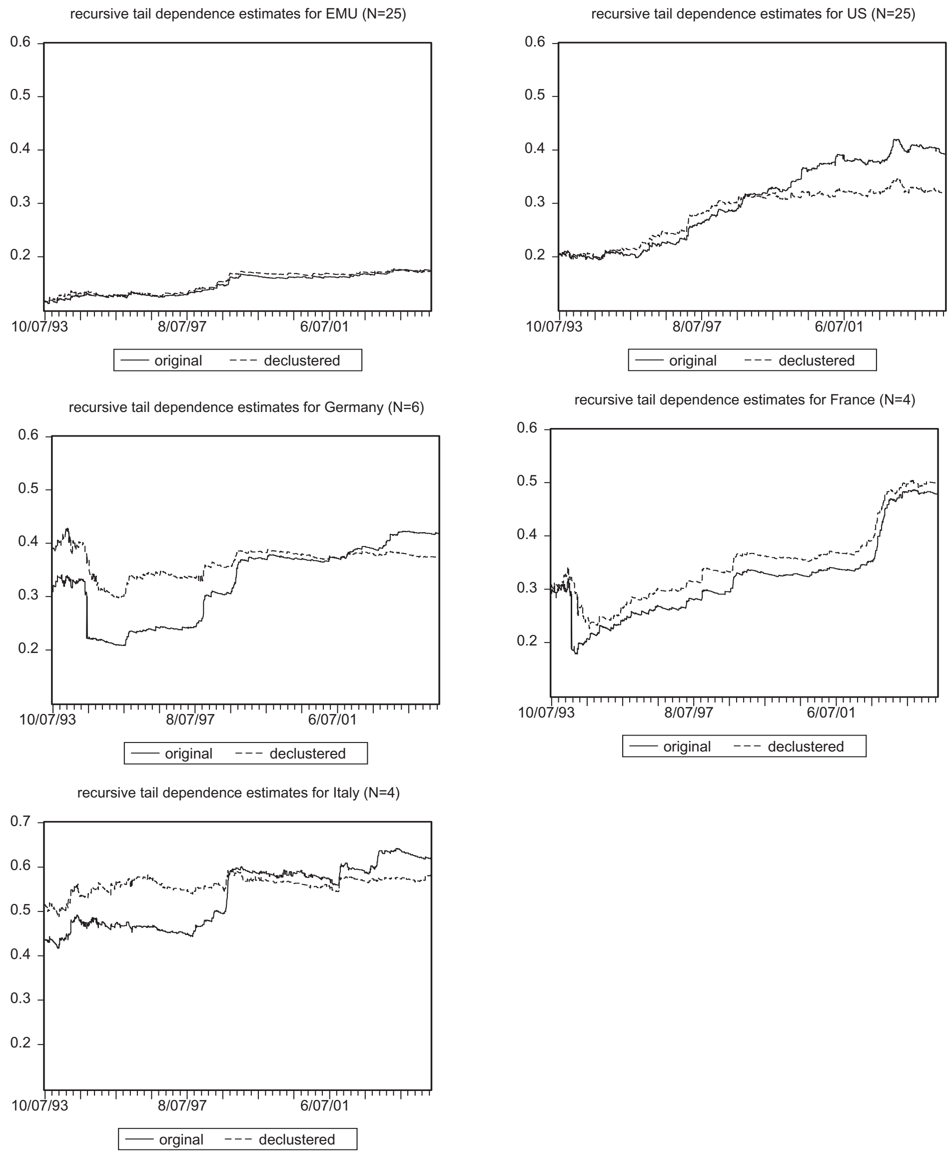

FIGURE 2. Comparisons of the evolution of extreme bank spillover risk across countries

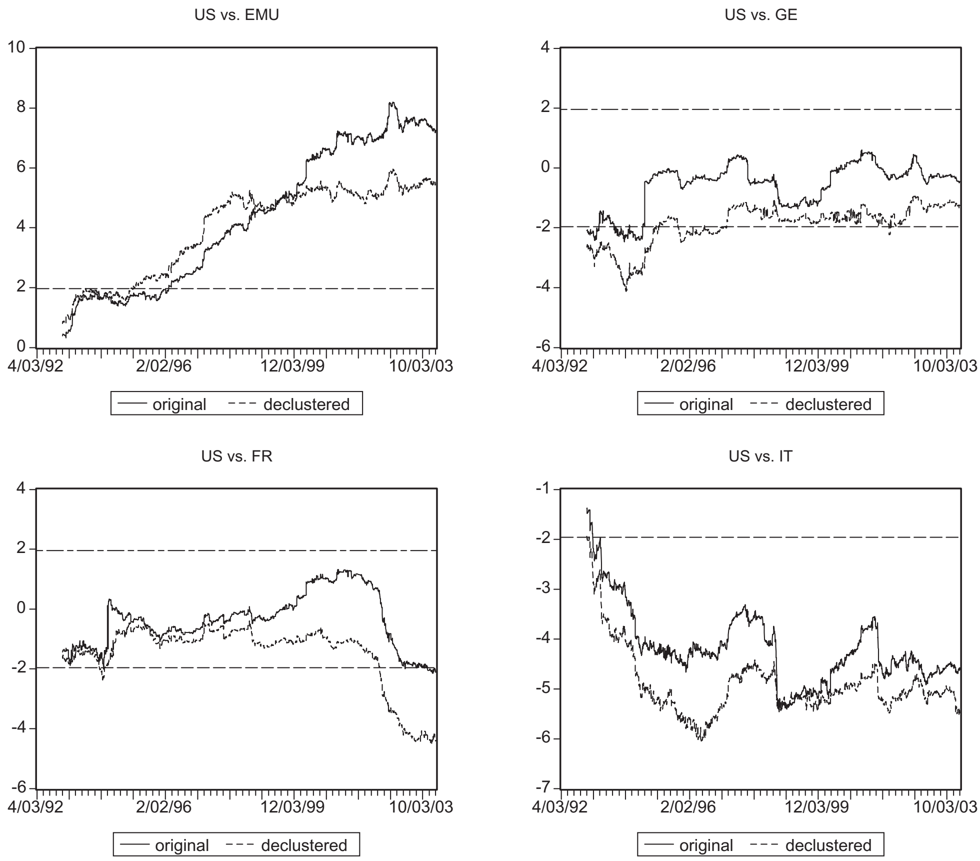

Table 11. Extreme systematic risk (tail-βs) of euro area banks: Time variation

Bank	Aggregate risk factor				
	Bank index	Stock index	Global bank	Global stock	Yield spread
DEUTSCHE	3/12/97 (45.3)	3/12/97 (57.7)	8/15/97 (53.3)	12/5/96 (86.1)	9/14/00 (153.4)
HYPO	7/21/97 (40.1)	10/22/97 (60.0)	9/9/97 (62.8)	10/22/97 (60.5)	10/4/00 (124.1)
DRESDNER	8/1/97 (69.1)	12/5/96 (53.1)	12/5/96 (48.5)	12/5/96 (59.5)	8/22/00 (44.1)
COMMERZ	7/21/97 (22.8)	3/19/97 (34.8)	8/1/97 (30.4)	8/21/97 (70.4)	10/3/00 (142.7)
BGBERLIN	12/3/96 (7.9)	12/3/96 (10.9)	12/5/96 (11.8)	7/3/97 (19.2)	1/4/01 (496.6)
DEPFA	7/5/96 (33.7)	7/15/96 (37.6)	8/21/97 (19.4)	8/12/97 (33.6)	9/13/00 (97.5)
BNPPAR	8/15/97 (34.7)	7/17/97 (41.1)	10/22/97 (27.5)	8/27/97 (34.0)	9/15/00 (77.3)
CA	10/5/00 (50.4)	9/19/00 (52.7)	10/9/00 (26.6)	9/19/00 (31.7)	7/21/00 (127.3)
SGENER	10/22/97 (40.9)	10/22/97 (35.4)	10/22/97 (37.4)	10/22/97 (42.6)	9/21/00 (114.5)
NATEXIS	12/5/96 (6.0)	12/3/96 (8.5)	8/28/97 (11.0)	8/28/97 (21.1)	9/15/00 (155.1)
INTESA	7/31/97 (25.6)	7/28/97 (39.7)	9/9/97 (14.5)	7/31/97 (24.4)	7/24/00 (183.9)
UNICRED	10/8/97 (23.8)	9/25/97 (14.2)	10/8/97 (18.7)	9/9/97 (18.0)	9/11/00 (123.4)
PAOLO	7/28/97 (52.6)	9/25/97 (51.4)	10/24/97 (43.8)	10/8/97 (58.7)	8/17/00 (218.4)
CAPITA	8/12/97 (17.0)	9/10/97 (15.7)	9/9/97 (13.1)	9/9/97 (16.0)	9/15/00 (170.6)
SANTANDER	7/23/97 (60.3)	5/27/97 (64.0)	8/21/97 (28.3)	10/8/97 (51.5)	9/15/00 (207.3)
BILBAO	10/8/97 (54.0)	10/16/97 (58.7)	10/7/97 (36.2)	10/22/97 (68.7)	9/11/00 (209.3)
BANESP	5/16/97 (6.3)	10/16/97 (5.3)	10/22/97 (2.5)	10/22/97 (2.3)	7/21/00 (29.3)
ING	11/26/96 (43.7)	10/22/96 (36.4)	8/21/97 (57.2)	7/5/96 (51.7)	9/20/00 (186.5)
ABNAMRO	11/26/96 (48.1)	12/5/96 (56.3)	7/4/96 (73.9)	7/4/96 (61.6)	9/15/00 (132.5)
FORTIS	3/17/97 (65.4)	12/10/96 (41.1)	12/10/96 (33.0)	7/17/97 (36.7)	9/15/00 (161.2)
ALMANIJ	3/14/97 (59.4)	1/23/97 (56.7)	1/23/97 (54.5)	8/7/97 (77.1)	9/14/00 (238.2)
ALPHA	2/24/97 (52.7)	2/27/97 (64.5)	1/8/97 (36.6)	2/6/97 (66.1)	9/29/00 (80.7)
BCP	6/16/97 (37.8)	7/3/97 (42.2)	8/26/97 (28.7)	7/17/97 (57.6)	9/15/00 (129.0)
SAMPO	10/16/97 (15.2)	10/24/97 (15.6)	10/24/97 (6.0)	10/16/97 (11.5)	8/16/00 (151.6)
IRBAN	8/12/97 (22.4)	3/12/97 (25.2)	8/21/97 (16.5)	8/20/97 (25.3)	9/29/00 (164.7)

Note: The table reports the results of tests examining the structural stability of the extreme systematic risks of euro area banks documented in table 6. This is done by testing for the constancy of the η tail dependence parameters (null hypothesis) that govern the tail-βs in table 6. Applying the recursive test (4.1) through (4.4) by Quintos et al. (2001), each cell shows the endogenously found break date and the test value in parentheses. Dates are denoted XX/YY/ZZ, where XX=month, YY=day and ZZ=year. The critical values of the test are 1.46, 1.78 and 2.54 for the 10%, 5% and 1% levels, respectively. A test value exceeding these numbers implies an increase in extreme dependence over time. The absence of a break over the sample period is marked with a dash.

FIGURE 3. Evolution of extreme systematic risk in the euro area and the US banking systems

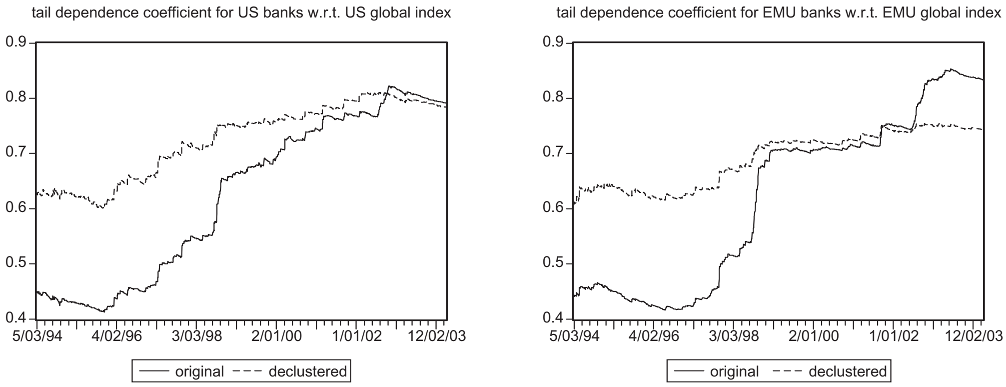

Table 12. Extreme systematic risk (tail-βs) of US banks: Time variation

Bank	Aggregate risk factor				
	Bank index	Stock index	Global bank	Global stock	Yield spread
CITIG	12/20/96 (28.0)	12/15/95 (17.8)	10/22/97 (34.0)	10/23/97 (30.8)	10/20/00 (93.5)
JPMORGAN	2/25/97 (34.1)	3/11/97 (28.3)	10/13/97 (33.1)	10/16/97 (40.0)	10/17/00 (87.4)
BOA	12/2/96 (27.4)	12/10/96 (27.9)	11/29/96 (33.1)	12/2/96 (38.6)	9/25/00 (64.7)
WACHO	3/10/97 (14.9)	12/10/96 (22.0)	2/26/97 (66.4)	2/26/97 (41.3)	10/10/00 (64.5)
FARGO	1/3/96 (14.4)	12/15/95 (14.7)	2/27/97 (23.4)	2/26/97 (15.6)	10/5/00 (35.4)
BONEC	12/6/95 (23.7)	12/13/95 (32.3)	11/29/96 (47.6)	2/19/96 (40.3)	10/5/00 (98.8)
WASHMU	2/27/97 (8.1)	2/23/96 (10.6)	10/16/97 (20.2)	2/24/97 (9.9)	11/21/00 (33.6)
FLEET	4/22/98 (33.8)	12/10/96 (25.5)	4/17/98 (39.2)	12/10/96 (36.2)	11/30/00 (52.6)
BNYORK	2/19/96 (20.2)	1/8/96 (17.7)	12/11/96 (41.3)	2/6/97 (47.0)	9/19/00 (77.8)
STATEST	3/11/97 (35.8)	12/2/96 (49.4)	12/2/96 (41.7)	10/16/97 (58.2)	10/5/00 (158.3)
NOTRUST	11/29/96 (33.8)	12/2/96 (51.7)	10/22/97 (35.3)	12/5/96 (52.8)	9/29/00 (107.8)
MELLON	12/4/95 (13.4)	12/13/95 (25.4)	10/24/97 (38.3)	10/24/97 (26.0)	10/11/00 (108.6)
USBANC	2/25/97 (40.1)	1/23/97 (48.3)	9/25/97 (57.9)	9/25/97 (39.5)	11/10/00 (37.0)
CITYCO	11/29/96 (26.7)	12/2/96 (28.8)	11/29/96 (45.9)	12/2/96 (44.7)	10/10/00 (38.9)
PNC	12/10/96 (24.3)	12/13/95 (26.3)	12/10/96 (34.6)	3/7/96 (34.5)	11/30/00 (51.6)
KEYCO	12/2/96 (12.1)	12/6/95 (18.1)	12/5/96 (19.5)	12/2/96 (27.3)	9/28/00 (56.7)
SUNTRUST	12/2/96 (29.0)	12/13/95 (38.7)	12/5/96 (31.8)	12/5/96 (31.6)	10/20/00 (40.8)
COMERICA	1/3/96 (11.3)	12/13/95 (17.9)	2/25/97 (27.8)	1/8/96 (23.4)	10/11/00 (64.2)
UNIONBAN	7/21/97 (29.6)	10/24/97 (44.6)	6/26/97 (6.4)	10/23/97 (17.2)	9/26/00 (19.6)
AMSOUTH	12/19/95 (18.4)	1/8/96 (24.9)	12/10/96 (23.8)	1/1/97 (17.5)	9/19/00 (45.4)
HUNTING	2/6/97 (34.2)	1/22/97 (67.3)	10/13/97 (29.9)	10/16/97 (40.9)	10/5/00 (30.3)
BBT	3/28/97 (22.3)	3/28/97 (24.7)	10/22/97 (16.7)	10/29/97 (19.4)	9/19/00 (24.6)
53BANCO	12/2/96 (31.6)	12/2/96 (26.2)	12/5/96 (59.2)	4/9/97 (34.3)	10/16/00 (42.0)
SOTRUST	2/26/97 (47.4)	2/24/97 (36.6)	10/13/97 (35.6)	10/8/97 (44.2)	12/1/00 (41.5)
RFCORP	3/7/96 (36.4)	2/23/96 (40.7)	12/10/96 (23.3)	12/10/96 (33.9)	10/10/00 (24.0)

Note: The table reports the results of tests examining the structural stability of the extreme systematic risks of US banks documented in table 7. This is done by testing for the constancy of the η tail dependence parameters (null hypothesis) that govern the tail-βs in table 7. Applying the recursive test (4.1) through (4.4) by Quintos et al. (2001), each cell shows the endogenously found break date and the test value in parentheses. Dates are denoted XX/YY/ZZ, where XX=month, YY=day and ZZ=year. The critical values of the test are 1.46, 1.78 and 2.54 for the 10%, 5% and 1% levels, respectively. A test value exceeding these numbers implies an increase in extreme dependence over time. The absence of a break over the sample period is marked with a dash.

Appendix A. Small sample properties of estimators and tests

A.1. **Small sample properties of the bivariate estimator.** In this section we investigate the small sample properties of our estimators. We limit our attention to the bivariate version, which could either be a spillover probability between two banks or a tail-β, and the respective dependence parameter. Without loss of generality, we will always refer to tail-β below. Three different data generating processes are investigated: The bivariate Pareto distribution, the bivariate Morgenstern distribution (1956) with Pareto marginals and the bivariate standard normal distribution. The first two distributions both have Pareto marginals, but only the first distribution exhibits asymptotic dependence (in which case $\eta = 1$). The bivariate normal is also asymptotically independent (as long as $|\rho| \neq 1$). The normal distribution has a dependence parameter η that varies with the correlation coefficient, and we investigate different configurations. The precise specifications of the distributions are as follows:

1/ Bivariate Pareto

$$
\begin{aligned}
F(x,y) &= 1 - x^{-\alpha} - y^{-\alpha} + (x+y-1)^{-\alpha}, \\
\rho &= 1/\alpha \text{ for } \alpha > 2, \\
\eta &= 1.
\end{aligned}
$$

2/ Bivariate Morgenstern distribution with Pareto marginals

$$
\begin{aligned}
F(x,y) &= \left(1 - x^{-\alpha}\right)\left(1 - y^{-\alpha}\right)\left(1 + \delta x^{-\alpha} y^{-\alpha}\right), \qquad -1 \leq \delta \leq 1, \\
\rho &= \delta\alpha(\alpha-2)(2\alpha-1)^{-2} \text{ for } \alpha > 2, \\
\eta &= 1/2.
\end{aligned}
$$

3/ Bivariate normal with correlation coefficient ρ and dependence parameter

$$
\eta = \frac{1+\rho}{2}.
$$

The three specific distributions have the advantage that they allow us to calculate the true value of η and the tail-β (τ_β). Thus, the estimation bias and asymptotic mean-squared error can be calculated explicitly. The true "benchmark" values of the tail-βs are:

$$\begin{aligned}
\tau_\beta &= \left(2-p^{1/\alpha}\right)^{-\alpha} \quad \text{(bivariate Pareto)},\\
\tau_\beta &= (1+\delta)\,p-2\delta p^2+\delta p^3 \quad \text{(bivariate Morgenstern)},\\
\tau_\beta &= \frac{\Phi\left(-x,-x,\rho\right)}{p}, \quad \text{(bivariate standard normal)},
\end{aligned}$$

where $p = P\{X > x\}$. In the tables below we evaluate the tail-βs and dependence parameters at $p = 0.05\%$ which is one of the marginal significance levels we also use in the empirical applications. Two different sample sizes are considered, a truly small sample of 500 observations and a larger sample of 3,106, corresponding to the actual sample size in the empirical application to bank stocks.

The following three tables report true values of τ_β as well as estimates of the average, bias and standard deviation of η and τ_β for 5,000 Monte Carlo replications. Notice that biases are reported in absolute and not in percentage terms. Back-of-the-envelope calculations of the relative (percentage) biases may nevertheless be handy for sake of comparing the bias across different parametrizations but were omitted for sake of space considerations.[35] Averages, biases and standard deviations are multiplied with 100 for sake of convenience. The estimates are conditioned on cutoff points m^* that minimize the Asymptotic Mean Squared error (AMSE). The AMSE is calculated for 5,000 Monte Carlo replications.[36]

We start with an evaluation for the Morgenstern distribution with Pareto marginals (see table A.1).

[Insert table A.1 about here]

Analytic tail-β values are small which makes this model the least realistic as a benchmark for comparison with the tail-βs we found in practice. We let both the tail index α and the parameter δ vary. The table shows that the Morgenstern bias in η and τ_β does depend on δ but not on α. This is not surprising given that α does not enter the analytic expression of the Morgenstern tail-β,i.e., the tail-β is independent from

[35]Relative or percentage measures of the bias can be calculated as $100\times\left(E\left(\widehat{\eta}\right)-\eta\right)/\eta$ and $100\times\left(E(\widehat{\tau}_\beta)-\tau_\beta\right)/\tau_\beta$ for the tail dependence parameter and the tail-β, respectively.

[36]If two (unit Pareto) random variables are independent, we previously noted that $P\{X > q, Y > q\} = p^2$ with $p = P\{X > q\} = P\{Y > q\}$. This exact Pareto tail allows the use of all extreme observations in estimation because of the unbiasedness of the Hill statistic under the Pareto law, i.e., $m^* = n-1$.

marginal properties in this case.[37] Biases are small for small δ but become substantial in both absolute and relative terms when δ is large. Also, the estimation accuracy - as reflected by the standard errors s.e. - is found to be higher for small values of δ.

Next we turn to the results for the Pareto distribution. The results are in table A.2.

[Insert table A.2 about here]

In contrast to table A.1, there now appears a considerable downward bias in absolute terms for both η and τ_β. However, the relative (percentage) biases can be shown to be smaller than in the Morgenstern case. Recall that the true value of η is equal to the boundary of 1 in this case, so that in any empirical exercise one expects at least some downward bias. Moreover, (absolute and relative) biases and standard errors decreases with a decrease in correlation (an increase in α).

Lastly, we consider the small sample performance for the bivariate normal distribution (see table A.3).

[Insert table A.3 about here]

For the normal distribution the estimators appear to behave quite reasonably. Absolute and relative biases are found to be smaller than in the Pareto case. Moreover, it may be difficult to distinguish the normal distribution from the Pareto distribution just on the basis of, say, the dependence parameter estimate. To this end it would be helpful to investigate the tail properties of the marginals as well.

A.2. **Small sample properties of the endogenous break test.** In this part of the appendix we investigate the small sample properties of the recursive test for a single endogenous break in η. This is done through a simulation study in which we use the bivariate normal as the data-generating process (see table A.4).

[Insert table A.4 about here]

Recall that in this case $\eta = (1+\rho)/2$. By changing the correlation coefficient, we can easily change the dependence parameter η.

The breaks are engineered at five different points in the sample (see r-columns in the table). Three different combinations of pre and post-break ηs are considered (see rows of the table). The sample size is 3,000. The table shows that the test has more difficulty in accurately locating the break if it is close to the start or the end of the sample. The reason is that in these cases one has fewer observations available for one of the two sub-samples. When the change in the dependence

[37] It can be easily shown that the analytic expressions for Morgenstern bias and AMSE do not depend on the marginal distributional properties like scale and tail indices.

parameter is small, then the standard errors tend to be more sizable. For example, the standard errors in the first and third scenario are about twice as large as in the second scenario. In sum, the cases in which we have to be more cautious in interpreting the test results are when the changes in η are small and when they occur close to the boundaries of the sample.

Table A.1. Small sample behavior of tail betas for bivariate Morgenstern distribution

		$\widehat{\eta}$			$\widehat{\tau}_{\beta}$ ($\times 100$)			τ_{β} ($\times 100$)
					$p = 0.05\%$			
$(\alpha;\delta)$	m^*	aver.	bias	s.e.	aver.	bias	s.e.	
				panel A: n=500				
(2; 0)	499	0.499	-0.001	0.013	0.052	0.002	0.021	0.05
(3; 0)	499	0.499	-0.001	0.013	0.052	0.002	0.021	0.05
(4; 0)	499	0.499	-0.001	0.013	0.052	0.002	0.021	0.05
(2; 0.5)	150	0.546	0.046	0.034	0.231	0.156	0.190	0.075
(3; 0.5)	150	0.545	0.045	0.034	0.226	0.151	0.189	0.075
(4; 0.5)	150	0.546	0.046	0.034	0.232	0.157	0.198	0.075
(2; 0.9)	134	0.570	0.070	0.036	0.424	0.329	0.338	0.095
(3; 0.9)	134	0.570	0.070	0.037	0.427	0.332	0.349	0.095
(4; 0.9)	134	0.570	0.070	0.037	0.419	0.324	0.327	0.095
				Panel B: n=3,106				
(2; 0)	3,105	0.500	0	0.005	0.050	0	0.008	0.05
(3; 0)	3,105	0.500	0	0.005	0.050	0	0.008	0.05
(4; 0)	3,105	0.500	0	0.005	0.050	0	0.008	0.05
(2; 0.5)	376	0.532	0.032	0.023	0.152	0.077	0.083	0.075
(3; 0.5)	376	0.532	0.032	0.023	0.151	0.076	0.083	0.075
(4; 0.5)	376	0.532	0.032	0.023	0.148	0.073	0.080	0.075
(2; 0.9)	335	0.543	0.043	0.025	0.225	0.130	0.121	0.095
(3; 0.9)	335	0.543	0.043	0.025	0.224	0.129	0.120	0.095
(4; 0.9)	335	0.543	0.043	0.025	0.225	0.130	0.120	0.095

Note: The table reports estimated values and true (analytic) values of the tail dependence parameter η and the tail-β (τ_{β}) for different sample sizes and different parameter configurations (α, δ). Tail-βs and corresponding biases, accuracy are expressed in percentage terms (%). Moreover, the linkage estimates are conditioned on the cutoff point m^* that minimizes the Asymptotic Mean Squared Error of $\widehat{\eta}$. The conditioning quantiles for the tail-β are chosen such that the corresponding marginal excess probabilities are equal to 0.05%.

TABLE A.2. Small sample behavior of tail betas for bivariate Pareto distribution

α	m^*	$\widehat{\eta}$			$\widehat{\tau}_{\beta}(p)$ $(\times 100)$			$\tau_{\beta}(p)$ $(\times 100)$	η
							$p = 0.05\%$		
		aver.	bias	s.e.	aver.	bias	s.e.		
					Panel A: n=500				
2	31	0.831	-0.169	0.113	15.44	-10.12	13.15	25.57	1
3	26	0.763	-0.237	0.126	8.33	-5.79	9.49	14.11	1
4	22	0.719	-0.280	0.134	5.49	-3.04	7.40	8.53	1
indep.	499	0.498	0	0.013	0.05	0	0.02	0.05	1/2
					Panel B: n=3,106				
2	89	0.889	-0.111	0.073	19.19	-6.38	8.73	25.57	1
3	45	0.832	-0.168	0.106	10.61	-3.50	7.51	14.11	1
4	42	0.777	-0.222	0.110	6.28	-2.25	5.37	8.53	1
indep.	3,105	0.500	0	0.005	0.05	0	0	0.05	1/2

Note: The table reports estimated values and true (analytic) values of the tail dependence parameter η and the tail-β (τ_{β}) for different sample sizes and different values of α. Tail-βs and corresponding biases, accuracy are expressed in percentage terms (%). Moreover, the linkage estimates are conditioned on the cutoff point m^* that minimizes the Asymptotic Mean Squared Error of $\widehat{\eta}$. The conditioning quantiles for the tail-β are chosen such that the corresponding marginal excess probabilities are equal to 0.05%.

TABLE A.3. Small sample behavior of tail betas for bivariate normal distribution

ρ	m^*	$\widehat{\eta}$			$\widehat{\tau}_{\beta}$ $(\times 100)$			τ_{β} $(\times 100)$	$\eta = \frac{1+\rho}{2}$
							$p = 0.05\%$		
		aver.	bias	s.e.	aver.	bias	s.e.		
					panel A: n=500				
3/4	138	0.795	-0.080	0.038	13.55	-4.59	5.11	18.14	0.875
1/2	154	0.684	-0.065	0.038	3.09	-1.12	1.69	4.21	0.75
1/4	233	0.583	-0.042	0.026	0.47	-0.19	0.27	0.67	0.625
0	499	0.499	-0.001	0.013	0.05	0	0.02	0.05	0.5
					Panel B: n=3,106				
3/4	299	0.815	-0.060	0.031	15.74	-2.40	4.10	18.14	0.875
1/2	403	0.699	-0.051	0.027	3.47	-0.74	1.20	4.21	0.75
1/4	574	0.594	-0.031	0.020	0.54	-0.12	0.20	0.67	0.625
0	3105	0.500	0	0.005	0.05	0	0	0.05	0.5

Note: The table reports estimated values and true (analytic) values of the tail dependence parameter η and the tail-β (τ_{β}) for different sample sizes and different correlations ρ. Tail-βs and corresponding biases, accuracy are expressed in percentage terms (%). Moreover, the linkage estimates are conditioned on the cutoff point m^* that minimizes the Asymptotic Mean Squared Error of $\widehat{\eta}$. The conditioning quantiles for the tail-β are chosen such that the corresponding marginal excess probabilities are equal to 0.05%.

TABLE A.4. Simulated breakpoints

	Estimated breakpoints (standard error)		
$(\eta_1; \eta_2)$	r=1/3	r=1/2	r=2/3
$(0.5; 0.7)$	0.364	0.514	0.617
	(0.190)	(0.166)	(0.117)
$(0.5; 0.9)$	0.264	0.485	0.636
	(0.095)	(0.078)	(0.092)
$(0.7; 0.9)$	0.394	0.508	0.587
	(0.209)	(0.172)	(0.194)

Note: Estimated breakpoints are reported for the tail dependence parameter of the bivariate normal df. The break estimates are reported for varying locations of the true breakpoints (r=1/3,1/2,2/3). The number of Monte Carlo replications is set to 1,000. The accompanying sampling errors are reported between brackets. Q-tests are calculated starting with a minimum sample size of 500. For sake of convenience, we set the number of upper order extremes used in estimating the tail index equal to $2n^{2/3}$

Appendix B List of banks in the sample

Table B.1: List of banks in the sample

Euro area		United States	
Bank name	**Abbreviation**	***Bank name***	**Abbreviation**
Germany		Citigroup	CITIG
Deutsche Bank	DEUTSCHE	JP Morgan Chase	JP MORGAN
Bayerische Hypo- und Vereinsbank	HYPO	Bank of America BOA	BAMERICA
Dresdner Bank	DRESDNER	Wachovia Corporation	WACHOVIA
Commerzbank	COMMERZ	Wells Fargo and Company	FARGO
Bankgesellschaft Berlin	BGBERLIN	Bank One Corporation	BONE
DePfa Group	DEPFA	Washington Mutual Inc	WASHING
France		Fleet Boston Financial Corporation	FLEET
BNP Paribas	BNPPAR	Bank of New York	BNYORK
Crédit Agricole	CA	State Street	SSTREET
Societe Generale	SGENER	Northern Trust	NTRUST
Natexis Banques Populaires	NATEXIS	Mellon	MELLON
Italy		US Bancorp	BCORP
Banca Intesa	INTESA	National City Corporation	CITYCO
UniCredito Italiano	UNICREDIT	PNC Financial Services Group	PNC
Sanpaolo IMI	PAOLO	Keycorp	KEYCO
Capitalia	CAPITA	Sun Trust	SUTRUST
Spain		Comerica Incorporated	COMERICA
Banco Santander Central Hispano	SANTANDER	Unionbancal Corporation	UNIONBANK
Banco Bilbao Vizcaya Argentaria	BILBAO	AmSouth Bancorp	AMSOUTH
Banco Espagnol de Credito	BANESP	Huntington Bancshares Inc	HUNTING
Netherlands		BBT Corporation	BBT
ABN AMRO	ABNAMRO	Fifth Third Bancorp	53BANCO
ING Bank	ING	Southtrust	SOTRUST
Belgium		Regions Financial Corporation	REGIONS
Fortis	FORTIS		
Almanij	ALMANIJ		
Finland			
Sampo Leonia	SAMPO		
Greece			
Alpha Bank	ALPHA		
Ireland			
Allied Irish Banks	IRBAN		
Portugal			
Banco Commercial Portugues	BCP		

Appendix C: Balance sheet data

Table C.1: Total assets of euro area banks (million US$)

Bank Name	2003	2002	2001	2000	1999	1998	1997	1996	1995	1994	1993	1992	Average	Average 1998-2003	Average 1992-1997
DEUTSCHE	934,434	730,301	641,826	647,186	569,127	555,446	419,892	386,645	461,180	352,740	308,790	297,200	525,397	679,720	371,075
BNPPAR	988,881	744,867	727,318	644,886	700,675	378,990	339,817	355,299	325,880	271,640	250,440	275,310	500,334	697,603	303,064
CA	1,105,378	609,055	496,421	498,433	441,524	455,781	419,971	477,591	387,130	328,130	282,870	292,090	482,864	601,099	364,630
ABNAMRO	707,801	583,073	526,450	505,419	460,000	504,122	414,655	343,699	340,640	290,800	252,990	246,980	431,386	547,811	314,961
HYPO	597,584	552,068	631,216	646,016	485,099	521,336	453,909	n.a.	203,960	173,600	151,150	134,300	413,658	572,220	223,384
SGENER	681,216	525,789	451,660	424,198	437,558	447,486	410,655	339,586	326,670	277,550	259,790	251,320	402,790	494,651	310,929
DRESDNER	602,461	433,489	446,238	449,036	397,944	424,620	372,779	n.a.	330,340	252,180	215,190	199,820	374,918	458,965	274,062
COMMERZ	481,653	442,333	441,510	422,867	371,134	374,896	294,671	n.a.	275,700	217,640	162,120	142,130	329,696	422,399	218,452
ING	684,004	500,326	390,725	378,149	351,234	326,813	190,269	179,933	154,050	125,330	105,880	109,540	291,354	438,542	144,167
INTESA	327,353	290,917	275,967	308,334	309,719	330,138	158,597	163,712	n.a.	n.a.	n.a.	n.a.	270,592	307,071	161,154
FORTIS	536,857	396,107	327,451	309,011	330,835	333,608	n.a.	n.a.	19,650	16,690	14,220	14,520	229,895	372,312	16,270
BILBAO	356,921	288,311	269,208	272,225	236,802	235,799	214,978	213,680	115,820	98,820	81,420	87,640	205,969	276,544	135,393
UNICREDIT	300,652	226,638	188,380	188,565	169,705	175,346	161,206	n.a.	n.a.	n.a.	n.a.	n.a.	201,499	208,214	161,206
BGBERLIN	191,936	182,046	165,227	189,389	192,212	217,785	195,372	206,377	34,060	20,650	n.a.	n.a.	159,505	189,766	114,115
SANTANDER	250,904	188,024	159,505	160,325	n.a.	n.a.	n.a.	n.a.	135,060	113,920	73,120	61,310	142,771	189,689	95,853
CAPITA	159,915	146,148	115,815	123,504	134,397	142,745	114,969	140,831	n.a.	n.a.	n.a.	n.a.	134,790	137,087	127,900
ALMANIJ	327,898	265,080	228,521	202,453	187,390	198,213	187,745	740	3,300	2,810	2,370	1,310	133,986	234,926	33,046
DEPFA	219,708	152,944	159,425	n.a.	n.a.	n.a.	n.a.	n.a.	103,580	76,800	62,850	56,150	118,779	177,359	74,845
NATEXIS	171,646	139,891	97,254	105,268	94,861	49,558	49,972	110,159	n.a.	n.a.	n.a.	n.a.	102,326	109,746	80,066
IRBAN	98,699	87,717	76,551	72,516	65,548	61,439	52,815	43,105	37,810	32,200	29,430	29,940	57,314	77,078	37,550
BANESP	72,923	51,919	39,384	41,296	39,958	42,800	36,606	42,715	41,760	43,120	53,210	61,750	47,287	48,047	46,527
BCP	85,483	64,861	55,479	57,552	35,211	33,955	29,662	n.a.	36,170	13,960	10,900	10,370	39,418	55,423	20,212
SAMPO	21,454	18,255	15,126	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	18,278	18,278	n.a.
ALPHA	38,902	30,123	26,052	28,420	25,445	16,372	12,409	11,680	9,250	7,130	5,610	5,020	18,034	27,552	8,517
PAOLO	8,807	7,073	5,586	6,133	5,375	6,056	5,163	4,791	4,643	4,100	3,729	4,608	5,505	6,505	4,506
Sum	9,953,470	7,657,353	6,958,293	6,681,182	6,041,753	5,833,304	4,536,112	3,020,543	3,346,653	2,719,810	2,326,079	2,281,308	5,638,347	7,348,608	3,641,882

Notes: BNP PARIBAS until 1995 BNP. Banks are ordered in declining size of average assets over the sample period. n.a. means data not available.

Data source: Bankscope and own calculations.

Appendix C: Balance sheet data

Table C.2: Total assets of US banks (million US$)

Bank Name	2003	2002	2001	2000	1999	1998	1997	1996	1995	1994	1993	1992	Average	Average 1998-2003	Average 1992-1997
CITIG	1,264,032	1,097,190	1,051,450	902,210	716,937	668,641	n.a.	n.a.	220,110	210,487	175,712	163,846	647,062	950,077	192,539
JP MORGAN	770,912	758,800	693,575	715,348	406,105	365,875	365,521	336,099	184,879	154,917	133,888	102,941	415,738	618,436	213,041
BAMERICA	736,445	660,458	621,764	642,191	632,574	617,679	264,562	185,794	163,398	147,670	136,693	133,449	411,890	651,852	171,928
BONE	326,563	277,383	268,954	269,300	269,425	261,496	115,901	101,848	n.a.	n.a.	n.a.	n.a.	236,359	278,854	108,875
FARGO	387,798	349,259	307,569	272,426	218,102	202,475	88,540	80,175	50,316	53,374	52,513	52,537	176,257	289,605	62,909
WACHOVIA	401,032	341,839	330,452	74,032	67,353	64,123	65,397	46,886	44,964	39,171	36,514	33,356	128,760	213,138	44,382
FLEET	200,356	190,589	203,638	179,519	190,692	104,554	85,690	85,555	11,037	9,757	8,246	8,288	106,493	178,225	34,762
BCORP	189,286	180,027	171,390	87,336	81,530	76,438	71,295	36,489	31,865	21,784	21,458	20,773	82,473	131,001	33,944
CITYCO	113,934	118,258	105,817	88,535	87,122	88,246	54,684	50,856	36,199	32,114	31,068	28,964	69,649	100,318	38,981
KEYCO	84,147	84,710	80,400	87,165	83,344	79,966	73,625	67,688	66,339	66,798	32,648	25,457	69,357	83,289	55,426
PNC	68,193	66,410	69,570	69,916	75,428	77,232	75,101	73,174	73,507	64,221	61,945	51,523	68,852	71,125	66,578
BNYORK	89,258	74,948	78,019	74,266	71,795	60,078	56,154	52,121	42,712	39,287	36,088	36,644	59,281	74,727	43,834
SSTREET	80,435	79,621	65,410	64,644	56,226	43,185	37,450	31,390	25,785	21,744	18,720	16,490	45,092	64,920	25,263
SOTRUST	51,885	50,570	48,850	45,170	43,203	38,054	30,715	13,339	n.a.	n.a.	n.a.	n.a.	40,223	46,288	22,027
BBT	90,467	80,217	70,870	59,340	43,481	34,427	29,178	21,247	15,992	9,179	7,794	6,256	39,037	63,134	14,941
53BANCO	91,143	80,899	71,026	45,857	41,590	28,922	21,375	20,549	17,057	14,973	11,981	10,232	37,967	59,906	16,028
MELLON	20,839	26,841	27,813	41,974	39,619	42,235	38,802	37,339	40,734	38,716	36,050	31,541	35,209	33,220	37,197
COMERICA	52,684	39,643	37,256	33,697	31,243	29,375	28,936	27,052	28,394	27,044	24,935	22,364	31,885	37,317	26,454
REGIONS	48,881	47,939	45,383	43,688	42,714	36,832	23,034	18,930	13,709	12,839	10,476	7,881	29,359	44,240	14,478
UNIONBANK	42,488	40,193	36,078	35,170	33,685	32,301	30,612	29,304	19,518	16,761	16,391	16,844	29,112	36,652	21,572
AMSOUTH	45,670	40,598	38,622	38,968	43,427	19,919	18,657	18,440	17,740	16,845	12,584	9,790	26,772	37,867	15,676
WASHING	29,327	26,723	31,639	34,715	35,036	32,466	26,070	21,241	21,633	18,458	15,827	n.a.	26,649	31,651	20,646
HUNTING	30,566	27,702	28,497	28,599	29,037	28,296	26,731	20,852	20,255	17,771	17,619	16,247	24,347	28,783	19,912
NTRUST	33,403	31,974	32,758	29,709	23,500	23,304	21,185	18,127	15,231	14,736	13,538	11,907	22,448	29,108	15,787
SUTRUST	n.a.	4,638	3,991	3,459	3,504	3,478	2,292	n.a.	46,472	42,534	40,728	36,647	18,774	3,814	33,735
Sum	5,249,743	4,777,430	4,520,789	3,967,235	3,366,670	3,059,596	1,651,505	1,394,493	1,207,844	1,091,179	953,416	843,975	2,879,044	4,157,546	1,350,913

Notes: Comerica until 1995 Comerica Detroit. Banks are ordered in declining size of average assets over the sample period. n.a. means data not available.

Data source: Bankscope and own calculations.

Appendix C: Balance sheet data

Table C.3: Due from banks for euro area banks (million US$)

Bank Name	2003	2002	2001	2000	1999	1998	1997	1996	1995	1994	1993	1992	Average	Average 1998-2003	Average 1992-1997
BNPPAR	205,797	153,641	164,469	121,536	160,510	83,169	82,147	103,735	96,870	77,920	72,780	87,370	117,495	148,187	86,804
DEUTSCHE	180,570	147,226	136,059	135,624	134,235	124,204	100,119	99,183	77,060	63,300	54,860	56,490	109,078	142,986	75,169
CA	119,534	70,083	56,052	61,259	62,275	79,898	78,699	112,656	98,490	78,040	68,290	63,250	79,044	74,850	83,237
DRESDNER	154,862	92,666	68,276	83,419	56,934	77,022	68,836	n.a.	55,910	40,830	29,470	32,300	69,139	88,863	45,469
SGENER	76,133	56,999	56,004	50,409	55,263	77,499	89,485	66,669	72,850	66,720	61,240	62,910	66,015	62,051	69,979
ABNAMRO	74,261	43,964	43,729	45,205	47,419	71,047	69,495	68,983	81,860	73,220	65,820	65,080	62,507	54,271	70,743
COMMERZ	65,191	56,900	55,770	69,266	50,026	67,994	49,210	n.a.	59,180	44,880	32,660	23,250	52,212	60,858	41,836
HYPO	66,489	60,068	78,634	84,804	56,089	67,207	68,637	0	25,000	17,000	18,050	12,910	50,444	68,882	28,319
FORTIS	105,699	87,860	57,640	60,307	82,766	68,522	n.a.	n.a.	2,150	2,620	2,530	2,570	47,266	77,132	2,468
INTESA	36,657	31,916	35,400	44,249	44,398	64,423	33,975	34,586	n.a.	n.a.	n.a.	n.a.	40,701	42,841	34,281
ALMANIJ	47,735	39,979	34,662	28,575	27,128	43,366	53,842	n.a.	n.a.	n.a.	n.a.	n.a.	39,327	36,907	53,842
ING	77,115	47,905	47,662	41,087	42,126	59,516	26,071	21,783	22,000	16,850	13,840	16,320	36,023	52,568	19,477
BGBERLIN	35,502	32,286	29,606	35,579	36,738	45,972	43,037	43,984	14,340	6,710	n.a.	n.a.	32,375	35,947	27,018
UNICREDIT	41,404	30,915	23,319	23,173	20,100	27,181	35,089	n.a.	n.a.	n.a.	n.a.	n.a.	28,740	27,682	35,089
BILBAO	12,129	12,371	8,691	19,582	22,621	31,674	41,493	43,787	35,430	31,930	27,030	24,580	25,943	17,845	34,042
SANTANDER	35,994	35,630	29,007	25,513	n.a.	n.a.	n.a.	n.a.	28,570	20,990	17,390	12,470	25,695	31,536	19,855
NATEXIS	54,015	38,767	14,694	14,853	23,422	7,821	8,874	20,808	n.a.	n.a.	n.a.	n.a.	22,907	25,595	14,841
CAPITA	21,622	21,410	17,360	15,500	18,592	23,072	23,793	26,081	n.a.	n.a.	n.a.	n.a.	20,929	19,593	24,937
DEPFA	23,323	14,117	12,373	n.a.	n.a.	n.a.	n.a.	n.a.	4,170	4,320	3,540	4,620	9,495	16,604	4,163
BANESP	5,461	2,521	1,804	4,663	4,965	7,802	6,486	8,069	10,470	8,410	7,920	6,940	6,293	4,536	8,049
IRBAN	4,069	5,198	5,828	4,312	4,122	6,186	6,270	4,645	3,950	4,070	3,740	2,980	4,614	4,953	4,276
BCP	4,724	3,515	4,104	5,531	2,376	3,568	5,951	n.a.	7,720	4,140	2,690	1,500	4,165	3,970	4,400
ALPHA	2,130	1,728	2,563	5,399	4,239	3,338	1,592	2,449	1,540	1,340	290	390	2,250	3,233	1,267
SAMPO	1,284	2,707	1,790	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	1,927	1,927	n.a.
PAOLO	2,323	1,681	1,262	1,528	863	1,690	1,391	1,233	1,356	1,226	1,298	1,577	1,453	1,558	1,347
Sum	1,454,021	1,092,053	986,757	981,372	957,208	1,042,172	894,490	658,649	698,916	564,516	483,438	477,507	956,035	1,105,375	790,906

Notes: BNP PARIBAS until 1995 BNP. Banks are ordered in declining size of average amounts due from banks over the sample period. n.a. means data not available.

Data source: Bankscope and own calculations.

Appendix C: Balance sheet data

Table C.4: Due from banks for US banks (million US$)

Bank Name	2003	2002	2001	2000	1999	1998	1997	1996	1995	1994	1993	1992	Average	Average 1998-2003	Average 1992-1997
SSTREET	21,628	28,133	20,306	21,289	16,902	12,008	10,076	7,562	5,975	4,847	5,148	4,803	13,223	20,044	6,402
CITIG	19,777	16,382	19,216	17,274	13,429	13,425	n.a.	n.a.	9,256	7,201	7,137	6,249	12,935	16,584	7,461
JP MORGAN	10,175	8,942	12,743	8,333	28,076	7,212	2,886	8,344	1,986	1,362	1,221	1,516	7,733	12,580	2,886
BAMERICA	8,051	6,813	5,932	5,448	4,838	6,750	2,395	1,843	5,899	6,771	2,956	2,779	5,040	6,305	3,774
NTRUST	8,766	8,267	6,954	5,191	2,291	3,264	2,282	2,060	1,567	1,865	2,090	1,860	3,871	5,789	1,954
BONE	3,093	1,503	1,030	5,210	6,645	4,642	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	3,687	3,687	n.a.
BNYORK	7,154	4,418	5,924	4,949	6,208	4,134	1,343	809	644	854	652	672	3,147	5,464	829
WACHOVIA	2,308	3,512	6,875	3,239	1,073	2,916	710	316	451	7	13	190	1,801	3,321	281
MELLON	2,770	1,768	4,089	2,349	657	991	925	790	553	433	889	992	1,434	2,104	764
FLEET	2,695	3,679	3,744	2,826	1,772	444	76	858	0	1,000	0	0	1,425	2,527	322
UNIONBANK	235	279	64	74	183	210	629	1,131	505	1,030	1,200	1,201	562	174	949
PNC	493	518	413	380	207	174	570	145	139	149	233	695	343	364	322
CITYCO	592	615	120	49	129	141	49	282	51	97	543	1,234	325	274	376
SUTRUST	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	29	56	476	695	314	n.a.	314
FARGO	988	352	206	95	421	113	47	1,238	10	7	0	0	290	363	217
BCORP	n.a.	434	625	200	897	76	238	50	11	7	33	46	238	446	64
COMERICA	23	14	43	24	13	8	1	26	1	377	897	1,231	221	21	422
KEYCO	186	112	83	34	35	20	531	217	45	381	14	141	150	78	221
REGIONS	n.a.	304	667	3	10	144	30	33	47	0	11	0	114	226	20
BBT	271	148	115	39	71	5	27	1	1	4	7	n.a.	63	108	8
53BANCO	58	198	152	109	82	51	27	31	1	11	1	1	60	108	12
HUNTING	34	37	21	5	7	103	40	2	284	3	13	134	57	34	79
WASHING	17	16	28	18	15	15	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	18	18	n.a.
AMSOUTH	7	28	12	61	24	29	0	0	1	1	1	0	14	27	0
SOTRUST	5	4	6	1	0	1	0	0	n.a.	n.a.	n.a.	n.a.	2	3	0
Sum	89,325	86,476	89,369	77,200	83,984	56,875	22,881	25,736	27,458	26,460	23,534	24,437	57,064	80,650	27,677

Notes: Comerica until 1995 Comerica Detroit. Banks are ordered in declining size of average amounts due from banks over the sample period. n.a. means data not available.

Data source: Bankscope and own calculations.

Appendix D: Return and spread data

Table D.1: Moments of euro area returns and correlations with aggregate risk factors

Bank	Mean	Standard Deviation	Skewness	Kurtosis	Correlation, Bank index	Correlation, Stock index	Correlation, Yield spread, 1998-2004	Correlation, Yield spread
DEUTSCHE	0.01	2.0	-0.1	4.0	76.8	69.2	-2.8	n.a.
HYPO	-0.01	2.4	0.1	6.1	65.7	57.1	-5.3	n.a.
DRESDNER	0.01	2.1	0.2	5.9	67.2	59.3	-2.8	n.a.
COMMERZ	0.00	2.0	0.2	6.9	68.2	62.3	-5.3	n.a.
BGBERLIN	-0.06	2.4	-1.4	32.8	20.4	17.6	-5.1	n.a.
DEPFA	0.05	1.9	0.2	6.2	31.2	30.3	-5.5	n.a.
BNPPAR	0.03	2.2	0.1	3.7	69.8	64.1	-1.3	n.a.
CA	0.02	1.4	-0.8	21.3	29.6	25.7	-2.6	n.a.
SGENER	0.04	2.2	0.1	3.9	72.7	66.1	-1.7	n.a.
NATEXIS	0.01	1.7	0.3	6.3	34.8	34.4	-2.7	n.a.
INTESA	0.02	2.5	0.3	2.9	55.5	48.8	-2.9	n.a.
UNICREDIT	0.04	2.3	0.9	8.5	57.5	52.2	-1.0	n.a.
PAOLO	0.00	2.3	0.2	2.1	65.5	59.5	-4.0	n.a.
CAPITA	-0.04	2.6	0.3	5.2	51.4	46.5	-5.0	n.a.
SANTANDER	0.04	2.1	-0.1	5.1	74.4	69.0	-1.8	n.a.
BILBAO	0.04	2.0	0.0	5.5	76.6	71.4	-1.3	n.a.
BANESP	-0.02	2.4	-14.5	543.2	23.3	19.9	-6.4	n.a.
ABNAMRO	0.04	2.0	-0.1	5.3	77.7	72.5	-1.3	n.a.
ING	0.04	2.2	-0.1	7.5	76.8	73.7	-3.1	n.a.
FORTIS	0.03	2.0	0.2	8.4	68.3	63.0	-1.3	n.a.
ALMANIJ	0.03	1.6	0.4	5.1	48.3	44.9	-1.9	n.a.
ALPHA	0.03	2.1	0.4	3.7	23.4	24.3	-6.1	n.a.
BCP	0.00	1.5	-0.2	12.2	39.4	37.6	-5.3	n.a.
SAMPO	0.07	2.8	0.3	7.7	26.5	27.6	-2.5	n.a.
IRBAN	0.05	1.7	-0.4	7.4	44.5	43.2	1.5	n.a.
POOLED Euro area	0.02	2.1	-0.7	41.2				
Bank index	0.02	0.5	-0.2	5.6				
Stock index	0.02	0.5	-0.3	3.5				
Yield spread, 1998-2004	8.05	3.2	0.6	-0.7				

Notes: Returns for individual bank stocks are daily excess returns, calculated as total return indices minus 1-month LIBORs. Returns for indices are calculated without substracting LIBOR. Means, standard deviations and correlation coefficients are in %. Return data series run from 2 April 1992 to 27 February 2004. n.a. means not
Data source: Datastream and own calculations.

Appendix D: Return and spread data

Table D.2: Moments of US returns and correlations with aggregate risk factors

Bank	Mean	Standard Deviation	Skewness	Kurtosis	Correlation, Bank index	Correlation, Stock index	Correlation, Yield spread, 1998-2004	Correlation, Yield spread
CITIG	0.08	2.2	0.1	4.3	80.0	68.8	-0.5	0.0
JP MORGAN	0.04	2.3	0.1	5.0	81.2	67.1	-1.5	-1.3
WACHOVIA	0.03	1.8	0.0	2.9	77.8	58.0	0.5	2.1
FARGO	0.05	1.7	0.1	2.2	74.1	54.3	0.0	1.5
BONE	0.02	1.9	-0.6	13.0	74.8	56.5	0.7	1.6
WASHING	0.06	2.1	0.3	3.8	53.0	40.3	0.8	1.6
FLEET	0.04	2.0	0.5	6.5	76.2	59.6	-0.7	-0.1
BNYORK	0.05	2.1	0.0	4.7	76.8	60.4	-2.6	-2.1
SSTREET	0.05	2.1	-0.2	6.7	67.8	57.5	-1.4	-1.3
NTRUST	0.05	2.0	0.6	6.5	68.5	58.4	-2.8	-2.7
MELLON	0.05	2.0	0.1	3.7	76.2	60.1	-1.6	-0.8
BCORP	0.07	1.9	0.5	16.4	61.8	45.7	-1.0	0.6
CITYCO	0.04	1.6	0.0	3.0	75.7	56.5	0.6	2.6
PNC	0.03	1.8	-0.2	5.0	77.3	59.3	-0.5	0.1
KEYCO	0.03	1.7	0.1	3.5	75.9	57.5	0.4	1.9
SUTRUST	0.04	1.6	0.0	3.5	79.6	61.4	-0.1	1.9
COMERICA	0.03	1.7	-0.7	12.0	74.0	57.3	-1.8	-0.5
UNIONBANK	0.06	2.1	-1.7	33.3	47.9	35.8	0.4	2.5
AMSOUTH	0.04	1.6	-0.6	14.5	65.0	48.1	1.0	3.4
HUNTING	0.03	1.9	0.1	9.6	60.4	47.3	0.9	3.0
BBT	0.05	1.6	0.5	5.9	68.4	53.0	0.0	1.9
53BANCO	0.05	1.7	0.3	2.6	66.5	53.3	-0.6	0.8
SOTRUST	0.05	1.7	0.0	4.0	64.2	48.6	1.2	3.8
REGIONS	0.03	1.7	0.0	3.2	66.2	51.1	1.2	4.3
BAMERICA	0.04	1.9	-0.2	2.8	82.8	59.1	0.7	2.0
POOLED US	0.04	1.9	-0.1	8.1				
Bank index	0.03	0.6	0.1	3.4				
Stock index	0.02	0.5	-0.1	4.1				
Yield spread, 1998-2004	6.18	1.9	0.4	-0.8				
Yield spread	5.41	1.7	1.0	0.1				

Notes: Returns for individual bank stocks are daily excess returns, calculated as total return indices minus 1-month LIBORs. Returns for indices are calculated without substracting LIBOR. Means, standard deviations and correlation coefficients are in %. Return data series run from 2 April 1992 to 27 February 2004. n.a. means not available. Data source: Datastream and own calculations.

Appendix D: Return and spread data

Table D.3: Correlations of euro area bank returns

	DEUTSCHE	HYPO	DRESDNER	COMMERZ	BGBERLIN	DEPFA	BNPPAR	CA	SGENER	NATEXIS	INTESA	UNICREDIT	PAOLO	CAPITA	SANTANDER	BILBAO	BANESP	ING	ABNAMRO	FORTIS	ALMANIJ	ALPHA	BCP	SAMPO	IRBAN
DEUTSCHE	100.0	60.8	67.6	64.8	16.8	24.7	48.6	19.5	52.6	24.2	33.6	35.9	43.1	31.9	48.0	49.1	12.6	55.9	56.2	47.7	33.8	17.1	27.9	17.4	27.1
HYPO	60.8	100.0	56.4	62.0	14.7	21.0	40.8	21.8	43.1	19.9	33.1	29.9	40.0	28.8	39.8	42.3	10.2	48.5	47.1	42.0	28.4	15.1	25.5	13.9	23.6
DRESDNER	67.6	56.4	100.0	61.3	13.6	21.5	42.9	19.1	43.6	22.0	31.9	28.1	37.3	25.2	42.4	43.8	13.6	50.0	49.6	43.9	31.0	15.0	25.7	17.3	23.5
COMMERZ	64.8	62.0	61.3	100.0	16.3	24.2	42.4	21.7	43.7	21.2	32.7	32.0	39.8	30.9	43.5	45.9	11.9	51.7	49.6	45.4	28.5	14.8	25.8	15.5	24.5
BGBERLIN	16.8	14.7	13.6	16.3	100.0	11.6	11.9	2.7	12.5	7.1	9.3	8.9	8.6	7.8	13.8	12.1	3.0	12.0	10.0	9.4	7.6	7.4	9.6	9.3	13.3
DEPFA	24.7	21.0	21.5	24.2	11.6	100.0	19.1	11.4	21.8	14.3	13.6	15.8	16.4	11.0	19.3	20.7	5.8	24.3	22.9	21.8	17.7	9.1	14.1	13.2	19.1
BNPPAR	48.6	40.8	42.9	42.4	11.9	19.1	100.0	25.0	66.1	31.1	34.8	37.4	42.8	33.9	49.8	51.0	16.7	54.2	52.8	46.3	29.9	14.2	25.4	19.0	30.3
CA	19.5	21.8	19.1	21.7	2.7	11.4	25.0	100.0	25.0	12.3	15.4	10.4	19.3	11.3	20.2	22.2	5.3	28.2	24.7	26.0	15.9	4.8	10.3	6.0	11.8
SGENER	52.6	43.1	43.6	43.7	12.5	21.8	66.1	25.0	100.0	29.9	34.1	38.9	44.1	32.9	51.3	52.5	15.4	57.2	55.3	48.8	32.7	17.3	24.9	19.6	33.8
NATEXIS	24.2	19.9	22.0	21.2	7.1	14.3	31.1	12.3	29.9	100.0	16.5	18.5	21.1	13.4	24.2	26.4	9.8	27.1	27.7	21.7	15.5	10.7	16.1	13.4	18.7
INTESA	33.6	33.1	31.9	32.7	9.3	13.6	34.8	15.4	34.1	16.5	100.0	46.5	49.3	48.1	36.3	38.1	11.1	39.6	37.9	36.8	23.7	11.9	20.5	15.3	22.1
UNICREDIT	35.9	29.9	28.1	32.0	8.9	15.8	37.4	10.4	38.9	18.5	46.5	100.0	50.5	48.3	35.7	39.5	12.3	40.1	40.6	34.6	23.6	9.0	18.4	13.6	21.9
PAOLO	43.1	40.0	37.3	39.8	8.6	16.4	42.8	19.3	44.1	21.1	49.3	50.5	100.0	47.6	46.1	47.9	12.2	48.6	48.5	41.3	27.4	12.3	24.4	17.3	26.0
CAPITA	31.9	28.8	25.2	30.9	7.8	11.0	33.9	11.3	32.9	13.4	48.1	48.3	47.6	100.0	34.3	36.6	9.5	34.6	33.3	30.7	19.6	5.6	16.2	13.9	20.8
SANTANDER	48.0	39.8	42.4	43.5	13.8	19.3	49.8	20.2	51.3	24.2	36.3	35.7	46.1	34.3	100.0	76.8	22.3	55.1	55.7	46.6	30.3	17.0	29.7	18.9	30.8
BILBAO	49.1	42.3	43.8	45.9	12.1	20.7	51.0	22.2	52.5	26.4	38.1	39.5	47.9	36.6	76.8	100.0	21.1	56.0	56.4	48.9	32.9	18.0	31.0	18.5	30.6
BANESP	12.6	10.2	13.6	11.9	3.0	5.8	16.7	5.3	15.4	9.8	11.1	12.3	12.2	9.5	22.3	21.1	100.0	12.5	13.0	11.0	6.4	5.1	10.8	5.8	9.0
ABNAMRO	56.2	47.1	49.6	49.6	10.0	22.9	52.8	24.7	55.3	27.7	37.9	40.6	48.5	33.3	55.7	56.4	13.0	73.7	100.0	59.1	40.0	18.1	28.5	19.1	33.6
ING	55.9	48.5	50.0	51.7	12.0	24.3	54.2	28.2	57.2	27.1	39.6	40.1	48.6	34.6	55.1	56.0	12.5	100.0	73.7	65.1	42.3	18.7	29.9	21.7	35.7
FORTIS	47.7	42.0	43.9	45.4	9.4	21.8	46.3	26.0	48.8	21.7	36.8	34.6	41.3	30.7	46.6	48.9	11.0	65.1	59.1	100.0	45.0	17.3	24.3	19.1	30.0
ALMANIJ	33.8	28.4	31.0	28.5	7.6	17.7	29.9	15.9	32.7	15.5	23.7	23.6	27.4	19.6	30.3	32.9	6.4	42.3	40.0	45.0	100.0	12.5	20.4	15.9	23.7
ALPHA	17.1	15.1	15.0	14.8	7.4	9.1	14.2	4.8	17.3	10.7	11.9	9.0	12.3	5.6	17.0	18.0	5.1	18.7	18.1	17.3	12.5	100.0	14.4	13.1	13.9
BCP	27.9	25.5	25.7	25.8	9.6	14.1	25.4	10.3	24.9	16.1	20.5	18.4	24.4	16.2	29.7	31.0	10.8	29.9	28.5	24.3	20.4	14.4	100.0	13.1	19.2
SAMPO	17.4	13.9	17.3	15.5	9.3	13.2	19.0	6.0	19.6	13.4	15.3	13.6	17.3	13.9	18.9	18.5	5.8	21.7	19.1	19.1	15.9	13.1	13.1	100.0	20.4
IRBAN	27.1	23.6	23.5	24.5	13.3	19.1	30.3	11.8	33.8	18.7	22.1	21.9	26.0	20.8	30.8	30.6	9.0	35.7	33.6	30.0	23.7	13.9	19.2	20.4	100.0

Notes: Correlation coefficients between individual banks are in %. Return data series run from 2 April 1992 to 27 February 2004. n.a. means not available.
Data source: Datastream and own calculations.

Appendix D: Return and spread data

Table D.4: Correlations of US bank returns

	CITIG	JP MORGAN	WACHOVIA	FARGO	BONE	WASHING	FLEET	BNYORK	SSTREET	NTRUST	MELLON	BCORP	CITYCO	PNC	KEYCO	SUTRUST	COMERICA	UNIONBANK	AMSOUTH	HUNTING	BBT	53BANCO	SOTRUST	REGIONS	BAMERICA
CITIG	100.0	64.8	55.9	51.7	52.6	38.1	55.7	55.8	51.6	50.6	55.0	41.2	53.0	54.4	53.2	56.5	51.7	33.5	46.1	41.1	50.0	47.0	45.0	44.3	61.0
JP MORGAN	64.8	100.0	59.2	54.6	56.7	39.3	60.9	61.2	52.7	52.1	60.7	43.4	56.4	58.1	56.8	58.2	55.6	33.7	47.9	44.4	50.3	47.5	46.1	48.6	64.7
WACHOVIA	55.9	59.2	100.0	56.6	60.2	40.5	60.0	56.9	50.0	51.8	58.6	48.6	61.2	61.6	61.9	64.5	59.2	38.4	51.3	48.5	55.0	51.7	48.8	51.5	65.9
FARGO	51.7	54.6	56.6	100.0	53.0	41.5	55.2	57.4	50.7	48.8	56.7	46.2	58.4	59.6	58.3	63.0	55.7	33.6	48.7	42.9	52.5	51.1	49.0	49.6	60.4
BONE	52.6	56.7	60.2	53.0	100.0	40.7	55.2	55.5	50.2	49.1	55.6	45.0	58.2	59.4	57.5	61.4	54.8	35.2	47.4	44.5	50.0	48.5	45.8	49.2	59.7
WASHING	38.1	39.3	40.5	41.5	40.7	100.0	39.3	40.7	39.1	40.6	41.6	35.1	43.9	44.2	45.1	43.9	42.4	27.4	37.5	34.1	41.9	41.7	41.5	40.3	41.2
FLEET	55.7	60.9	60.0	55.2	55.2	39.3	100.0	59.6	51.4	52.8	60.5	48.9	60.6	60.4	59.0	62.6	59.6	36.8	52.2	46.7	53.8	51.0	49.0	52.3	59.3
BNYORK	55.8	61.2	56.9	57.4	55.5	40.7	59.6	100.0	58.0	59.1	63.4	49.2	58.4	61.6	59.5	63.7	59.7	35.7	50.6	46.9	54.5	52.2	47.9	51.8	60.1
SSTREET	51.6	52.7	50.0	50.7	50.2	39.1	51.4	58.0	100.0	59.8	58.1	45.3	51.4	53.5	50.6	56.2	51.8	33.9	46.6	43.8	46.3	49.5	44.4	47.2	52.4
NTRUST	50.6	52.1	51.8	48.8	49.1	40.6	52.8	59.1	59.8	100.0	55.3	48.4	51.7	54.9	52.7	54.4	53.1	37.2	48.2	46.6	50.0	51.9	46.9	49.8	49.9
MELLON	55.0	60.7	58.6	56.7	55.6	41.6	60.5	63.4	58.1	55.3	100.0	48.6	59.1	62.9	60.5	63.5	57.7	37.0	51.5	45.1	53.8	50.1	50.7	52.9	60.5
BCORP	41.2	43.4	48.6	46.2	45.0	35.1	48.9	49.2	45.3	48.4	48.6	100.0	49.9	51.0	49.5	50.3	48.8	33.4	45.6	44.0	48.7	43.1	45.3	46.5	46.2
CITYCO	53.0	56.4	61.2	58.4	58.2	43.9	60.6	58.4	51.4	51.7	59.1	49.9	100.0	62.3	63.0	65.9	60.6	36.9	54.6	49.0	54.1	53.1	52.7	54.4	61.3
PNC	54.4	58.1	61.6	59.6	59.4	44.2	60.4	61.6	53.5	54.9	62.9	51.0	62.3	100.0	64.0	66.2	62.2	36.7	52.7	47.8	55.7	53.2	52.3	53.8	62.0
KEYCO	53.2	56.8	61.9	58.3	57.5	45.1	59.0	59.5	50.6	52.7	60.5	49.5	63.0	64.0	100.0	66.2	63.1	37.4	52.7	51.1	57.1	53.9	53.4	55.9	59.3
SUTRUST	56.5	58.2	64.5	63.0	61.4	43.9	62.6	63.7	56.2	54.4	63.5	50.3	65.9	66.2	66.2	100.0	64.1	40.0	55.6	48.9	56.9	55.5	53.7	57.2	64.7
COMERICA	51.7	55.6	59.2	55.7	54.8	42.4	59.6	59.7	51.8	53.1	57.7	48.8	60.6	62.2	63.1	64.1	100.0	37.7	53.7	50.0	55.9	54.1	51.4	55.6	58.6
UNIONBANK	33.5	33.7	38.4	33.6	35.2	27.4	36.8	35.7	33.9	37.2	37.0	33.4	36.9	36.7	37.4	40.0	37.7	100.0	37.2	31.8	35.6	31.7	36.6	35.2	38.4
AMSOUTH	46.1	47.9	51.3	48.7	47.4	37.5	52.2	50.6	46.6	48.2	51.5	45.6	54.6	52.7	52.7	55.6	53.7	37.2	100.0	46.1	51.1	45.5	48.9	52.0	50.3
HUNTING	41.1	44.4	48.5	42.9	44.5	34.1	46.7	46.9	43.8	46.6	45.1	44.0	49.0	47.8	51.1	48.9	50.0	31.8	46.1	100.0	49.2	46.7	48.0	47.8	46.2
BBT	50.0	50.3	55.0	52.5	50.0	41.9	53.8	54.5	46.3	50.0	53.8	48.7	54.1	55.7	57.1	56.9	55.9	35.6	51.1	49.2	100.0	52.5	51.7	52.0	52.5
53BANCO	47.0	47.5	51.7	51.1	48.5	41.7	51.0	52.2	49.5	51.9	50.1	43.1	53.1	53.2	53.9	55.5	54.1	31.7	45.5	46.7	52.5	100.0	49.4	49.5	48.8
SOTRUST	45.0	46.1	48.8	49.0	45.8	41.5	49.0	47.9	44.4	46.9	50.7	45.3	52.7	52.3	53.4	53.7	51.4	36.6	48.9	48.0	51.7	49.4	100.0	52.0	49.4
REGIONS	44.3	48.6	51.5	49.6	49.2	40.3	52.3	51.8	47.2	49.8	52.9	46.5	54.4	53.8	55.9	57.2	55.6	35.2	52.0	47.8	52.0	49.5	52.0	100.0	51.2
BAMERICA	61.0	64.7	65.9	60.4	59.7	41.2	59.3	60.1	52.4	49.9	60.5	46.2	61.3	62.0	59.3	64.7	58.6	38.4	50.3	46.2	52.5	48.8	49.4	51.2	100.0

Notes: Correlation coefficients between individual banks are in %. Return data series run from 2 April 1992 to 27 February 2004. n.a. means not available.
Data source: Datastream and own calculations.

Appendix E. Results for GARCH-filtered data

A widely recognized feature of financial market returns is volatility clustering (see, e.g., Bollerslev, Chou and Kroner, 1992). So, a question that comes to mind is to which extent the extreme dependence between bank stock returns and its changes we discover in this paper is associated with changes in volatility. In this appendix we therefore reproduce the results of the paper for return data that are filtered of conditional heteroskedasticity.

Before providing some answers to this question, we need to first establish the relationship between the filtered data and the objectives of our paper. The main objective of our work is to measure systemic risk in banking on the basis of market data. The amount of systemic risk in banking is instrumental for the assessment of financial stability and for the design of policies to preserve the stability of financial systems, such as banking regulation and crisis management.

The indicators of banking system stability we are using are designed to satisfy the demand by policy makers who need to have a view about the likelihood of crises and who need to devise the best financial regulations to preserve financial stability. To assess system stability banking supervisors need to know how likely it is that one or several banks break down given that other banks break down or how likely it is that one or several banks break down given that there is an adverse macroeconomic shock. They are not interested in two-sided volatility of bank stock returns per se or in its persistence. In addition, banking regulations are determined in advance for longer periods of time. They cannot be changed within a few days. So, they need to be based on long-term structural risk assessments and not on the likelihood of volatility tomorrow given today's volatility. This is why for the questions we are interested in straight returns are preferable to volatility of returns and unconditional modelling is preferable to conditional models. In contrast, conditional models will be preferable for short-term volatility forecasting, as today's volatility is informative for tomorrow's volatility. This type of analysis maybe more important for short-term pricing of financial instruments.

Although the indicators (2.1) and (2.2) are the right ones for answering the questions of interest in this paper, we may learn from unclustered return data more about the statistical components of spillover and extreme systematic risk in banking. For example, Poon et al. (2004) argue that conditional heteroskedasticity is an important source of extreme dependence in stock markets in general, but not the only one.

So, in this appendix we ask to which extent the extreme dependence of bank stock returns uncovered above results from univariate volatility clustering or multivariate dependence in volatilities. The next subsection reports the multivariate spillover probabilities (2.1) for unclustered return data and the subsequent one the tail-β estimations (2.2). The filter used in both cases is a standard GARCH(1,1) process.

E.1. **Bank contagion risk.** Tables E.1 through E.5 reproduce tables 3, 4, 5, 9 and 10 in the main text for GARCH-filtered returns. While extreme dependence generally tends to decrease, the qualitative results are quite similar to the ones for plain bank returns. Only very few of the spillover risk changes in Europe (table 9) seem to be entirely related to volatility clustering. But clustering plays more of a role in the differences between domestic and cross-border spillovers (table 4). Multivariate spillover risk in the US and Europe, as well as its changes over time seem little related to volatility clustering (tables 5 and 10). This is also confirmed by the dotted lines in figures 1 and 2, which describe the same stastics as the solid lines for GARCH-filtered returns.

E.2. **Aggregate banking system risk.** Tables E.6 through E.10 reproduce tables 6, 7, 8, 11 and 12 in the main text for unclustered returns. As for the spillover risk above, dependencies generally decrease, but none of the qualitative results is fundamentally changed. Again this is also confirmed by the dotted lines in figure 3, which illustrate the more muted changes in GARCH-filtered tail-βs and the same direction of their movements.

Overall, we can conclude that in line with the results of Poon et al. (2004) for stock markets in general, part of the extreme dependencies in bank stock returns we find in this paper are related to time-varying volatility and volatility clustering. From the little exercise in this appendix we can not ascertain whether this phenomenon is related to the marginal distributions or to multivariate dependence of volatilities. Nevertheless, the primary results that supervisors should pay attention to in order to assess general banking system stability and decide upon regulatory policies are the unadjusted spillover and systematic risk probabilities.

TABLE E.1. Domestic versus cross-border extreme spillover risk among euro area banks for GARCH-filtered data: Estimations

Largest bank	$\widehat{P}_1$	$\widehat{P}_2$	$\widehat{P}_3$	$\widehat{P}_4$	$\widehat{P}_5$
	Conditioning banks: German				
Germany	12.3	63.7	70.7	57.0	35.0
Netherlands	5.1	23.3	35.9	6.3	19.4
France	1.6	20.7	32.1	9.4	10.3
Spain	1.8	12.1	14.4	8.9	31.0
Italy	1.5	3.7	6.6	1.2	5.5
Belgium	3.1	18.0	18.7	6.5	4.2
Ireland	1.9	4.2	7.4	7.4	19.8
Portugal	1.4	6.7	11.2	5.6	8.3
Finland	0.6	2.5	5.4	1.0	3.3
Greece	0.7	0.9	2.5	0.2	0.8
	Conditioning banks: French				
France	1.4	30.2	6.6		
Germany	0.4	15.0	3.0		
Netherlands	1.6	14.8	7.7		
Italy	0.7	5.3	1.7		
Spain	1.3	23.4	5.2		
Belgium	0.9	12.0	4.3		
Ireland	0.8	3.2	3.0		
Portugal	1.0	4.9	10.1		
Finland	0.1	0.6	1.5		
Greece	0.2	0.7	0.3		
	Conditioning banks: Italian				
Italy	3.2	13.4	18.9		
Germany	2.4	8.8	7.6		
Netherlands	1.5	10.2	8.2		
Spain	1.1	9.1	3.7		
France	1.2	6.6	2.4		
Belgium	1.1	5.5	2.5		
Ireland	1.1	2.3	3.6		
Portugal	0.5	1.1	1.9		
Finland	0.4	1.4	1.5		
Greece	1.6E-0.2	0.3	0.6		
	Conditioning banks: Spanish				
Spain	21.6	13.5			
Germany	3.8	3.0			
Netherlands	6.4	6.8			
France	7.0	7.8			
Italy	0.8	1.9			
Belgium	3.6	1.5			
Ireland	2.7	1.9			
Portugal	1.4	0.6			
Finland	0.3	0.5			
Greece	0.5	0.4			

Note: The table shows the same results as table 3 in the main text for data that have been filtered for volatility clustering. The returns used here are the residuals of a GARCH(1,1) process fitted on the original excess returns. The table reports estimated extreme spillover probabilities between banks, as defined in (2.1). Each column $\widehat{P}_j$ shows the spillover probabilities for the largest bank of the country mentioned on the left-hand side conditional on a set of banks j from either the same country or other countries. The number of conditioning banks varies from 1 to 5 for Germany (top panel), 1 to 3 for France (upper middle panel), 1 to 3 for Italy (lower middle panel) and 1 to 2 for Spain (bottom panel). For example, the $\widehat{P}_2$ column contains probabilities for a stock market crash of the largest bank in each country, conditional on crashes of the 2nd and 3rd largest bank in Germany, France, Italy or Spain. All probabilities are estimated with the extension of the approach by Ledford and Tawn (1996) described in section 3 and reported in %. Univariate crash probabilities (crisis levels) are set to $p = 0.05\%$.

TABLE E.2. Domestic versus cross-border extreme spillover risk among euro area banks for GARCH-filtered data: Tests

Largest bank	T_1	T_2	T_3	T_4	T_5
	Conditioning banks: German				
Netherlands	1.49	1.56	0.84	0.81	0.11
France	***3.30	1.23	0.30	0.51	1.06
Spain	***2.93	**2.11	-0.18	-0.28	0.29
Italy	***2.82	***3.75	-0.35	-0.13	-0.50
Belgium	**2.07	1.55	0.46	-0.26	-0.76
Ireland	**2.47	***3.34	-1.54	1.20	0.91
Portugal	***3.06	***3.71	0.46	1.31	0.29
Finland	***4.21	***2.67	-1.55	-0.10	-0.83
Greece	***3.59	***4.12	***-3.15	-1.31	-0.61
	Conditioning banks: French				
Germany	**2.02	-0.49	0.85		
Netherlands	-0.25	1.25	1.37		
Spain	0.07	-0.84	0.22		
Italy	0.84	-1.53	-0.03		
Belgium	0.63	0.84	1.28		
Ireland	0.58	***-3.34	-1.39		
Portugal	0.36	-1.50	1.13		
Finland	***2.91	***-4.22	**-2.21		
Greece	**2.29	***-3.76	***-2.77		
	Conditioning banks: Italian				
Germany	0.26	0.28	-0.09		
Netherlands	1.18	1.06	0.21		
Spain	1.51	-0.59	-0.27		
France	1.32	0.28	-0.09		
Belgium	1.25	-0.52	-0.72		
Ireland	1.07	-0.75	-1.00		
Portugal	**2.01	-0.65	-1.42		
Finland	**2.54	-0.90	-1.47		
Greece	***3.36	-1.86	**-2.20		
	Conditioning banks: Spanish				
Germany	***2.88	-0.69			
Netherlands	**2.17	-0.30			
France	*1.82	-0.05			
Italy	***4.35	-0.57			
Belgium	***2.84	-0.62			
Ireland	***2.82	-0.91			
Portugal	***4.03	-0.77			
Finland	***5.55	-1.05			
Greece	***4.47	-1.29			

Note: The table shows the same results as table 4 in the main text for data that have been filtered for volatility clustering. The returns used here are the residuals of a GARCH(1,1) process fitted on the original excess returns. The table reports the statistics for the cross sectional test (4.5). Within each panel the degree of extreme domestic spillover risk is compared with the degree of extreme cross-border spillover risk for a given fixed number of conditioning banks. So, each T-statistic describes whether the differences between domestic and cross-border values of η that entered the estimations in table 3 are statistically significant. For example, in the top panel the test statistic in the row "Netherlands" and the column T_1 indicates whether the difference between the η for the spillover probability between ABN AMRO and HypoVereinsbank and the η between Deutsche Bank and HypoVereinsbank is statistically signifcant. The null hypothesis is that the respective two ηs are equal. Insignificant T-statistics imply that the domestic and cross-border spillover risks are indistinguishable. A significant rejection with positive sign implies that cross-border spillover risk is statistically smaller than its domestic counterpart; and a rejection with negative sign implies that cross-border risk is larger than domestic risk. The critical values of the test are 1.65, 1.96 and 2.58 for the 10%, 5% and 1% levels, respectively. Asterisks *, ** and *** indicate rejections of the null hypothesis at 10%, 5% and 1% significance.

Table E.3. Domestic and cross-border extreme spillover risk among euro area banks for GARCH-filtered data: Time variation

Largest bank	$\widehat{\eta}_1$	$\widehat{\eta}_2$	$\widehat{\eta}_3$	$\widehat{\eta}_4$	$\widehat{\eta}_5$
	Conditioning banks: German				
Germany	-	-	-	9/30/98 (2.8)	-
Netherlands	4/14/00 (6.1)	9/9/97 (3.8)	8/27/01 (5.6)	-	10/27/97 (2.6)
France	-	9/11/97 (8.9)	9/9/97 (7.8)	8/15/97 (6.0)	8/15/97 (3.9)
Spain	3/31/97 (2.8)	10/22/97 (6.8)	10/16/97 (6.2)	8/27/97 (2.4)	1/22/99 (6.5)
Italy	10/24/97 (16.9)	9/9/97 (8.6)	1/20/94 (8.6)	8/21/97 (6.6)	10/24/97 (5.6)
Belgium	8/4/98 (8.7)	2/28/01 (6.2)	1/19/94 (3.5)	-	10/22/97 (3.0)
Ireland	10/22/97 (5.0)	10/22/97 (2.2)	-	-	10/24/97 (2.2)
Portugal	2/4/94 (5.3)	2/4/94 (10.9)	1/25/94 (21.7)	8/28/97 (5.2)	10/22/97 (2.1)
Finland	10/22/97 (5.4)	6/6/94 (15.0)	6/6/94 (31.9)	10/16/97 (12.1)	7/23/97 (6.7)
Greece	5/29/97 (14.1)	5/29/97 (8.7)	5/29/97 (10.3)	8/15/97 (8.3)	-
	Conditioning banks: French				
France	10/10/00 (26.5)	1/25/02 (32.6)	6/7/95 (34.0)		
Germany	10/9/00 (22.4)	11/21/00 (29.3)	12/11/01 (33.8)		
Netherlands	10/9/00 (17.8)	9/20/00 (39.5)	10/22/97 (44.0)		
Italy	2/19/01 (10.2)	10/24/97 (44.3)	8/22/97 (50.8)		
Spain	10/10/00 (11.4)	9/19/00 (27.3)	10/22/97 (37.9)		
Belgium	2/21/01 (15.1)	2/3/94 (68.2)	8/4/98 (67.2)		
Ireland	9/20/00 (3.1)	2/1/94 (19.2)	12/7/01 (13.4)		
Portugal	10/12/00 (5.5)	10/10/00 (27.6)	6/19/97 (34.3)		
Finland	4/14/00 (3.9)	5/31/94 (49.2)	3/1/96 (43.2)		
Greece	8/4/98 (10.2)	7/23/98 (27.3)	12/7/01 (34.2)		
	Conditioning banks: Italian				
Italy	-	-	-		
Germany	7/31/97 (4.6)	10/8/97 (10.1)	9/9/97 (5.5)		
Netherlands	8/4/98 (3.4)	8/7/97 (17.7)	8/6/97 (11.8)		
Spain	8/5/98 (2.9)	4/22/98 (16.2)	10/8/97 (8.8)		
France	8/7/98 (3.5)	4/15/94 (4.6)	4/21/94 (9.1)		
Belgium	6/18/97 (17.4)	10/8/97 (25.2)	10/8/97 (15.1)		
Ireland	-	2/21/94 (6.1)	2/21/94 (7.6)		
Portugal	2/21/94 (7.4)	8/1/97 (11.9)	2/21/94 (12.4)		
Finland	-	6/13/94 (9.0)	6/17/94 (7.4)		
Greece	2/12/97 (10.3)	9/9/97 (16.9)	9/9/97 (22.7)		
	Conditioning banks: Spanish				
Spain	10/1/97 (7.2)	1/14/99 (3.4)			
Germany	2/24/97 (10.0)	3/31/99 (4.4)			
Netherlands	10/8/97 (4.9)	3/9/99 (6.5)			
France	10/22/97 (9.2)	1/14/99 (5.9)			
Italy	9/10/97 (3.4)	1/25/99 (6.3)			
Belgium	11/26/96 (10.5)	2/4/94 (3.0)			
Ireland	12/10/96 (6.3)	3/8/99 (5.1)			
Portugal	9/10/97 (15.5)	6/27/97 (6.0)			
Finland	10/16/97 (3.6)	3/3/99 (4.0)			
Greece	5/15/97 (16.7)	2/27/97 (9.5)			

Note: The table shows the same results as table 9 in the main text for data that have been filtered for volatility clustering. The returns used here are the residuals of a GARCH(1,1) process fitted on the original excess returns. The table reports the results of tests examining the structural stability of the extreme spillover risks documented in table E.1. This is done by testing for the constancy of the η tail dependence parameters (null hypothesis) that govern the spillover probabilities in table E.1. Applying the recursive test (4.1) through (4.4) by Quintos et al. (2001), each cell shows the endogenously found break date and the test value in parentheses. Dates are denoted XX/YY/ZZ, where XX=month, YY=day and ZZ=year. The critical values of the test are 1.46, 1.78 and 2.54 for the 10%, 5% and 1% levels, respectively. A test value exceeding these numbers implies an increase in extreme dependence over time. The absence of a break over the sample period is marked with a dash.

TABLE E.4. Multivariate extreme spillover risk among euro area and US banks for GARCH-filtered data

Country/Area		Estimations		Cross-sectional
		$\widehat{\eta}$	$\widehat{P}$	test T
United States	(N=25)	0.32	4.7E-6	$H_0 : \eta_{US} = \eta_{EA}$
Euro area	(N=25)	0.17	3.9E-15	$T = 5.58$
Germany	(N=6)	0.38	2.3E-4	
France	(N=4)	0.50	2.6E-2	
Italy	(N=4)	0.58	2.7E-0.3	

Note: The table shows the same results as table 5 in the main text for data that have been filtered for volatility clustering. The returns used here are the residuals of a GARCH(1,1) process fitted on the original excess returns. The table reports in the column $\widehat{\eta}$ the coefficient that governs the multivariate extreme tail dependence for all the banks of the countries/areas detailed on the left-hand side. In the column $\widehat{P}$ it shows the probabililty that all banks of a specific country/area crash given that one of them crashes. Both statistics are estimates of system-wide extreme spillover risks. Univariate crash probabilities (crisis levels) are set to $p = 0.05\%$. The right-hand column describes the cross-sectional test (4.5) for the whole US and euro area banking systems. A positive (negative) test statistic indicates that the US (euro area) η is larger than the euro area (US) η. The critical values of the test are 1.65, 1.96 and 2.58 for the 10%, 5% and 1% levels, respectively. Note that η values for countries/areas with different numbers of banks may not be comparable.

TABLE E.5. Multivariate extreme spillover risk among euro area and US banks for GARCH-filtered data: Time variation

Country/Area		Full sample break test	Second sub-sample break tests	
			Endogenous	Exogenous
United States	(N=25)	11/13/95 (4.8)	-	n.a.
Euro area	(N=25)	12/5/96 (4.9)	(B) 1/18/99 (5.3)	(1.5)
Germany	(N=6)	-	-	(1.6)
		-	-	
France	(N=4)	6/7/95 (19.1)	11/27/01 (23.7)	(-2.8)
		(B) 3/4/97 (4.6)	(B) 8/25/00 (3.8)	
Italy	(N=4)	-	-	(1.4)

Note: The table shows the same results as table 10 in the main text for data that have been filtered for volatility clustering. The returns used here are the residuals of a GARCH(1,1) process fitted on the original excess returns. The table reports tests and estimations assessing time variation in the multivariate spillover probabilities of table E.4. The column on the left displays estimated break dates and values from the recursive Quintos et al. (2001) test (4.1) through (4.4) applied to the η parameter governing the extreme tail dependence of the banks located in the countries/areas displayed on the extreme left. Dates are denoted XX/YY/ZZ, where XX=month, YY=day and ZZ=year. The forward recursive version of the test is used, unless marked otherwise. (B) marks the backward recursive version of the test. The critical values of the test are 1.46, 1.78 and 2.54 for the 10%, 5% and 1% levels, respectively. The middle columns show pre- and post-break estimates for η. The columns on the right display two tests that assess the occurrence of further breaks in the second half of the sample. The first one is the same as the one on the left-hand side. The second one is a simple differences-in-means test based on (4.5). The exogenous break point is chosen to be 1/1/99, the time of the introduction of the euro. Critical values for this test are 1.65, 1.96 and 2.58 for the 10%, 5% and 1% significance levels. Note that η values for countries/areas with different numbers of banks may not be comparable.

Table E.6. Extreme systematic risk (tail-βs) of euro area banks for GARCH-filtered data

Bank	Aggregate risk factor				
	Bank index	Stock index	Global bank	Global stock	Yield spread
DEUTSCHE	34.3	19.1	8.1	4.2	9.0E-6
HYPO	12.7	6.9	1.7	1.2	3.0E-2
DRESDNER	20.1	17.3	7.1	3.7	7.7E-3
COMMERZ	14.8	11.0	3.0	1.9	6.9E-2
BGBERLIN	2.0	1.4	0.6	0.4	7.3E-2
DEPFA	2.1	2.1	0.7	0.9	6.2E-2
BNPPAR	12.7	8.5	5.3	3.6	3.9E-2
CA	2.2	1.4	0.4	0.6	0.2
SGENERAL	19.3	11.8	5.8	4.2	4.8E-2
NATEXIS	0.8	1.0	1.5	0.7	3.5E-2
INTESA	4.6	3.5	1.7	1.9	1.7E-0.2
UNICREDIT	4.3	3.7	3.6	2.2	6.8E-2
PAOLO	10.7	10.8	4.3	2.9	6.0E-2
CAPITA	6.1	5.5	2.3	2.6	0.1
SANTANDER	9.8	10.9	4.5	3.4	7.0E-2
BILBAO	16.0	11.6	6.0	5.3	7.0E-2
BANESP	1.5	0.9	0.6	0.3	2.0E-3
ING	22.7	23.4	8.5	4.2	8.5E-2
ABNAMRO	14.3	12.3	6.7	3.6	4.5E-2
FORTIS	17.2	10.1	4.9	2.7	2.2E-2
ALMANIJ	2.7	3.1	1.8	1.0	8.5E-2
ALPHA	1.9	2.5	0.9	0.6	2.2E-2
BCP	4.0	3.2	2.3	1.3	0.1
SAMPO	1.6	1.9	0.6	0.5	3.8E-2
IRBAN	6.3	6.5	2.0	1.7	1.8E-2
average	9.8	7.6	3.4	2.2	6.5E-2
st. dev.	8.5	6.1	2.5	1.5	4.4E-2

Note: The table shows the same results as table 6 in the main text for data that have been filtered for volatility clustering. The returns used here are the residuals of a GARCH(1,1) process fitted on the original excess returns. The table exhibits the estimates of extreme systematic risk (2.2) (tail-βs) for individual euro area banks and for the euro area banking system as a whole. The entries show the probability that a given bank crashes given that a market indicator of aggregate risk crashes (or in the case of the yield spread booms). Results are reported for five different aggregate risk factors: The euro area banking sector sub-index, the euro area stock index, the world banking sector sub-index, the world stock index and the euro area high-yield bond spread. Data for the euro area yield spread are only available from 1998 to 2004. All probabilities are estimated with the extension of the approach by Ledford and Tawn (1996) described in section 3 and reported in %. Univariate crash probabilities (crisis levels) are set to $p = 0.05\%$. The average and the standard deviation at the bottom of the table are calculated over the 25 individual tail-βs in the upper rows, respectively.

TABLE E.7. Extreme systematic risk (tail-βs) of US banks for GARCH-filtered data

Bank	Aggregate risk factor				
	Bank index	Stock index	Global bank	Global stock	Yield spread
CITIG	32.6	24.8	6.3	11.7	6.9E-2
JPMORGAN	24.9	9.0	3.3	4.9	0.1
BOA	28.2	12.4	5.9	7.2	0.2
WACHO	25.2	10.5	4.1	5.2	0.2
FARGO	14.6	7.5	4.5	6.5	4.1E-2
BONEC	27.1	12.6	3.6	6.0	0.1
WASHMU	9.8	4.5	2.3	2.4	0.1
FLEET	15.2	13.9	5.4	6.4	0.2
BNYORK	17.5	9.5	4.9	7.1	0.1
STATEST	16.0	14.3	7.2	10.3	0.4
NOTRUST	14.6	9.9	4.2	5.6	0.2
MELLON	25.0	19.6	5.7	10.2	0.3
USBANC	10.9	3.8	3.5	2.4	6.4E-2
CITYCO	24.9	11.8	4.7	7.0	9.9E-2
PNC	14.6	10.4	5.3	6.9	0.1
KEYCO	23.6	11.0	2.3	4.9	8.8E-2
SUNTRUST	19.7	15.4	5.7	8.9	0.2
COMERICA	24.3	14.0	4.7	7.3	0.2
UNIONBAN	5.9	2.7	2.3	2.8	0.1
AMSOUTH	10.5	6.5	6.6	4.5	0.2
HUNTING	10.4	5.5	4.3	3.3	0.1
BBT	9.8	5.0	4.1	4.2	0.1
53BANCO	11.2	5.9	2.0	2.5	9.7E-2
SOTRUST	12.6	4.3	3.0	2.6	0.1
RFCORP	11.4	9.5	3.8	4.5	0.2
average	17.6	78.4	4.4	5.8	0.1
st. dev.	7.3	4.7	1.4	2.6	7.1E-2

Note: The table shows the same results as table 7 in the main text for data that have been filtered for volatility clustering. The returns used here are the residuals of a GARCH(1,1) process fitted on the original excess returns. The table exhibits the estimates of extreme systematic risk (2.2) (tail-βs) for individual US banks and for the US banking system as a whole. The entries show the probability that a given bank crashes given that a market indicator of aggregate risk crashes (or in the case of the yield spread booms). Results are reported for five different aggregate risk factors: The US banking sector sub-index, the US stock index, the world banking sector sub-index, the world stock index and the US high-yield bond spread. All probabilities are estimated with the extension of the approach by Ledford and Tawn (1996) described in section 3 and reported in %. Univariate crash probabilities (crisis levels) are set to $p = 0.05\%$. The average and the standard deviation at the bottom of the table are calculated over the 25 individual tail-βs in the upper rows, respectively.

TABLE E.8. Comparisons of extreme systematic risk across different banking systems for GARCH-filtered data

Banking system	Aggregate risk factor				
	Bank index	Stock index	Global bank	Global stock	Yield spread
$\overline{\eta}_{US}$	0.83	0.78	0.72	0.74	0.53
$\overline{\eta}_{EA}$	0.76	0.74	0.69	0.67	0.50
$\overline{\eta}_{FR}$	0.74	0.71	0.69	0.67	0.50
$\overline{\eta}_{GE}$	0.79	0.76	0.69	0.66	0.50
$\overline{\eta}_{IT}$	0.74	0.74	0.70	0.69	0.53
Null hypothesis					
$\overline{\eta}_{US} = \overline{\eta}_{EA}$	**2.09	1.25	0.85	**2.28	0.71
$\overline{\eta}_{US} = \overline{\eta}_{FR}$	**2.25	**1.99	1.12	**2.35	0.72
$\overline{\eta}_{US} = \overline{\eta}_{GE}$	0.91	0.56	1.16	***2.72	0.87
$\overline{\eta}_{US} = \overline{\eta}_{IT}$	*1.92	1.14	0.54	1.60	0.19

Note: The table shows the same results as table 9 in the main text for data that have been filtered for volatility clustering. The returns used here are the residuals of a GARCH(1,1) process fitted on the original excess returns. The table exhibits the average tail dependence parameters η that govern the tail-β estimates reported in tables E.6 and E.7 for the US, euro area, French, German and Italian banking system (upper panel) and the statistics of tests examining differences in extreme systematic risk between the US and euro area banking systems (lower panel). Each $\overline{\eta}$ is calculated as the mean of tail-β dependence parameters across all the banks in our sample for the respective country/area. The tests are applications of the cross-sectional test (4.5). The null hypothesis is that extreme systematic risk in the US banking system is the same as in the other banking systems. A positive (negative) test statistic indicates that extreme systematic risk in the US banking system (in the respective euro area banking system) is larger than in the respective euro area (US) banking system. The critical values of the test are 1.65, 1.96 and 2.58 for the 10%, 5% and 1% levels, respectively. All results are reported for the five different aggregate risk factors: The euro area/US banking sector sub-index, the euro area/US stock index, the world banking sector sub-index, the world stock index and the euro area/US high-yield bond spread. Univariate crash probabilities (crisis levels) are set to $p = 0.05\%$.

Table E.9. Extreme systematic risk (tail-βs) of euro area banks for GARCH-filtered data: Time variation

Bank	Aggregate risk factor				
	EMU banks	EMU stocks	World Banks	World Stocks	Yield spread
DEUTSCHE	10/8/97 (2.9)	-	12/3/96 (7.0)	12/3/96 (4.3)	9/14/00 (139.5)
HYPO	-	-	3/13/98 (3.3)	10/22/97 (7.1)	10/4/00 (135.7)
DRESDNER	-	12/5/96 (1.9)	12/3/96 (9.6)	12/5/96 (8.5)	9/13/00 (123.3)
COMMERZ	-	-	-	10/22/97 (4.5)	8/22/00 (158.6)
BGBERLIN	-	2/27/97 (1.9)	2/6/97 (2.8)	2/24/97 (3.3)	9/27/00 (188.4)
DEPFA	7/4/96 (5.1)	9/21/95 (4.4)	-	9/21/95 (4.8)	9/13/00 (118.2)
BNPPAR	10/8/97 (3.8)	10/8/97 (5.2)	8/28/97 (6.8)	8/26/97 (5.2)	9/15/00 (128.5)
CA	10/10/00 (17.4)	10/5/00 (13.3)	2/19/01 (12.4)	9/19/00 (11.9)	7/21/00 (133.2)
SGENERAL	10/22/97 (3.3)	-	12/5/96 (8.0)	12/5/96 (6.6)	9/21/00 (152.9)
NATEXIS	-	-	10/27/97 (3.9)	8/28/97 (5.8)	7/21/00 (172.7)
INTESA	-	7/4/96 (3.2)	-	9/10/97 (2.8)	7/24/00 (142.9)
UNICREDIT	8/1/97 (1.8)	-	9/9/97 (5.6)	10/22/97 (4.9)	8/15/00 (168.0)
PAOLO	9/9/97 (2.6)	2/4/94 (4.5)	9/25/97 (7.1)	9/9/97 (6.9)	8/17/00 (186.1)
CAPITA	-	-	9/9/97 (3.9)	9/10/97 (3.3)	9/15/00 (141.8)
SANTANDER	10/8/97 (4.3)	12/5/96 (9.1)	12/10/96 (9.1)	12/10/96 (7.3)	9/12/00 (162.0)
BILBAO	10/22/97 (6.7)	11/26/96 (9.3)	12/10/96 (13.1)	10/8/97 (24.7)	10/3/00 (172.9)
BANESP	-	-	-	-	7/6/00 (33.1)
ING	-	-	8/21/97 (13.3)	7/5/96 (8.4)	9/11/00 (144.6)
ABNAMRO	8/4/98 (3.3)	7/12/96 (4.0)	7/4/96 (8.1)	7/4/96 (4.5)	9/15/00 (136.5)
FORTIS	2/16/96 (5.6)	-	7/17/97 (14.8)	7/3/97 (6.7)	9/14/00 (127.0)
ALMANIJ	8/8/97 (5.2)	3/8/96 (4.8)	6/1/94 (8.5)	9/21/94 (13.3)	9/21/00 (234.4)
ALPHA	2/27/97 (19.3)	5/29/97 (18.0)	2/26/97 (12.0)	7/3/97 (19.1)	7/26/00 (92.5)
BCP	1/31/94 (5.4)	2/4/94 (8.6)	2/4/94 (10.7)	2/4/94 (16.5)	8/31/00 (106.7)
SAMPO	5/20/94 (3.6)	5/20/94 (3.2)	12/18/97 (4.6)	12/17/97 (2.5)	8/1/00 (209.2)
IRBAN	6/6/96 (2.4)	-	-	-	9/29/00 (106.3)

Note: The table shows the same results as table 11 in the main text for data that have been filtered for volatility clustering. The returns used here are the residuals of a GARCH(1,1) process fitted on the original excess returns. The table reports the results of tests examining the structural stability of the extreme systematic risks of euro area banks documented in table E.6. This is done by testing for the constancy of the η tail dependence parameters (null hypothesis) that govern the tail-βs in table E.6. Applying the recursive test (4.1) through (4.4) by Quintos et al. (2001), each cell shows the endogenously found break date and the test value in parentheses. Dates are denoted XX/YY/ZZ, where XX=month, YY=day and ZZ=year. The critical values of the test are 1.46, 1.78 and 2.54 for the 10%, 5% and 1% levels, respectively. A test value exceeding these numbers implies an increase in extreme dependence over time. The absence of a break over the sample period is marked with a dash.

Table E.10. Extreme systematic risk (tail-βs) of US banks for GARCH-filtered data: Time variation

Bank	Aggregate risk factor				
	Bank index	Stock index	Global bank	Global stock	Yield spread
CITIG	-	-	7/4/96 (7.7)	11/18/94 (8.4)	10/24/00 (97.9)
JPMORGAN	-	-	2/19/96 (3.6)	1/8/96 (3.3)	10/16/00 (74.8)
BOA	-	4/1/96 (5.4)	12/5/96 (13.6)	2/15/96 (11.8)	9/26/00 (65.7)
WACHO	-	-	9/16/94 (8.7)	12/4/95 (5.2)	10/16/00 (66.4)
FARGO	3/7/96 (2.9)	-	9/21/95 (7.2)	1/8/96 (5.6)	9/28/00 (35.3)
BONEC	9/15/95 (2.2)	10/19/95 (3.8)	10/23/95 (7.1)	6/5/95 (9.0)	10/20/00 (78.8)
WASHMU	3/1/96 (1.8)	2/26/96 (2.2)	2/27/97 (10.8)	2/23/96 (7.2)	12/13/00 (57.6)
FLEET	12/6/95 (2.1)	3/12/97 (7.7)	10/7/97 (13.7)	1/9/96 (12.2)	10/5/00 (52.3)
BNYORK	-	1/8/96 (1.9)	7/4/96 (10.6)	1/8/96 (13.9)	9/22/00 (49.5)
STATEST	12/15/95 (12.9)	12/15/95 (11.9)	9/29/95 (12.1)	9/15/95 (7.5)	10/11/00 (139.1)
NOTRUST	12/3/96 (6.1)	12/15/95 (4.2)	10/7/97 (3.3)	12/5/96 (5.7)	9/29/00 (60.3)
MELLON	9/15/95 (2.8)	10/19/95 (4.2)	9/9/97 (7.7)	11/18/94 (10.2)	10/16/00 (90.3)
USBANC	12/15/95 (5.4)	12/11/95 (2.1)	10/13/97 (9.2)	9/15/95 (8.0)	2/19/01 (58.3)
CITYCO	12/10/96 (2.4)	12/2/96 (4.7)	1/8/96 (9.6)	12/15/95 (11.4)	10/5/00 (37.7)
PNC	3/7/96 (2.2)	10/19/95 (5.5)	7/4/96 (18.8)	10/20/95 (14.5)	11/9/00 (39.4)
KEYCO	-	10/24/95 (3.1)	6/19/96 (2.4)	10/24/95 (7.1)	1/1/01 (44.7)
SUNTRUST	10/6/95 (5.3)	12/4/95 (5.1)	10/24/95 (8.7)	10/24/95 (16.9)	12/5/00 (42.4)
COMERICA	-	1/8/96 (2.3)	7/4/96 (7.0)	9/15/95 (10.2)	10/4/00 (61.1)
UNIONBAN	6/27/97 (6.3)	3/4/98 (5.4)	1/5/98 (2.9)	1/5/98 (6.5)	10/25/00 (32.3)
AMSOUTH	11/13/95 (3.4)	12/4/95 (4.3)	12/10/96 (7.7)	1/5/96 (4.4)	10/17/00 (54.5)
HUNTING	2/4/97 (5.9)	1/22/97 (8.2)	2/27/97 (9.1)	1/22/97 (9.3)	10/5/00 (50.5)
BBT	3/6/96 (4.7)	7/20/98 (7.2)	5/22/98 (14.0)	3/7/96 (8.1)	10/5/00 (35.5)
53BANCO	1/2/96 (2.3)	12/13/95 (1.3)	1/8/96 (9.1)	12/7/95 (3.9)	10/17/00 (44.5)
SOTRUST	2/26/97 (10.6)	6/17/96 (9.2)	7/4/96 (9.0)	3/7/96 (7.0)	11/21/00 (41.1)
RFCORP	3/7/96 (4.1)	2/23/96 (12.3)	12/5/96 (9.2)	2/23/96 (12.7)	9/20/00 (46.4)

Note: The table shows the same results as table 12 in the main text for data that have been filtered for volatility clustering. The returns used here are the residuals of a GARCH(1,1) process fitted on the original excess returns. The table reports the results of tests examining the structural stability of the extreme systematic risks of US banks documented in table E.7. This is done by testing for the constancy of the η tail dependence parameters (null hypothesis) that govern the tail-βs in table E.7. Applying the recursive test (4.1) through (4.4) by Quintos et al. (2001), each cell shows the endogenously found break date and the test value in parentheses. Dates are denoted XX/YY/ZZ, where XX=month, YY=day and ZZ=year. The critical values of the test are 1.46, 1.78 and 2.54 for the 10%, 5% and 1% levels, respectively. A test value exceeding these numbers implies an increase in extreme dependence over time. The absence of a break over the sample period is marked with a dash.

ESTIMATING SYSTEMIC RISK IN THE INTERNATIONAL FINANCIAL SYSTEM

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Abstract

Using a unique dataset, this paper develops three distinct methods to quantify the risk of a systemic failure in the global banking system. We examine a sample of 334 banks (representing 80% of global bank equity) in 28 countries around 6 global financial crises (such as the Asian and Russian crises and September 11, 2001), and show that these crises did not create large probabilities of global financial system failure. We show that cumulative negative abnormal returns for the subset of banks not directly exposed to a negative shock (unexposed banks) rarely exceed a few percent. More precise point estimates of the likelihood of systemic failure are obtained from structural models. These estimates suggest that systemic risk is limited even during major financial crises. For example, maximum likelihood estimation of bank failure probabilities implied by equity prices suggests the Asian crisis induced less than a 1% increase in the probability of systemic failure. Also, we demonstrate that estimates of systemic risk can be obtained from default probabilities of banks that are implied in their equity option prices. The largest values are obtained for the Russian crisis and September 11 and these show increases in estimated average default probabilities of only around 1-2%. The findings of low probabilities of a breakdown of the international financial system suggests that the distress of central bankers, regulators and politicians about such events may be overrated, and that existing policies and intervention methods are likely to be adequate for limiting systemic risk.

Keywords: Systemic risk, default risk, credit risk, banks, exposure, emerging markets, 9/11

JEL Classification: G3, F4, F3

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The authors gratefully acknowledge research funding by the Center for Financial Research of the FDIC, Lancaster University, Lancaster University Management School, the Leverhulme Trust, and The Bank of America Faculty Development Fund, as well as support by Global Reports, Perfect Information, Fitch Ratings and Thomson Financial in establishing the dataset. The authors also thank Robert Bliss, Hans Degryse, Jean Dermine, Eva Gutierrez, Philipp Hartmann, Shelagh Heffernan, Jean Helwege, Armen Hovakimian, Donald Morgan, Roberto Rigobon, Anthony Saunders, Lynn Shibut, Christian Upper and Giuseppe Vulpes as well as seminar participants at the FDIC Summer Research Workshop, the FIRS conference in Capri, the 2005 NBER conference on "Risks of Financial Institutions", NBER's 2005 Universities Research Conference on "Structural Changes in the Global Economy: Implications for Monetary Policy and Financial Regulation", the Fourth Joint Central Bank Research Conference on "Risk Measurement and Systemic Risk", the 2005 American Finance Association Annual Meeting, the 2004 European Finance Association Annual Meeting, the 2004 Financial Management Association Annual Meeting, the 2005 Australasian Conference on Banking and Finance, the EMG/ESRC workshop on "International Diversification and Contagion" at Cass Business School, The Bank of England, Darden School of Business, Lancaster University, Temple University, University of North Carolina, University of Texas at Austin, Vanderbilt University and Wake Forest University. Florian Bardong and Nishad Kapadia provided excellent research assistance.

"In practice, the policy choice of how much, if any, extreme market risk should be absorbed by government authorities is fraught with many complexities. Yet we central bankers make this decision every day, either explicitly, or implicitly through inadvertence. Moreover, we can never know for sure whether the decisions we make are appropriate. The question is not whether our actions are seen to have been necessary in retrospect; the absence of a fire does not mean that we should not have paid for fire insurance. Rather, the question is whether, ex ante, the probability of a systemic collapse was sufficient to warrant intervention. Often, we cannot wait to see whether, in hindsight, the problem will be judged to have been an isolated event and largely benign."

International Financial Risk Management, Remarks by Chairman Alan Greenspan before the Council on Foreign Relations, Washington, D.C. November 19, 2002

Systemic risk in the banking system has rightly attracted the attention of financial researchers (as well as regulators and policymakers) literally since the genesis of the discipline; bank failure and either simultaneous or subsequent macroeconomic collapse represents a financial dislocation with large and far-reaching consequences. Recently, dramatic increases in capital mobility, relaxations in international lending restrictions, and changes in capital allocation rules have raised the spectre that credit and currency crises in emerging markets might bleed into developed credit markets via disruptions in local lending channels. Others have argued that recent financial innovations (the burgeoning credit derivatives market for instance) and the increased activity of non-banking financial intermediaries (re-insurance companies, for example) may have lessened the risk that systemic shocks are transmitted throughout the global banking system. Indeed, much of the argument over Basel II credit allocation rules has focused upon the ability of large financial institutions to internally measure and manage the risk of credit crises without transmitting such shocks to other banks.

Using unique data on exposure measures, this paper directly tests the strength of the transmission mechanism between banks under the assumption of capital (equity) market efficiency for a large sample of international banks; in essence, it uses systematic risk to test for systemic risk. Specifically, we examine a sample of banks around significant emerging market currency and credit crises and show that there are no abnormal returns to banks without exposure to the crises, whereas exposed banks tend to have abnormal returns over the crisis period. Furthermore, using a modified version of the Merton structural model of the firm, we extract the default probabilities associated with both exposed and unexposed banks both pre- and post-crisis and show that there are no "flow-through" effects of the crisis on a bank's probability of failure, conditional on its exposure level. Lastly, we demonstrate the feasibility of an approach using option data and equity prices to infer systemic probabilities of bank failure. The implication here is that using three separate approaches to infer the increased risk of systemic banking failure provides little evidence of systemic transmission of financial shocks through developed economies even prior to the imposition of Basel II capital rules.

Financial economists in academia, central banks and international organizations alike have intensely studied various facets of the recent financial crises in Latin America, Asia and Russia. While theoretical models, e.g. by Freixas, Parigi and Rochet (2000), Allen and Gale (1998), and Rochet and Triole (1996), analyze systemic risk in interbank lending relationships, nearly all of the empirical work focuses indeed not on systemic risk *per se*, but on contagion effects in order to identify the mechanics and channels through which these crises spread across markets and countries.[1] To illustrate, Kho, Lee and Stulz (2000) study the effect of currency crises and the LTCM crisis on a sample of 78 U.S. banks and document that banks with exposures to a crisis country are adversely affected by crisis events and positively by IMF bailout announcements. Similarly, Kho and Stulz (2000) examine the impact of the Asian crisis on bank indices in four developed and six Asian countries. Bae, Karolyi and Stulz (2003) study the probability of joint occurrences of extreme returns across countries (co-exceedances) and find that contagion depends on interest rates, exchange rate changes, and conditional volatility, and that the United States are not immune from contagion from Latin America, but are insulated from Asian contagion. Linkages between economies in crisis periods and potential spillover effects from one country to another may, for instance, exist in the form of trade (Glick and Rose, 1999; Van Rijckeghem and Weder, 2001), or through financial linkages (Baig and Goldfajn, 1999; Goldfajn and Valdés, 1998). In contrast, the analysis in this paper pertains directly to the phenomenon of systemic risk and attempts to provide an empirical assessment of the likelihood of a failure of the global banking system. It thus addresses the important issue of quantifying the consequences of contagious effects, rather than explaining their existence.

Conceptually, a systemic failure in the global banking system could be defined as a failure (seizing) of the global inter-bank payment system or a loss of confidence in banks which results in a global 'bank-run'. For example, payment failures could mean that banks not receiving payments on loans (explicit or implicit) would become technically insolvent. Cascading bank insolvencies and bank-runs could cause additional financial and economic spillovers such as rapid

[1] Karolyi (2003) gives an excellent analysis and critique of different approaches to define and measure contagion. De Bandt and Hartmann (2000) offer a broad review of the theoretical and empirical literature on contagion and its systemic implications.

credit reduction, and ultimately, macroeconomic contraction (see, for example, Bernanke (1983)). Prior research has discussed how different types of shocks might cause systemic risk. For example, Kaufman (2000) describes systemic risks that can arise from a "big shock" (e.g., failure of a major bank), "spillovers" (e.g., East Asian contagion), and "common shock" (e.g., 9/11). Other researchers have distinguished between credit and operational risks. Since there does not exist an easy or accepted way of classifying shocks by type (and we examine only a few events), we do not attempt to draw conclusions about how different types of shocks affect changes in systemic risk probabilities.

Our first method for estimating this risk of a systemic failure relies on measuring the impact of global financial shocks on the stock price of a subset of banks that are not directly exposed to the shock. Specifically, the abnormal performance of these stocks should reflect primarily the probability of systemic failure in the banking system. In efficient capital markets, negative information such as devaluations of emerging market currencies or the tragedy of 9/11 will affect bank stock prices only if banks are exposed to the particular events. In contrast, unexposed bank stock prices should be largely unaffected by these events. As a result, stock market reactions of unexposed banks to crisis events can be interpreted as a crude measure of systemic risk. This is because negative returns of these banks are not due to direct exposure to the crises *per se*, but they are the result of negative returns of exposed banks that affect unexposed banks through the financial system.[2] Our analysis is based primarily on a sample of 334 banks in 28 countries representing about 80% of global bank equity. The first of our three approaches examines equity returns of unexposed banks during financial crises. Both raw returns and cumulative abnormal returns (CARs) for unexposed banks show relatively small declines (typically less than 4%) regardless of time horizon or exposure definition. The exception is immediately after 9/11 when CARs for unexposed banks are in the range of -4% to -6%.

We also provide more precise point estimates of the likelihood of systemic failure based on stock return and options data. With regard to stock return data, we use structural credit risk models such as Merton (1974) and Leland and Toft (1996) to derive maximum likelihood estimates of default for the sample banks. In particular, we can estimate the default probability of a bank as a function of its characteristics such as market value, face value of debt, expected return,

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[2] Even in the absence of systemic failure, financial crises could on average have a negative effect on global economies and therefore on banks in general. If we measure this effect, it will bias our estimates of systemic risk upward.

etc. While the models rely on several simplifications, model misspecification may largely wash out in intertemporal comparisons of the recovered default probabilities. Consequently, we interpret the difference between average pre-crisis and intra-crisis probabilities as a measure of systemic failure. Our results suggest very little chance of increased systemic failure during any of the crises, although there is a noticeable reaction to the LTCM credit crisis in the aftermath of the Russian shock. For example, the largest increase in average default probabilities for unexposed banks occurs during the Asian crisis when probabilities increase from 2.1% to 2.8%. Our estimates of increases in systemic failure are less than 1% across all crises, with much of the impact on unexposed banks generated by European banks.

Our third approach for assessing systemic risk in the banking system comes from estimating bank default probabilities implied by equity option prices. This method has the advantage of not relying on relatively infrequent (and stale) accounting data. In addition, the model can be estimated real-time using exclusively live market quotations thus making it a potentially valuable regulatory tool. Our analysis assumes a particular model for option prices that explicitly includes the probability of bankruptcy. Parameters of the model are estimated using a large set of publicly traded options on a subset of European and U.S. banks. The model makes the important assumption that over a finite horizon stocks follow a delta-geometric random walk (see Câmara (2004)) and thus have a finite chance of going bankrupt. The valuation equations can be inverted to yield the probability of bankruptcy. Because of data limitations, the sample is restricted to 14 European and 62 U.S. banks. Again, we study the difference in implied default probabilities between exposed and unexposed banks and find that none of the crises are associated with a substantial increase in systemic risk. The crises events with the largest impacts are the Russian/LTCM crisis and 9/11, but these events engender an average increase of only about 2% in the default probability for the unexposed banks.

The results in this paper have important policy implications. While *a priori* a justifiable and sensible concern, the findings of low probabilities of a meltdown of the international financial system suggest that the distress of central bankers, regulators and politicians about such events may be disproportionate. In essence, this would be empirical confirmation of the simulation evidence presented by Gould, Koury, and Naftilan (2004). Of course, the lack of systemic risk may also be a result of contemporaneous and judicious policy actions by central bankers and regulators. Thus, the findings could be interpreted as justifying the responses of these actors during the crises. Either way, given that chances of systemic failure appear low even during major financial crises, it seems that financial intermediaries on a global scale are more efficient and robust than often thought (or feared), and that current policy tools and responses may be more than sufficient.

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A LARGE SPECULATOR IN CONTAGIOUS CURRENCY CRISES: A SINGLE "GEORGE SOROS" MAKES COUNTRIES MORE VULNERABLE TO CRISES, BUT MITIGATES CONTAGION

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Abstract

This paper studies the implications of the presence of a large speculator like George Soros during a contagious currency crisis. The model shows that the presence of the large speculator makes countries more vulnerable to crises, but mitigates contagion of crises across countries. The model presents policy implications as to financial disclosure and size regulation of speculators such as hedge funds. First, financial disclosure by speculators eliminates contagion, but may make countries more vulnerable to crises. Second, regulating the size of speculators (e.g., prohibiting hedge funds from high-leverage and thereby limiting the amount of short-selling) makes countries less vulnerable to crises, but makes contagion more severe.

JEL classifications: F31; E58; D82; C72

Keywords: Contagion; Currency Crises; Global Game

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†The author is deeply grateful to Steven N. Durlauf for his invaluable advice and constant encouragement. The author also thanks Yeon-Koo Che, Charles Engel, Bruce Hansen, Graciela L. Kaminsky, Bob Staiger and the stuff of the Bank of Japan for helpful suggestions. All possible remaining errors are mine. The views expressed in this paper are those of the author and do not necessarily reflect the official views of the Bank of Japan or IMES.

"Has anyone noticed just how small a player the IMF really is? That $18 billion U.S. contribution to the IMF, which has finally been agreed upon after countless Administration appeals and conservative denunciations, is about the same as the short position that [George] Soros single-handedly took against the British pound in 1992 — and little more than half the position Soros' Quantum Fund, Julian Robertson's Tiger Fund, and a few others took against Hong Kong last August [in 1997]."

— Paul Krugman, Soros' Plea: Stop Me![1]

1 Summary

This paper studies the implications of the presence of a large speculator like George Soros during a contagious currency crisis.

The names of recent financial crises, such as the Mexican *Tequila* crises in 1994, the Asian *Flu* in 1997, the Russian *Virus* in 1998, and the Brazilian *Sneeze* in 1999, suggest a common feature. Clearly the common feature is "contagion," where a financial crisis begins locally, in some region, country, or institution, and subsequently spreads elsewhere. The international transmission of financial shocks per se is not always a surprising phenomenon. What is quite surprising in recent contagion episodes, however, is that the financial crises in small economies like Thailand or Russia have devastating effects on economies of very different sizes and structures, thousands of miles apart, with few direct trade or financial links, and in very severe and unexpected ways.[2] Put another way, it is quite surprising that severe contagion of crises has happened across seemingly "unrelated" countries, originating from crises in small economies. Why did Australian and South African stock market indices fall by 14% in the turmoil over the Asian Flu?[3] Why did the Brazilian stock market fall by over 50% and the sovereign spreads of Brazil rise sharply during the Russian Virus?[4]

[1] See Krugman (1998).

[2] Regarding the Russian Virus, Calvo, Izquierdo, and Talvi (2003) argue that "it was hard to even imagine, ex ante, that a crisis in a country that represents less than 1 percent of world output would have such devastating effect on the world capital market." (p.4)

[3] See Forbes (2004).

[4] See Forbes and Rigobon (2001).

While several contagion channels have been proposed in the literature, none seem able to explain entirely the extent of contagion. This paper provides a complement to the growing literature by extending the model presented in Taketa (2004).

Closely related to the issue of contagion, is the issue of "large" speculators. Large speculators, like George Soros or Julian Robertson, have not only been blamed for destabilizing the market unnecessarily during the turmoil of contagious currency crises, but also for triggering these contagious crises by themselves. For instance, during the turmoil of the Asian Flu, the then prime minister of Malaysia, Mahathir Mohamad, accused George Soros and others of being "the anarchists, self-serving rogues and international brigandage".[5] There are two main reasons that these large speculators are often blamed. First, they are considered to be able to affect the whole market to some degree. As opposed to small traders, they can exercise a disproportionate influence on the likelihood and severity of a financial crisis by fermenting and orchestrating attacks against weakened currency pegs, as the opening quote of this paper suggests. Second, their personal funds are often registered in so-called tax havens, typically small islands in the Caribbean, Europe, and Asia Pacific. These "offshore" funds typically do not forward financial information about themselves to other tax and financial authorities, since regulation in the tax havens is often less stringent than that of major industrialized countries. Therefore, they are often thought of as "monsters" whose true nature is unknown. Regardless of whether this is factually correct, it is quite important to investigate how such speculators can affect the market during contagious currency crises.

Following recent financial crises, the issue of contagion and that of large speculators have been arguably the most serious concerns for policy makers in international finance. Recent international policy discussions have revolved around questions on how to stop, mitigate, or prevent contagion of financial crises in the presence of George Soros-like speculators. In order to answer these questions, it is important to clarify two things: the possible channels for contagion, and the influence of large speculators on the spread of financial crises.

This paper attempts to answer these questions. To my knowledge, this work is the first

[5]Financial Times, July 25, 1997.

to investigate in a unified framework the issue of contagion across unrelated countries and that of a large speculator. By investigating these issues together, it becomes clear that the presence of the large speculator, who typically does not disclose financial information about himself to the regulatory authorities or to the market, has important implications during a contagious currency crisis. The large speculator's financial information (i.e., his "type") is private information. However, under some special situations such as financial crises, this private information is revealed to the market to a limited degree. This revealed information about his "type" can change the optimal behavior of other speculators who did not know the information before the crisis, which in turn can cause contagion of crises across unrelated countries.

The main findings of this paper are summarized as follows.

First, a single large speculator ("George Soros") *mitigates* contagion compared with small speculators, because he makes other small speculators more aggressive in attacking the currency peg. This seems paradoxical, but can be explained as follows. I model contagion using Bayesian updating to portray each speculator's belief about other speculators' types. When other speculators' behavior differs greatly, the change in behavior due to Bayesian updating becomes quite large, which in turn makes the contagion more severe. Because one "George Soros" makes other small speculators more aggressive in attacking the currency peg, speculators' behavior converges even when their types are different. This means that Bayesian updating in each speculator's belief about other speculators' types does not matter much. Even when a speculator can distinguish between different types of speculators, it is inconsequential since speculators of different types behave in a similarly aggressive way due to the presence of a single "George Soros."

Second, if the regulatory authorities can have large speculators such as George Soros disclose their financial information, they can eliminate contagion but may make countries *more vulnerable* to crises. This follows immediately from point two above. If small speculators know the exact type of Soros from the beginning due to financial disclosure, there is no room for Bayesian updating in belief about Soros' type. No Bayesian updating means no contagion in my model. However, if small speculators initially know that Soros is truly the most aggressive type, they can mimic this aggression by attacking the currency peg, which makes countries more vulnerable to crises.

Third, if the regulatory authorities can limit the size of speculators by regulating the amount of short-selling, they can make countries less vulnerable to crises but may make contagion *more severe*. This is a mirror image of the finding that one large "George Soros" makes countries more vulnerable to crises, but mitigates contagion.

2 Future Research

In some cases it is challenging to estimate the theoretical models due to data constraint. In this section I argue that experimental analysis would be able to provide some useful information to accompany the literature.

Corsetti, Dasgupta, Morris, and Shin (2004) show theoretically that the presence of a large speculator causes all the remaining speculators to be more aggressive than the case where there is no large speculator, as small speculators attack the currency when fundamentals are stronger. Meanwhile, empirical evidence on the role of large speculators is mixed.[6] One reason for the mixed empirical results might be due to data constraint. Their personal funds are typically registered in the so-called tax havens and they do not have to disclose data as regulations in tax havens are far less stringent. As a result, it is hard to obtain sufficiently detailed data to decisively determine the role of the large speculator in financial crises.

Taketa, Suzuki-Löffelholz and Arikawa (2007) complement the literature by using experimental analysis. As Roth (1995) argued, an experimental approach gives us a controlled environment that "allows observations to be unambiguously interpreted in relationship to the theory." They report the results of experiments designed to test the predictions of Corsetti, Dasgupta, Morris, and Shin (2004). In particular, the experiments test (a) whether speculators are more likely to attack the peg when the economic fundamentals are weaker, and (b) whether the large speculator makes small speculators more aggressive

[6] See Brown, Goetzmann, and Park (1998), Fung and Hsieh (2000), Fung, Hsieh, and Tsatsaronis (2000), and Corsetti, Pesenti, and Roubini (2002) among others.

in attacking the peg. Moreover, the experiments also test (c) whether the effect of the recognition that "Soros appears" is symmetric to the effect of the recognition that "Soros disappears" even though Corsetti, Dasgupta, Morris, and Shin (2004) do not deal with this issue. This investigation would provide some possible clues to construct a dynamic theoretical model in the future. The results of the experiments not only support the predictions of Corsetti, Dasgupta, Morris, and Shin (2004) but also suggest that the effect of "Soros appears" is not symmetric to the effect of "Soros disappears". Therefore, the results indicate how we could extend the model of Corsetti, Dasgupta, Morris, and Shin (2004) to explain the asymmetric effect.

For future research, I am planning to conduct experiments to test related theoretical papers. Bannier (2005) highlights the role that the market sentiment has on the impact of a large trader on a currency crisis. Corsetti, Guimarães, and Roubini (2005) investigate the role of the official creditor (the IMF or an international lender of last resort) as a large player in the world economy. It is very likely that it is challenging to estimate these models due to data constraint. Experimental analysis would be useful to complement the literature.

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SESSION 5

RISK MEASUREMENT AND MARKET DYNAMICS

BANK CREDIT RISK, COMMON FACTORS, AND INTERDEPENDENCE OF CREDIT RISK IN MONEY MARKETS

OBSERVED VS. FUNDAMENTAL PRICES OF BANK CREDIT RISK

NAOHIKO BABA* AND SHINICHI NISHIOKA**

Abstract

This paper empirically reexamines the role of TIBOR/LIBOR as indicators of bank credit risk and investigates the interdependence of bank credit risk in money markets within and across the border since the 1990s. Empirical results are summarized as follows. (i) Observed risk premiums constructed from TIBOR/LIBOR contain two common factors, global and currency factors, which explain most of the variance of the risk premiums; (ii) thus the generalized impulse response of risk premiums from the shocks of the same currency markets are much larger than the responses from then shocks of the same bank groups; and (iii) the conditional correlations, derived from a Multivariate GARCH model, of the same bank groups' risk premiums between the yen and dollar markets fluctuate around zero, while the correlations between Japanese and foreign banks' risk premiums in the same currency market are very high; (iv) after controlling for these common factors, we successfully derived the fundamental prices of bank credit risk both particularly for Japanese banks using a state space model; (iv) these fundamental prices show plausible time-series properties such as a high degree of impulse response from the shocks of the same bank groups, and a high conditional correlation of the same bank groups' credit risk prices between the yen and dollar two markets; (v) however, the fundamental prices account for only a tiny portion of the total variance of risk premiums.

JEL Classification: E43, G14, G15

Key Words: LIBOR, TIBOR, Credit Risk, Factor Analysis, State Space Model, Kalman Filter, Cointegration, , Generalized Impulse Response, Multivariate GARCH

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This paper is prepared for the fourth joint central bank research conference on risk measurement and systemic risk held at the European Central Bank in Frankfurt, Germany on November 8-9, 2005. We greatly benefited from discussions with Joachim Coehe (discussant), Masaaki Shirakawa, Ken Singleton, Kazuo Ueda and Yoichi Ueno. We also benefited from interviews with many traders in the Tokyo FX swap market. Any remaining errors are solely our responsibility. The views expressed in this paper are those of the authors and do not necessarily reflect those of the Bank of Japan.

I. Introduction

This paper aims to empirically reexamine the role of TIBOR/LIBOR[1] as indicators of bank credit risk as well as investigate the interdependence of bank credit risk in money markets within and across the border. Our main objective lies in shedding light on how money market interest rates functioned as a price discovery tool for bank credit risk since the 1990s.

Credit risks of Japanese and foreign banks are expected to be priced in TIBOR/LIBOR since the majority of referenced banks for TIBOR/LIBOR are Japanese/foreign banks, respectively. Indeed, the so-called "Japan premium", generally defined as the difference between U.S. dollar-TIBOR and LIBOR, rose sharply to nearly 100 bps at the height of the Japanese banking crisis in 1997-98. The Japan premium was considered to reflect western banks skepticism on opaque Japanese accounting and banking supervision system. Around 2001 to 2002 the vulnerability of Japanese banks became highlighted again mainly due to their low earnings and newly emerging nonperforming loans. This time, however, the Japan premium did not appear. Ito and Harada [2004] assert that the Japan premium lost its role of showing market perception about the vulnerability of Japanese banks.

Specifically, in this paper, we attempt to extract the fundamental credit risk prices for Japanese and foreign banks from the observed risk premiums constructed from the daily yen- and U.S. dollar- TIBOR/LIBOR during the period from 1992/8/3 to 2005/2/2. In this period ,the Japanese banking system experienced unprecedented situations including (a) the instability arising from the non-performing loan problem in the late 1990s and (b) a ultra low interest rate environment put in force by the Bank of Japan (BOJ) under the name of the Quantitative Monetary Easing Policy (QMEP) since March 2001.

[1] TIBOR and LIBOR are abbreviations for Tokyo Interbank Offered Rate and London Interbank Offered Rate, respectively.

During the period of financial instability, which was initiated by a series of failure of Japanese major financial institutions in late 1997, Hanajiri [1999] argues that the arbitrage relationship collapsed between the yen and the U.S. dollar cash markets.[2] Also, under the QMEP, Baba et al. [2005a,b] argue that Japanese money markets almost ceased to function as a pricing mechanism of banks' creditworthiness in that money market interest rates have been so lowered that they hardly reflect the differences in credit risk among individual banks.

There are few studies that investigated the relationship between TIBOR and LIBOR with the notable exceptions of Covrig, Low, and Melvin [2004], Peek and Rosengren [2001], and Nishioka and Baba [2004].[3] Covrig, Low, and Melvin [2004] investigated the determinants of Japan premium and concluded that lower Japanese interest rates, a flatter yield curve, and a decline in stock prices raised the Japan premium. Peek and Rosengren [2001] attributed the Japan premium to Japanese banks' financial soundness, net worth, and default risk. Also, Nishioka and Baba [2004] discussed the equilibrium relationship among yen- and U.S. dollar-TIBOR and LIBOR to explore the cause of the "negative" nominal yen funding costs for foreign banks in the FX swap market.[4] We aim to add another line of research to these studies by rigorously analyzing the fundamental prices of bank credit risk included in yen- and U.S. dollar TIBOR/LIBOR and the interdependence structure among these fundamental risk prices.

To extract the fundamental credit risk prices for Japanese and foreign banks from the

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[2] In November 1997, concern over the financial stability heightened following a series of failures of four financial institutions: Sanyo Securities (November 3), Hokkaido Takushoku Bank (November 17), Yamaichi Securities (November 24), and Tokuyo City Bank (November 26). The concern over the financial instability subsided after the nationalization of Long-Term Credit Bank of Japan (October 23, 1998) and Nippon Credit Bank (December 13, 1998).

[3] In addition, Lo, Fung, and Morse [1995] investigated the relationship between yen-LIBOR and yen interest rate on negotiable certificate of deposits (NCDs).

[4] It is around 1995 when we first observed negative yen funding costs in the FX swap market. In the periods of financial instability and the QMEP, we frequently witnessed negative FX yen funding costs. They have sometimes yielded "negative nominal uncollaterarized call rate" particularly under the QMEP. See Nishioka and Baba [2004] and Baba et al. [2005] for more details.

observed risk premiums, we first find some common factors that do not reflect creditworthiness of banks and thus pay a role of control variables using factor analysis. Recent empirical studies on the U.S. credit spreads show that the structural (fundamental) factors specific to each referenced entity are important, but can explain only a small portion of the credit spreads. For instance, Collin-Dufresne, et al. [2001] show that structural factors can explain only a quarter of the changes in the U.S. credit spreads, indicating that systematic factors, common to the aggregate corporate bond market, have much more contribution to the changes in credit spreads.[5] Thus, we conjecture that major part of the risk premium variation in short-term money markets are also likely to be accounted for by some common factors as in the case of the U.S. credit spreads. And then, using these common factors as control variables, we extract the fundamental prices of bank credit risk based on the state space model in which shadow prices of bank credit risk govern the fundamental prices of credit risk for Japanese and foreign banks, respectively.

After estimating the fundamental prices of bank credit risk, we investigate their time-series properties to explore the dynamic interdependence structure of bank credit risk within and across the border, using the interdependence structure of the observed risk premiums as a benchmark for comparison. The basic methodologies we use are (a) Johansen's [1991, 1995] conintegration analysis, (b) VAR (Vector Autoregressive) Model or VECM (Vector Error Correction Mode)-based Granger causality test and the generalized impulse response function, and (c) M-GARCH (Multivariate Generalized Autoregressive Conditional Heteroscedasticity) models.[6] Main objective in this part is to clarify the difference between the fundamental prices of bank credit

[5] Elton, et al. [2001] also show that systematic risk of the equity market is more important determinants of the U.S. credit spreads than expected default loss and tax premium. On the other hand, Driessen [2004] decomposes the term structure of credit spreads, finding a similar result.

[6] The univariate ARCH and GARCH models were developed by Engle [1982] and Bollerslev [1986], respectively. The univariate GARCH model was extended to a multivariate framework by Bollerslev, Engle, and Wooldrige [1988]. Using M-GARCH models, King et al. [1994] analyze the volatility transmission between national stock markets, while Kearney and Patton [2000] investigate the volatility transmission in the EMS. Also, Kim et al. [2005] analyze the volatility transmission between stock and bond markets in the EMS.

risk and the observed risk premiums in terms of the dynamic interdependence structure.

The rest of the paper is organized as follow. Section II derives the equilibrium relationships among money market interest rates based on the foreign currency funding structure of Japanese and foreign banks including the FX swap market. Section III describes risk premium data we use in this paper. Section IV briefly explains the overall empirical strategy and the methodologies adopted in this paper to decompose the risk premiums and extract the fundamental credit risk prices as well as analyze their time-series properties. Section V reports and discusses the empirical results. Section VI concludes the paper.

II. Theoretical Relationships Linking Money Market Interest Rates

(i) Foreign Currency Funding Structure of Japanese and Foreign Banks

Following Nishioka and Baba [2004], we show that active arbitrage transactions in the FX swap markets create a transmission channel of risk premiums for Japanese and foreign banks between the yen and U.S. dollar markets. Specifically, we consider the no-arbitrage conditions for Japanese and foreign banks' foreign currency funding costs. The following three markets are under study: (a) the yen cash market, (b) the U.S. dollar cash market, and (c) the FX swap market.[7]

As shown in Figure 1, FX swap transaction has been active since the early 1990s except the period of financial instability from late 1997 to 1998. The FX swap transaction plays a role of a funding source of foreign currencies for both Japanese and foreign banks, alternative to the direct funding from cash markets. Thus, active FX swap transaction creates two no-arbitrage conditions for yen and U.S. dollar funding, which in turn creates an equilibrium condition linking four risk

[7] A typical FX swap transaction is a contract in which Japanese banks borrow U.S. dollars from, and lend yen to, foreign banks at the same time.

premiums: yen- and U.S. dollar risk premiums for both Japanese and foreign banks.

(ii) No-arbitrage and Equilibrium Conditions

The funding costs in the cash markets can be written as the sum of the risk-free interest rate anc the risk premium for Japanese or foreign banks. Let i and i^* denote the yen and dollar risk-free interest rates, JY and JD the risk premiums for Japanese banks in the yen and dollar market, and FY and FD the risk premiums for foreign banks in the yen and dollar market, respectively. Also, let F and S denote the yen-dollar forward and spot rate of foreign exchange.

As shown in Figure 2, Japanese banks have two alternative funding sources of dollars (a) raising dollars directly from the dollar market, and (b) raising yen from the yen market anc exchanging it for dollars in the FX swap market. Then, if these funding sources are perfec substitutes for Japanese banks, the following no-arbitrage condition holds

$$1+i^*+JD=\frac{S}{F}\left(1+i+JY\right). \qquad (1)$$

The left-hand side of equation (1) is the dollar interest rate for Japanese banks, while the right-hanc side is the dollar funding cost for Japanese banks in the FX swap market.

Similarly, foreign banks have two alternative funding sources of yen: (a) raising yer directly from the yen market, and (b) raising dollars raised from the dollar market and exchanging those for yen in the FX swap market. Then, if these two funding sources are perfect substitutes fo foreign banks, the following no-arbitrage condition holds

$$1+i+FY=\frac{F}{S}\left(1+i^*+FD\right). \qquad (2)$$

The left-hand side of equation (2) is the yen interest rate for foreign banks, while the right-hanc side is the yen funding cost for foreign banks in the FX swap market. Substituting equation (1) into equation (2) yields the following equilibrium condition:

$$\frac{1+i+JY}{1+i+FY}=\frac{1+i^{*}+JD}{1+i^{*}+FD}. \qquad (3)$$

Equation (3) creates a transmission channel for interest rates within and across the border. Approximation of equation (3) enables us to find its significance more intuitively:

$$JY-JD=FY-FD\,. \qquad (4)$$

The left-hand side of equation (4) shows the difference in risk premiums for foreign banks between the yen and dollar markets, while the right-hand side shows the difference in risk premiums for foreign banks between the two markets. The significance of this result is that to achieve equilibrium we do not need the "parity" of risk premiums for the same bank groups between the yen and dollar markets. In section V, we explore the relationships among these four variables with due attention to the equilibrium condition (4).[8]

III. Data

(i) Data Description

In this paper, we use 90-day yen- and dollar-LIBOR (London Interbank Offered Rate) and TIBOR (Tokyo Interbank Offered Rate) to construct risk premiums for Japanese and foreign banks. Of 16 referenced banks that comprise yen-TIBOR/LIBOR, 14 banks are Japanese banks in yen-TIBOR,

[8] Another interesting extension of equilibrium condition (3) is to decompose the FX swap yen funding cost for foreign banks, which frequently have moved below zero under the QMEP. See Appendix 1 for more details. Nishioka and Baba [2004] show that this negative FX swap yen funding cost is closely linked to negative nominal money market interest rates that have been observed in Japan since 2001.

while 11 banks are foreign banks in yen-LIBOR.[9] In a similar fashion, of 10 banks referenced by dollar-TIBOR, 8 banks are Japanese banks, while of 16 banks referenced by dollar-LIBOR, 14 banks are foreign banks. Appendix 2 provides more details of the data.

While LIBOR forms the pricing basis for floating rate securities and loans settled during European trading hours, Asia-Pacific issuers or borrowers need settlement during Asia-Pacific trading hours to avoid interest rate risk. TIBOR forms the basis for such settlement. It should be noted, however, that LIBOR is quoted at 11 am London time, while TIBOR is quoted at 11 am Tokyo time. Since the 11 am London time corresponds to 7 or 8 pm Tokyo time, LIBOR reflects the market events that occurred in Japan's afternoon. To accommodate this time difference Covrig, Low, and Melvin [2004] use the same day quotes for TIBOR and the one-day lag quotes for LIBOR in investigating the determinants of "Japan Premium", which they defined as a yen-TIBOR/LIBOR spread. We tried both versions, the same-day quotes for TIBOR/LIBOR and one-day lag for LIBOR, but no distinct differences were found in estimation results. Thus, in what follows, we report only the results using the same-day quotes.

As risk-free interest rates, we use Japanese and the U.S. Treasury bill rates. Thus, JY/FY that appeared in section II are computed as yen-TIBOR/LIBOR minus Japanese Treasury bill rate and JD/FD are computed as dollar-TIBOR/LIBOR minus the U.S. Treasury bill rate. Figure 3 shows the risk premiums for Japanese and foreign banks thus constructed. An interesting point to note here is that the dollar risk premiums are almost always higher than the yen risk premiums irrespective of Japanese and foreign banks and the differences are pronounced in the period of financial instability from 1997 to 1998. As shown by equation (4), we do not need the equality of

[9] The relative impreciseness of yen-LIBOR as a proxy for foreign banks' yen interest rate resulted in a poor performance of the extracted yen-market fundamental price of foreign banks' credit risk. We will discuss this issue in session V.

risk premiums for the same bank groups between the yen and dollar markets to attain equilibrium and a casual observation suggests that equilibrium condition (4) holds over the sample period except the period of financial instability around 1998.

(ii) Statistical Properties of Risk Premiums

Table 1 shows summary statistics of the risk premiums we use in our empirical analysis. As shown in Table 1(i), means and standard deviations of the yen risk premiums are much smaller than those of the dollar risk premiums. Also, all of the risk premiums have positive skewness and excess kurtosis, which can be jointly confirmed by the Jarque-Bera test. Positive skewness of risk premiums implies that the total return including the capital gain/loss has negative skewness, fixing the underlying risk-free rates, which is consistent with the notion of default risk.[10] And, the high degree of kurtosis suggests a fat-tailed property of the risk premiums. In addition, we tested for serial correlations of both the level of the variables themselves and squared ones up to the 12th order using the Ljung-Box *Q* test denoted LB(12) and $LB^2(12)$, respectively. Both statistics show a very high degree of serial correlations. These properties of the risk premiums support the use of the GARCH models particularly with the multivariate Student *t* distribution.

On the other hand, Table 1(ii) reports correlation matrix between each pair of risk premiums. A noteworthy point here is that the correlations between JY and FY (JD and FD) are higher than the correlations between JY and JD (FY and FD). That is, the correlations of risk premiums for the same bank groups between the yen and dollar markets are lower than the correlations of risk premiums in the same currency market between Japanese and foreign banks.

[10] The possibility of extreme negative returns on credit instruments in the case of a credit event creates negatively-skewed distributions. See Chapter 13 of Duffie and Singleton [2002] for more details.

Also, note that correlations between JY and FD (JD and FY) are higher than the correlation between FY and FD. Since the pairs of JY and FD (JD and FY) do not have common attributes in terms of the referenced bank groups and the denominated currency, we can infer that some common factors rather than credit fundamentals of referenced bank groups contribute to moving these risk premiums in the same direction.[11] This finding actually motivated us to decompose the risk premiums into common factors and credit risk fundamentals.

Table 2 reports the results of two unit root tests: the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test. The test results show that all of the risk premiums are I(0).[12] Thus, we should not use Johansen's cointegration analysis to test for the equilibrium condition among risk premiums shown by equation (4) and instead use the VAR (Vector Autoregressive)-based models to investigate the dynamic time-series properties and interdependence among the risk premiums.

IV. Empirical Strategy and Methodologies

(i) Empirical Strategy

Our empirical strategy goes as follows. First, we attempt to decompose risk premiums to extract fundamental prices of bank credit risk that are specific either to Japanese or foreign banks. To that end, as a preliminary step, we employ factor analysis to derive common factors and then construct a state space model using common factors as control variables. In the state space model fundamental prices of bank credit risk is linked to state variables that act as noisy shadow prices of credit risk..

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[11] This tendency is pronounced in terms of the conditional correlations derived from an M-GARCH model. See section V for details.
[12] The lag length is determined by the Schwarz criterion as suggested by Hayashi [2000].

Next, we investigate the time-series properties of the derived fundamental prices of bank credit risk using the risk premiums themselves as a benchmark. As for the risk premiums, we (a) conduct the Granger causality test, (b) derive the generalized impulse response function based on the VAR system and (c) estimate an M-GARCH model to investigate dynamic interdependency among the risk premiums. As for the fundamental prices of bank credit risk, we first conduct Johansen's [1991,1995] cointegrating analysis since the fundamental prices of bank credit risk are I(1) by construction. Then, we explore the properties of dynamic interdependency by conducting the Granger causality test and deriving the generalized impulse response function based on the VECM (Vector Error Correction Model) as well as estimating an M-GARCH model.

(ii) Empirical Methodologies

A. Decomposition of Risk Premiums

a. Preliminary Step: Factor Analysis

As a preliminary step, we derive common factors from four risk premiums. Our approach is to use the following traditional orthogonal factor analysis that does not need any *a priori* assumptions about common factors:[13]

$$\mathbf{R}_t = \boldsymbol{\mu} + \mathbf{B}\mathbf{F}_t + \boldsymbol{\varepsilon}_t , \tag{5}$$

where $\mathbf{R}_t$ denotes a vector of four risk premiums $\left[JY_t, JD_t, FY_t, FD_t\right]'$, $\mathbf{F}_t$ a vector of K

[13] Driessen, Melenberg, and Nijman [2003] successfully found a linear factor model with five factors that explains 96.5% of the variation of international bond returns using factor analysis. An alternative approach is to assume factor structure in advance. In the context of international bond returns, Barr and Priestley [2004] assume that the world bond index and individual local market bond index are common factors, for instance. In the case of TIBOR/LIBOR, however, such indices do not exist, so we use factor analysis to derive common factors.

common factors to be estimated, $\mathrm{cov}(\mathbf{F}_t, \boldsymbol{\varepsilon}_s) = 0$ for all t and s, $\mathrm{E}[\mathbf{F}_t] = \mathrm{E}[\boldsymbol{\varepsilon}_t] = 0$, $\mathrm{var}(\mathbf{F}_t) = \mathbf{I}_K$, and $\mathrm{var}(\boldsymbol{\varepsilon}_t) = \mathbf{G}$. Here, $\mathbf{G}$ is a diagonal matrix with σ_i^2 along the diagonal. Then, the covariance matrix of risk premiums $\boldsymbol{\Omega}$ can be decomposed as

$$\boldsymbol{\Omega} = \mathbf{B}\mathbf{B}' + \mathbf{G}.$$

We use principal factor method with no rotation to extract common factors.[14] As discussed in section V, factor analysis above successfully extracted two relevant common factors: (a) the global factor denoted Fg_t, which is almost equally common to all of the risk premiums, and (b) the currency factor denoted Fc_t, which captures the difference between the yen and dollar markets such that when $Fc_t > 0$, it raises/lowers risk premiums in the dollar/yen market irrespective of the bank groups.

b. Decomposition Framework

Using the common factors derived by factor analysis above, in what follows, we explain the methodology to extract fundamental prices of bank credit risk from risk premium data. Following Blanco, Brennan, and Marsh [2005], suppose that the unobservable shadow prices of credit risk for Japanese banks J_t^*, and foreign banks F_t^*, follows a random walk process, respectively:[15]

$$J_t^* = J_{t-1}^* + e_t^j, \qquad \text{and} \qquad F_t^* = F_{t-1}^* + e_t^f, \tag{6}$$

where e_t^j and e_t^f are the noises with zero mean and constant variance. We assume that the observed risk premiums, JY_t, JD_t, FY_t, and FD_t are equal to the sum of (a) the fundamental

14 Researchers often rotate the initial solution for ease of interpretation, but the rotation entails arbitrariness. To avoid such arbitrariness, we use the initial solution obtained by the principal factor method. See Chan, Karceski, and Lakonishok [1998] for a review of factor analysis and factor models.
15 Blanco, Brennan, and Marsh [2004] investigate the relationship between corporate bond yields and CDS (credit default swap) spreads.

price of bank credit risk in each market, denoted $JYPRICE_t$, $JDPRICE_t$, $FYPRICE_t$ $FDPRICE_t$, respectively, (ii) non-transient common factors, Fg_t and Fc_t, and (iii) stochasti terms including transient microstructural noises, e_t^{jy} , e_t^{jd} , e_t^{fy} and e_t^{fd} . The structure i summarized as follows:

Japanese banks:
$$JY_t = JYPRICE_t + a_t^g Fg_t + a_t^c Fc_t + e_t^{jy} \tag{7}$$

$$JD_t = JDPRICE_t + b_t^g Fg_t + b_t^c Fc_t + e_t^{jd} \tag{8}$$

Foreign banks:
$$FY_t = FYPRICE_t + c_t^g Fg_t + c_t^c Fc_t + e_t^{fy} \tag{9}$$

$$FD_t = FDPRICE_t + d_t^g Fg_t + d_t^c Fc_t + e_t^{fd}\ , \tag{10}$$

where
$$JYPRICE_t = a_0^{jy} + a_1^{jy} J_t^* + e_t^{jyprice}, \quad JDPRICE_t = a_0^{jd} + a_1^{jd} J_t^* + e_t^{jdprice}$$

$$FYPRICE_t = a_0^{fy} + a_1^{fy} F_t^* + e_t^{fyprice}, \quad FDPRICE_t = a_0^{fd} + a_1^{fd} F_t^* + e_t^{fdprice}\ .$$

Here, coefficients of the sensitivity to each common factor are allowed to move over time, and th fundamental prices of bank credit risk in each market are assumed to be linearly linked to th fundamental prices of credit risk for Japanese and foreign banks with noises.

c. State Space Model

To express the above decomposition framework and estimate each parameter and fundamenta price of bank credit risk, we construct the following state space model. In this model, tw random-walk state variables are assumed to govern the fundamental prices of bank credit risk afte controlling for the effects of common factors derived by factor analysis, Fg_t and Fc_t:[16]

$$\begin{bmatrix} JY \\ JD \\ FY \\ FD \end{bmatrix}_t = \begin{bmatrix} JYPRICE \\ JDPRICE \\ FYPRICE \\ FDPRICE \end{bmatrix}_t + \begin{bmatrix} s4 & s6 \\ s5 & s7 \\ s14 & s16 \\ s15 & s17 \end{bmatrix}_t \begin{bmatrix} Fg \\ Fc \end{bmatrix}_t + \begin{bmatrix} e1 \\ e2 \\ e11 \\ e12 \end{bmatrix}_t, \tag{11}$$

where

$$\begin{bmatrix} JYPRICE \\ JDPRICE \end{bmatrix}_t = \begin{bmatrix} c3 \\ c4 \end{bmatrix} + \begin{bmatrix} c1 \\ c2 \end{bmatrix} s3_t + \begin{bmatrix} e3 \\ e4 \end{bmatrix}, \quad \begin{bmatrix} FYPRICE \\ FDPRICE \end{bmatrix}_t = \begin{bmatrix} c13 \\ c14 \end{bmatrix} + \begin{bmatrix} c11 \\ c12 \end{bmatrix} s13_t + \begin{bmatrix} e13 \\ e14 \end{bmatrix},$$

$$\begin{bmatrix} s3 \\ \vdots \\ s7 \end{bmatrix}_t = \begin{bmatrix} s3 \\ \vdots \\ s7 \end{bmatrix}_{t-1} + \begin{bmatrix} e5 \\ \vdots \\ e9 \end{bmatrix}_t, \text{ and } \begin{bmatrix} s13 \\ \vdots \\ s17 \end{bmatrix}_t = \begin{bmatrix} s13 \\ \vdots \\ s17 \end{bmatrix}_{t-1} + \begin{bmatrix} e15 \\ \vdots \\ e19 \end{bmatrix}_t.$$

Here, s with numbers denote state variables, c constant coefficients, and e Gaussian noise Among these state variables, $s3_t$ and $s13_t$ correspond to the random-walk shadow prices J_t^* and F_t^* in equation (6) that govern the fundamental prices of credit risk for Japanese and foreig banks, JYPRICE/JDPRICE and FYPRICE/FDPRICE, respectively. Note, here, that we allow fo the difference in fundamental prices of credit risk priced between the yen and dollar markets. Thi is mainly due to the differences in risk averseness of market participants, which is related t $c1/c2$ and $c11/c12$. We can test the differences in these constant terms using the Wald tes Also note that we allow for time-varying sensitivities to common factors and (constant) covariance across relevant equations.[17] In estimating the model, we use the Kalman filter that is a recursiv algorithm for sequentially updating the one-step ahead estimate of the state variables given nev information.[18] Marquardt method is used as an optimization algorithm.

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[16] The model can be regarded as an extension of "state space representation of the local level model" in which the observed asset price is assumed to be the sum of a ransom walk fundamental component and a Gaussian error term. See Durbin and Koopman [2001] for details. Extensive surveys of applications of state space models in econometrics are found in Chapter 13 in Hamilton [1994] and Chapters 3 and 4 in Harvey [1989].

[17] See Table 4 for the assumed covariance structure.

[18] We initialize the states and variances using priors and adopt the maximum likelihood estimation techniques

B. Analysis of Time-Series Properties

a. Johansen's Cointegration Test

Since the fundamental prices of bank credit risk are I(1) by construction, we use Johansen's [1991, 1995] cointegration test to investigate the long-term relationships among those prices. Let $\mathbf{R}$ denote a vector that includes p non-stationary time series (p =4 in our case), all of which have property of I(1).[19] Suppose the following VAR (vector autoregression) representation of $\mathbf{R}_t$:[20]

$$\mathbf{R}_t = \mathbf{a}_1\mathbf{R}_{t-1} + \mathbf{a}_2\mathbf{R}_{t-2} + \ldots + \mathbf{a}_k\mathbf{R}_{t-k} + \boldsymbol{\varepsilon}_t = \sum_{i=1}^{k}\mathbf{a}_{t-i}\mathbf{R}_{t-i} + \boldsymbol{\varepsilon}_t , \qquad (12)$$

where $\mathbf{a}_i$ is a coefficient matrix and $\boldsymbol{\varepsilon}_t$ is a error vector. Equation (12) can be rewritten as VECM (Vector Error Correction Model):

$$\Delta\mathbf{R}_t = \boldsymbol{\Pi}\mathbf{R}_{t-1} + \sum_{i=1}^{k-1}\boldsymbol{\Gamma}_i\Delta\mathbf{R}_{t-i} + \boldsymbol{\varepsilon}_t , \qquad (13)$$

where $\boldsymbol{\Pi} = \sum_{i=1}^{k}\mathbf{A}_i - \mathbf{I}$ and $\boldsymbol{\Gamma}_i = -\sum_{j=i+1}^{k}\mathbf{a}_j$.

Granger's representation theorem states that if the coefficient matrix $\boldsymbol{\Pi}$ has reduced rank $r < p$ then there exist $p \times r$ matrices $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ with rank r such that $\boldsymbol{\Pi} = \boldsymbol{\alpha\beta}^T$, where $\boldsymbol{\beta}^T\mathbf{R}_t$ is I(0).[21] Here, r is the number of cointegrating relations (cointegrating rank) and each column of $\boldsymbol{\beta}$ is the cointegrating vector. Johansen's method is to estimate the $\boldsymbol{\Pi}$ matrix from an unrestricted VAR and to test whether we can reject the restrictions implied by the reduced rank of $\boldsymbol{\Pi}$. The number of cointegrating relations is determined by the trace statistic and the maximum eigenvalue statistic.

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from Durbin and Koopman [2001].

[19] In fact, yen- and dollar-TIBOR/LIBOR, and the fundamental prices of bank credit risk derived by a state space model are found to be I(1). See Table 2 and session V for details.

[20] For ease of notations, we ignore a constant term and exogenous variables throughout this section.

[21] See Engel and Granger [1987] for details.

b. Stability Tests of Cointegration Relationships

We test for potential structural breaks of cointegrating relationships among fundamental credit risk preces using the rolling test proposed by Pascual [2003] and others, although Hansen and Johansen's [1999] recursive tests are often used in this context. There are two types of recursive tests under the VECM representation. In the "Z-representation", all of the parameters of the VECM are recursively re-estimated over the sample period. On the other hand, in the "R-representation", the short-run parameters $\mathbf{\Gamma}_i$ are fixed to their full sample values and only the long-run (error correction) parameters $\mathbf{\Pi}$ are recursively re-estimated. Thus, in the recursive tests, the sample size increases one-by-one as the relevant parameters are recursively re-estimated.

The recursive tests have one potential shortcoming by nature: the power of the test becomes higher as the sample size for estimation increases, which will bias toward rejection of the null hypothesis of no cointegration. In fact, our test results show this property.[22] To avoid such a bias, Pascual [2003] proposed a rolling test, in which equation (13) and thus the trace and maximum eigenvalue statistics are re-estimated using the same sample size (fixed rolling window).

c. Generalized Impulse Response Function

We use the "generalized" impulse responses proposed by Pesaran and Shin [1998] instead of the impulse responses derived from the usual "orthogonalized" Cholesky decomposition following Sims [1980]. The generalized impulse responses have an advantage in that they are invariant to the order of the variables in the VAR model. Let us briefly describe the method as follows.

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[22] The same tendency is observed in Pascual [2003] and Rangvid [2001]. We also used a residual-based stability test of cointegration relationships proposed by Gregory and Hansen [1996], but did not find meaningful results. We do not report these results.

Under the assumption that $\mathbf{R}_t$ is covariance-stationary, equation (12) can be rewritte as the infinite moving average representation as follows:

$$\mathbf{R}_t = \mathbf{A}_0\boldsymbol{\varepsilon}_t + \mathbf{A}_1\boldsymbol{\varepsilon}_{t-1} + \ldots + \mathbf{A}_\infty\boldsymbol{\varepsilon}_{t-\infty} = \sum_{i=0}^{\infty}\mathbf{A}_i\boldsymbol{\varepsilon}_{t-i}\,, \tag{14}$$

where $\mathbf{A}_i = \mathbf{a}_1\mathbf{A}_{i-1} + \mathbf{a}_2\mathbf{A}_{i-2} + \ldots + \mathbf{a}_k\mathbf{A}_{i-k}$ and $\mathbf{A}_0 = \mathbf{I}_p$. The conventional approach b Sims [1980] is to apply the Cholesky decomposition to $E\left(\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t^T\right) = \boldsymbol{\Sigma}$ such that $\mathbf{Q}\mathbf{Q}^T = \boldsymbol{\Sigma}$ wher $\mathbf{Q}$ is a $p \times p$ lower triangular matrix. Hence, $p \times 1$ vector of the orthogonalized impuls response function of a unit shock to the j th equation on $\mathbf{X}_{t+n}$ is given by

$$\boldsymbol{\psi}_j^o(n) = \mathbf{A}_n\mathbf{Q}\mathbf{e}_j\,, \tag{15}$$

where $\mathbf{e}_j$ is a $p \times 1$ selection vector with unity as its j th element and zeros elsewhere.

On the other hand, the approach by Pesaran and Shin [1998] directly uses the followin simplified version of the definition of the generalized impulse response function proposed b Koop et al. [1996]:

$$GI_x\left(n,\delta_j,\boldsymbol{\Omega}_{t-1}\right) = \mathrm{E}\left[\mathbf{X}_{t+n}\middle|\boldsymbol{\varepsilon}_{jt} = \delta_j,\boldsymbol{\Omega}_{t-1}\right] - \mathrm{E}\left[\mathbf{X}_{t+n}\middle|\boldsymbol{\Omega}_{t-1}\right], \tag{16}$$

where $\boldsymbol{\Omega}_{t-1}$ denotes the conditioning information set at time t-1. Note here that instead o shocking all the elements of $\boldsymbol{\varepsilon}_t$, as in Koop et al. [1996], Pesaran and Shin [1998] choose to shoc only one element and integrate out the effects of other shocks using the historically observe distribution of the errors. Under the assumption that $\boldsymbol{\varepsilon}_t$ follows a multivariate norma distribution, we get the generalized impulse response function as

$$\boldsymbol{\psi}_j^G(n) = \sigma_{jj}^{-\frac{1}{2}}\Sigma\mathbf{e}_j\,, \tag{17}$$

where σ_{jj} is the jj the element of the residual covariance matrix $\boldsymbol{\Sigma}$.

d. Multivariate GARCH Model

We use multivariate GARCH (M-GARCH) models to derive conditional correlations between each pair of variables. The basic structure can be written as

$$\mathbf{R}_t = \sum_{i=1}^{k} \mathbf{a}_{t-i}\mathbf{R}_{t-i} + \boldsymbol{\varepsilon}_t \qquad \boldsymbol{\varepsilon}_t \big| \boldsymbol{\Omega}_{t-1} \sim D(0, \mathbf{H}_t), \tag{18}$$

where we assume that the mean equation can be described by the same VAR (or VECM) system as in equation (12) (or (13)) and the residuals follow a multivariate Student *t* distribution D that can capture the fat-tailed property of each variable.[23,24]

There exist numerous methods of parameterizations of the conditional covariance matrix $\mathbf{H}_t$ in equation (18).[25] The specification we adopt is the BEKK[26] model proposed by Engle and Kroner [1995]. The BEKK model is sufficiently general and guarantees a positive definite conditional covariance matrix. The BEKK (1,1) model is given by [27]

$$\mathbf{H}_t = \mathbf{C}^T\mathbf{C} + \mathbf{A}^T\left(\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}_{t-1}^T\right)\mathbf{A} + \mathbf{B}^T\mathbf{H}_{t-1}\mathbf{B}\,, \tag{19}$$

where $$\mathbf{H}_t = \begin{bmatrix} h_{11,t} & h_{12,t} & h_{13,t} & h_{14,t} \\ h_{21,t} & h_{22,t} & h_{23,t} & h_{24,t} \\ h_{31,t} & h_{32,t} & h_{33,t} & h_{34,t} \\ h_{41,t} & h_{42,t} & h_{43,t} & h_{44,t} \end{bmatrix},\ \mathbf{C} = \begin{bmatrix} c_{11} & c_{12} & c_{13} & c_{14} \\ 0 & c_{22} & c_{23} & c_{24} \\ 0 & 0 & c_{33} & c_{34} \\ 0 & 0 & 0 & c_{44} \end{bmatrix},$$

[23] We adopt the following two-step estimation strategy: (a) estimate the VAR (ECM) mean system and (b) apply the M-GARCH model to the residuals derived from the VAR system. This treatment is just for securing efficiency of M-GARCH model estimation, which has 42 parameters to be estimated only in the residual-covariance terms.
[24] See Cambell, Lo, and Mackinlay [1997] for the relevance of the use of the multivariate Student *t* assumption.
[25] We prefer the BEKK model to the so-called "diagonal vec model" proposed by Bollerslev, Engle, and Wooldridge [1988] since the latter model does not guarantee positive definiteness of the conditional covariance matrix. For a survey of ARCH-type models, see Bollerslev, Chou, and Kroner [1992], Bollerslev, Engle, and Nelson [1994], and Pagan [1996]. For a survey of multivariate GARCH models in particular, see Bauwens, Laurent, and Rombouts [2005].
[26] BEKK is the acronym for Baba, Engle, Kraft, and Kroner [1990].
[27] In practice, GARCH (1,1) specification suffices since it corresponds to ARCH(∞).

$$\mathbf{A} = \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} \\ a_{31} & a_{32} & a_{33} & a_{34} \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix}, \text{ and } \mathbf{B} = \begin{bmatrix} b_{11} & b_{12} & b_{13} & b_{14} \\ b_{21} & b_{22} & b_{23} & b_{24} \\ b_{31} & b_{32} & b_{33} & b_{34} \\ b_{41} & b_{42} & b_{43} & b_{44} \end{bmatrix}.$$

Equation (19) is estimated under the assumption that the residuals follow the following multivariat Student *t* distribution with υ degree of freedom and the scale matrix $\mathbf{S}_t$:

$$f(\boldsymbol{\varepsilon}_t) = \frac{\Gamma[(\upsilon+k)/2]}{(\pi\upsilon)^{k/2}\Gamma(\upsilon/2)} \frac{|\mathbf{S}_t|^{-1/2}}{\left[1+\boldsymbol{\varepsilon}_t^T \mathbf{S}_t^{-1} \boldsymbol{\varepsilon}_t/\upsilon\right]^{(\upsilon+k)/2}}, \tag{20}$$

where k is a dimension of $\boldsymbol{\varepsilon}_t$, $\Gamma(\bullet)$ is the gamma function. $\mathbf{S}_t$ is given by

$$\mathbf{S}_t = \frac{\upsilon-2}{\upsilon}\mathbf{H}_t,$$

where the degree of freedom υ, simultaneously estimated with other parameters, should satisf $\upsilon > 2$. The Student *t* distribution converges to the normal distribution as υ increases, but ha kurtosis $3+(6/(\upsilon-4))$, which exists if and only if $\upsilon > 4$.

The time-varying conditional correlation between i th and j th variables is given by

$$\rho_{ij,t} = \frac{h_{ij,t}}{\sqrt{h_{ii,t}h_{jj,t}}}. \tag{21}$$

In the above BEKK model, the off-diagonal parameters are of particular interest in terms o volatility transmission across markets and banks. For instance, a_{ij} measures the transmission o the squared values of the shocks from i th variable in the previous period to the j th variable i the current period. Similarly, b_{ij} measures the transmission of the conditional volatility of th i th variable in the previous period to j th variable in the current period.

V. Empirical Results

(i) Decomposition of Risk Premiums

A. Factor Analysis

Table 3 and Figure 4 report the estimation results of factor analysis by principal factor method. We did not assume the number of factors in advance. Table 3 shows that three factors were retained in terms of a positive eigenvalue. Eigenvalues of the first two factors exceed one and these two factors account for about 96% of the total variance. In particular, note the importance of the first factor, which account for about 70% of the total variance.

Table 3(ii) and Figure 4(i) show that the first factor has almost equal factor loadings across all of the risk premiums. We call this factor "global factor". On the other hand, the second factor has positive loadings on the dollar risk premiums, JD and FD, and negative loadings on the yen risk premiums, JY and FY. We call this factor "currency factor". Although the relevant factors are limited to these two factors in terms of the magnitude of eigenvalues and explanatory power, the third factor deserves our attention since it has positive loadings on the risk premiums for foreign banks, FY and FD, and negative loadings on the risk premiums for Japanese banks, JY and JD. This third factor is likely to correspond to the relative degree of credit fundamentals between Japanese and foreign banks, which we call "credit factor". Thus, it seems appropriate to control for the effects of the first two factors in extracting fundamental prices of credit risk for Japanese and foreign banks from risk premium data.

Figure 4(ii) shows the time-series movement of these three factors.[28] During the period

[28] As a robustness check, we also used the method of independent component analysis. Independent component analysis is a recently developed linear transformation method that can decompose non-Gaussian data into the "statistically independent" factors. Using this method, we derived four factors from four risk premiums. The derived factors show a very similar movement to those derived by traditional factor analysis.

of financial instability from 1997 to 1998, the global factor and the credit factor experienced two large spikes and dips, respectively, and the currency factor has one dip. Since the credit and currency factors move in the opposite direction regarding the risk premiums for Japanese banks, JY and JD from the factor loadings, all of these factors, particularly the global and currency factors, are likely to have contributed a substantial rise in risk premiums for Japanese banks in this period.

B. State Space Model

Table 4 reports estimation results of the state space model. First, all of the coefficients, which link between the shadow prices of credit risk for Japanese and foreign banks, common to the yen and dollar markets, and the fundamental prices of bank credit risk, differently priced in the yen and dollar market, are estimated significantly at the 1% level. This result indicates that the relation between both prices are stable, although they contain positive noises. Also, it should be noted that $c2 / c12$ are found to be significantly larger than $c1 / c11$ as shown by the Wald test, as shown in Table 4(ii). In our interpretation, these coefficients are closely related to risk averseness of market participants in either yen or dollar market. Thus, the Wald test results suggest that the dollar market is significantly more risk averse than the yen market irrespective of the priced bank group, Japanese or foreign banks..

Next, all of the variance and covariance terms are significantly estimated at least at the 5% level. The significant estimates of the covariance terms indicate that cross-equation correlation structure for error terms, both between the yen and dollar markets for the same bank groups and between Japanese and foreign banks in the same currency markets, cannot be ignored.[29]

See Hyvarinen [1999], for details of independent component analysis.

[29] We estimated the same state space model without the covariance structure, but failed to get robust

Figure 5 compares the estimated shadow prices and the fundamental prices in either yen or dollar market.[30] We can see that among the fundamental prices, JYPRICE/ JDPRICE and FDPRICE move almost in parallel with the shadow prices of Japanese and foreign banks' credit risk, while FYPRICE seems quite insensitive to the shadow price of foreign banks' credit risk.

Table 5 reports summary statistics of the fundamental prices of bank credit risk. First, Table 5(i) shows that means of fundamental prices are almost the same as the corresponding risk premiums, but standard deviations are much lower. Also, skewness is negative for FYPRICE and FDPRICE, which was positive for FY and FD. The reason for this result may be that in our sample period, credit risk of foreign banks were not worried about in contrast to the Japanese banks and thus fundamental credit prices did not experience large spikes. Second, Table 5(ii) reports the correlation matrix between the fundamental prices of bank credit risk and the corresponding risk premiums. We find that correlations between fundamental prices for Japanese banks are high, while the correlations for foreign banks are even negative. This result suggests that factors other than credit fundamentals govern the variation of the observed risk premiums for foreign banks. Third, Table 5(iii) shows that the fundamental prices of bank credit risk explain only a small portion of the total variance of risk premiums: 2.6-2.7% for Japanese banks, and 0.5-2.3% for foreign banks. Particularly poor performance of FY is likely to arise from the relative impreciseness of yen-LIBOR as a proxy for foreign banks' yen interest rate.[31]

parameter estimates of both constant coefficients and variance terms.

[30] We ignored the first five observations from the estimated shadow and fundamental prices of bank credit risk due to instability of the estimates, which is inherent in the Kalman filter setup.

[31] As mentioned in Section III, the number of foreign banks in yen-LIBOR is 11 out of 16 referenced banks.

(ii) Time-Series Analysis

A. Risk Premiums

a. Granger Causality Test and Generalized Impulse Response Function

Now, let us move on to the time-series analysis of both risk premiums. Table 6 reports the estimation results of the VAR model and the corresponding Granger causality test. The lag length is determined by the Schwarz Criterion. As is evident from Table 6(ii), we can observe a high degree of informational interdependence between risk premiums except between the dollar risk premiums for Japanese banks (JD) and the yen risk premiums for foreign banks (FY).

Figure 6 shows the generalized impulse response function. As a general tendency, the impulse responses from the shocks of the same currency markets are much larger than the responses from the shocks of the same bank groups. Also, the impulse responses from the shocks of the same currency markets respond faster and are exponentially decayed compared with those from the shocks of the same bank groups. This result suggests that the global and currency factors are more important determinants in pricing banks' risk than the credit fundamentals themselves particularly in the short term.

b. M-GARCH Model

Table 7 reports estimation results of the M-GARCH model. The shape parameter υ is significantly larger than 2, indicating a much higher degree of fat tails than normal distribution. The Ljung-Box Q tests applied to the standardized residuals show that serial correlation of the risk premiums remains. However, our BEKK model did a fairly good job to eliminate the heteroscedasticity in squared standardized residuals.

Now, let us look at the estimation results of both ARCH and GARCH terms. All of the diagonal parameters are significant, which implies a high degree of persistence in conditional standard deviations. Regarding the estimation results of off-diagonal parameters, which measure the degree of volatility spillovers, 4 parameters out of 12 ARCH parameters and 8 parameters out of 12 GARCH parameters are significant. In particular, insignificance of the parameters a12, a21 a34 of ARCH parameters is of interest since they measure the interdependence of volatility between the same bank groups.[32]

Figure 7 shows the conditional correlations derived from the M-GARCH model. We can see that most conditional correlations widely fluctuate, which supports the use of time-varying correlations instead of usual constant correlations. Notable properties of the estimated conditional correlations are as follows. First, correlations of the same bank groups' risk premiums between the yen and dollar markets (JY vs. JD and FY vs. FD) fluctuate around zero. This is rather a surprising result since if the risk premiums properly reflect credit fundamentals of the bank groups, the correlations between JY and JD and between FY and FD should be high enough.

Second, throughout the whole period, correlations between Japanese and foreign banks' risk premiums in the same currency markets (JY vs. FY and JD vs. FD) are very high. This result is suggestive of the importance of a currency or global factor in decomposing the risk premiums.

[32] Note here that in assessing the volatility spillover, not the sign but only the significance level of the parameters is important since only squared ARCH and GARCH terms enter into the volatility spillover paths. Signs of ARCH and GARCH terms are important, however, in computing the conditional correlations.

B. Fundamental Prices of Credit Risk

a. Cointegrating Relationships

Since our fundamental prices of bank credit risk are I(1) by construction, we first analyze cointegrating relationships. Figure 8 shows the trace and maximum eigenvalue statistics from the stability test of cointegrating relationships among the four fundamental prices, JYPRICE, JDPRICE, FYPRICE, and FDPRICE.[33] Throughout the sample periods, three cointegrating relationships were found in a very stable manner.[34] Thus, we use full sample period to derive the cointegrating vectors, which is shown in Table 8. As is easily expected, the cointegration rank test shows that there are three cointegrating vectors among JYPRICE, JDPRICE, FYPRICE, and FDPRICE. LR test for the equilibrium relationship [1,-1,-1,1,C] shows, however, that the cointegration restriction is rejected at the 1% significance level.

b. Granger Causality Test and Generalized Impulse Response Function

Table 9 reports the estimation results of VECM and the Granger causality test. Lag length of the VECM is determined by the Schwarz Criterion. As shown in Table 9(ii), a higher degree of informational interdependence are found than in the case of risk premiums reported in Table 6(ii). Indeed, each of the four fundamental prices significantly Granger-causes other three prices.

Figure 9 shows the generalized impulse response function of each fundamental price. In contrast to the risk premiums, each fundamental price of bank credit risk responds larger from

[33] We use 1,000 observations for the size of the rolling window. We followed Banerjee, Lumsdaine, and Stock [1992], who recommend that the size of the rolling window should be one-third of total number of observations in the context of the stability of unit-root tests. Since we have 3,086 observations in total, the choice of 1,000 observations correspond to their recommendation.

[34] The sole exception is around September 1999. But, if we adopt the 10% significance level, three cointegrating relationships are found.

the shocks of the same bank groups than from the shocks of the same currency markets. This result suggests that estimated fundamental prices of bank credit risk properly reflect credit fundamentals.

c. M-GARCH Model

Table 10 reports estimation results of the M-GARCH model consisting of four fundamental prices. The shape parameter υ is significantly larger than 2 as in the case of risk premiums. The Ljung-Box Q tests show that serial correlation remains in the fundamental prices of Japanese banks' credit risk, JYPRICE and JDPRICE. However, our BEKK model did a fairly good job to eliminate the heteroscedasticity in the fundamental prices of foreign banks' credit risk, FYPRICE and FDPRICE.

Next, let us look at the estimation results of ARCH and GARCH terms. First, all of the diagonal parameters are significant. Second, regarding the estimation results of off-diagonal parameters, 8 parameters out of 12 ARCH parameters and 8 parameters out of 12 GARCH parameters were significant. In particular, it is noteworthy that the parameters that measure the interdependence of volatility between the same bank groups, a12, a21, a34 of ARCH parameters are significant unlike the case of risk premiums.

Figure 10 shows the conditional correlations between four fundamental prices. There are several points to note here, as compared to the case of risk premiums shown in Figure 7. First, the fundamental prices for the same bank groups, JYPRICE/JDPRICE and FYPRICE/FDPRICE are highly correlated almost throughout the sample period. In particular, the correlation between JYPRICE and JDPRICE is found to be almost unity. Second, the fundamental prices of different bank groups in the same currency market, JYPRICE/FYPRICE and JDPRICE/FDPRICE, are negatively correlated in marked contrast to the case of risk premiums in which JY/FY and JD/FD shows a very high correlations. Also, the fundamental prices of difference banks in different currency markets, JYPRICE/FDPRICE and JDPRICE/FYPRICE, are negatively correlated in many phases. This result indicates that credit risks of Japanese banks and foreign banks have moved in an opposite direction during the sample period. This is consistent with our experience in that Japanese banks have struggled hard to dispose of their non-performing loans until quite recently , while the U.S. banks recovered from the S&L crisis and Latin American crisis occurred in the 1980s from the 1990s.

Put these results together, we infer that we successfully derived the fundamental prices of each bank group. And the global and currency common factors are likely to create spurious correlations between observed risk premiums for different bank groups between the different currency markets.

VI. Concluding Remarks

This paper has investigated the role of TIBOR/LIBOR as indicators of bank credit risk and the interdependence structure of bank credit risk in the money markets within and across the border In doing so, we decomposed the risk premiums for Japanese and foreign banks constructed from TIBOR/LIBOR to extract fundamental prices of credit risk. Our findings can be summarized as follows.

(i) Observed risk premiums constructed from TIBOR/LIBOR contain two common factors global and currency factors, which explain most of the variation of the observed risk premiums.

(ii) Thus, the generalized impulse response of risk premiums from the shocks of the same currency markets are much larger than the responses from the shocks of the same bank groups. And the conditional correlations of the same bank groups' risk premiums between the yen and dollar markets fluctuate around zero, while the correlations between Japanese and foreign banks' risk premiums in the same currency market are very high.

(iii) After controlling for these common factors, we successfully derived the fundamental prices of bank credit risk both for Japanese and foreign banks using the state space model. These fundamental prices show plausible time-series properties such as a high degree of impulse response from the shocks of the same bank groups, and a high correlation of the same bank groups' credit risk between the two markets. However, the fundamental prices account for only a tiny portion of the total variance of risk premiums.

Put these results together, although TIBOR/LIBOR have played the role of indicators of bank credit risk since the 1990s, the importance has been substantially reduced, as asserted by Ito and Harada [2004]. We conclude this paper by mentioning three possible causes of this result. The first one is that Japanese banks have been required to put up cash collaterals to raise dollars in the money markets since around 2000-2001. The second one is that weaker banks have already exited from the international money markets. These possibilities are pointed out by Ito and Harada [2004]. The third one is that money markets ceases to properly function as a price discovery mechanism in a very low interest rate environment, particularly in Japan. Baba, et al. [2006] supports this view by analyzing the dispersion and credit curves of interest rates on NCDs issued by individual Japanese banks. To determine the relative importance of these hypotheses is beyond the scope of this paper. This is one of our future tasks.

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Appendix 1: Negative FX Swap Yen Funding Cost for Foreign Banks

In this Appendix, we try to decompose the FX swap yen funding cost for foreign banks, which has been frequently negative in recent years. Let us restate the yen funding costs in net terms c for foreign banks in the FX swap market as

$$1 + c = \frac{F}{S}\left(1 + i^{*} + FD\right) \tag{1a}$$

Equilibrium condition (3) implies that

$$1 + c = \frac{F}{S}\left(1 + i^{*} + FD\right) = \frac{1 + i + JY}{1 + i^{*} + JD}\left(1 + i^{*} + FD\right)$$

$$\Leftrightarrow c \approx i + FD - \left[JD - JY\right] \tag{2a}$$

Equation (2a) shows that the yen funding costs for foreign banks in the FX swap market can be decomposed into the following three factors: (a) the yen risk-free interest rate, (b) the risk premium for foreign banks in the dollar market, and (c) the difference in the risk premiums for Japanese banks between the dollar and yen markets.

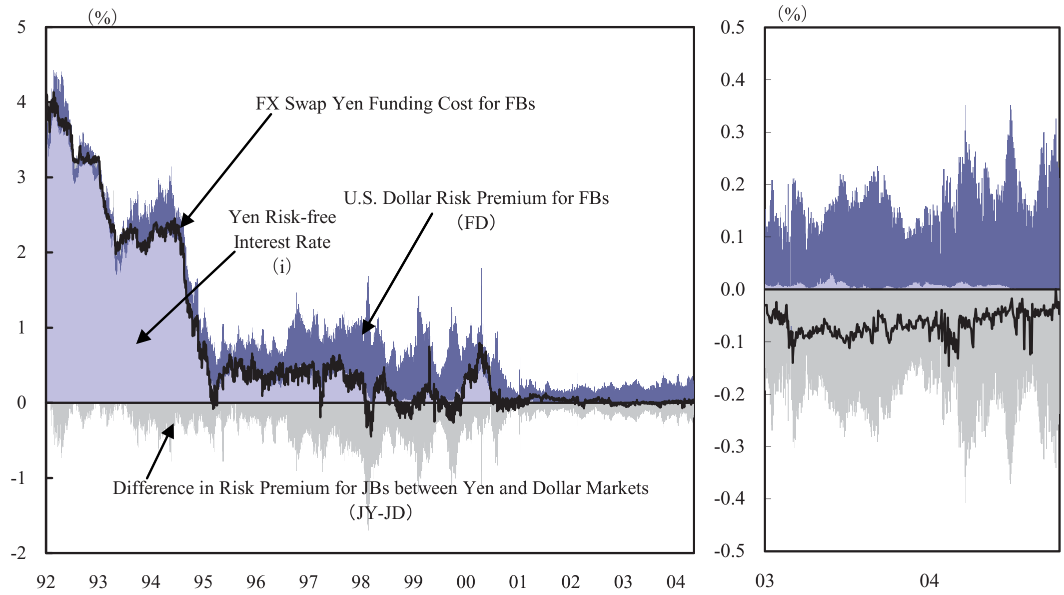
If the difference in the risk premiums for Japanese banks between the two markets is zero, that is, $JD = JY$, the yen funding costs for foreign banks boil down to the usual form of funding costs: the sum of the yen risk-free interest rate and the risk premium for foreign banks.[35] Put differently, the fact that the yen funding costs differ from the usual form of funding costs stems from the difference in the risk evaluation of Japanese banks between the dollar and the yen markets.

Appendix Figure shows the decomposition result based on this asymmetry in risk evaluation between the two markets. This figure reveals that in a quite low interest rate environment

[35] Note that equation (4) yields $FY = FD = \overline{\theta}$ when $JY = JD$.

in recent years, the difference in risk premiums for Japanese Banks between yen and dollar markets causes negative FX swap yen funding cost for foreign banks.

Appendix Figure: Decomposition of FX Swap Yen Funding Cost for Foreign Banks



Note: Left figure uses TIBOR/LIBOR as the proxy for the interest rates for Japanese banks (JBs) and foreign banks (FBs), respectively. Right figure uses yen and U.S. dollar bid interest rates exclusively for Japanese and foreign banks in the Euro markets. The bid rates are available only from May 2004.

Source: Meitan Tradition Co. (left figure). For the data source of right figure, see Appendix 2.

Appendix 2: Data Details

We use 90-day TIBOR/LIBOR defined as the average of the interest rates offered by reference banks as the proxy for the interest rates for Japanese banks and foreign banks, respectively. Data sources are as follows:

Sample Period: 1992/8/3 to 2005/2/2 (Number of Observations: 3,086)

i +JY	Yen Interest Rate for Japanese Banks	Japanese Bankers Association (Yen-TIBOR)
i +FY	Yen Interest Rate for Foreign Banks	British Bankers Association (Yen-LIBOR)
i^* +JD	U.S. Dollar Interest Rate for Japanese Banks	QUICK (U.S. Dollar-TIBOR)
i^* +FD	U.S. Dollar Interest Rate for Foreign Banks	British Bankers Association (U.S. Dollar-LIBOR)
i	Treasury Bill Rate in Japan	Bloomberg
i^*	Treasury Bill Rate in the U.S.	FRB, *FRED*
S	Domestic Currency Value of the Spot Exchange Rates.	Bank of Japan
$F-S$	Forward Premium	Bank of Japan

The reference banks of TIBOR and LIBOR are as follows:

Yen-TIBOR	**Mizuho Bank**, **Sumitomo Mitsui Banking Co**., JP Morgan Chase, **the Bank of Tokyo Mitsubishi**, **Saitama Resona Bank**, **UFJ Bank**, **Shinsei Bank**, **the Chuo Mitsui Trust and Banking Co**., **the Mitsubishi Trust and Banking Co**., **the Sumitomo Trust and Banking Co**., **Mizuho Corporate Bank**, **Mizuho Trust and Banking Co**., **the Shoko Chukin Bank**, UBS AG, **Shinkin Central Bank**, **the Norinchukin Bank**
U.S. Dollar-TIBOR	**Sumitomo Mitsui Banking Co**., **the Bank of Tokyo Mitsubishi**, **UFJ Bank**, **Mizuho Corporate Bank**, **the Norinchukin Bank**, **the Mitsubishi Trust and Banking Co**., **the Sumitomo Trust and Banking Co**., **the Chuo Mitsui Trust and Banking Co**., Citibank NA, UBS AG
Yen-LIBOR	Bank of America, Barclays Bank Plc, Citibank NA, Deutsche Bank AG, HSBC, JP Morgan Chase, Lloyds TSB Bank Plc, Rabobank, The Royal Bank of Scotland Group, UBS AG, Westdeutsche Landesbank AG, **the Bank of Tokyo Mitsubishi**, **Sumitomo Mitsui Banking Co**., **Mizuho Corporate Bank**, **UFJ Bank**, **the Norinchukin Bank**
U.S. Dollar-LIBOR	Abbey National Plc, Bank of America, Barclays Bank Plc, Citibank NA, Credit Suisse First Boston, Deutsche Bank AG, HBOS, HSBC, JP Morgan Chase, Lloyds TSB Bank Plc, Rabobank, The Royal Bank of Scotland Group, UBS AG, Westdeutsche Landesbank, **the Bank of Tokyo Mitsubishi**, **the Norinchukin Bank**

Note: Bold letters indicate Japanese banks.

Table 1: Summary Statistics (i)

(i) Basic Statistics

Sample Period: 1992/8/3 to 2005/2/2 (Number of Observations: 3,086)

(%)	Mean	Std.Dev.	Skewness	Kurtosis	Jarque-Bera	LB(12)	$LB^2(12)$
JY	0.169	0.139	2.047	7.974	5330.08***	30023***	21107***
JD	0.483	0.311	1.729	6.960	3549.75***	32020***	30681***
FY	0.129	0.093	1.475	5.432	1877.01***	24999***	21107***
FD	0.398	0.216	1.324	5.579	1754.67***	29536***	26392***

(ii) Correlation Matrix

	JY	JD	FY	FD
JY	1.000			
JD	0.664	1.000		
FY	0.918	0.529	1.000	
FD	0.349	0.895	0.294	1.000

Notes: 1. LB(12) and $LB^2(12)$ are Ljung-Box Q test statistics for serial correlations of the variables themselves and squared variables up to the 12th order.
2. *** denotes the 1% significance level.

Table 2: Unit Root Test

Specification: $\Delta y_t = \mu + \alpha_0 y_{t-1} + \alpha_1 \Delta y_{t-1} + \cdots \alpha_N \Delta y_{t-N} + bt + \varepsilon_t$

Sample Period: 1992/8/3 to 2005/2/2 (Number of Observations: 3,086)

	ADF (Augmented Dickey-Fuller) Test		PP (Phillips-Perron) Test	
	Test Statistic	Lags	Test Statistic	Bandwidth
JY	-5.462***	0	-5.405***	9
JD	-4.363***	2	-4.334***	15
FY	-7.958***	2	-8.847***	4
FD	-5.132***	3	-6.361***	1

Notes: 1. The number of lags is chosen based on Schwarz Criterion.
2. *, **, and *** show that the null hypothesis of the existence of a unit root is rejected at the 10%, 5% and 1% significance level, respectively.

JY : Japanese Banks' Yen Risk Premium JD : Japanese Banks' Dollar Risk Premium
FY: Foreign Banks' Yen Risk Premium FD: Foreign Banks' Dollar Risk Premium

Table 3: Estimation Results of Factor Analysis (i)

(i) Importance of Factors

Sample Period: 1992/8/3 to 2005/2/2 (Number of Observations: 3,086)

	Factor 1	Factor 2	Factor 3
Eigenvalue	2.820	1.000	0.085
Proportion of the total variance	0.705	0.250	0.021
Cumulative proportion of the total variance	0.705	0.955	0.976

(ii) Factor Loadings

	Factor 1	Factor 2	Factor 3
JY	0.883	-0.448	-0.131
JD	0.921	0.372	-0.136
FY	0.807	-0.511	0.179
FD	0.736	0.633	0.132

Notes: 1. The method of principal factor is used.
2. The result is before rotation.

JY : Japanese Banks' Yen Risk Premium JD : Japanese Banks' Dollar Risk Premium
FY: Foreign Banks' Yen Risk Premium FD: Foreign Banks' Dollar Risk Premium

Table 4: Estimation Results of State Space Model

(i) Specification

$$\begin{bmatrix} JY \\ JD \\ FY \\ FD \end{bmatrix}_t = \begin{bmatrix} JYPRICE \\ JDPRICE \\ FYPRICE \\ FDPRICE \end{bmatrix}_t + \begin{bmatrix} s4 & s6 \\ s5 & s7 \\ s14 & s16 \\ s15 & s17 \end{bmatrix}_t \begin{bmatrix} Fg \\ Fc \end{bmatrix}_t + \begin{bmatrix} e1 \\ e2 \\ e11 \\ e12 \end{bmatrix}_t ,$$

where

$$\begin{bmatrix} JYPRICE \\ JDPRICE \end{bmatrix}_t = \begin{bmatrix} c3 \\ c4 \end{bmatrix} + \begin{bmatrix} c1 \\ c2 \end{bmatrix} s3_t + \begin{bmatrix} e3 \\ e4 \end{bmatrix}, \quad \begin{bmatrix} FYPRICE \\ FDPRICE \end{bmatrix}_t = \begin{bmatrix} c13 \\ c14 \end{bmatrix} + \begin{bmatrix} c11 \\ c12 \end{bmatrix} s13_t + \begin{bmatrix} e13 \\ e14 \end{bmatrix},$$

$$\begin{bmatrix} s3 \\ \vdots \\ s7 \end{bmatrix}_t = \begin{bmatrix} s3 \\ \vdots \\ s7 \end{bmatrix}_{t-1} + \begin{bmatrix} e5 \\ \vdots \\ e9 \end{bmatrix}_t, \text{ and } \begin{bmatrix} s13 \\ \vdots \\ s17 \end{bmatrix}_t = \begin{bmatrix} s13 \\ \vdots \\ s17 \end{bmatrix}_{t-1} + \begin{bmatrix} e15 \\ \vdots \\ e19 \end{bmatrix}_t .$$

(ii) Parameter Estimates and Wald Test Results

Sample Period: 1992/8/3 to 2005/2/2 (Number of Observations: 3,086)

	Parameter	Std. error
c1	0.069***	5.01E-07
c2	0.150***	9.47E-09
c3	-0.349***	0.010
c4	-0.650***	0.022
c11	0.020***	3.49E-08
c12	0.105***	1.46E-05
c13	-0.442***	0.108
c14	-2.847***	0.564
lnVar(e1)	-18.505***	3.44E-06
lnVar(e2)	-14.543***	0.001
lnVar(e3)	-17.037***	6.29E-05
lnVar(e4)	-14.465***	0.026
lnVar(e5)	-4.789***	4.23E-05
lnVar(e6)	-16.008***	0.009
lnVar(e7)	-15.946***	1.47E-04
lnVar(e8)	-15.209***	0.001
lnVar(e9)	-14.545***	4.58E-06
lnVar(e11)	-9.820***	0.024
lnVar(e12)	-9.210***	0.009
lnVar(e13)	-10.203***	0.001
lnVar(e14)	-10.991***	0.001
lnVar(e15)	-5.954***	0.002
lnVar(e16)	-10.747***	0.013
lnVar(e17)	-10.144***	0.003
lnVar(e18)	-9.875***	0.041
lnVar(e19)	-9.901***	0.001
cov(e1,e2)*10^3	3.54E-05***	2.67E-06
cov(e3,e4)*10^3	2.35E-05***	6.00E-06
cov(e6,e7)*10^3	6.59E-05***	3.20E-09
cov(e8,e9)*10^3	2.20E-04***	1.62E-07
cov(e11,e12)*10^3	-2.67E-04***	1.03E-07
cov(e13,e14)*10^3	0.001***	8.90E-10
cov(e16,e17)*10^3	0.009***	6.31E-07
cov(e18,e19)*10^3	-7.67E-05***	1.77E-09
cov(e1,e11)*10^3	0.001***	1.75E-05
cov(e2,e12)*10^3	2.80E-04***	3.05E-05
cov(e3,e13)*10^3	0.001***	2.27E-08
cov(e4,e14)*10^3	0.008***	4.22E-05
cov(e5,e15)*10^3	-0.060**	0.028
cov(e6,e16)*10^3	0.001***	9.10E-06
cov(e7,e17)*10^3	0.001***	2.22E-05
cov(e8,e18)*10^3	0.002***	4.94E-05
cov(e9,e19)*10^3	0.003***	1.35E-05
Log likelihood	42617.07	

Wald Test	
Null Hypothesis (H0)	χ^2
c2-c1=0	2.74E+10***
c12-c11=0	3.38E+07***

Notes: 1. Marquardt method is used as an optimization algorithm.
2. *, ***, and *** denote the 10%, 5%, and 1% significance level, respectively.

Table 5: Summary Statistics (ii)

(i) Basic Statistics

Sample Period: 1992/8/7 to 2005/2/2 (Number of Observations: 3,081)

	Mean	Std.Dev.	Skewness	Kurtosis	Jarque-Bera	LB(12)	$LB^2(12)$
JYPRICE	0.002	0.001	2.043	7.956	5303.88***	30023***	21107***
JDPRICE	0.005	0.003	1.731	6.968	3565.92***	32020***	30681***
FYPRICE	0.001	0.001	1.470	5.409	1856.78***	24999***	21107***
FDPRICE	0.004	0.002	1.325	5.582	1760.55***	29536***	26392***

(ii) Correlation Matrix

	JY	JD	FY	FD
JYPRICE	1.000			
JDPRICE	0.664	1.000		
FYPRICE	0.918	0.529	1.000	
FDPRICE	0.349	0.895	0.294	1.000

Notes: 1. LB(12) and $LB^2(12)$ are Ljung-Box *Q* test statistics for serial correlations of the variables themselves and squared variables up to the 12^{th} order.
2. *** denotes significance at the 1% level.

(iii) Importance of Factors: Proportion of the Total Variance

	Global Factor	Currency Factor	Fundamental Price	Three Factors
JY	0.724	0.250	0.027	0.999
JD	0.805	0.169	0.026	0.999
FY	0718	0.278	0.005	0.999
FD	0.681	0.293	0.023	0.997

JYPRICE : Fundamental Price of Credit Risk for Japanese Banks in the Yen Market
JDPRICE : Fundamental Price of Credit Risk for Japanese Banks in the Dollar Market
FYPRICE : Fundamental Price of Credit Risk for Foreign Banks in the Yen Market
FDPRICE : Fundamental Price of Credit Risk for Foreign Banks in the Dollar Market

JY : Japanese Banks' Yen Risk Premium JD : Japanese Banks' Dollar Risk Premium
FY: Foreign Banks' Yen Risk Premium FD: Foreign Banks' Dollar Risk Premium

Table 6: Estimation Results of VAR Model

(i) Estimation Results

Sample Period: 1992/8/3 to 2005/2/2 (Number of Observations: 3,086)

	JY	JD	FY	FD
Constant	0.005***	0.006**	0.003***	0.011***
	(0.001)	(0.003)	(0.001)	(0.002)
JY(-1)	0.850***	0.139***	0.261***	-0.052
	(0.026)	(0.056)	(0.028)	(0.051)
JY(-2)	-0.063**	-0.150**	-0.016***	-0.076
	(0.031)	(0.069)	(0.034)	(0.062)
JY(-3)	0.087***	-0.016	0.007	0.039
	(0.025)	(0.054)	(0.027)	(0.049)
JD(-1)	0.090***	0.781***	0.004	0.097***
	(0.016)	(0.035)	(0.017)	(0.031)
JD(-2)	0.038**	0.193***	-0.005	-0.003
	(0.019)	(0.041)	(0.020)	(0.037)
JD(-3)	-0.060***	0.021	-0.022	-0.047
	(0.016)	(0.035)	(0.017)	(0.032)
FY(-1)	0.143***	-0.043	0.686***	-0.002
	(0.023)	(0.050)	(0.025)	(0.046)
FY(-2)	-0.017	0.096*	0.027	0.107**
	(0.026)	(0.058)	(0.028)	(0.053)
FY(-3)	-0.054**	-0.007	0.116***	-0.016
	(0.023)	(0.050)	(0.025)	(0.046)
FD(-1)	-0.098***	0.119***	-0.016	0.750***
	(0.017)	(0.038)	(0.019)	(0.034)
FD(-2)	-0.026	-0.175***	0.032	0.051
	(0.020)	(0.044)	(0.022)	(0.040)
FD(-3)	0.059	0.044	0.011	0.125***
	(0.017)	(0.038)	(0.019)	(0.035)
Adj. R-squared	0.968	0.969	0.915	0.947

(ii) Granger Causality Test Statistics ($\chi 2$ Statistics)

	JY	JD	FY	FD
Excluded				
JY		8.629**	93.541***	7.597*
JD	102.221***		6.201	16.427***
FY	48.262***	3.633		8.370**
FD	82.461***	16.978***	8.274**	
ALL	147.017***	27.650***	137.078***	21.510**

Notes: 1. Figures in parentheses are standard errors.
2. ***, **, and * denote the 1%, 5%, and 10% significance level, respectively.
3. Lag length is chosen based on Schwarz Criterion.
4. Figures in (ii) denote the $\chi 2$ test statistics.

JY : Japanese Banks' Yen Risk Premium JD : Japanese Banks' Dollar Risk Premium
FY: Foreign Banks' Yen Risk Premium FD: Foreign Banks' Dollar Risk Premium

Table 7: Estimation Result of M-GARCH Model (i)

Sample Period: 1992/8/3 to 2005/2/2 (Number of Observations: 3,086)

	Parameter	std. error	*t*-value
	ARCH		
a11	0.408***	0.026	15.840
a12	0.080	0.058	1.390
a13	-0.310***	0.027	-11.580
a14	-0.055	0.054	-1.027
a21	0.007	0.009	0.870
a22	0.419***	0.040	10.036
a23	0.041***	0.011	3.726
a24	0.030	0.034	0.859
a31	-0.103***	0.018	-5.788
a32	-0.045	0.055	-0.815
a33	0.632***	0.037	17.120
a34	0.042	0.053	0.805
a41	0.002	0.009	0.261
a42	-0.026	0.038	-0.679
a43	-0.035**	0.011	-3.162
a44	0.351***	0.039	8.901
	GARCH		
b11	0.938***	0.004	220.000
b12	-0.030*	0.016	-1.896
b13	0.064***	0.005	11.930
b14	0.011	0.014	0.800
b21	-0.011***	0.002	-5.118
b22	0.911***	0.009	99.630
b23	-0.012***	0.003	-4.083
b24	-0.022***	0.008	-2.665
b31	0.032***	0.005	7.170
b32	0.021	0.017	1.219
b33	0.892***	0.006	151.300
b34	-0.017	0.015	-1.098
b41	0.006***	0.002	3.097
b42	-0.015	0.009	-1.575
b43	0.006**	0.003	2.433
b44	0.934***	0.009	109.600
	Diagnostic Statistics		
υ (Student *t*)	2.786***	0.098	7.984
LB(12) JY	63.66***		
JD	23.36**		
FY	221.16***		
FD	29.71**		
$LB^2(12)$ JY	0.09		
JD	15.03		
FY	5.55		
FD	12.16		

Notes: 1. υ is the shape parameter (degree of freedom) of the Student *t* distribution for the four joint error processes. *t*-values are computed based on the null and alternative hypotheses $\upsilon=2$ and $\upsilon>2$, respectively.

2. a_{ij} and b_{ij} measure the volatility transmission from *i*-th to *j*-th risk premiums (1:JY, 2:JD, 3:FY, 4:FD).

3. LB(12) and $LB^2(12)$ are Ljung-Box *Q* tests for white noise in the linear and squared standardized residuals up to the 12^{th} order.

4. *, ***, and *** denote the 10%, 5%, and 1% significance level, respectively.

5. Estimation results of constant terms are omitted due to the limitation of space.

Table 8: Cointegration Test

Sample Period: 1992/8/3 to 2005/2/2 (Number of Observations: 3,086)

Cointegration Rank Test					
H0	H1	Eigenvalue	Trace Statistic	Max-Eigen Statistic	Lags
$r \leq 0$	$r = 1$	0.201	1098.999***	689.867***	3
$r \leq 1$	$r = 2$	0.099	409.132***	323.981***	
$r \leq 2$	$r = 3$	0.020	85.151***	63.814***	
$r \leq 3$	$r = 4$	0.007	21.337***	21.337***	

Cointegrating Vectors				
JYPRICE	JDPRICE	FYPRICE	FDPRICE	Constant
1.000	0.000	0.000	0.677***	-0.454***
0.000	1.000	0.000	1.476***	-1.102***
0.000	0.000	1.000	-0.195***	-0.103***

Test of Cointegration Restrictions				
1.000	-1.000	-1.000	1.000	-26.734*** -34.833*** 8.033***
LR test : $\chi 2$ (1)=557.725***				

Notes 1. JBs and FBs denote Japanese banks and foreign banks, respectively.
2. We took logarithm of interest rates.
3. The number of lags is chosen based on Schwarz Criterion.
4. r denotes the number of cointerating ranks.
5. LR test denotes the Log-Likelihood Ratio test for the equilibrium relationship [1,-1,-1,1,C], where C is constant
6 *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

Table 9: Estimation Results of VECM

(i) Estimation Results

Sample Period: 1992/8/3 to 2005/2/2 (Number of Observations: 3,086)

	Δ (JYPRICE)	Δ (JDPRICE)	Δ (FYPRICE)	Δ (FDPRICE)
Error 1	-1.536**	-1.378	-0.746	15.161***
	(0.723)	(1.589)	(0.481)	(1.159)
Error 2	0.693**	0.608	0.342	-6.960***
	(0.330)	(0.726)	(0.220)	(0.530)
Error 3	0.174***	0.352***	-0.365***	-0.504***
	(0.042)	(0.091)	(0.028)	(0.067)
Δ (JYPRICE(-1))	-0.785	-1.780	0.126	-9.938***
	(0.766)	(1.685)	(0.510)	(1.229)
Δ (JYPRICE(-2))	1.565***	3.494***	-0.820**	-3.722***
	(0.599)	(1.318)	(0.399)	(0.961)
Δ (JYPRICE(-3))	-0.043	-0.149	-0.007	-3.773***
	(0.377)	(0.830)	(0.251)	(0.605)
Δ (JDPRICE(-1))	0.233	0.540	-0.014	4.560***
	(0.352)	(0.775)	(0.235)	(0.566)
Δ (JDPRICE(-2))	-0.805**	-1.798***	0.422	1.687***
	(0.277)	(0.609)	(0.184)	(0.444)
Δ (JDPRICE(-3))	0.019	0.064	0.014	1.729***
	(0.174)	(0.383)	(0.116)	(0.280)
Δ (FYPRICE(-1))	0.003	0.018	-0.074**	0.526***
	(0.050)	(0.110)	(0.033)	(0.080)
Δ (FYPRICE(-2))	-0.131***	-0.285***	0.039	0.226***
	(0.047)	(0.102)	(0.031)	(0.075)
Δ (FYPRICE(-3))	0.040	0.097	-0.022	0.272***
	(0.035)	(0.078)	(0.024)	(0.057)
Δ (FDPRICE(-1))	-0.016	-0.038	-0.005	-0.233***
	(0.018)	(0.040)	(0.012)	(0.029)
Δ (FDPRICE(-2))	0.050***	0.111***	-0.023***	-0.035*
	(0.012)	(0.025)	(0.008)	(0.019)
Δ (FDPRICE(-3))	-0.020**	-0.045**	0.005	-0.060***
	(0.009)	(0.019)	(0.006)	(0.014)
Adj. R-squared	0.299	0.299	0.275	0.133

(ii) Granger Causality Test Statistics ($\chi 2$ Statistics)

	JYPRICE	JDPRICE	FYPRICE	FDPRICE
Excluded				
JYPRICE		24.222***	10.227**	77.841***
JDPRICE	22.599***		10.731**	76.870***
FYPRICE	15.147***	15.716***		52.538***
FDPRICE	28.422***	29.066***	10.798**	
ALL	43.257***	47.153***	102.239***	88.699***

Notes: 1. Figures in parentheses are standard errors.
2. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.
3. Lag length is chosen based on Schwarz Criterion.
4. Figures in B denote the test statistics following $\chi 2$ distribution with degree of freedom 2 when one variable i excluded and 6 when all the variables are excluded.

Table 10: Estimation Results of M-GARCH Model (ii)

Sample Period: 1992/8/3 to 2005/2/2 (Number of Observations: 3,086)

		Parameter	std. error	t-value
		ARCH		
	a11	0.891***	0.030	30.150
	a12	0.799***	0.105	7.642
	a13	-0.381*	0.212	-1.798
	a14	-5.885***	0.732	-8.041
	a21	-0.115***	0.020	-5.664
	a22	0.270***	0.071	3.831
	a23	0.148	0.098	1.520
	a24	2.613***	0.336	7.772
	a31	-0.001	0.016	-0.049
	a32	0.004	0.035	0.116
	a33	0.414***	0.026	15.690
	a34	0.132***	0.048	2.736
	a41	0.001	0.007	0.873
	a42	0.001	0.015	0.124
	a43	-0.002***	0.007	-2.730
	a44	0.207***	0.025	8.277
		GARCH		
	b11	0.749***	0.015	49.320
	b12	-0.320***	0.028	-11.590
	b13	0.001	0.044	0.148
	b14	2.152***	0.149	14.450
	b21	0.039***	0.006	6.881
	b22	0.983***	0.009	11.110
	b23	0.007	0.020	0.358
	b24	-0.957***	0.069	-13.840
	b31	-0.010**	0.004	-2.139
	b32	-0.024***	0.010	-2.445
	b33	0.943***	0.004	23.490
	b34	-0.051***	0.012	-4.415
	b41	0.001	0.002	0.371
	b42	0.005*	0.004	1.361
	b43	0.002	0.002	1.002
	b44	1.004***	0.005	206.500
		Diagnostic Statistics		
	υ (Student t)	2.587***	0.078	7.517
LB(12)	JYPRICE	15.33		
	JDPRICE	10.63		
	FYPRICE	41.00***		
	FDPRICE	30.17***		
$LB^2(12)$	JYPRICE	0.42		
	JDPRICE	16.32		
	FYPRICE	65.73***		
	FDPRICE	454.04***		

Notes: 1. υ is the shape parameter (degree of freedom) of the Student t distribution for the four joint error processes. t-values are computed based on the null and alternative hypotheses υ =2 and υ >2, respectively.

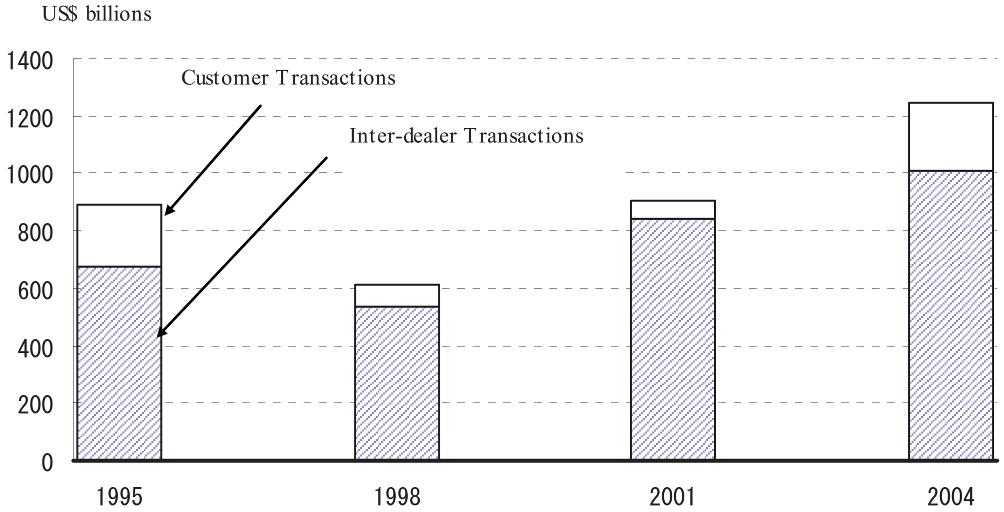
2. a_{ij} and b_{ij} measure the volatility transmission from i-th to j-th risk premiums (1:JYPRICE, 2:JDPRICE, 3:FYPRICE, 4:FDPRICE).

3. LB(12) and $LB^2(12)$ are Ljung-Box Q tests for white noise in the linear and squared standardized residuals up to the 12th order.

4. *, ***, and *** denote the 10%, 5%, and 1% significance level, respectively.

5. Estimation results of constant terms are omitted due to the limitation of space.

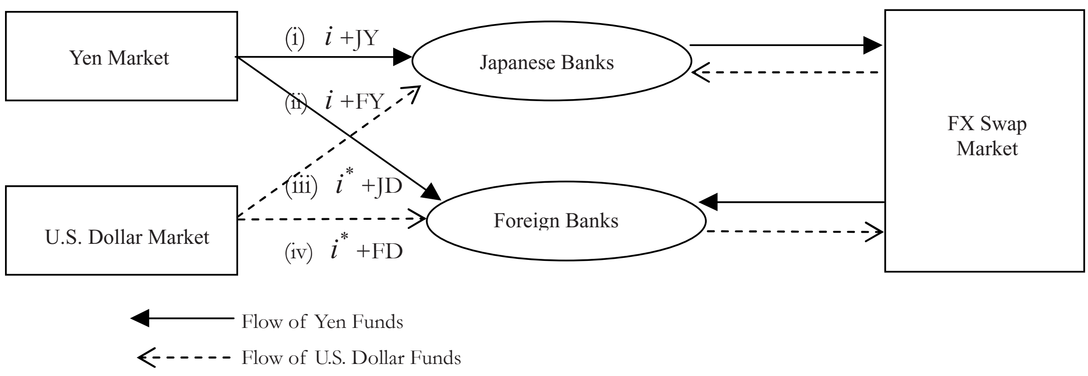
Figure 1: Transaction Volume of FX Swap Market



Note: The data is as of April.

Source: "Central Bank Survey of Foreign Exchange and Derivatives Market Activity", Bank of Japan

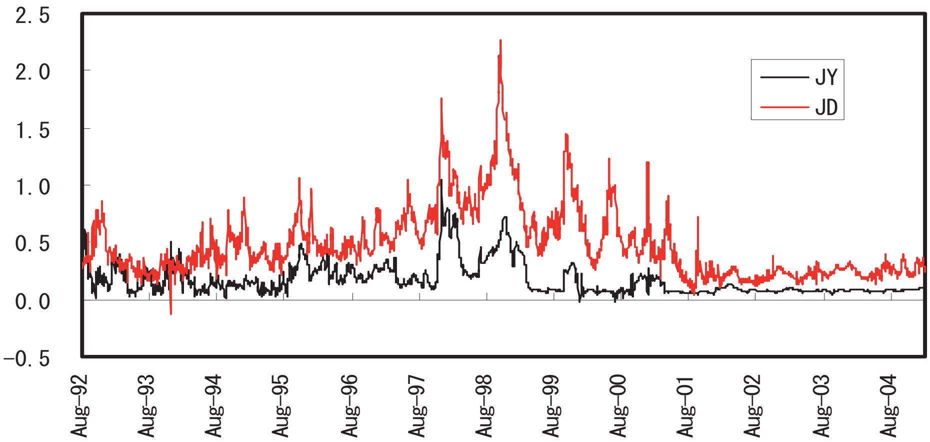
Figure 2: Foreign Currency Funding Structure of Japanese and Foreign Banks



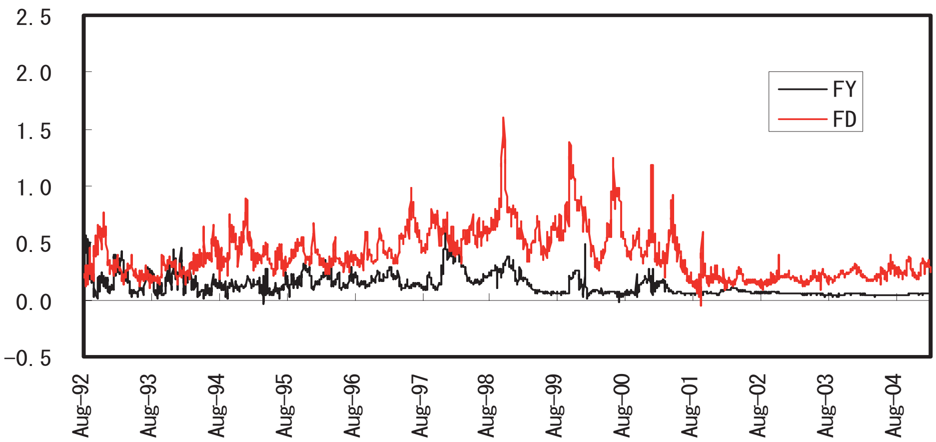
JY : Japanese Banks' Yen Risk Premium JD : Japanese Banks' Dollar Risk Premium
FY: Foreign Banks' Yen Risk Premium FD: Foreign Banks' Dollar Risk Premium

Figure 3: Risk Premiums

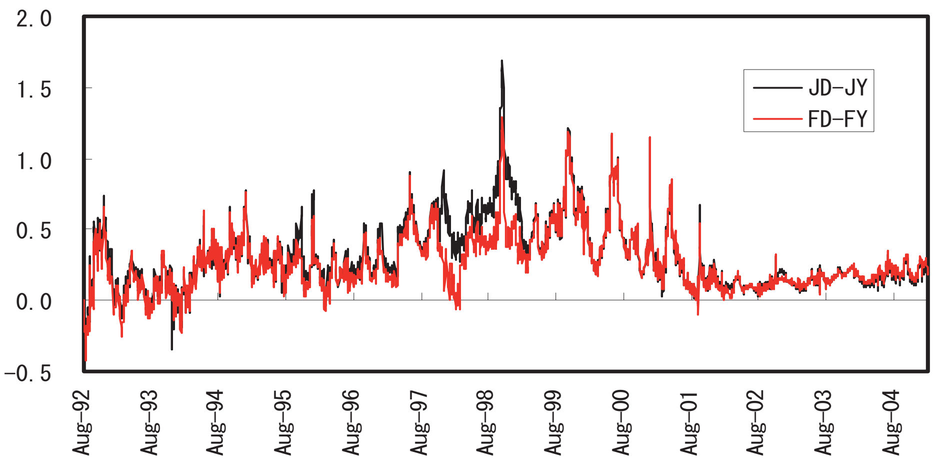
(i) Risk Premiums for Japanese Banks



(ii) Risk Premiums for Foreign Banks



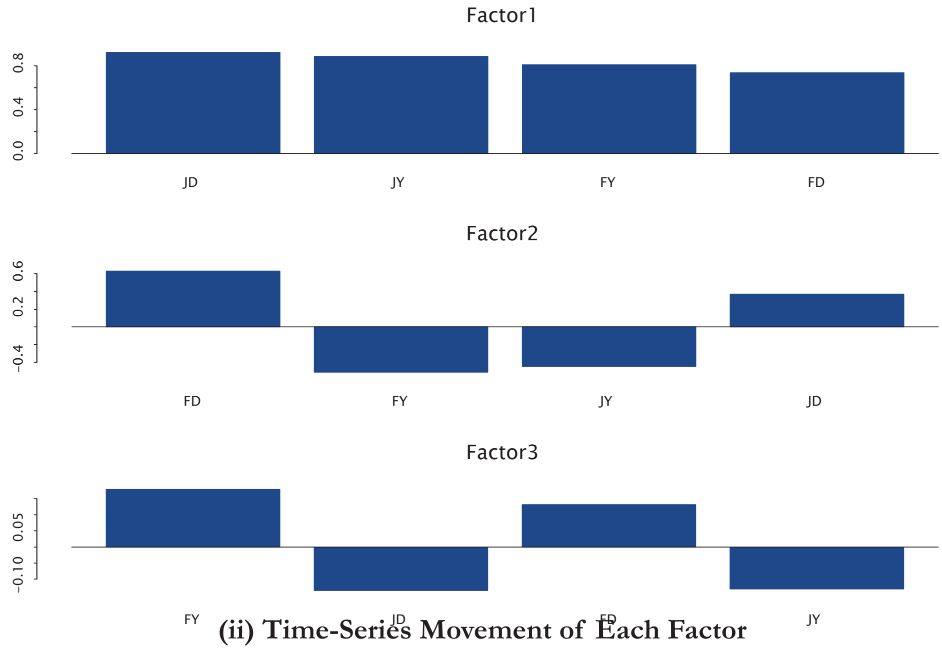
(iii) Difference in Risk Premiums between Dollar and Yen Markets



JY : Japanese Banks' Yen Risk Premium JD : Japanese Banks' Dollar Risk Premium
FY: Foreign Banks' Yen Risk Premium FD: Foreign Banks' Dollar Risk Premium

Figure 4: Estimation Results of Factor Analysis (ii)

(i) Factor Loadings



(ii) Time-Series Movement of Each Factor

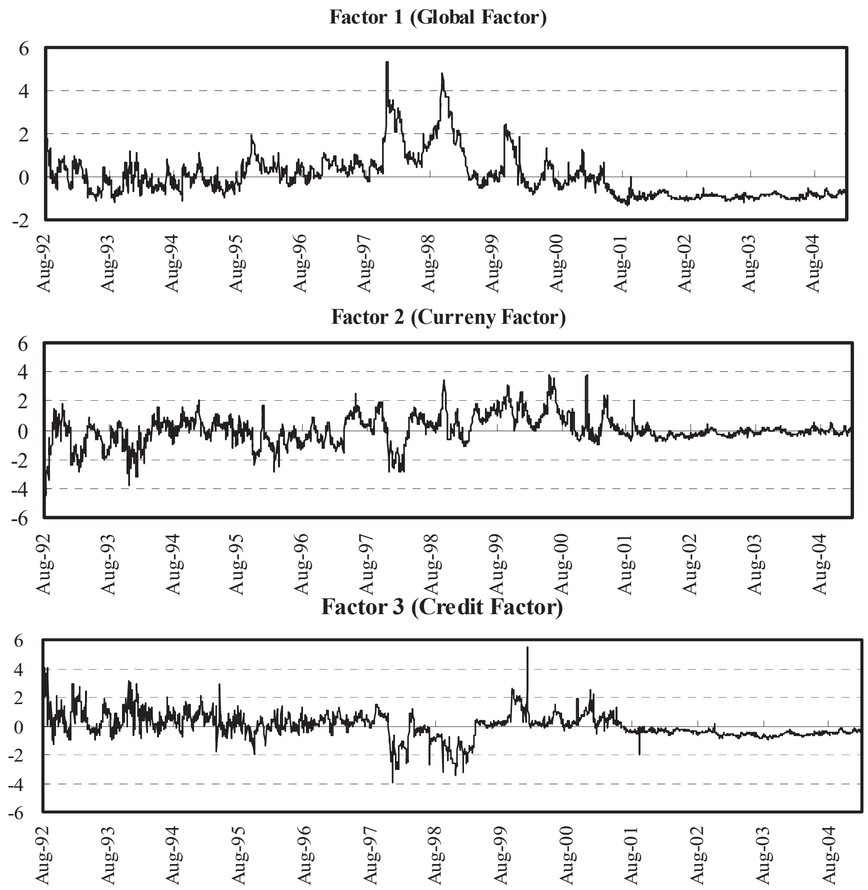
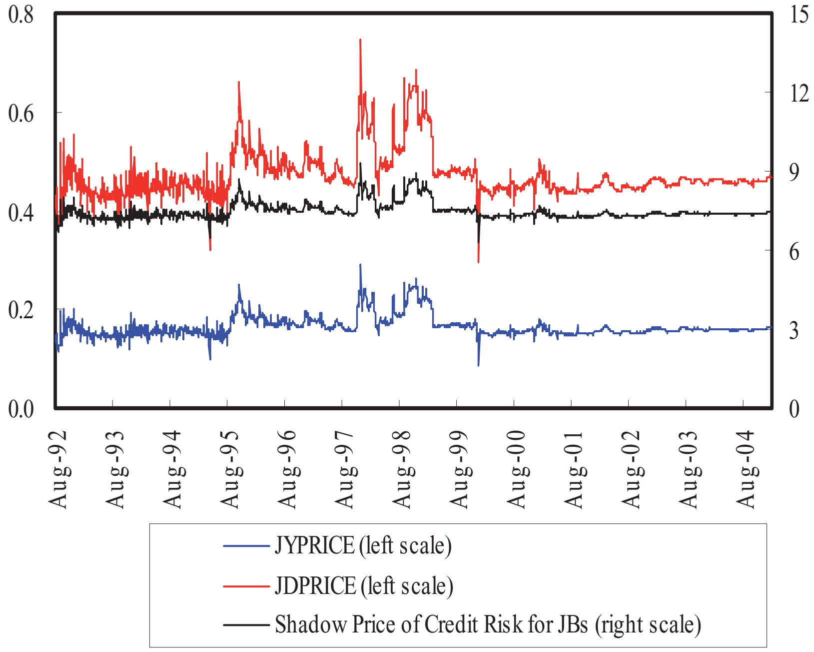
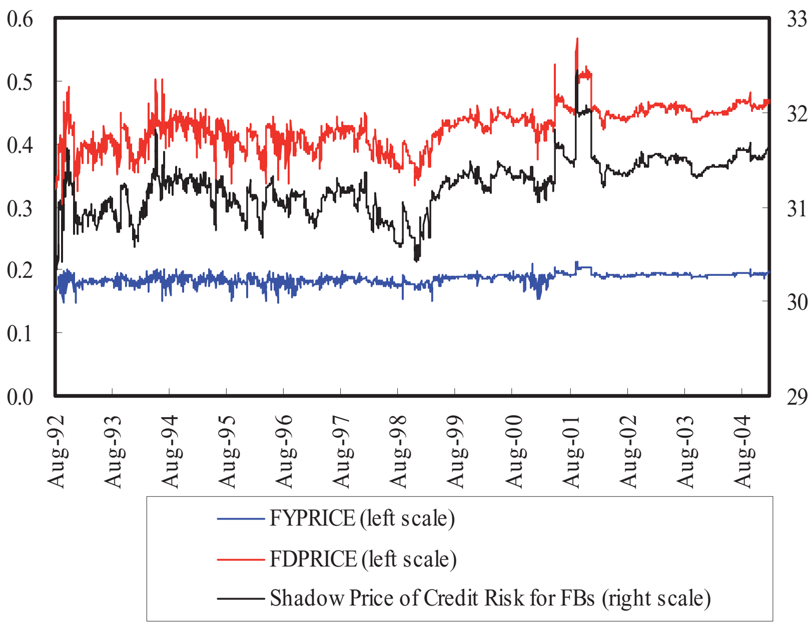


Figure 5: Shadow and Fundamental Prices of Credit Risk

(i) Japanese Banks (JBs)

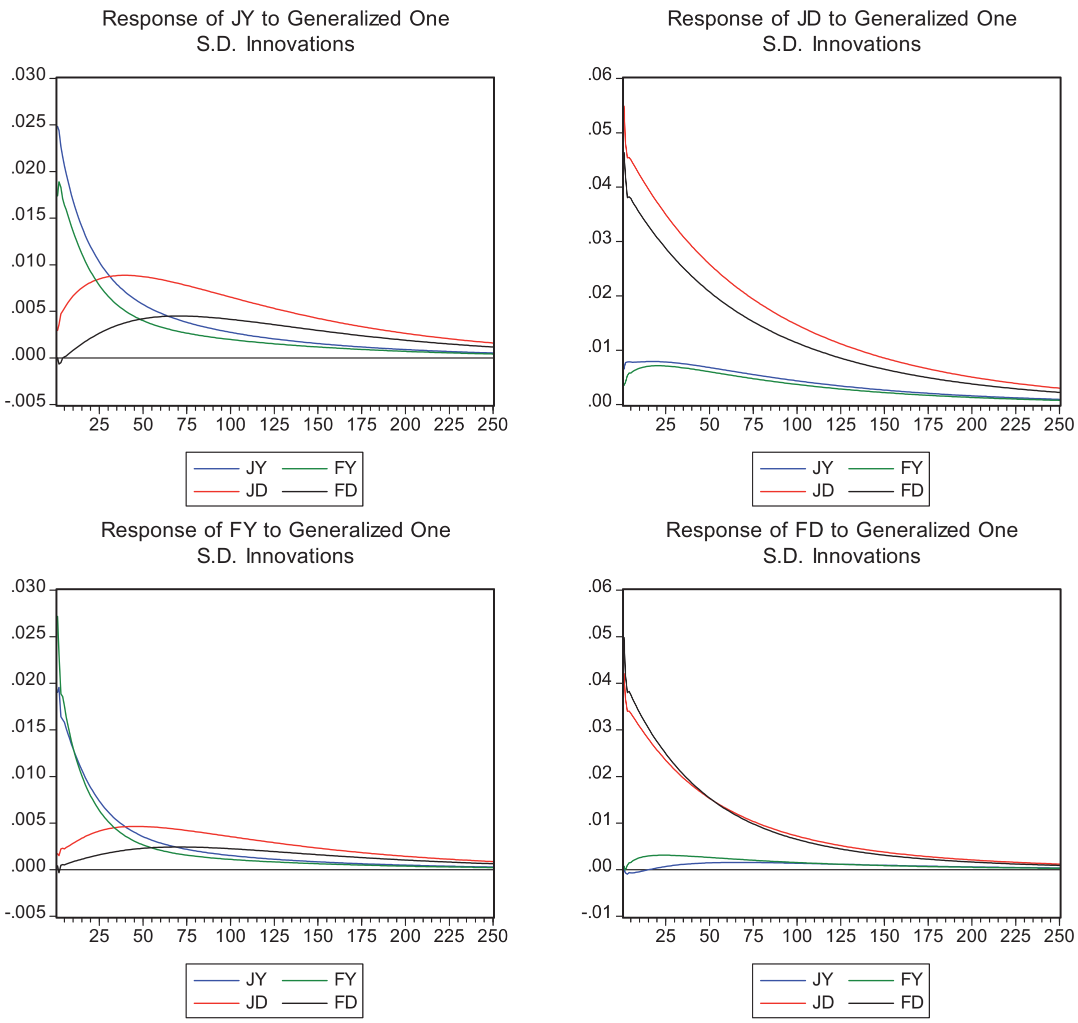


(ii) Foreign Banks (FBs)



JYPRICE	: Fundamental Price of Credit Risk for Japanese Banks in the Yen Market
JDPRICE	: Fundamental Price of Credit Risk for Japanese Banks in the Dollar Market
FYPRICE	: Fundamental Price of Credit Risk for Foreign Banks in the Yen Market
FDPRICE	: Fundamental Price of Credit Risk for Foreign Banks in the Dollar Market

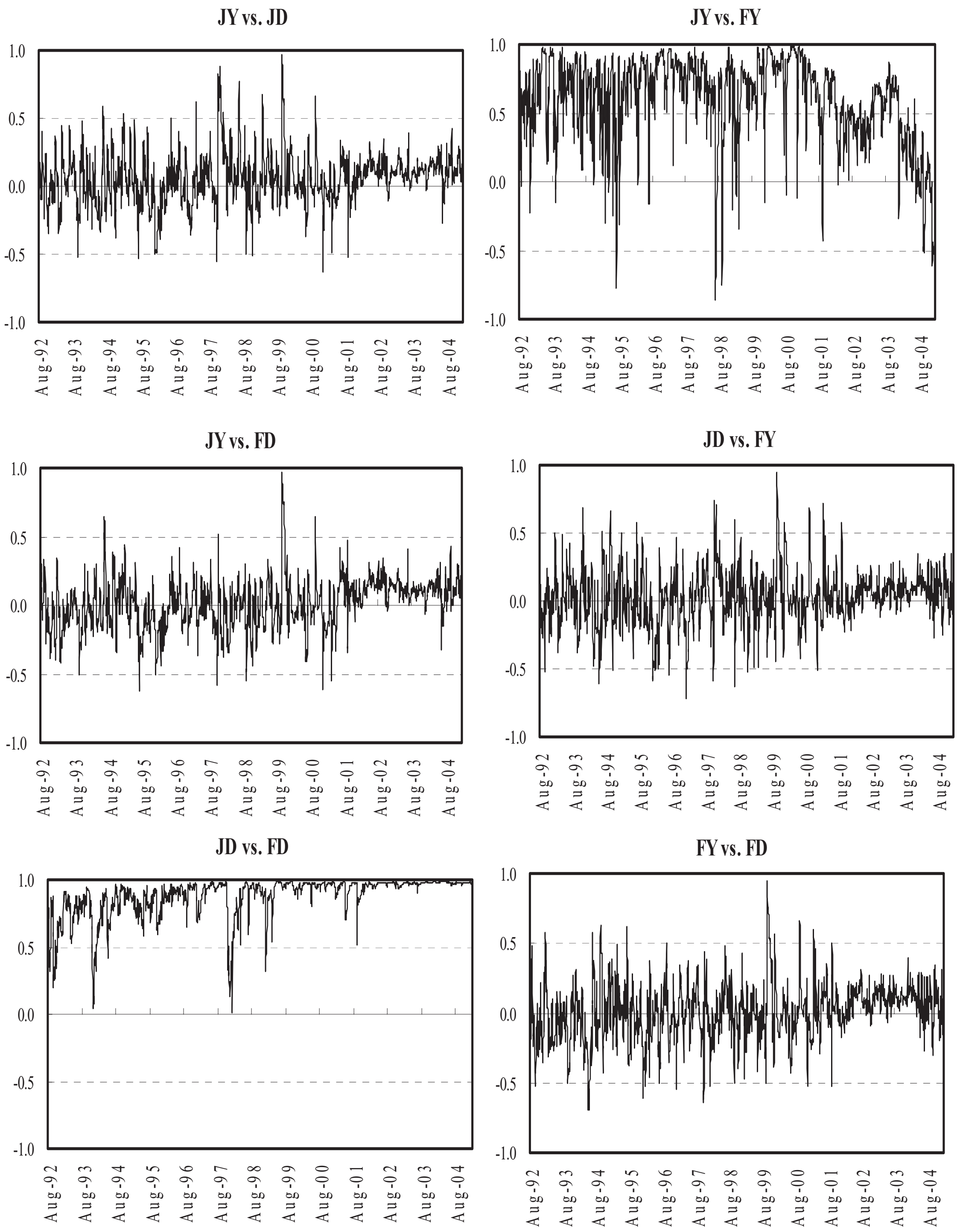
Figure 6: Generalized Impulse Response Functions (i)



JY : Japanese Banks' Yen Risk Premium JD : Japanese Banks' Dollar Risk Premium
FY: Foreign Banks' Yen Risk Premium FD: Foreign Banks' Dollar Risk Premium

Note: Impulse response functions are based on the estimation results of the VAR model reported in Table 4(i).

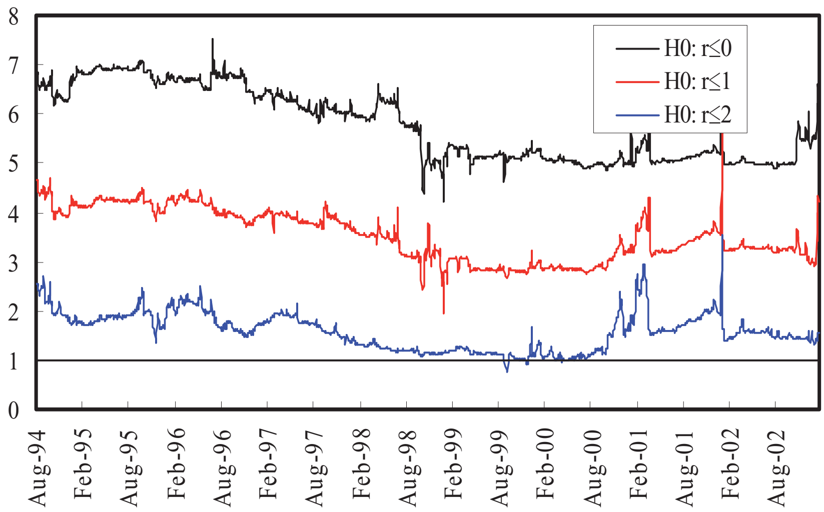
Figure 7 : Conditional Correlations by M-GARCH Model (i)



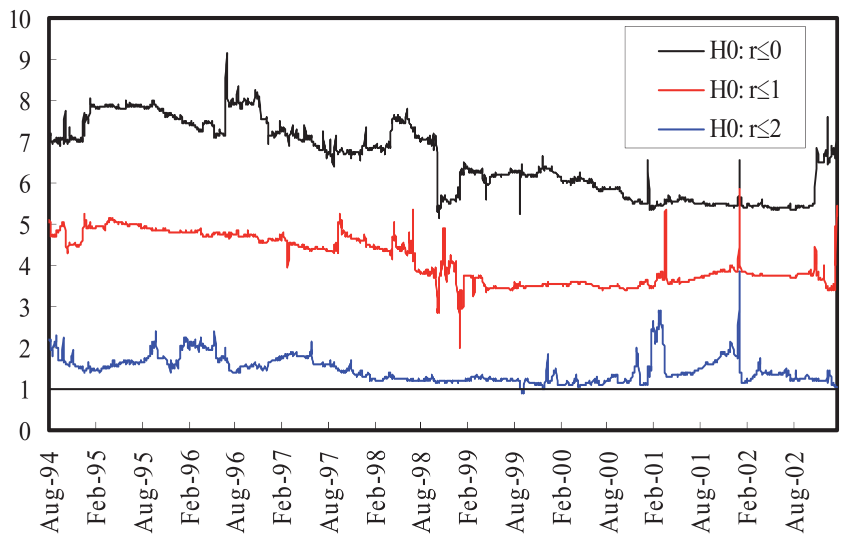
JY : Japanese Banks' Yen Risk Premium JD : Japanese Banks' Dollar Risk Premium
FY: Foreign Banks' Yen Risk Premium FD: Foreign Banks' Dollar Risk Premium

Figure 8: Stability Test of Cointegrating Relationships

(i) Trace Statistic



(ii) Maxmum Eigenvalue Statistic

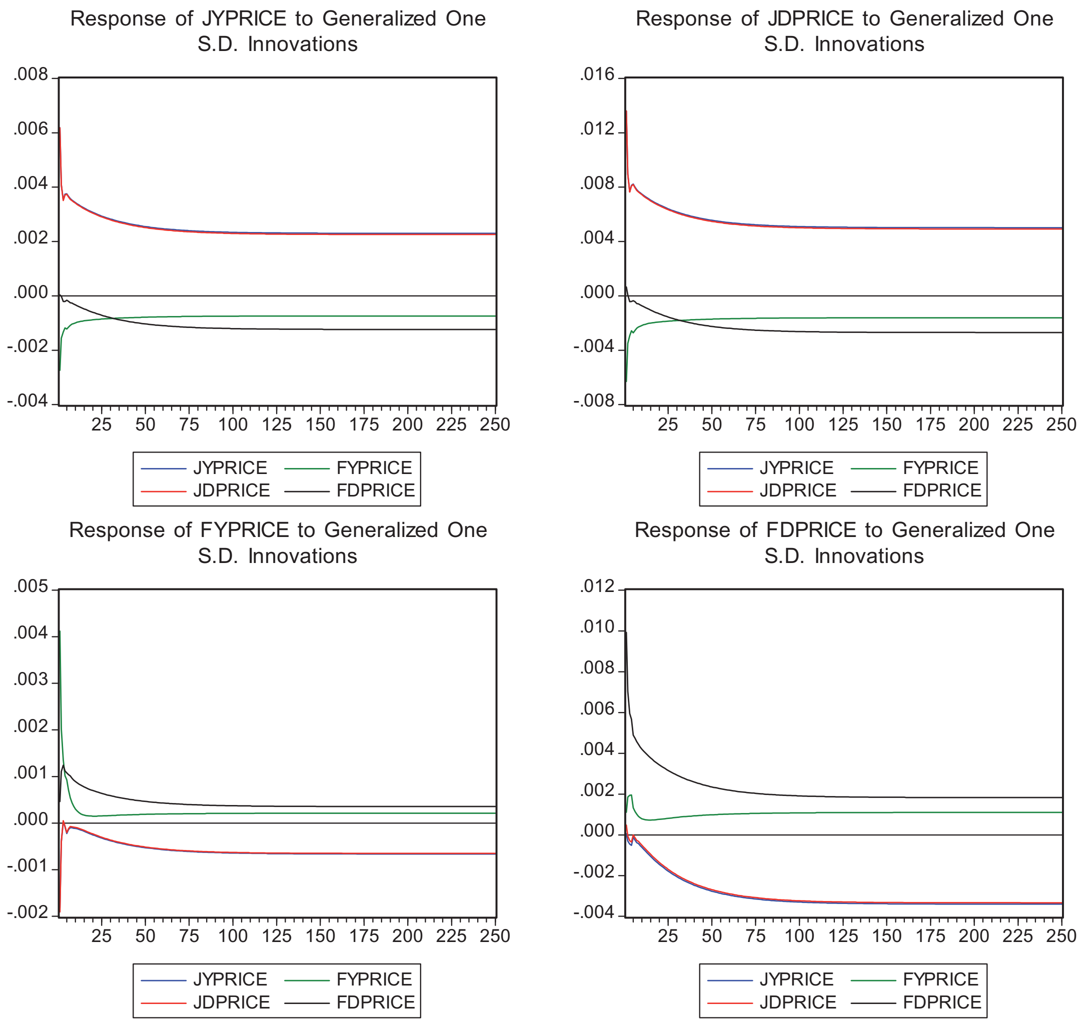


Notes: 1. r denotes the number of cointegrating ranks.

2. Test statistics are divided by the critical values that correspond to the 5% significance level. Thus, statistics above 1 means that null hypotheses H0 can be rejected at the 5% significance level.

3. Time scale corresponds to the mid-period of the rolling window (1,000 observations).

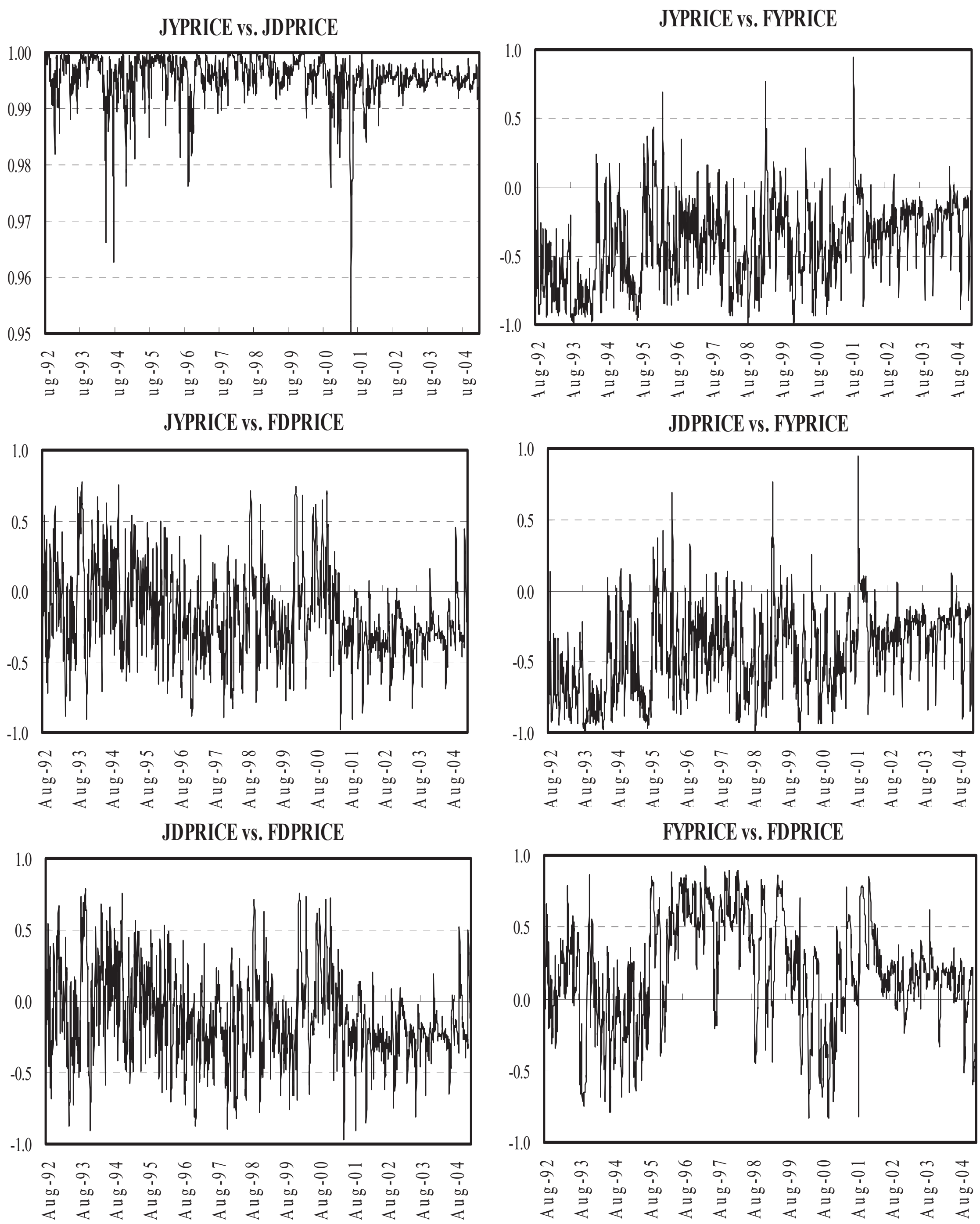
Figure 9: Generalized Impulse Response Functions (ii)



JYPRICE	: Fundamental Price of Credit Risk for Japanese Banks in the Yen Market
JDPRICE	: Fundamental Price of Credit Risk for Japanese Banks in the Dollar Market
FYPRICE	: Fundamental Price of Credit Risk for Foreign Banks in the Yen Market
FDPRICE	: Fundamental Price of Credit Risk for Foreign Banks in the Dollar Market

Note: Impulse response functions are based on the estimation results of the error correction model reported in Table 9(i).

Figure 10 : Conditional Correlations by M-GARCH Model (ii)



JYPRICE	: Fundamental Price of Credit Risk for Japanese Banks in the Yen Market
JDPRICE	: Fundamental Price of Credit Risk for Japanese Banks in the Dollar Market
FYPRICE	: Fundamental Price of Credit Risk for Foreign Banks in the Yen Market
FDPRICE	: Fundamental Price of Credit Risk for Foreign Banks in the Dollar Market

FIRM HETEROGENEITY AND CREDIT RISK DIVERSIFICATION*

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TIL SCHUERMANN‡

March 2006

Abstract

This paper considers a simple model of credit risk and derives the limit distribution of losses under different assumptions regarding the structure of systematic and idiosyncratic risks and the nature of firm heterogeneity. It documents a rich and complex interaction between the underlying model parameters and the resulting loss distributions. The theoretical results indicate that neglecting heterogeneity in firm returns and/or default thresholds leads to *under*estimation of expected losses (EL), and its effect on portfolio risk is ambiguous. But once EL is controlled for, neglecting parameter heterogeneity leads to *over*estimation of risk. These results are verified empirically where it is shown that heterogeneity in the default threshold or unconditional probability of default, measured for instance by a credit rating, is of first order importance in affecting the shape of the loss distribution: including ratings heterogeneity alone results in a more than one-quarter drop in loss volatility and a more than one-half drop in 99.9% VaR, the level to which the risk weights of the New Basel Accord are calibrated.

JEL Classifications: C33, G13, G21.
Key Words: Risk management, correlated defaults, factor models, portfolio choice.

* We would like to thank Richard Cantor, Paul Embrechts, Rafael Repullo, Joshua Rosenberg, Jose Scheinkman, Zhenyu Wang, and especially David Lando, as well as participants at the 13th Annual Conference on Pacific Basin Finance, Economics, and Accounting at Rutgers University, June 2005, the BIS-ECB 4th Joint Central Bank Research Conference in Frankurt, November 2005, the NBER conference on Risks of Financial Institutions, Cambridge, MA, November 2005, and seminar participants at the Newton Institute, University of Cambridge, UMass Amherst and the Federal Reserve Bank of New York for helpful comments and suggestions. We are also grateful to Yue Chen and Chris Metli for research assistance.
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EVALUATING VALUE-AT-RISK MODELS WITH DESK-LEVEL DATA[#]

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PETER CHRISTOFFERSEN[2]
DENIS PELLETIER[3]

Abstract

We present new evidence on disaggregated profit and loss and VaR forecasts obtained from a large international commercial bank. Our dataset includes daily P/L generated by four separate business lines within the bank. All four business lines are involved in securities trading and each is observed daily for a period of at least two years. We also collected the corresponding daily, 1-day ahead VaR forecasts for each business line. Given this rich dataset, we provide an integrated, unifying framework for assessing the accuracy of VaR forecasts. Our approach includes many existing backtesting techniques as special cases. In addition, we describe some new tests which are suggested by our framework. A thorough Monte Carlo comparison of the various methods is conducted to provide guidance as to which of these many tests have the best finite-sample size and power properties.

[#] Christoffersen acknowledges financial support from FQRSC, IFM2, and SSRHC and Pelletier acknowledges financial support from the North Carolina State University Edwin Gill Research Grant.

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SESSION 6

STRESS TESTING AND FINANCIAL STABILITY POLICY

NON-LINEARITIES AND STRESS TESTING

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ANDREW J. PATTON[‡]
LONDON SCHOOL OF ECONOMICS
AND BANK OF ENGLAND
STEFFEN SORENSEN[§]
BANK OF ENGLAND

Abstract

We explore the impact of possible non-linearities on aggregate credit risk in a vector autoregression framework. By using aggregate data on corporate credit in the UK we investigate the non-linear transmission of macroeconomic shocks to aggregate corporate default probability. We show two important results: firstly, we find that non-linearities matter for the level and shape of impulse response functions of credit risk following small as well as large shocks to systematic risk factors. Secondly, we show that ignoring estimation uncertainty in stress tests can lead to a substantial underestimation of credit risk, particularly in extreme conditions.

Keywords: credit risk, impulse response functions, stress testing, nonlinear time series, VAR models

J.E.L. Codes: G33, C32.

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[*]The authors would like to thank Prasanna Gai, Denis Pelletier, Christoph Schleicher, Martin Summer, Paolo Surico and participants of the Fourth Joint Central Bank Research Conference on Risk Measurement and Systemic Risk 2005 for useful suggestions. This paper represents the views of the authors and do not necessarily reflect those of the Bank of England or the Monetary Policy Committee members. All errors remain our responsibility.

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1 Introduction

Stress tests have become a well-established risk management tool to assess the impact of severe but plausible events on banks' exposures. A "stress test" is an estimate of the impact of a (large) shock to a systematic risk factor on a given set of exposures, an estimate that is closely related to traditional impulse response analyses. For market risk, stress tests are routinely undertaken and are used to complement Value-at-Risk (VaR) measures (see BIS (2005)). However, quantitative stress tests for credit risk are not yet as well-developed, though a lot of banks extensively undertake qualitative stress tests. In the future, this is likely to change as stress tests have to be undertaken for banks to be eligible for the internal ratings approach under Basel II. Stress tests have also recently gained increased prominence as a tool to assess the financial stability of banking systems. For example, more than 90 "stress tests" have been currently completed/in progress as part of the IMF's Financial Stability Assessment Programme.

One of the main challenges stress tests face is that the models used are generally specified in (log-) linear form. Of course, if the underlying data generating process (DGP) is linear, then this assumption is correct. Alternatively, if interest lies in studying the impact of small shocks around the equilibrium of the process, then a standard linear model may produce adequate forecasts even if the true DGP is non-linear. In such a case the linear model may be interpreted as a first-order Taylor series approximation to the true DGP. However, stress tests do not consider small shocks, and it is not likely that the relevant data generating processes are all log-linear. In Drehmann *et al.* (2006) we explore the generally made assumption of log-linearity and the impact of large macro shocks on firm specific PDs. This companion paper looks at the same questions, but investigates the impact of large macro shocks on aggregate liquidation rates often used to proxy aggregate credit risk in stress testing models. We show that allowing for non-linearities leads to substantially different predictions of losses in scenarios typically considered for stress testing.

Sorge (2004) provides an excellent overview of the current state of the macro stress testing literature. Broadly speaking there are three strands of macro stress testing models, reduced form models, portfolio credit risk models and structural models. Reduced form models are often based on time series or panel-analysis which link write-offs or provisions to macroeconomic factors. These reduced form equations are then used to assess how severe macro scenarios impact on provisions or write-offs of banks. Pain (2004) constructs such a model for the UK and shows that in particular real GDP growth, real interest rates and lagged aggregate lending growth have a strong impact on banks' provisioning.

Another class of models which is extensively used is based on the idea of CreditPortfolioView (see Wilson, 1997a and 1997b). Here, the default process it modelled using a Probit model which relates macroeconomic factors to the probability of default of companies. In this spirit Boss (2002) develops a stress testing model for the aggregate Austrian banking sector, whereas Virolainen (2004) applies such a model to the Finnish banking system.

So far, few structural models for stress testing have been developed. One such model is at the core of the Bank of England's stress testing agenda (see Bunn *et al.* (2005)). This model starts by feeding shocks through the Bank's structural macroeconomic model, then through a structural "satellite" model linking macroeconomic variables to arrears and liquidation rates, and then finally to a reduced-form model assessing the impact of liquidations rates and arrears on banks' write-offs and profits. DeBandt and Oung (2004) describe a structural model for France. Generally, structural models are very useful from a central bank's perspective as they are tractable and conform to the way central bankers communicate. Hence, they provide an ideal framework to discuss financial stability risks. By design these models assume a linear relation between macro factors and credit risk. Even in a Probit specification, as used in applications of Credit PortfolioView, the underlying relationship is modelled in a linear fashion. But as discussed above, it is not clear whether the DGP is linear, especially when focusing on extreme down side risks.

This paper studies the aggregate corporate liquidation rate, often used in macro stress tests. We start by estimating a non-linear vector autoregression model (VAR) of the underlying macroeconomic drivers of risk. We concentrate on the three key macroeconomic factors: GDP growth, inflation and the interest rate. We then investigate how macroeconomic shocks feed through to the aggregate liquidation rate.

Nonlinear models for macroeconomic variables have been studied by Koop *et al.* (1996) and Jorda (2005), *inter alia.* We employ the methodology of Jorda (2005) in this paper. Jorda's approach builds on the fact that a standard VAR can be interpreted as a first-order approximation to the true unknown DGP. Thus, a more flexible approximation may be obtained by considering, for example, a quadratic or cubic approximation. An important implication of considering a standard linear VAR as a linear approximation to the true DGP is that it is no longer clear that forecasts or stress tests of horizons greater than one period should be obtained by iterating the one-period model forward, which is the standard practice when deriving impulse response functions for VAR models. As Jorda (2005) points out, if the one-period model is mis-specified, then iterating it forward may well lead to a compounding of mis-specification error. He suggests an alternative approach, namely to estimate a different model for each horizon of interest. If the DGP is truly a VAR then this approach is consistent but not efficient, while if the DGP is not a VAR then this approach offers the best approximation at each horizon, rather than just at the one-quarter horizon. This modelling approach has its roots in the direct multi-step versus iterated forecasting approaches (see for example Stock and Watson (1999)). A benefit of this approach is that simple ordinary least squares (OLS) techniques can be used to obtain the impulse response functions from the non-linear VAR used in the stress tests.

In this paper we show that the results of the non-linear VAR are significantly different to results using standard linear models, especially when considering large shocks. This can be seen in the simple three variable macro model of inflation, GDP growth and a short term interest rate. More importantly, we show that accounting for non-linearities in the underlying macroeconomic environment leads to substantially different conclusions for credit risk projections in stressed conditions.

The remainder of the paper is as follows. In Section 2 we briefly discuss the more formal motivation for the consideration of non-linear multivariate models when studying the impact of large shocks as presented in Drehmann *et al.* (2006). In Section 3 we discuss the estimation of the macro model and the resulting impulse response functions. Further we introduce the model for the corporate liquidation rate and present the results of our analysis of large macroeconomic shocks on default probabilities. Section 4 concludes. Technical details and estimation results are presented in the Appendix.

2 Why non-linearities matter

Suppose we are interested in a scalar variable y_t, which is follows the following general process:

$$y_t = h\left(y_{t-1}, \varepsilon_t; \theta\right), \quad t = 1, 2, ... \tag{1}$$

where the residual ε_t is independent of y_{t-1}, h is some (possibly non-linear) function, and θ is a parameter vector. In the standard linear setting we would have

$$h\left(y_{t-1}, \varepsilon_t; \theta\right) = \phi_0 + \phi_1 y_{t-1} + \varepsilon_t \tag{2}$$

and so y_t would follow a first-order autoregressive process. In this case the conditional mean function,

$$\mu\left(y\right) \equiv E\left[y_t | y_{t-1} = y\right] = \phi_0 + \phi_1 y \tag{3}$$

is affine in y_{t-1} and so a first-order Taylor series approximation of μ corresponds exactly to μ. For other data generating processes the conditional mean function need not be affine in y_{t-1}. For example, in the Appendix we describe a simple non-linear specification for h, under which y_t is stationary and unconditionally normally distributed, with first-order autocorrelation coefficient of 0.5, and a nonlinear conditional mean function. The conditional mean function is plotted in Figure 1.

Figure 1 illustrates why linear approximations may be inadequate for stress testing: such approximations may work satisfactorily in the middle of the distribution, but can perform poorly in the tails. In this example the linear approximation matches the true conditional mean function reasonably well for $|Y_{t-1}| \leq 1.5$, but deviates outside this region[1]. For the study of "small" shocks to Y_{t-1} the linear approximation may be acceptable, but for the study of large shocks (two or more standard deviations) it is not. For example, if $Y_{t-1} = -3$, corresponding to a three standard deviation shock in this setting, the linear approximation would predict $Y_t = -1.5$, while the true conditional mean of Y_t is -2.7. Consider now a quadratic approximation to the conditional mean function, also plotted in Figure 1. This approximation is very close to the true conditional mean function for $|Y_{t-1}| \leq 2$. More importantly, for our interest in studying large shocks, the quadratic approximation also does a lot better in the tails. Continuing our previous example, if $Y_{t-1} = -3$ the quadratic approximation predicts $Y_t = -2.8$, close to the true value of -2.7. This simple example highlights the potential for more flexible models to provide better estimates of the impact of "large" shocks.

2.1 A nonlinear VAR(p) model

Consider a $(k \times 1)$ vector of macroeconomic variables, $\mathbf{Y}_t$. The most widely used model for the dynamics of macroeconomic time series is the linear vector autoregression.

$$\mathbf{Y}_t = B_0 + B_1 \mathbf{Y}_{t-1} + ...B_p \mathbf{Y}_{t-p} + \mathbf{e}_t \tag{4}$$

More generally, we can think about the mapping between $\mathbf{Y}^p_{t-1} \equiv \left[\mathbf{Y}'_{t-1}, ..., \mathbf{Y}'_{t-p}\right]'$ and $\mathbf{Y}_t$ as some general unknown function, $\mathbf{g} : \mathbb{R}^{pk} \rightarrow \mathbb{R}^k$

$$\mathbf{Y}_t = \mathbf{g}\left(\mathbf{Y}^p_{t-1}\right) + \mathbf{e}_t \tag{5}$$

and interpret the standard VAR above as a simple first-order Taylor series approximation to the

[1] The linear approximation to the true conditional mean function is obtained by noting that the optimal mean squared error approximation is a line through zero with slope equal to one-half. This follows from the fact that $E[Y_t] = 0$, $V[Y_t] = 1$ and $Cov[Y_t, Y_{t-1}] = 0.5$. The quadratic approximation can similarly be derived analytically from the properties of the joint distribution of (Y_t, Y_{t-1}).

unknown function $\mathbf{g}$. For notational simplicity let us assume that all variables have mean zero.

$$\begin{aligned}\mathbf{g}\left(\mathbf{Y}_{t-1}^{p}\right) &\approx \mathbf{g}\left(\mathbf{0}\right)+\nabla\mathbf{g}\left(\mathbf{0}\right)\mathbf{Y}_{t-1}^{p} \\ &\equiv B_0+B_1^p\mathbf{Y}_{t-1}^{p} \\ &\equiv B_0+B_1\mathbf{Y}_{t-1}+...+B_p\mathbf{Y}_{t-p} \qquad (6)\end{aligned}$$

If we are primarily interested in studying the dynamics of $\mathbf{Y}_t$ "near" its unconditional mean, then the first-order approximation of $\mathbf{g}$ provided by a standard VAR may be sufficiently accurate. By convention, VAR studies show impulse response functions to one standard deviation shocks. But it is well known (see for example Koop *et al.* (1996)) that for standard linear VAR models the magnitude of the shock has no impact on the shape of the impulse response function; it merely affects the scale. As discussed above, in stress testing studies interest lies not in small- or medium-sized shocks, but extreme shocks. Considering three or five standard deviation shocks means considering the dynamics of the variables "far" from their unconditional mean. In such case the first-order Taylor series approximation may be a poor approximation to the true, unknown data generating process.

An obvious extension is to expand to a second or third-order Taylor series approximation of $\mathbf{g}$. As shown in the Appendix, the mean function, up to a second order approximation[2], will be given by:

$$\mathbf{g}\left(\mathbf{Y}_{t-1}^{p}\right)=B_0+\sum_{m=1}^{p}B_{1m}\mathbf{Y}_{t-m}+\sum_{i=1}^{p}\sum_{j=i}^{p}B_{2ij}vech\left(\mathbf{Y}_{t-i}\mathbf{Y}_{t-j}^{\prime}\right) \qquad (7)$$

where $vech\left(X\right)$ stacks only the lower triangle of the matrix X. We use the $vech$ function rather than the vec function as $\mathbf{Y}_{t-1}^{p}\mathbf{Y}_{t-1}^{p\prime}$ includes both $Y_{1,t-1}Y_{2,t-1}$ and $Y_{2,t-1}Y_{1,t-1}$, for example, and we can collect such terms. The number of unknown parameters is larger for the second-order Taylor series approximation relative to the first-order approximation. The first-order approximation has $k+pk^2$ free parameters while the more flexible model has $k+pk^2+pk^2\left(p+1\right)\left(k+1\right)/4$ free parameters. Several possibilities exists for reducing the number of free parameters. First, one could restrict all second-order effects in equation i to include $Y_{t-m,i}$. Alternatively, we could restrict the second-order terms to only include lagged squared terms. Possibly due to the high parameterisation of non-linear VAR models, these are not widely-used. In the next section we describe a method, proposed by Jorda (2005), to estimate non-linear VAR models.

[2] The same analysis can easily be repeated for the third-order Taylor series approximation, adding greater flexibility at the cost of additional parameters.

3 Estimation results for the non-linear macro VAR

3.1 Estimation of flexible non-linear approximations

We employ a third-order approximation in our models of the relationships between the macroeconomic variables and the measures of corporate default. In the interests of parsimony we drop all cross-product terms from this approximation, and consider only one lag of the higher-order terms. Thus, our model for the macroeconomic variables at the one-quarter horizon is:

$$Y_{jt} = \beta_{0j} + \sum_{m=1}^{p} \boldsymbol{\beta}'_{1jm}\mathbf{Y}_{t-m} + \boldsymbol{\gamma}'_{2j}\mathbf{Y}_{t-1} \odot \mathbf{Y}_{t-1} + \boldsymbol{\gamma}'_{3j}\mathbf{Y}_{t-1} \odot \mathbf{Y}_{t-1} \odot \mathbf{Y}_{t-1} + e_{jt} \tag{8}$$

for $j = 1, 2, 3$, where $\odot$ is the Hadamard product. This model is estimable via OLS, and thus is very simple to implement.

As discussed in the introduction, an implication of considering a standard linear VAR as an *approximation* to the true DGP, rather than as the DGP itself, is that it is no longer clear that forecasts or stress tests of horizons greater than one period should be obtained by iterating the one-period model forward. Jorda (2005) proposes an alternative approach, namely to estimate a different approximation model for each horizon of interest. Following this argument, one can estimate a set of models for the three macroeconomic variables and eight horizons:

$$Y_{j,t+h-1} = \beta^{h}_{0j} + \sum_{m=1}^{p} \boldsymbol{\beta}^{h\prime}_{1jm}\mathbf{Y}_{t-m} + \boldsymbol{\gamma}^{h\prime}_{2j}\mathbf{Y}_{t-1} \odot \mathbf{Y}_{t-1} + \boldsymbol{\gamma}^{h\prime}_{3j}\mathbf{Y}_{t-1} \odot \mathbf{Y}_{t-1} \odot \mathbf{Y}_{t-1} + e^{h}_{jt} \tag{9}$$

for $j = 1, 2, 3$ and $h = 1, 2, ..., 8$. For each variable and each horizon this model is estimable via OLS.

Estimating the model for each horizon of interest it is simple to obtain the confidence intervals on the impulse responses, or stress tests: they come directly from the covariance matrix of the parameters estimated for each horizon. This is in contrast with standard linear VAR approach, where the confidence intervals for horizons greater than one period must be obtained either via the "delta" rule, or a bootstrap procedure.

3.2 Data

We use quarterly data on three key UK macroeconomic variables, GDP growth, the three-month Treasury bill rate, and inflation, to summarise the state of the macro economy. To proxy for corporate credit risk we use the corporate liquidation rate defined as the number of defaulting companies in a given quarter relative to the total number of companies. Our macro model is small relative to some of the macroeconomic models used in the analysis of credit risk, Pesaran *et al.* (2005) being a prominent example. But it is large enough to convey the main ideas of this paper.

The sample period is 1992Q4 to 2004Q3. These series are available for a much longer period, but we focus on data after 1992Q4, as at this point the UK adopted an inflation targeting regime and it has been recognized that inflation targeting in the UK and other countries lead to a significant reduction in the volatility of macroeconomic series (see for example Kuttner and Posen (1999) or Benati (2004)). It is, therefore, reasonable to assume that the introduction of inflation targeting induced a structural break in the UK macroeconomic time series in 1992Q4. In Figure 3 we plot the macroeconomic variables and some descriptive statistics of the data set can be found in Table 1.

3.3 The estimated macroeconomic non-linear VAR

One of the properties of a standard linear VAR is that the size and the sign of the shock, as well as the starting values of the variables, do not change the shape of the impulse response function[3] (IRF) (see Koop *et al.* (1996)). In the non-linear VAR, however, the size, the sign and starting values are important. In all cases we evaluate the IRF holding all non-shocked variables at their unconditional averages[4]. Consistent with the existing macroeconomic literature we order the variables as GDP growth, inflation, interest rate.

In line with Jorda (2005) and much of the VAR literature, we use a Cholesky factorisation of the covariance matrix of errors to obtain the scenarios. The use of a simple Cholesky factorisation may be restrictive, but for the purpose of this paper this method is sufficient to illustrate our results. The methodology outlined below, however, is general enough to consider any type of scenario. To distinguish between small and large shocks we consider the impact on variables in the VAR from unexpected one and three standard deviation shocks to GDP growth, inflation and the interest rate.

In Figures 4 to 7 we plot the impulse response functions (IRFs) of the three-variable macroeconomic VAR to shocks of various sizes and signs. Figure 4 reveals that in most one-standard deviation IRFs the cubic and the linear models yield similar results. But the response of interest rates to GDP growth shocks and interest rate shocks do differ substantially: the response of inter-

[3] Given the correspondence between impulse response functions and stress tests in our study, we will use these terms interchangeably.

[4] For details on the computation of IRFs in this setting see Jordà (2005).

est rates to a GDP growth shock and an interest rate shock is significantly greater, for horizons 1 through 4 quarters, if cubic terms are considered than if these are ignored.

Figure 5 shows the IRFs for a -1 standard deviation shock. For the linear model this figure is just a sign change of the plots in Figure 4, whereas this is not necessarily so for the cubic model. For example, the response of interest rates to a positive GDP shock was significantly greater using the cubic model than the linear model, whereas this difference between the two models essentially disappears for a negative GDP shock.

In Figure 6 we present the IRFs for a positive 3 standard deviation shock. For the linear model these IRFs are just 3 times the IRFs from Figure 4, while this is not so for the cubic model. Some interesting differences appear comparing Figures 4 and 6. For example, the response of interest rates to a 1 standard deviation inflation shock was small and positive (negative) for the linear (cubic) model, slowly increasing as the horizon approached eight quarters. However, for a three standard deviation shock the cubic model suggests a large positive response of interest rates for the first 5 quarters, followed by a decrease in interest rates at the 8th quarter. This indicates a difference between small shocks to inflation, which lead to modest changes in interest rates, and very large shocks to inflation, which lead to much different interest rate reactions.

3.4 Impulse response function for the liquidation rate

To estimate the impact of macroeconomic shocks on the aggregate liquidation rate we estimate the following Logit model:

$$\Delta^h \Lambda^{-1}\left(P_{t+h-1}\right) = \beta_0^h + \alpha_1^h \Delta \Lambda^{-1}\left(P_{t-1}\right) + \boldsymbol{\beta}_{1j}^{h\prime} \mathbf{Y}_{t-1} + \boldsymbol{\gamma}_{2j}^{h\prime} \mathbf{Y}_{t-1} \odot \mathbf{Y}_{t-1} + \boldsymbol{\gamma}_{3j}^{h\prime} \mathbf{Y}_{t-1} \odot \mathbf{Y}_{t-1} \odot \mathbf{Y}_{t-1} + e_{t+h-1} \tag{10}$$

for $h = 1, 2, ..., 8$, where $\Delta^h X_t \equiv X_t - X_{t-h}$, $\Lambda(x) = 1/\left(1 + e^{-x}\right)$ is the standard logistic function and $\mathbf{Y}_t = \left[Y_{1t}, Y_{2t}, Y_{3t}\right]'$ is the vector of the three macroeconomic variables. Since the model above involves a nonlinear transformation of the liquidation rate we use a simulation-based method[5] to obtain the results from a stress test, or impulse response functions. Although we estimate the model in differences (of the transformed rates), we present the impulse responses for the liquidation rate in levels as this is the object of economic interest.

[5] The stress test results and confidence intervals are obtained by estimating the above model and then simulating 10,000 draws from the asymptotic distribution of the parameter estimates, and a Normal distribution for the regression residual, to obtain an estimated impact of a shock above what would be observed when all variables are held at their unconditional values.

In Figure 8-11 we present the results of the stress tests for the liquidation rate. Again, in all cases we evaluate the IRF holding all non-shocked variables at their unconditional averages. Since the variable of interest is a probability, it is more natural to present the results as a proportion of the base case, i.e. as $E\left[\tilde{P}^{(j)}_{t+h-1}\left(\tilde{\mathbf{Y}}_{t-1}\right)/\bar{P}^{(j)}_{t+h-1}\right]$, rather than as a difference from the base case, $E\left[\tilde{P}^{(j)}_{t+h-1}\left(\tilde{\mathbf{Y}}_{t-1}\right)-\bar{P}^{(j)}_{t+h-1}\right]$. Hence to interpret the impulse response function, a value of 2 corresponds a doubling of the probability of default relative to the sample average.

Figure 8 presents the results of a 1 standard deviation shock to each of the three macroeconomic variables, using either the linear or the cubic model. This figure reveals that the mean impact on the corporate liquidation rate from a macroeconomic shock is relatively small: the largest impact on the liquidation rate occurs 8-quarters after a shock to GDP (as estimated from the cubic model) where the liquidation rate increases by almost 10% from its sample average. In Figure 9 we show the results of the 3 standard deviation macroeconomic shocks. In comparison to Figure 8 it is clear that large shocks have a significantly different impact on the liquidation rate than small shocks. For a positive 3 standard deviation shock to GDP the non-linear model predicts a significant fall in the liquidation rate 2 quarters ahead - based on the linear VAR one would falsely conclude that the liquidation rate does not change in the quarters following large GDP shocks.

In all cases, the confidence bounds on the impulse responses are wide. In some applications the fact that the confidence intervals always include 1, the base case, would be taken as evidence that corporate liquidations are independent of business cycle shocks. But the estimation uncertainty is important for regulators as well as banks to set capital at a sufficiently conservative level. Therefore, we should pay more attention to the upper confidence interval bound which is the upper bound on the mean impact of a shock to each of these variables at the 95% confidence level in our figures. Following a 1 standard deviation shock the upper bound is approximately 1.1 for all three shocks at the one-quarter horizon, and is between 1.3 and 1.4 at the eight-quarter horizon. Thus it is plausible that the mean impact of a one standard deviation shock is a 30% to 40% increase in the probability of default, meaning that the liquidation rate could move from 1.32% to as high as 1.85%, a substantial increase. This effect is even more significant if the shocks are large, where the impact from macro shocks can lead to a more than a 100% increase of PDs at a 95% confidence level.

Of course, the upper confidence interval bound could be made arbitrarily close to 100% by including more and more, potentially irrelevant, variables in the model for the liquidation rate. Doing so would increase the estimation error, increasing the uncertainty surrounding the estimated impact of a shock, and thus increase the upper confidence bound. For this reason it is important to carefully consider which variables to include in the model and the degree of flexibility to allow. By including numerous irrelevant variables we will likely obtain an upper confidence bound that is too conservative; by excluding the possibility of non-linearities and other effects we may instead obtain an upper confidence bound that is too low that does not reflect the true uncertainty.

Our conclusions are confirmed when looking at the impact of small and large negative shocks (Figure 10 and 11 in the Appendix). Following a negative 3 standard deviation shock to GDP the liquidation rate increases significantly (borderline) in the second quarter by roughly 50% relative to the sample average. Independent of the forecast horizon we find that the liquidation rate falls strongly, and significantly, in the quarters after large negative shocks to the interest rate. The maximum fall occurs after 8 quarters when the liquidation rate is roughly 30% lower than on average. Overall, our results suggest that large positive as well as negative unexpected changes in interest rates have some impact on the corporate liquidation rate both in the very short and in the more intermediate term (up to 2 years).

3.5 Estimating the non-linear VAR over different samples

Looking at the write-off ratio of UK banks, Hoggarth *et al.* (2005) find that the sample period is important for their conclusions on the link between credit risk and macroeconomic shocks. In particular, they find that the impact of a shock to output, relative to potential, is stronger in the years after the UK adopted an inflation targeting regime. As discussed in Section 3.2, this may be due to a structural break in the relation between the macroeconomic variables. Obviously, if a structural break is present in 1992 then it would be better to focus on the post 1992 estimations as we have done so far. However, we extend our sample back to 1985Q1 for comparison. This sample period includes the recession of the early 1990s, which may contain useful information for stress testing. The IRFs from the estimated VAR based on the longer sample shocks can be found in Figure 12 and 13. We only show the impact on the liquidation rate following large macroeconomic shocks as small shocks have an insignificant impact on the liquidation rate at all horizons.

This robustness check leads to some interesting conclusions. First, using the cubic model, we find that large positive GDP shocks imply a significant fall in the corporate liquidation rate up to 1 year following the shock. Although negative GDP shocks are found to increase the corporate liquidation rate in the short run the impact is insignificant - the maximum impact from a large negative GDP shock is after 3 quarters, rather than 2 quarters using the 1992Q4-2004Q3 sample. Second, we find a substantially different impact from interest rate shocks on the corporate liquidation rate in comparison with the VAR estimated on the 1992Q2-2004Q3 sample. Large positive shocks to the interest rate increases the corporate liquidation rate significantly at all horizons with a maximum impact after 8 quarters, which is 8 times as high as its sample average. Large negative interest rate shocks, on the other hand, decrease the corporate liquidation rate significantly, in particular 2-6 quarters following the interest rate shock. The largest fall in the liquidation rate after large negative interest rate shocks is in the fifth quarter when the level of the liquidation rate is around 90% lower relative to its sample average.

The results from this alternative sample period indicate that the corporate liquidation rate is much more strongly related to the interest rate once the recession of the early 1990s is included in the sample. Large negative shocks to GDP do not lead to a significant increase in the corporate liquidation rate whereas both large positive GDP and large negative interest rate shocks imply a fall in the corporate liquidation rate. These results emphasise that some care must be taken in the choice of sample period: in our case this involved trading off valuable information from the recession of the early 1990s against the use of data from a different statistical regime.

4 Conclusion

In this paper we investigate the impact of possible non-linearities on credit risk in a VAR setup. As standard VAR models are unable to deal with non-linearities we use the methodology proposed by Jorda (2005). The key insight of Jorda was to interpret a general VAR as a first order Taylor series approximation of an unknown data generating process. His approach allows to estimate more flexible approximations, which capture possible non-linearities in the data. We apply this methodology to a small model of the macro economy and extend it to analyse the interaction between the aggregate corporate liquidation rate and macroeconomic variables. We show that the results of the non-linear VAR are different to results using standard linear models, especially when considering large shocks. This was illustrated using a simple three variable macro model. Most importantly, we show that accounting for non-linearities in the underlying macroeconomic environment leads to substantially different conclusions for aggregate credit risk projections. In contrast to most other papers we explicitly account for the underlying estimation uncertainty of the models. We show that this can have significant implications for the estimated level of credit risk, especially when looking at the tails of the credit risk distribution.

Overall, our analysis confirms the findings of previous papers (see for example Benito *et al.* (2001)) which suggest that large increases in interest rates are a key driver of credit risk, and that large positive shocks to GDP tend to reduce risk significantly. Our analysis also points to a stronger relation between the liquidation rate and the macroeconomic variables, in particular interest rates, once the early 1990s is included in the sample.

5 Appendix

5.1 A simple non-linear model

To illustrate the importance of different approximations to a non-linear data generating process consider (y_t, y_{t-1}) the following joint distribution:

$$(y_t, y_{t-1}) \sim F = C_C (\Phi, \Phi; \kappa)$$

where F is some bivariate distribution with standard normal marginal distributions (denoted Φ) connected with Clayton's copula, C_C, with dependence parameter κ. This type of time series process was first studied in economics by Chen and Fan (2004). This implies that we can write

$$\begin{aligned}
y_t &= h\left(y_{t-1}, \varepsilon_t; \kappa\right) \\
\text{where } \varepsilon_t | y_{t-1} &\sim N(0,1) \\
C_C(u|v;\kappa) &\equiv \frac{\partial C_C(u,v;\kappa)}{\partial v} \\
h(y,\varepsilon;\kappa) &\equiv C_C^{-1}\left(\Phi(\varepsilon)\,|\Phi(y);\kappa\right)
\end{aligned}$$

which is a general, stationary, non-linear data generating process that is simple to simulate. In Figure 4 we show one simulated sample path from this process for $k = 1.1$, which yields $Corr\left[y_t, y_{t-1}\right] = 0.5$.

5.2 A second order Taylor expansion

Consider the second order expansion for the first element of $\mathbf{g}$, denoted g_1, where $g_1 : \mathbb{R}^{pk} \rightarrow \mathbb{R}$

$$g_1\left(\mathbf{Y}_{t-1}^{p}\right) \approx g_1(\mathbf{0}) + \nabla g_1(\mathbf{0})\,\mathbf{Y}_{t-1}^{p} + \frac{1}{2}\mathbf{Y}_{t-1}^{p\prime}\nabla^2 g_1(\mathbf{0})\,\mathbf{Y}_{t-1}^{p} \tag{11}$$

We can re-write this expression in a more convenient form by making use of the *vec* operator and the Kronecker product (denoted $\otimes$):

$$
\begin{aligned}
\underset{(1\times 1)}{g_1\left(\mathbf{Y}_{t-1}\right)} &\approx \underset{(1\times 1)}{g_1\left(\mathbf{0}\right)} + \underset{(1\times pk)}{\nabla g_1\left(\mathbf{0}\right)} \underset{(pk\times 1)}{\mathbf{Y}_{t-1}^{p}} + \frac{1}{2} \underbrace{vec(\underbrace{\nabla^2 g_1\left(\mathbf{0}\right)}_{(pk\times pk)})'}_{(1\times p^2k^2)} \underbrace{(\underset{(pk\times 1)}{\mathbf{Y}_{t-1}^{p}} \otimes \underset{(pk\times 1)}{\mathbf{Y}_{t-1}^{p}})}_{(p^2k^2\times 1)} \\
&= g_1\left(\mathbf{0}\right) + \nabla g_1\left(\mathbf{0}\right) \mathbf{Y}_{t-1}^{p} + \frac{1}{2} vec\left(\nabla^2 g_1\left(\mathbf{0}\right)\right)' vec\left(\mathbf{Y}_{t-1}^{p} \mathbf{Y}_{t-1}^{p\prime}\right)
\end{aligned}
$$

We can stack the equations to obtain:

$$
\begin{aligned}
\mathbf{g}\left(\mathbf{Y}_{t-1}\right) &\approx \mathbf{g}\left(\mathbf{0}\right) + \nabla \mathbf{g}\left(\mathbf{0}\right) \mathbf{Y}_{t-1}^{p} + \frac{1}{2} \begin{bmatrix} vec\left(\nabla^2 g_1\left(\mathbf{0}\right)\right)' \\ vec\left(\nabla^2 g_2\left(\mathbf{0}\right)\right)' \\ \vdots \\ vec\left(\nabla^2 g_k\left(\mathbf{0}\right)\right)' \end{bmatrix} vec\left(\mathbf{Y}_{t-1}^{p} \mathbf{Y}_{t-1}^{p\prime}\right) \\
\text{Let } \nabla^2 \mathbf{g}\left(\mathbf{0}\right) &\equiv \begin{bmatrix} vec\left(\nabla^2 g_1\left(\mathbf{0}\right)\right)' \\ vec\left(\nabla^2 g_2\left(\mathbf{0}\right)\right)' \\ \vdots \\ vec\left(\nabla^2 g_k\left(\mathbf{0}\right)\right)' \end{bmatrix} \\
\text{Then } \underset{(k\times 1)}{\mathbf{g}\left(\mathbf{Y}_{t-1}^{p}\right)} &= \underset{(k\times 1)}{\mathbf{g}\left(\mathbf{0}\right)} + \underset{(k\times pk)}{\nabla \mathbf{g}\left(\mathbf{0}\right)} \underset{(pk\times 1)}{\mathbf{Y}_{t-1}^{p}} + \frac{1}{2} \underset{(k\times p^2k^2)}{\nabla^2 \mathbf{g}\left(\mathbf{0}\right)} \underbrace{\left(\mathbf{Y}_{t-1}^{p} \otimes \mathbf{Y}_{t-1}^{p}\right)}_{(p^2k^2\times 1)} \\
&\equiv \underset{(k\times 1)}{B_0} + \underset{(k\times pk)}{B_1^{p}} \underset{(pk\times 1)}{\mathbf{Y}_{t-1}^{p}} + \underset{(k\times pk(pk+1)/2)}{B_2^{p}} \underbrace{vech\left(\mathbf{Y}_{t-1}^{p} \mathbf{Y}_{t-1}^{p\prime}\right)}_{(pk(pk+1)/2\times 1)}, \text{ collecting terms} \\
&\equiv \underset{(k\times 1)}{B_0} + \sum_{m=1}^{p} \underset{(k\times k)}{B_{1m}} \underset{(k\times 1)}{\mathbf{Y}_{t-m}} + \sum_{i=1}^{p} \sum_{j=i}^{p} \underset{(k\times k(k+1)/2)}{B_{2ij}} \underbrace{vech\left(\mathbf{Y}_{t-i} \mathbf{Y}_{t-j}'\right)}_{(k(k+1)/2\times 1)}, \text{ collecting terms}
\end{aligned}
$$

where $vech\left(X\right)$ stacks only the lower triangle of the matrix X. We use the $vech$ function rather than the vec function as $\mathbf{Y}_{t-1}^{p}\mathbf{Y}_{t-1}^{p\prime}$ includes both $Y_{1,t-1}Y_{2,t-1}$ and $Y_{2,t-1}Y_{1,t-1}$, for example, and we can collect such terms. Moving from the penultimate to the final line above also follows from a collection of terms, further reducing the number of free parameters.

5.3 Tables

Table 1

Descriptive statistics	Mean	Standard deviation	Skewness	Kurtosis
Corporate liquidation rate	0.0132	0.0046	1.2919	4.3303
GDP growth	0.0072	0.0032	0.4080	1.9562
Interest rate	0.0130	0.0025	-0.1474	2.1483
Inflation	0.0062	0.0046	0.2076	2.7698

Descriptive statistics for data in VAR. 1992Q4-2004Q4.

5.4 Charts

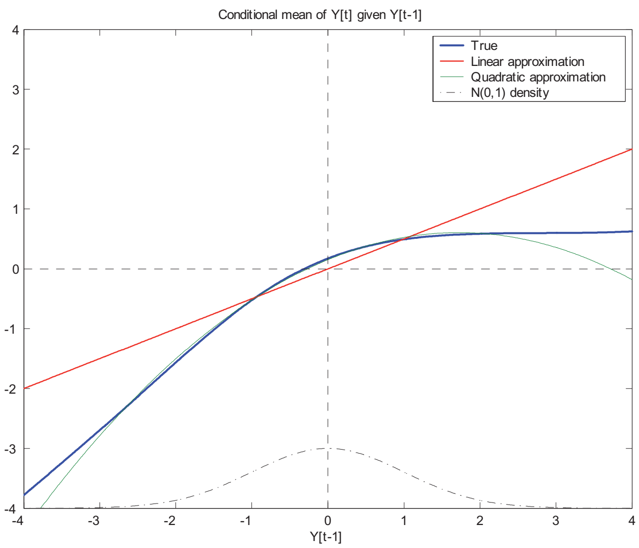

Figure 1: The conditional mean of Y_t given Y_{t-1} assuming $Y_t \sim N(0,1)$ and using a Clayton copula implying first-order autocorrelation of 0.5.

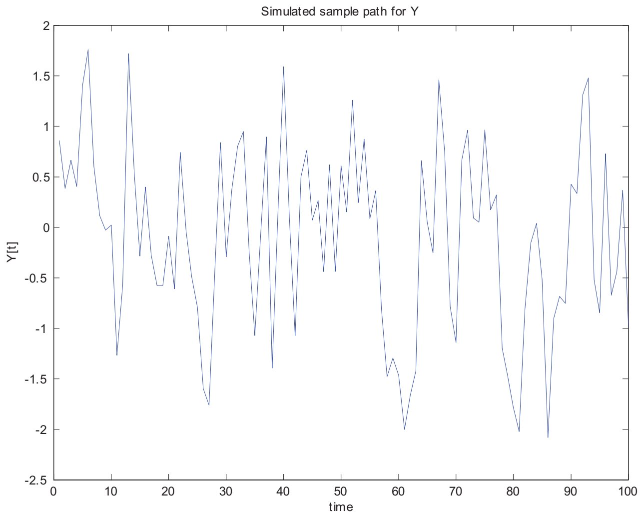

Figure 2: One sample path for Y_t using a nonlinear DGP.

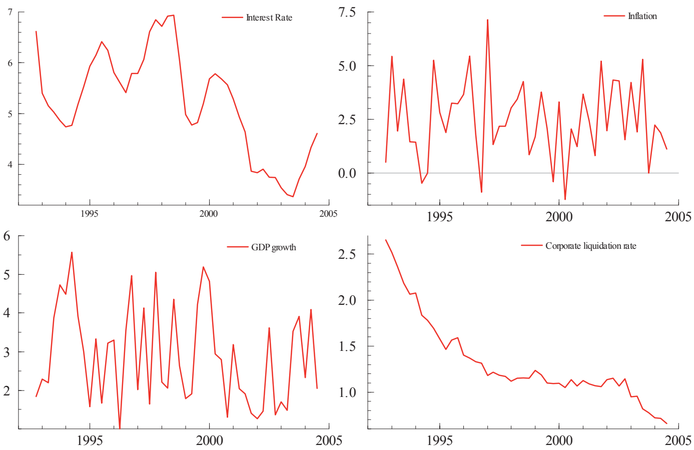

Figure 3: The Corporate liquidation rate and macroeconomic variables included in the VAR.

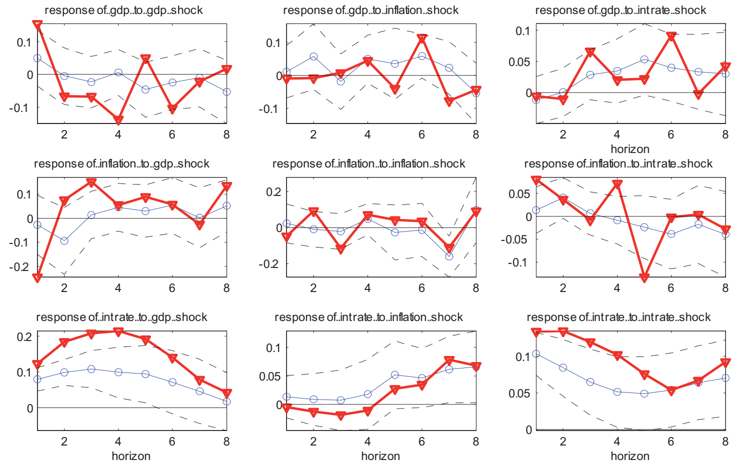

Figure 4: The thick line marked with triangles is the impulse response for a 1 standard deviation shock from the cubic projection; the thin line marked with circles is the impulse response from the linear projection; the dashed lines are the 95% confidence bounds on the impulse response from the linear projection.

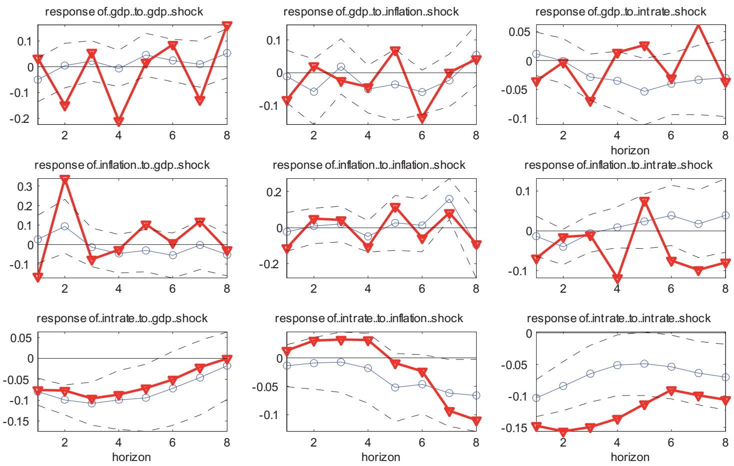

Figure 5: The thick line marked with triangles is the impulse response for a -1 standard deviation shock from the cubic projection; the thin line marked with circles is the impulse response from the linear projection; the dashed lines are the 95% confidence bounds on the impulse response from the linear projection.

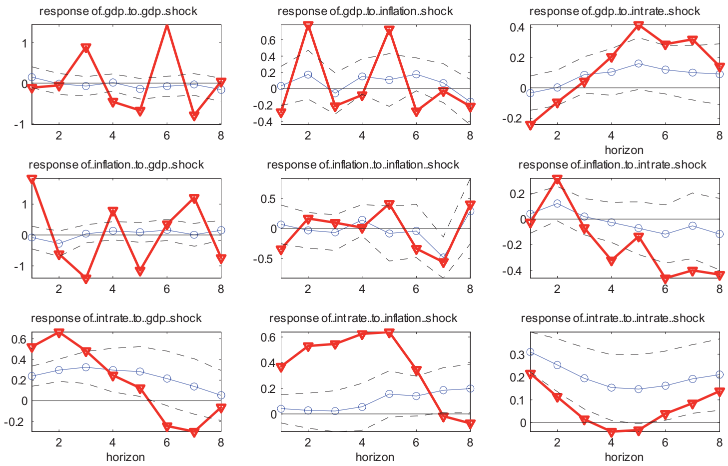

Figure 6: The thick line marked with triangles is the impulse response for a 3 standard deviation shock from the cubic projection; the thin line marked with circles is the impulse response from the linear projection; the dashed lines are the 95% confidence bounds on the impulse response from the linear projection.

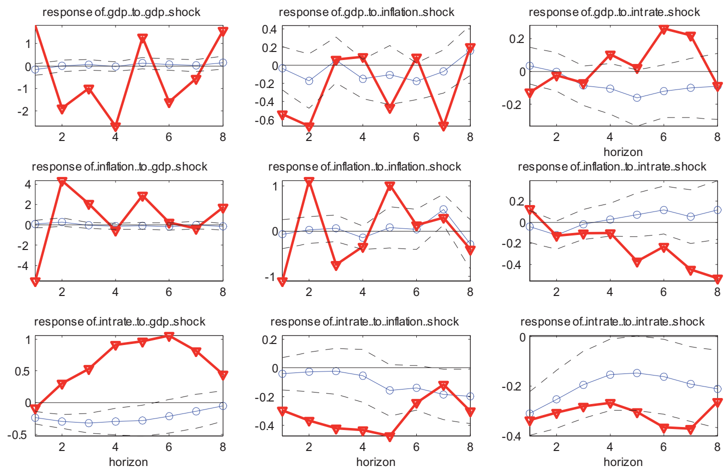

Figure 7: The thick line marked with triangles is the impulse response for a -3 standard deviation shock from the cubic projection; the thin line marked with circles is the impulse response from the linear projection; the dashed lines are the 95% confidence bounds on the impulse response from the linear projection.

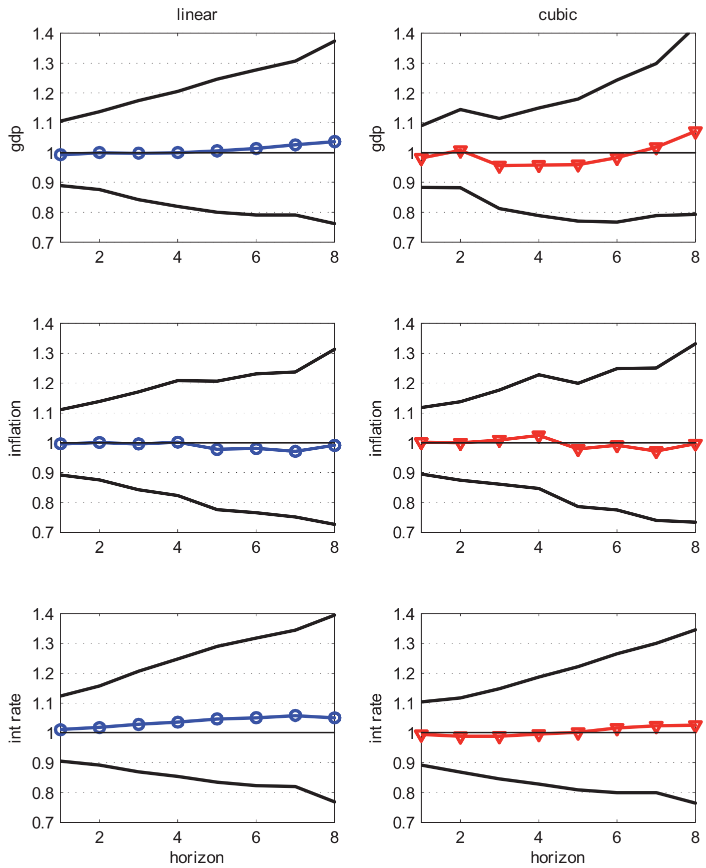

Figure 8: These figures show the response of the liquidation ratio to a 1 standard deviation shock, relative to the baseline liquidation ratio of 1.32% per year. The rows indicate the shocked variables; the columns show the model used, either a linear projection or a cubic projection. 95% confidence intervals are denoted with a thick line.

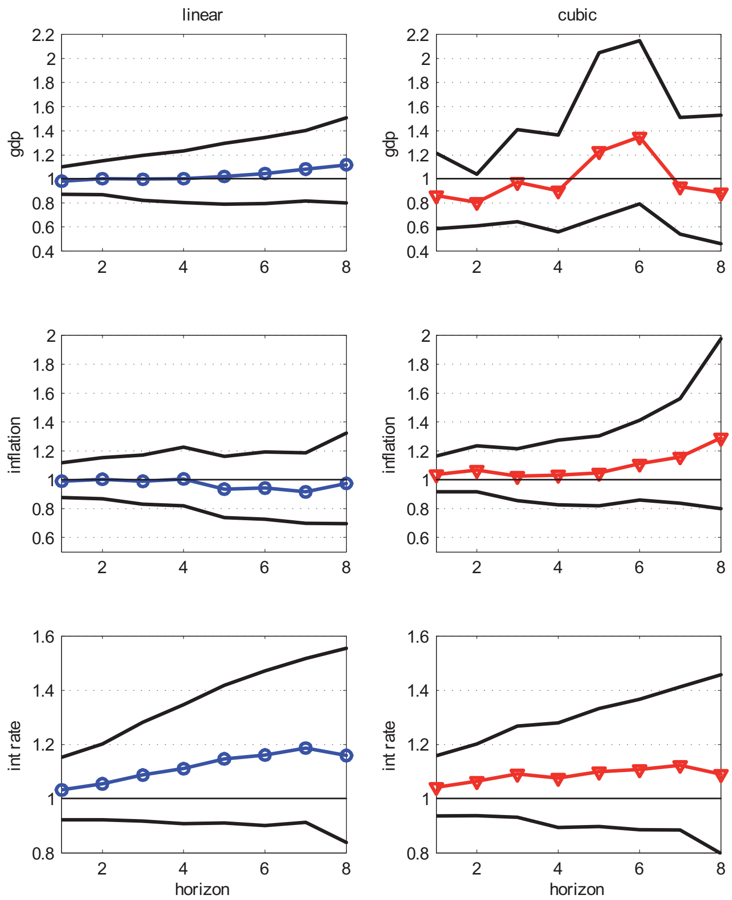

Figure 9: These figures show the response of the liquidation ratio to a 3 standard deviation shock, relative to the baseline liquidation ratio of 1.32% per year. The rows indicate the shocked variables; the columns show the model used, either a linear projection or a cubic projection. 95% confidence intervals are denoted with a thick line.

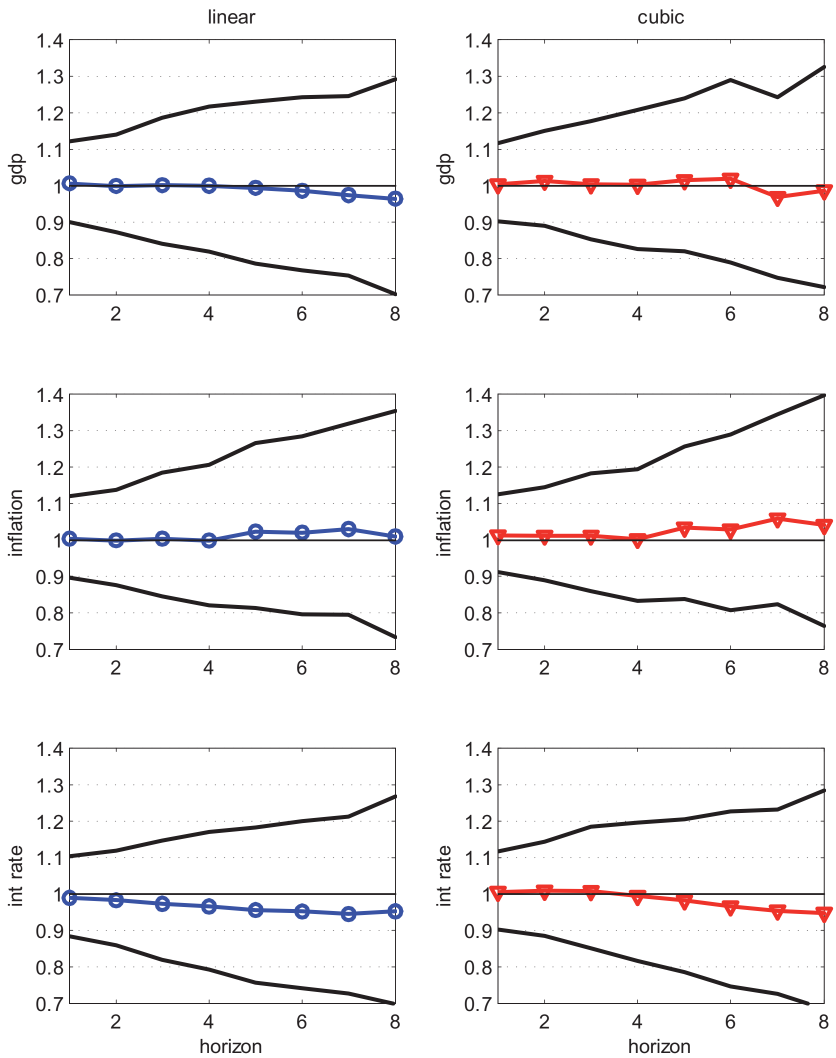

Figure 10: These figures show the response of the liquidation ratio to a -1 standard deviation shock, relative to the baseline liquidation ratio of 1.32% per year. The rows indicate the shocked variables; the columns show the model used, either a linear projection or a cubic projection. 95% confidence intervals are denoted with a thick line.

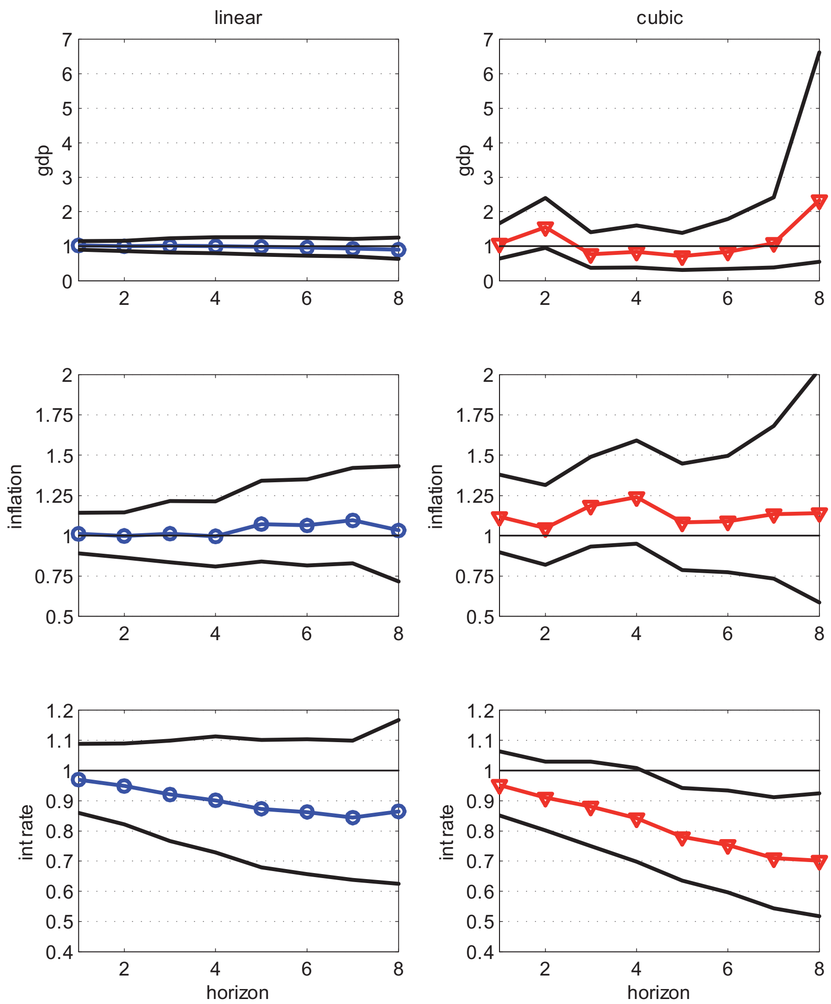

Figure 11: These figures show the response of the liquidation ratio to a -3 standard deviation shock, relative to the baseline liquidation ratio of 1.32% per year. The rows indicate the shocked variables; the columns show the model used, either a linear projection or a cubic projection. 95% confidence intervals are denoted with a thick line.

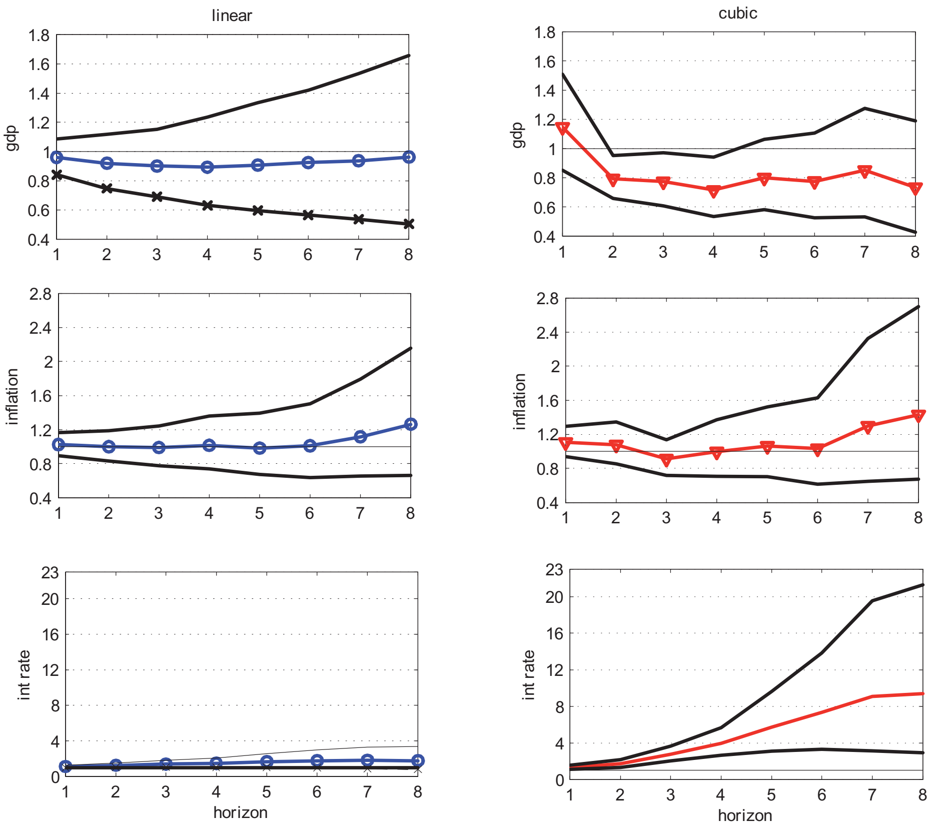

Figure 12: These figures show the response of the liquidation ratio to a +3 standard deviation shock, relative to the baseline liquidation ratio of 1.32% per year. The rows indicate the shocked variables; the columns show the model used, either a linear projection or a cubic projection. 95% confidence intervals are denoted with a thick line. Using sample from 1985Q1-2004Q3.

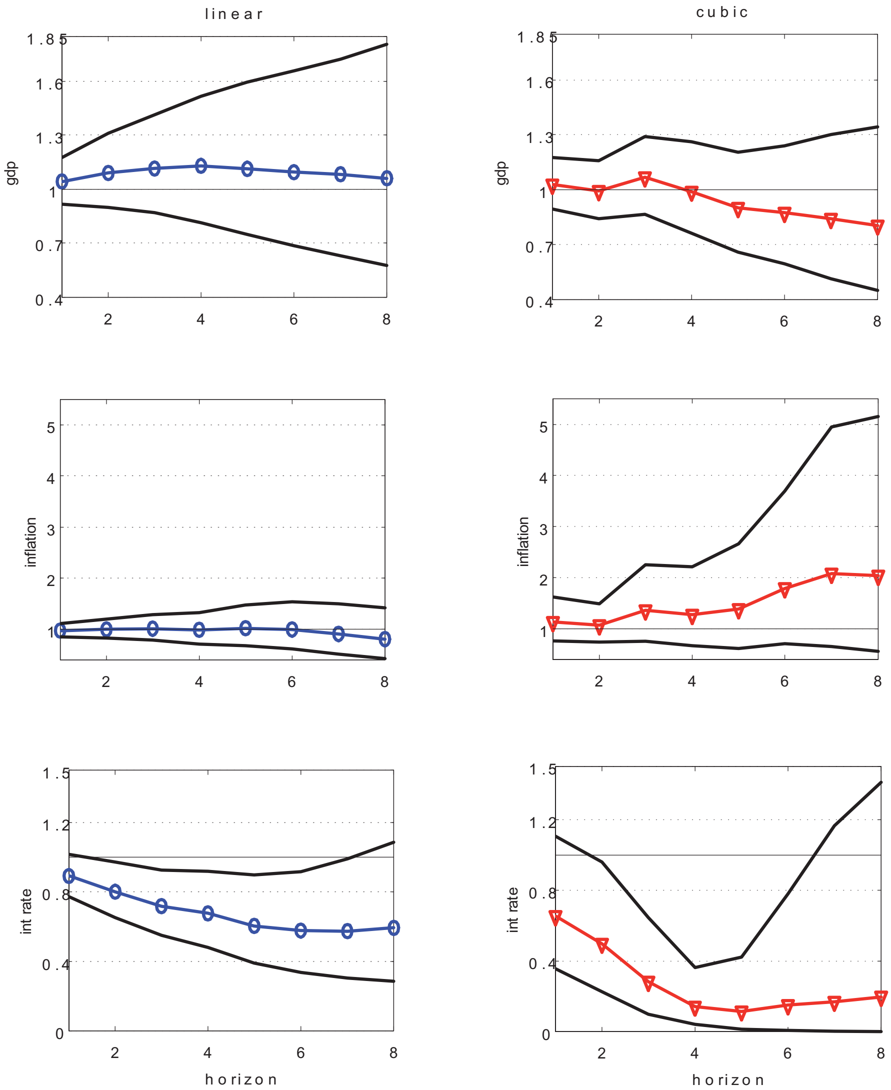

Figure 13: These figures show the response of the liquidation ratio to a -3 standard deviation shock, relative to the baseline liquidation ratio of 1.32% per year. The rows indicate the shocked variables; the columns show the model used, either a linear projection or a cubic projection. 95% confidence intervals are denoted with a thick line. Using sample from 1985Q1-2004Q3.

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EXPLORING INTERACTIONS BETWEEN REAL ACTIVITY AND THE FINANCIAL STANCE☆

TOR JACOBSON*, JESPER LINDÉ, KASPER ROSZBACH

Abstract

In this paper we empirically study interactions between real activity and the financial stance. Using aggregate data we examine a number of candidate measures of the financial stance of the economy. We find strong evidence for substantial spillover effects on aggregate activity from our preferred measure. Given this result, we use a large micro-data set for corporate firms to develop a macro–micro-model of the interaction between the financial and real economy. This approach implies that the impulse responses of a given aggregate shock will depend on the portfolio structure of firms at any given point in time.

JEL classification: C41; G21; G33; G38

Keywords: Default-risk models; Business cycles; Financial stability; Price stability; Financial and real economy interaction

☆ We have benefitted from comments by participants at the "Regulation and Financial Stability Conference" at the Federal Reserve Bank of Atlanta (23–24 September 2004), especially our discussant Charles Evans. Moreover, we have benefitted from presentations at the BIS 2003 autumn economist meeting on "The interaction between the financial and real side of the economy", University of Verona and the Bank of England workshop on macro-stress testing. Special thanks to Rikard Nilsson for superb research assistance. The views expressed in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Executive Board of Sveriges Riksbank.

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1. Introduction

In this paper we empirically study the interactions between Swedish firms' balance sheets and the evolution of the Swedish economy. Most economists would consider it trivially true that macroeconomic conditions influence the state of the firms' balance sheets: good times result in prosperous firms with strong balance sheets, likewise a slowdown in the economy will be reflected by weak balance sheets. In that same view, the evolution of the macroeconomy will ultimately be determined by its firms' relative successes. Nevertheless, quantifying such relationships has turned out to be non-trivial. Most research has focused on either identifying the impact of macroeconomic conditions on firms' balance sheets, or the consequences of firms' balance sheets (generally through a bank channel) on the macroeconomy. The purpose of this paper is to explore the *interaction and feedback* between firms' balance sheets and the macroeconomy. It turns out that by using aggregate credit risk, approximated by firms' bankruptcy frequency over time, we find a useful link between the micro- and the macro-perspective.

Among policymakers, there appears to exist a broad consensus that market imperfections and instability in the financial sector can have significant and long-lasting effects on the real economy, cf. Lowe (2001). For academics, however, the role of the financial sector and credit in the macroeconomy has been a source of frequent debate, with some economists, see e.g. Poole (1993) arguing that credit only plays a role of its own in periods of financial crises. Others, see e.g. Bernanke (1993) and Calomiris and Glenn Hubbard (1989), hold that credit markets *generally* and continuously affect the macroeconomy through the so-called credit channel.

Bernanke and Gertler (1995) describe the credit channel as "set of factors that amplify and propagate conventional interest rate effects" of monetary policy through endogenous changes in the external finance premium. Adherents of this "credit view" have identified two main linkages between central banks' actions and credit markets: a (borrowers') balance-sheet channel and a bank lending channel.[1] The first link stresses the importance of borrowers' balance sheets and income statements, acknowledging that changes in monetary policy will have an impact on variables such as borrowers' net worth, cash flow and liquid assets. A second transmission mechanism focuses on the potential effect of monetary policy on the supply of loans by financial institutions. A common premise is, however, that frictions interfere with the smooth functioning of financial markets, creating a wedge between the cost of externally raised funds and the opportunity cost of internal funds.

A large number of studies has explained and tested the mechanisms by which shocks to the financial sector are propagated into the real sector of the economy and found evidence in support of the existence of a balance-sheet channel. As far as the bank lending channel is concerned, the evidence in favor and against is still very much under debate. One of the studies that revived the debate on the balance-sheet channel is Bernanke (1983). In his study of non-monetary effects of the financial crisis during the Great Depression, he contends that the financial crisis of the 1930s "affected the macroeconomy by reducing the quality of certain financial services, primarily credit intermediation", which in its turn disrupted the

[1] The balance sheet channel has sometimes also been called the broad credit channel. See for example Repullo and Suarez (2000).

normal flow of bank credit. He also brings forward evidence of how the increase in defaults and bankruptcies and the progressive erosion of borrowers' collateral relative to their debt burdens during this period increased the cost of credit intermediation. Banks reacted to these changes by stopping to make loans to lower-quality investors, to which they had lent before.[2] The events in the financial sector ultimately affected the bearing of the macroeconomy because the resulting higher effective cost of credit reduced businesses demand for current-period goods and services. An analysis of the determinants of output by Bernanke shows that two proxies for the financial crisis—changes in the deposits of failing banks and changes in the liabilities of failing businesses have substantial additional explanatory power for the growth rate of industrial production. In related work Coe (2002) use a Markov switching model to estimate conditional probabilities of a financial crisis occurring. He finds that these estimated probabilities have additional explanatory power in an model of real output, evidence that supports Bernanke's findings. Bernanke and Gertler (1989) develop a small model in which they use the inverse relationship between borrower net worth and the agency costs of investment to explain why changes in the condition of borrowers' balance sheets can be a source of business cycle fluctuations—without any financial crisis preceding the shocks.[3] In a companion paper, Bernanke and Gertler (1990) also argue that financial factors can have quantitatively significant real effects by demonstrating how changes in the creditworthiness of borrowers affect investment spending, expected returns and the overall economy.

More recently research efforts have attempted to meet the criticism that earlier studies of the credit channel failed to isolate supply shocks from demand shocks and persuasively establish the existence of real effects. To avoid identification issues, this later work has tested the cross-section implications of the credit view. For example, Gertler and Gilchrist (1993, 1994) find that larger firms have better access to credit and typically respond to unexpected adverse conditions by increasing short-term borrowing, while smaller firms instead respond by squeezing inventories and cutting production. Bernanke et al. (1996) obtain similar findings when they split up firms according to their degree of bank dependency rather than based on size. Samolyk (1994) examines the relationship between banking conditions and economic performance at the US states level and finds that local bank balance-sheet conditions help to predict the performance of regional economies in a way that is consistent with the existence of credit market imperfections. Ludvigson (1998) uses automobile credit data from bank and non-bank sources and finds evidence for the presence of a bank lending channel. Peek and Rosengren (2000) study the effects of the Japanese banking crisis on construction activity in the US. Their work makes clear that the retrenchment of Japanese lending had a substantial impact on US. real estate activity, indicating that at least some borrowers were not able to obtain alternative financing and that credit markets thus were suffering from imperfections. Repullo and Suarez (2000) develop a theoretical model that can compare the macro-implications of both the balance-sheet channel and the bank lending channel and conclude that the presence of a balance-sheet channel is most likely.

[2] An important indicator of this phenomenon is the bond spread between Baa corporate bonds and Treasury bonds, that increased from 2.5% in 1929–1930 to nearly 8% in mid-1932. See Bernanke (1983) p. 266.

[3] Bernanke and Gertler (1990) define financial instability ("fragility") as a situation in which potential borrowers have low wealth relative to the sizes of their projects.

This paper is closely related to the above work as we study the interaction between real activity and firms' balance sheets. Unlike earlier studies, however, that primarily seek to identify a one-way linkage between the macroeconomy and financial markets, we combine a microeconometric model of firms' financial default behavior and a macroeconometric model to study how macro-aggregates and the aggregate effects of changes in individual firms' balance sheets and income statements interact with each other. Our focus is less on the existence of a "credit channel" but rather on the interaction between the economy's financial stance at the firm level and the economy's aggregate behavior. Although our link between micro-conditions and the macro-model is not derived from micro-foundations, we believe that this eclectic approach offers a number of advantages. For one thing, we will be able to investigate if macroeconomic policy will affect businesses equally, both cross-sectionally and through time. We will also be able to look into the relative importance of firm-specific and aggregate disturbances.[4]

We model the macroeconomy by a set of macroeconomic variables, including the aggregate bankruptcy frequency, in a quarterly vector autoregressive model. Furthermore, the impact of firms' balance-sheet variables on bankruptcy risk is modeled in a dynamic panel data model, where we also condition on macroeconomic variables. To this end we have collected an extensive data set containing balance-sheet information on the entire population of Swedish incorporated firms (some quarter of a million firms) for 40 consecutive quarters, 1990Q1 – 1999Q2 (in total, close to 8 million firm-observations). This sample period covers the "banking crisis" period in Sweden (1991–1993) and also a benign period characterized by high growth in the late 1990s.

The empirical model is a system made up of three blocks. The first one is a vector autoregressive (VAR) model for the macroeconomic variables we consider. Based on work by Lindé (2002), we choose to include the following endogenous variables in the VAR; output, inflation, the nominal interest rate (the REPO rate), and the real exchange rate. Since Sweden is a small open economy it is necessary to condition on a set of foreign variables that enters the model exogenously. As another exogenous variable in the VAR we include our preferred measure of the financial stance, the aggregated default frequency of incorporated firms, a variable that is highly positively correlated with the banking sector credit losses during the 1990s. An important first step in the analysis is to use a multivariate Granger-causality test, or block-exogeneity test, in order to examine what extent various financial indicator variables are helpful predictors of the macroeconomy. This exercise is undertaken for a larger set of financial variables, and we find that the aggregate default frequency is the most important one.

In the second block we have a logit model for the default risk at the firm level where the macroeconomic variables as well as various balance-sheet variables enter as regressors. The logit model will carefully follow the methods that have been applied in earlier studies on company default, such as Altman and Saunders (1997), Shumway (2001) and Carling et al. (2004). Let $D_{i,t}$ denote default status of firm i in period t. By computing $\left(\sum_i D_{i,t}\right)/N_t$, where N_t is the number of firms each time period, we retrieve a time-series of the aggregate

[4] Although we are aware of the importance of job and business creation, our focus here is on interaction between the macroeconomy and business default (destruction).

default frequency that can be inserted into the VAR-model. So, once equipped with a VAR-model and the estimated logit model, we can simulate the effects of various disturbances in the economy. For instance, we can study the dynamic effects of a shock to monetary policy on inflation and the default frequency in a joint framework.

The third block in the empirical model is an attempt to estimate how the balance-sheet variables that are included in the logit model depend on the macroeconomic variables. Due to the panel-data nature of our firm-level data set, we estimate a dynamic panel VAR-type model for the balance-sheet variables (that are included in the logit model) letting the macro-variables enter as regressors. We can then study if the macroeconomic variables are quantitatively important for explaining variation in the balance-sheet variables.

Our main findings are as follows. First, we find that the aggregate default frequency is a significantly and quantitatively important link from the financial to the real side of the economy, whereas other commonly considered financial indicators appear less so. Second, we find that macroeconomic variables are important for explaining a time-varying default frequency. Firm-specific variables are very useful in ranking the riskness of firms, but macroeconomic variables are of crucial importance for explaining changes in absolute default risk. Third, most of the variation in balance-sheet variables are of idiosyncratic origin. Fourth, the empirical model implies that the effects of monetary policy on the default frequency and the inflation rate are state dependent: monetary policy appears to be more potent under recessions than during booms. Finally, we find that our empirical model appears to more accurately produce joint forecasts of inflation and the aggregate default frequency in comparison to a standard VAR-model where the default frequency is included as an endogenous variable.

The remainder of this paper is structured as follows. In the next section, we present our micro- and macro-data sets. The dependency of the real side of the economy on the set of financial variables we study is examined in Section 3. In Section 4, we test for the dependency of the financial variables for the macro-variables. In Section 5, we summarize the empirical models that are used to examine the interaction between the real and financial side of the economy. The empirical micro–macro-model is then used in Section 6 to shed light on some interesting policy issues. In this section, we also compare the properties of this model with those of a VAR-model where the aggregate default frequency is included as an endogenous variable. Finally, Section 7 concludes.

2. Data

2.1. Micro-data

In this subsection, we provide a detailed description of our data set at the firm level.

The final data set is a panel consisting of 7,652,609 quarterly observations on incorporated firms, covering 10 years of quarterly data for all Swedish *aktiebolag* companies that have issued a financial statement between 1 January 1990, and 30 June 1999. *Aktiebolag* are by approximation the Swedish equivalent of US corporations and UK limited businesses. Swedish law requires every *aktiebolag* to have at least SEK 100,000 (approximately US$ 10,000) of equity to be eligible for registration at the Swedish Patent and Registration

Office (PRV). Firms are also required to submit an annual report to PRV. Small firms such as general partnerships, limited partnerships and sole proprietors will be disregarded, since, as reported by Jacobson and Lindé (2000), incorporated firms by far account for the largest fraction of loans and, also, display the most cyclical variation in default risk.

The firm-data come from Upplysningscentralen AB (UC), a major credit bureau in Sweden, and are from two general sources of information. First, UC has provided us with balance-sheet and income statement data from the firms' annual reports submitted to PRV. These annual report data cover the period 1 January 1989–31 December 1999. Second, UC has provided us with historical data on events related to payment remarks and payment behavior for the firms and for their principals. The UC-data are available at different frequencies, varying from daily for payment remarks to (most often) annually for accounting data. We will discuss the specifics of the data in greater detail below.

The accounting data contains information on most standard balance-sheet and income statement variables. Appendix A[5], which is available upon request, contains a complete list of annual report variables. In addition to the annual report data, we have information on the firms' track records regarding payment behavior as recorded by remarks for 61 different credit and tax related events. The storage and usage of payment remarks are regulated by the Credit Information Act, the Personal Data Act and overseen by the Swedish Data Inspection Board. Examples of events that are registered are: delays in tax payments, the repossession of delivered goods, the seizure of property, the resettlement of loans and actual bankruptcy. In practice, with a record of payment remarks individuals will not be granted any new loans and businesses can find it very difficult to open new lines of credit. Appendix B[5], which is available upon request, contains the complete list of payment remarks.

We define the population of existing firms in quarter t as the firms, which have issued a financial statement covering that quarter and are classified as "active". For a firm to be classified as active, we require that is has total sales and total assets over 1000 SEK (roughly US$ 100). In addition to these firms, we add the firms which according to the data set on remarks are classified as defaulted firms.[6] The adopted definition of default is the one used by UC.[7]

In Table 1, we report all descriptive statistics for the employed accounting ratios and other variables, such as payment remarks and average delayed time to the last issued financial report for the defaulted and non-defaulted firms. Because of varying availability of data, the statistics in Table 1 were calculated based on different numbers of observations. For firms where accounting data are not available, we replace missing values by the panel mean for the defaulted/non-defaulted firms. In part A of Table 1, showing non-truncated data, there are some accounting data observations that clearly are severe outliers. These observations would seriously distort the estimation results if they were to be included in

[5] Available upon request.

[6] There is a simple reason why we need to add firms that have defaulted to the population of firms defined by the accounting data. Many firms that default choose not to submit their compulsary annual reports in the year, or even years, prior to default. Hence, the only records of their existence that we have come from the remark registers.

[7] According to the UC-definition, a firm has default status if any of the following more important events have occured: the firm is declared bankrupt in the legal sense, it has suspended payments, it has negotiated a composition settlement, it is undergoing a re-construction, or, distraint with no assets. We differ somewhat from the credit bureau's definition though, in that we use a one quarter horizon, whereas they currently employ a 1-year horizon.

Table 1
Descriptive statistics for the micro-data

Firm type	N	μ	σ	Statistic				
				min	1%	50%	99%	max
Part A: non-truncated data								
Non-defaulted	7549041							
EBITDA/TA	7471212	−0.12	220.40	−256885	−1.03	0.11	0.85	66424
TL/TA	7474248	3.56	1351.21	−408	0.03	0.73	2.42	1703742
LA/TL	7451325	1.09	109.37	−71203	0	0.13	7.94	54655
I/TS	7355762	4.84	6254.23	−26845	0	0.01	2.18	16500000
TL/TS	7474248	2.32	120.73	−32.25	0	0.08	17.02	48536
IP/(IP + EBITDA)	7457030	−1.7E10	2.8E13	0	−3.59	0.10	3.95	2.2E16
Defaulted	103568							
EBITDA/TA	67093	−6.04	1201.38	−215719	−5.40	0.03	1.23	164895
TL/TA	67110	208.17	25784.42	−23304	0.01	0.94	18.97	5407312
LA/TL	66729	0.57	24.20	−436	0	0.02	4.87	3258
I/TS	63138	27.05	6319	−0.19	0	0.03	5.21	1587085
TL/TS	67110	0.80	8.46	−0.08	0	0.12	9.53	787
IP/(IP + EBITDA)	66670	0.35	28.53	−1216	−6.09	0.23	6.90	5794
Part B: truncated data								
Non-defaulted	7549041							
EBITDA/TA	7471212	0.11	0.25	−1.05	−1.03	0.11	0.84	0.84
TL/TA	7474248	0.71	0.35	0.03	0.03	0.73	2.42	2.46
LA/TL	7451325	0.53	1.12	0	0	0.13	7.81	7.81
I/TS	7355762	0.12	0.29	0	0	0.01	2.13	2.13
TL/TS	7474248	0.58	2.08	0	0	0.08	14.74	18.61
IP/(IP + EBITDA)	7457030	0.15	0.76	−3.55	−3.55	0.10	3.91	3.91
PAYDIV (%)	7549041	13.15	33.80	0				1
REMARK1 (%)	7549041	0.33	5.77	0				1
REMARK2 (%)	7549041	3.06	17.21	0				1
TTLFS (%)	7549041	1.54	12.30	0				1
Defaulted	103568							
EBITDA/TA	67093	−0.03	0.35	−1.05	−1.05	0.03	0.84	0.84
TL/TA	67110	1.00	0.0	0.03	0.03	0.94	2.46	2.46
LA/TL	66729	0.21	0.82	0	0	0.02	4.87	7.81
I/TS	63138	0.18	0.38	0	0	0.03	2.13	2.13
TL/TS	67110	0.57	1.75	0	0	0.12	9.52	18.61
IP/(IP + EBITDA)	66670	0.24	0.99	−3.55	−3.55	0.23	3.91	3.91
PAYDIV (%)	103568	0.70	8.31	0				1
REMARK1 (%)	103568	14.90	35.61	0				1
REMARK2 (%)	103568	40.60	49.11	0				1
TTLFS (%)	103568	33.42	47.17	0				1

Notes: The definition of variables are: EBITDA = earnings before taxes, interest payments and depreciations; TA = total assets; TL = total liabilities; LA = liquid assets; I = inventories; TS = total sales; IP = sum of net interest payments on debt and extra-ordinary net income; PAYDIV = a dummy variable equal 1 if the firm has paid out dividends during the accounting period and 0 otherwise; REMARK1 = a dummy variable taking the value of 1 if the firm has a payment remark due to one or more of the following events in the preceding four quarters; (i) a "non-performing loan" at a bank, or (ii) a bankruptcy petition, or (iii) issuance of a court order to pay a debt, or (iv) seizure of property; REMARK2 = a dummy variable taking the value of 1 if the firm is in various tax arrears; TTLFS = a dummy variable equal to 1 if the firm has not submitted an annual report in the previous year, and 0 otherwise.

the logit model. Therefore, we have truncated the top and bottom 1% observations for the accounting variables.[8] Given the large number of observations, this approach is more or less equivalent to simply deleting 1% of the observations that have accounting data that fall outside a certain region. Part B of Table 1 shows the descriptive statistics for the truncated micro-data set.[9]

As financial reports issued by firms typically become available with a significant time lag, it cannot in general be assumed that accounting data for year τ are available during or even at the end of year τ to forecast default risk in year $\tau + 1$. To account for this, we have lagged all accounting data by four quarters in the estimations. For most firms, who report balance-sheet and income data over calendar years, this means that data for year τ is assumed to have been available in the first quarter of year $\tau + 1$.

For a number of firms some transformation had to be applied to the accounting variables to adjust for reporting periods that did not coincide with the calendar year, to assure that each variable is measured in identical units for all firms. Some firms, for example, report accounting information referring to 3- or 4-month periods for one or several years. In such cases, annual balance-sheet figures were calculated as weighted averages of the multiple period values. In other cases companies did report numbers for a 12-month period, but the period did not coincide with the calendar year. The 1995 figures, for example, could refer to the period 1 April 1995 until 31 March 1996. In these cases, such "deviations" were accounted for by adjusting the "four quarter lag" (and thus the date at which the information is assumed to have been available) correspondingly.

Before we decided to restrict our attention to the set of financial ratios that are shown in Table 1, we studied a number of commonly used accounting ratios that were employed in frequently cited articles studying bankruptcy risk and the balance-sheet channel, but the ones reported show the strongest correlation with default risk.[10] In our empirical model, we employ six accounting ratios: earnings before interest, depreciation, taxes and amortization over total assets (earnings ratio); interest payments over the sum of interest payments and earnings before interest, depreciation, taxes and amortization (interest coverage ratio); total liabilities over total assets and total liabilities over total sales (debt ratios); cash in relation to total liabilities (cash ratio); and inventories over total sales (turnover ratio).[11] These

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[8] This approach is quite common in the literature, and e.g. Shumway (2001) also truncate 1% of the top and bottom observations. It should be emphazied that the results are not at all sensitive when varying the truncation rate between 0.5 and 2%.

[9] From Table 1, comparison of the descriptive statistics for the untruncated data makes it clear that defaulted firms are unproportionally more affected when truncating all the observations simultaneously. Since the REMARK1, REMARK2, PAYDIV and TTLFS are dummy variables that are unaffected by our truncation procedure, it may lead to underestimation of the importance of the accounting data variables in the default risk model relative to these dummy variables. To check the robustness of our chosen approach, we used an alternative approach where we truncated the healthy and defaulted firms separately. As expected, the estimation results of the default-risk model with this alternative truncation suggested a somewhat larger role for the accounting ratios, but the over-all picture remains the same.

[10] See Altman (1968, 1971, 1973, 1984), Carling et al. (2004), Frydman et al. (1985), and Shumway (2001).

[11] It should be noted that the level of debt, in addition to the leverage ratio ($TL_{i,t}/TA_{i,t}$) for firm i in period t, appears to contain predictive power for default risk. We therefore decided to include $TL_{i,t}$ as separate variable, but scaled it with average total sales in period t to obtain a stationary accounting ratio. So the debt to sales ratio is actually defined as $TL_{i,t}/TS_t$, where TS_t denotes average total sales in period t.

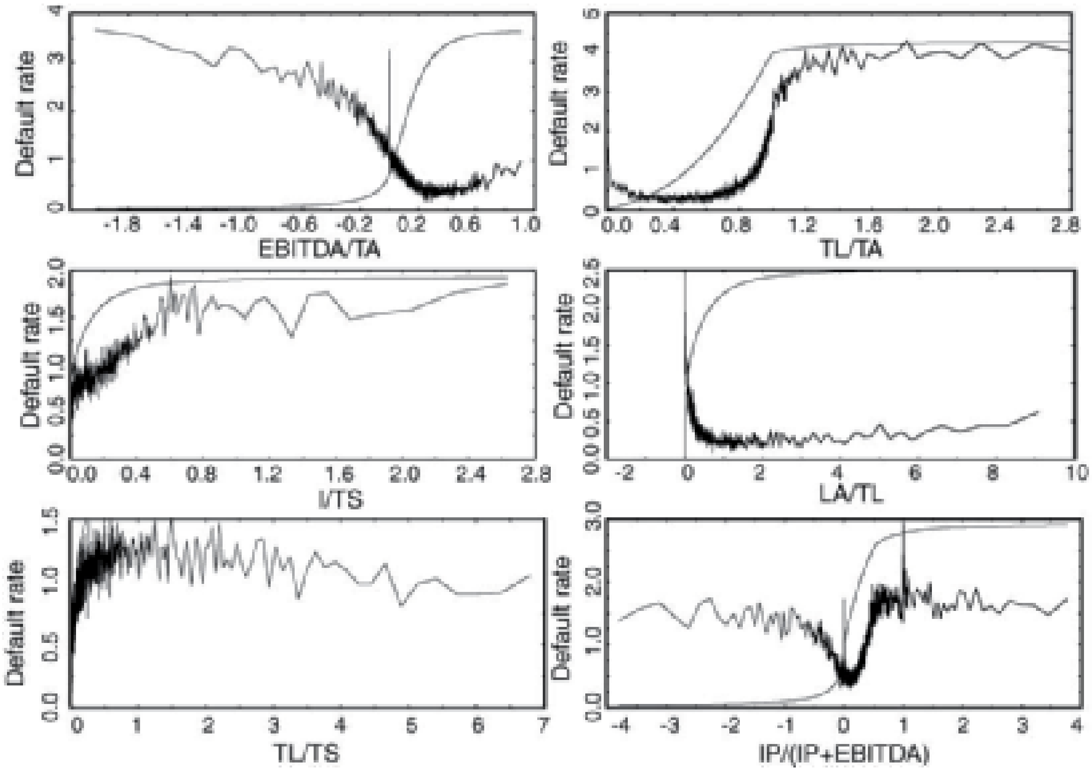

Fig. 1. Default rates and the cumulative distribution functions for the accounting data.

six ratios were selected following a two-step procedure. First, the univariate relationship between the ratio and default risk was investigated. By visual inspection, ratios that lacked any correlation with default risk were deleted from the set of candidate explanatory variables. Fig. 1 illustrates this for the six selected ratios by comparing default rates (solid line) and the cumulative distributions of the variables (dotted line). The default rate for a given observation of a ratio is calculated as an average over the interval of ± 5000 adjacent observations in the empirical distribution of the ratio at hand. Given the density of the observations, there is a positive relationship between default risk and the leverage, interest coverage and turnover ratios, while the figure suggests a negative relationship for both the debt and the liquidity ratios. The diagrams in Fig. 1 suggest that the relationship between default-risk and the earnings ratio, total liability over total sales ratio and interest costs over the sum of interest costs and earnings are non-linear. For instance, for the interest coverage variable, this relationship is perhaps what one would have expected; low (negative earnings) can turn this ratio highly negative if interest costs are high but earnings are slightly more negative, and this event is naturally associated with an increased default risk.

On the other hand, high interest payments and low earnings will also make this ratio large, and is likewise associated with an increased default risk. Similar reasoning can be applied to the other ratios as well. What is important to note is that this feature for some of the financial ratios does not imply that these variables are uninformative for default risk in the empirical model. The reason for this being that the correlations between these financial ratios in the cross section are substantial, which makes each of these variables contribute to predicting default risk in the joint empirical model.[12] Taking these insights into account, Fig. 1 confirms the picture emerging from Table 1: there is a clear difference between healthy and defaulted firms for these variables.

For the remark variables, we employ the same approach as in Carling et al. (2004) and use simple dummy variables by setting them to unity if certain remarks existed for the firm during the year prior to quarter *t,* and 0 otherwise. An intuitively reasonable starting point was to find remark events that (i) lead default as much as possible and (ii) are highly correlated with default. As it turned out, many remark variables are either contemporaneously correlated with default or lack a significant correlation with default behavior. For our final model, we constructed the REMARK1-variable as a composite dummy of four events: a bankruptcy petition, the issuance of a court order – because of absence during the court hearing – to pay a debt, the seizure of property, and "having a non-performing loan", and the REMARK2-variable reflects if the firm is in various tax arrears. In the accounting data, we also have information whether a firm has paid out dividends or not. We therefore included this information as a dummy variable (PAYDIV) in the model, taking the value of 1 if the firm has paid out dividends and 0 otherwise.

In addition, we have included a dummy variable, denoted TTLFS, which equals unity if a firm has not issued a financial statement one and a half year prior to default, and zero otherwise.[13] The reason for including this variable in the default-risk model is the notion that firms who are about to default are less willing to report information about their financial status. By comparing defaulting and healthy firms in Table 1 we see that this mechanism is at work in the panel.

2.2. *Macro-data*

The macro-data used in this paper is adopted from Lindé (2002) and covers the period 1986Q3–2002Q4. We restrict the sample to this period because Swedish financial markets were heavily regulated prior to 1986. The domestic variables are y_t^d – the output-gap (i.e., deviation of GDP around its trend value), π_t^d – the annual inflation rate (measured as the fourth difference of the GDP-deflator), R_t^d – the REPO nominal interest rate (a short-

[12] For instance, taking the square of the interest coverage ratio, which judging by Fig. 1, would seem appropriate in a single variable analysis, reduces the explanatory power of this variable in the multivariate model.

[13] There are three things worth noting in connection with the definition of TTLFS. First, this information is assumed to be available with a 6 quarter time lag since financial statements for year τ are typically available in the third quarter in year $\tau + 1$. By letting this dummy variable equal unity with a 6 quarter time lag we do take the real-world time delay into account. Second, given the way we define the population of existing firms, firms that are newly registered and enter into the panel would automatically be assigned TTLFS = 1 in the third quarter of their existence since they have not issued any financial statement prior to entering. For these new firms, TTLFS has been set to 0 and the accounting data variables have been taken from their first yearly balance sheet and income statements. Third, for defaulting firms that are in the panel but have never reported any accounting data prior to default, we also set TTLFS equal to 0. This is the case for 38,352 out of 103,568 defaulting firms in the panel. So although TTLFS turns out to be very important in the default-risk model, by construction the importance of this variable is down-played rather than exaggerated.

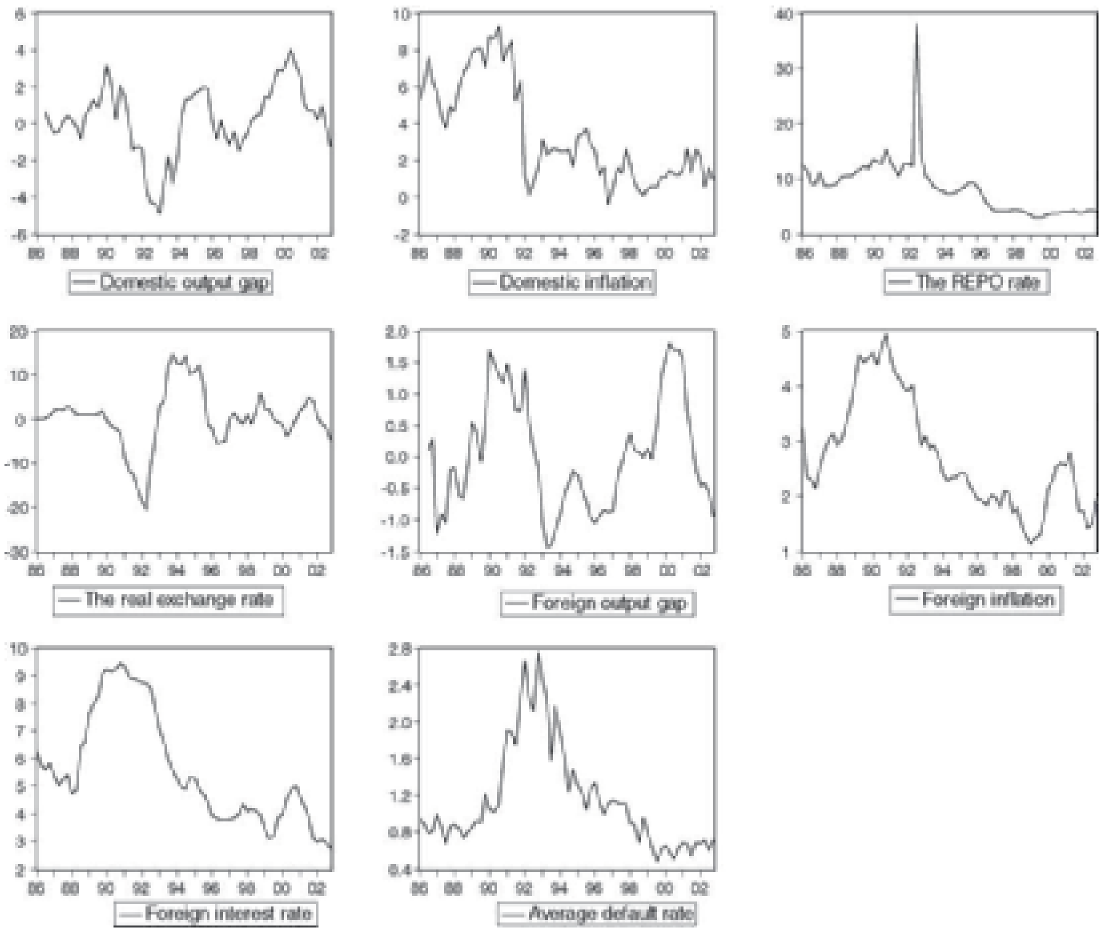

Fig. 2. Macro-data used in the estimated VAR-models.

term interest rate, controlled by the Riksbank), and q_t – the real exchange rate.[14] Because there is a strong trend for the real exchange rate during the sample period, this variable is detrended as well.[15] Since Sweden is an open economy, it is important to condition on foreign variables in the VAR-model. Consequently, we also include y_t^f – the foreign output gap (computed by Lindé, 2002), π_t^f – foreign inflation rate, and R_t^f – the 3-month nominal interest rate as exogenous variables. To acquire data on the aggregate default frequency, denoted df_t for the sample outside the panel period 1990Q1–1999Q2, we linked the panel series depicted in Fig. 2 for 1986Q3–1989Q4 with the aggregate default frequency data for all business firms (made available by Statistics Sweden), and for the period 1999Q3–2002Q4

[14] The real exchange rate is measured as the nominal TCW-weighted (TCW = trade competitive weights) exchange rate times the TCW-weighted foreign price level (CPI deflators) divided by the domestic CPI deflator.

[15] Lindé (2002) estimates a VAR with two lags for the period 1986Q3–2002Q4 and generates a trend for the variables by doing a dynamic simulation of the estimated VAR under the assumption of no shocks hitting the equations. The detrended variables are then computed as actual values minus the trend values. It should be noted, however, that using HP-filtered data for output and the real exchange rate produces very similar results to those reported.

with the aggregate default frequency for incorporated firms (again, source Statistics Sweden).

3. The dependency of real variables on financial variables

In this section, we use aggregate data to examine if there is a feedback from the financial side to the real side of the economy. Throughout the analysis, we will work with the VAR-model estimated by Lindé (2002) as the tool to study this issue. The VAR(p)-model with p lags is specified as

$$X_t = C_{\mathrm{d}} + \delta_1 D_{923} + \delta_2 D_{931013} + \tau_{\mathrm{d}} T_t + \sum_{i=0}^{p} F_i Z_{t-i} + \sum_{i=1}^{p} B_{\mathrm{d},i} X_{t-i} + u_{\mathrm{d},t}, \qquad (1)$$

where D_{923} is a dummy variable equal to 1 in 1992Q3 and 0 otherwise, D_{931013} is a dummy variable equal to 1 in 1993Q1 and thereafter, T_t is a linear time-trend, and Z_t is a vector with the exogenous variables. The dummy variable for the third quarter in 1992 is included to capture the exceptionally high interest rate increase (up to 500%) implemented by the Riksbank in order to defend the fixed Swedish exchange rate. Despite the efforts to defend the Swedish krona, Sweden entered into a floating exchange rate regime in late November 1992, and the dummy variable D_{931013} is included in order to capture possible effects of the new exchange rate regime.

The variables in X_t and Z_t are

$$X_t = \begin{bmatrix} y_{\mathrm{t}}^{\mathrm{d}} & \pi_{\mathrm{t}}^{\mathrm{d}} & R_{\mathrm{t}}^{\mathrm{d}} & q_t \end{bmatrix}' \quad \text{and} \quad Z_t = \begin{bmatrix} y_{\mathrm{t}}^{\mathrm{f}} & \pi_{\mathrm{t}}^{\mathrm{f}} & R_{\mathrm{t}}^{\mathrm{f}} \end{bmatrix}'. \qquad (2)$$

Lindé (2002) shows that two lags is sufficient (i.e., we set $p = 2$), and that the foreign variables are block exogenous with respect to the domestic variables, i.e., the variables in Z_t are not affected by the variables in X_t.

One natural way to test if there is a feedback from the financial sector into the real side of the economy is to augment the specification in (1) with lags of the financial variable, i.e., include df_{t-1} and df_{t-2} and examine if they contain useful information for predicting the endogenous variables in the model. This has the flavor of a multivariate Granger-causality test. Essentially, one simultaneously test if the coefficients for the lags are significantly different from zero or not. By using the block-exogeneity test described in detail by Hamilton (1994), cf. pages 309–312, we find that the p-value for the null of zero coefficients is around 0.02, indicating that the macroeconomic variables in X_t are not exogenous with respect to the aggregate default frequency.

An alternative way to quantify the dependence of the real economy on the default frequency is to include df_t, ordered last, in the X_t-vector and estimate a five-variable VAR-model. If the impulse response functions in the estimated VAR-model for a shock to df_t, identified via a so-called Cholesky-decomposition, are close to zero, then the quantitative feedback from the default frequency to the real economy is small. In Fig. 3, we show the impulse response functions a positive shock to the df_t variable. We see that the outcome of the block-exogeneity test is confirmed, the financial shock has significant effects on the real economy. Output and inflation falls, while the nominal interest rate increases (although

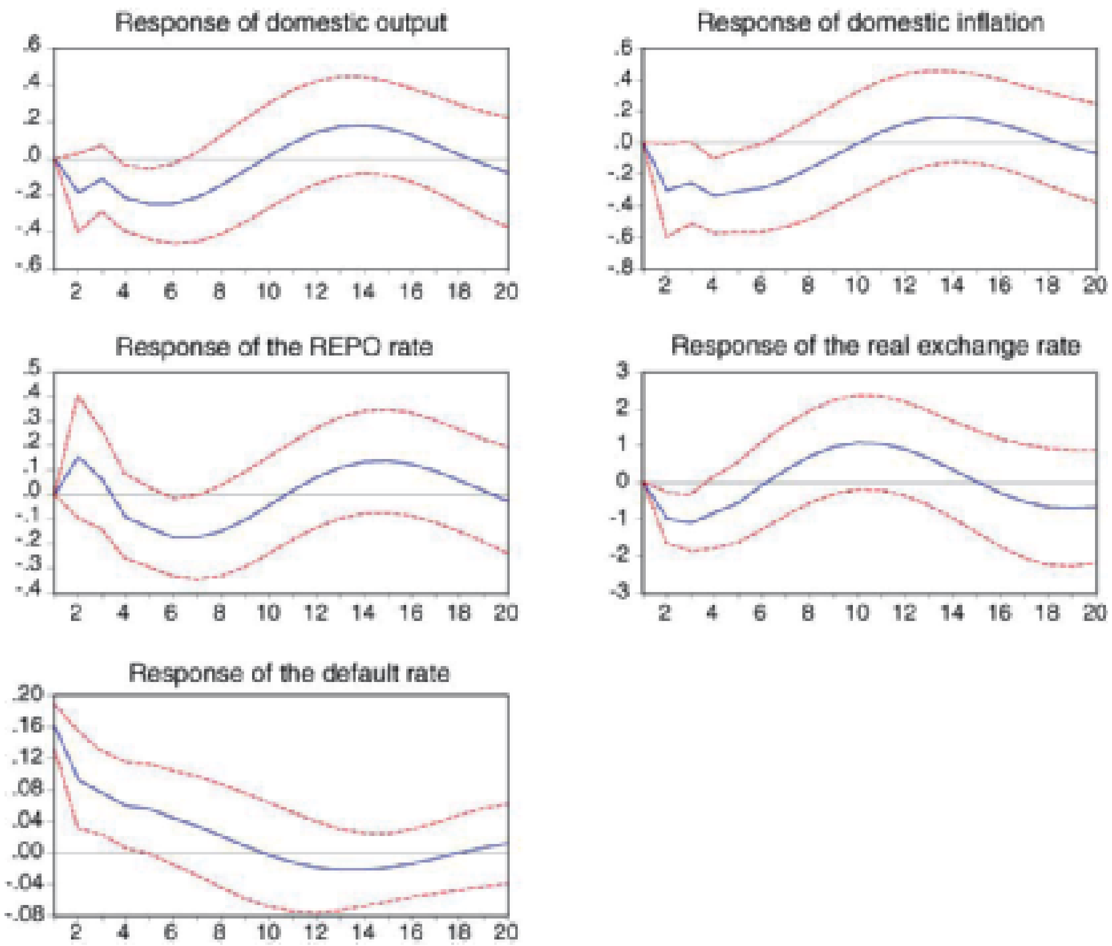

Fig. 3. Impulse response functions to a aggregate default frequency shock in the estimated VAR where default frequency is included in X_t.

not significantly), and the real exchange rate appreciates. According to the VAR, exogenous variations in the default rate account for as much as 20% of the variation of the other variables.

We have also investigated whether the average balance sheets ratios (depicted in Fig. 4) explain the variation in the macrovariables over and above the explanatory power of the default rate variable and the other macrovariables included in the VAR. Since we only have data on the balance sheets ratios for the period 1990Q1–1999Q2, we regressed the VAR-residuals for this period on the balance-sheet ratios equation by equation with OLS. A simple F-test revealed that the balance-sheet ratios conveyed no information w.r.t. the VAR residuals, the average p-value being around 0.60 and the lowest p-value 0.25 (real exchange rate residuals). Consequently, we will adopt the approximation in the rest of the paper that the macrovariables included in the VAR above are not directly affected by the balance-sheet ratios that we consider. We will, however, allow for indirect effects via the average default rate.

To complete the analysis, we have also applied the block-exogeneity tests for other commonly used measures of the financial stance of the economy such as the term-structure,

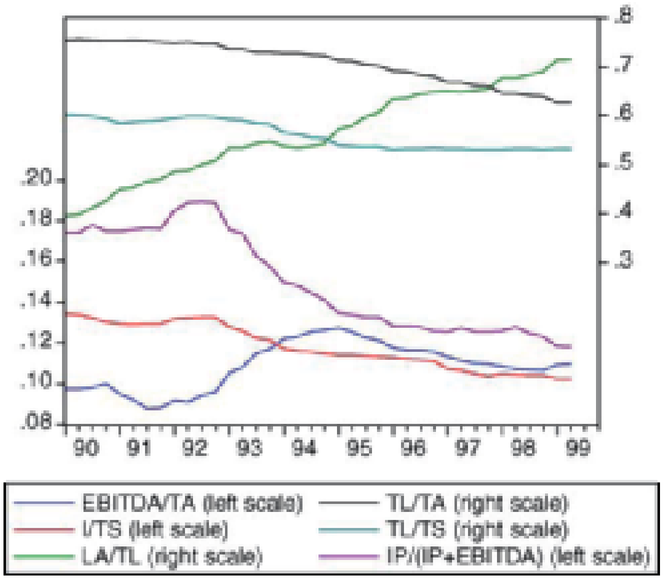

Fig. 4. Averaging accounting data over time 1990Q1–1999Q2 in the panel.

the change in the stock of loans by banks to firms and households, the change in stock prices and the change in housing prices. We obtained the following p-values; term structure – 0.39 annual change in stock of outstanding loans – 0.25, quarterly change in stock prices – 0.90 and quarterly change in housing prices – 0.01 Notice that for the variables in changes, we considered both quarterly and annual changes in respective indicator, but here we only report the results with the lowest p-values. These findings suggest that only housing prices contain significant predictive power for the real economy during this sample period. Since stock markets are supposedly forward-looking, it is perhaps surprising that stock prices appear to contain little predictive power. The reason is simply that there is excessive volatility in stock prices, which is not transmitted into the real economy. Although we find evidence that housing prices are important, the default rate is slightly more important in the sense that if we redo the block-exogeneity test for the VAR for housing prices when the default rate is included, we find that the p-value being 0.13. The converse experiment, i.e., testing for the predictive power of the average default frequency given that the first difference of the housing prices are included in the VAR, we obtain a p-value of 0.09. Based on the evidence above, and since we are in disposal of very interesting micro-data on firms default behavior, we will work with this variable as the link between the financial and real side of the economy, but future research should further address the link between the housing prices and the real economy.

Despite our encouraging statistical evidence in favor of our choice of using the average default frequency for incorporated firms as a link between the real and financial side of the economy, we still need to motivate from an economic perspective why the aggregate default rate is an appropriate measure of the financial stance of the economy. There are several arguments why we think this is the case. First, as shown in Fig. 5, we see that the average (aggregate) default frequency displays a very similar pattern to credit-losses over the stock of loans to non-financial firms, the correlation coefficient being

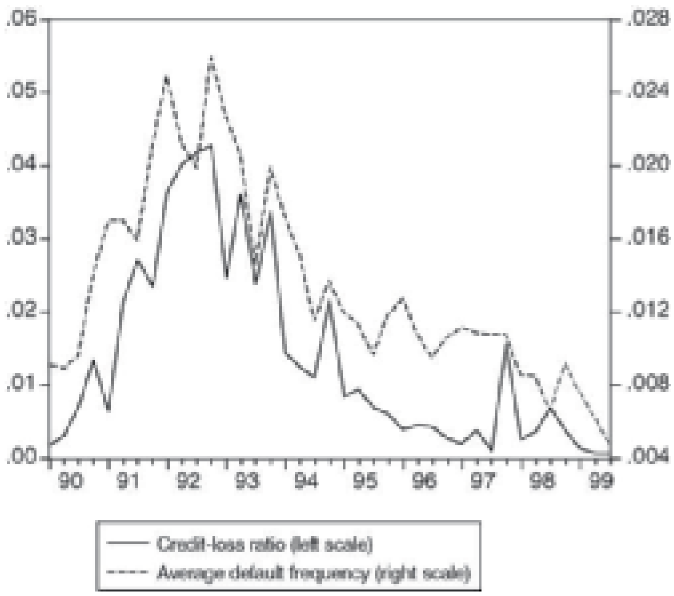

Fig. 5. Average default frequency over time in the panel and credit losses by non-financial firms relative to loan stock.

0.90.[16] In particular, the co-movement of the variables is large at the lower frequencies, but there are some differences at the higher frequencies, e.g. the upturn of credit losses during the Asian and Russian crisis. In our view, the lower frequency component of these variables are most interesting, since they are arguably more related to the systematic risks in the banking sector. Second, neither credit-losses, nor defaults, are leading or lagging the other variable. Third, Fig. 5 suggests that our choice of restricting the analysis to default risk and not studying implied credit-losses (e.g. by using total liabilities) due to lack of accounting data for many defaulted firms, does not seem to be a serious restrictive approximation. Fourth, from a financial stability perspective, we think that this variable should be of high relevance given that it is forecastable, whereas e.g. operational risks are much harder to forecast. For instance, it would have been extremely difficult for a central bank to foresee the Barings bank affair. Fifth, and finally, we think that our variable ought to capture the leverage/systematic risk in the banking system in the sense that when a bank experiences high default-/credit-risk, it is most likely that other banks will too if there are common factors that drive default risk (e.g. if macroeconomic factors are important for the absolute level of default-risk, which is what we find). Thus we conclude that our variable ought to be a good operational predictor of the systematic risk in the banking sector and the financial stance of the economy.

The conclusions from the analysis above are that (i) there seems to be an important link from the financial side of the economy to the real side of the economy which is not only

[16] Credit losses are here defined as the credit losses to non-financial firms incurred by the four major banks in Sweden (SEB, Nordea, SwedeBank and SHB) in relation to their stocks of loans to non-financial firms.

statistically, but also quantitatively important and (ii) that the aggregate default rate is a good measure of the financial stance of the economy.

4. The dependency of financial variables on aggregate activity

In this section, we examine if default risk at the firm level is affected by aggregate shocks over and above firm-specific information. Moreover, we will present some brief evidence of the balance-sheet channel by investigating to what extent standard balance-sheet ratios are affected by aggregate shocks.

4.1. The default-risk model

In this subsection we present a reduced form statistical model for estimation of probability of default for all Swedish incorporated firms. The general idea is to enter factors that determine the probability of default and quantify how these contribute towards predicting default realizations. With such estimated probabilities we may proceed to calculate the expected aggregate default frequency over time.

So far relatively few empirical studies contain a rigorous analysis of the effects from macro-economic conditions on default behavior and credit risks at the firm level, see e.g. Carling et al. (2004) for a discussion. The logit model of the default probability that we present in this subsection includes both idiosyncratic and macroeconomic explanatory variables.[17] The reason for including aggregate variables in the model is clear by inspection of Figs. 4 and 5. In Fig. 4, we plot the mean values of the idiosyncratic financial variables that are used in the model 1990Q1–1999Q2. It is obvious that there are no dramatic changes in the variables during the deep recession 1992–1993. Therefore, a model with only idiosyncratic variables included is unlikely to fully account for the higher default frequency outcomes at the aggregate level depicted in Fig. 2. Therefore, we conjecture that it is important to use aggregate variables in the model.

The macroeconomic variables that we use in the model are the same as included in the domestic VAR-model given by (1), i.e., the output gap, the domestic annual inflation rate, the REPO rate, and the real exchange rate. A priori, we think that these should have a measurable impact on the default risk of any given firm. Starting with the output gap, it may supposedly work as an indicator of demand conditions, i.e., increased demand in the economy reducing default risk. Fig. 5 seems, at large, consistent with this view, although there are some spikes in the default rate that presumable have to be attributed to other variables. Also, it is clear from Fig. 2 that there has been some variation the output gap around 1996–1998, which has not been met with an increased default rate. Therefore, there must be some other aggregate variables that ought to be important as well. Here, we decided to include the nominal interest rate (i.e., the REPO rate) because we know that

[17] For simplicity, we estimate a logit model rather than a duration model as is done in Carling et al. (2004). Although Carling et al., in contrast with Shumway (2001), found significant evidence of a duration dependence, we believe that this approximation may not be of decisive importance. But an interesting extension of this work is to test for duration dependence in the model.

the nominal interest rate was very high during the recession in the beginning of the 1990s, but has came down substantially after the introduction of the inflation target in Sweden. Given the fact that the export to GDP ratio being around 0.40, the real exchange rate is also a potentially important variable, a deprecation leading to improved competitiveness of Swedish firms. The inflation rate may also be important for firms pricing decisions; higher inflation rates are potentially associated with less certainty about correct relative prices, and may thus lead to potentially higher default risk. Of course, it also convenient to work with variables that can be generated from the VAR-model in the previous section. This is the reason why we did not experiment with neither a term structure variable, nor measures of household expectations as in Carling et al. (2004). Finally, as can be seen from Fig. 2, there is a large spike in the REPO rate in the third quarter 1992 due to the fact that the Riksbank raised the so-called marginal interest rate to 500% in order to defend the fixed exchange rate. If the REPO rate is not adjusted for this exceptional event, the estimation procedure leads to underestimation of the importance of financial costs for default behavior. We therefore decided to adjust the REPO rate series in the third quarter of 1992.[18]

In order to highlight how various variables contribute to default risk, we present three models in Table 2. One model with accounting ratios only, a second augmented with the dummy variables (PAYDIV, REMARK and TTLFS variables), and finally one with the macroeconomic variables added.[19]

The results in Table 2 show that both idiosyncratic and aggregate information is important for explaining default behavior. The variables for omitted (non-reported) financial statements and remarks on firms payment record are the strongest determinants of default in the model. A nice feature of the estimations is that the coefficients for each variable does not change substantially when the model is augmented with more variables. In particular, the accounting ratios in Model I yield roughly the same coefficients as in the complete Model III. The predictive power of the accounting data is somewhat less important than the dummy variables, although the liability-to-assets ratios (TL/TA and TL/TS) and earnings ratios are quite useful.[20] The turnover ratio for inventories, liquid asset over total liabilities and the

[18] The estimated dummy coefficient in the VAR equals 28.2 in the REPO rate equation. On the basis of this, we adjusted the REPO rate for this quarter to equal 9.8% instead of 38%.

[19] Since no data on the payment records of firms (i.e., the dummy variables REMARK1 and REMARK2) exist prior to 1992Q3 for legal storage reasons, the estimation results of Models II and III reported in Table 2 also includes one additional variable (not reported) which is constructed to be an estimate of the average value of the sum of the payment record variables REMARK1 and REMARK2 for the quarters 1990Q1–1992Q2. This variable was constructed by estimating a logit model for the event of either of the dummy variables REMARK1 and REMARK2 taking on the value 0 or 1 for the period 1992Q3–1999Q2, using all the variables in Model III (except REMARK1 and REMARK2 as explanatory variables, of course). The imputed average value for this variable for the period 1990Q1–1992Q2 (after 1992Q2, it is set to nil) was then constructed as the average estimated probability for each firm and period, i.e., $\mathrm{RD}_t = \frac{1}{N_t}\sum_i \hat{p}_{i,t}$ where $\hat{p}_{i,t}$ denotes the estimated probability for firm i in period t to have either a REMARK1 or a REMARK2 greater than zero, and N_t denotes the number of firms in period t. The largest gain in including this variable is that the effects of the macroeconomic variables are more accurately estimated. For the coefficients of the idiosyncratic variables this variable is of little importance.

[20] Regarding the importance of the accounting data in the model, we would like to emphasize the following features. First, firms typically issue annual financial statements, which we transform into quarterly observations by assuming that they remain the same throughout the reporting period. Given that we define a default event at the

Table 2
Logit estimation results of the default-risk model[a]

Type of regressor	Model I		Model II		Model III	
	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
Constant	−4.76	0.018	−5.22	0.025	−5.88	0.059
Idiosyncratic variables[b]						
EBITDA/TA	−1.07	0.022	−1.10	0.028	−1.09	0.046
TL/TA	1.07	0.015	0.54	0.020	0.52	0.0233
LA/TL	−0.10	0.014	−0.15	0.017	−0.16	0.028
I/TS	0.27	0.016	0.20	0.021	0.21	0.034
TL/TS	0.19	0.004	0.23	0.005	0.22	0.007
IP/(IP+EBITDA)	0.09	0.007	0.07	0.009	0.08	0.015
PAYDIV			−1.91	0.080	−1.85	0.138
REMARK 1			1.73	0.032	1.89	0.051
REMARK2			2.66	0.020	2.74	0.033
TTLFS			3.32	0.019	3.27	0.031
Aggregate variables[c]						
Output gap – $y_{d,t}$					−0.110	0.008
Inflation rate – $\pi_{d,t}$					−0.005	0.009
Nominal interest rate – $R_{d,t}$					0.072	0.006
Real exchange rate – q_t					−0.006	0.002
Summary statistics[d]						
Mean log-likelihood	−0.0669		−0.0491		−0.0484	
Pseudo R^2	0.16		0.37		0.39	
Aggregate R^2	0.26		0.36		0.94	
Number of observations	2066206		1607049		765263[a]	

[a] Since we have as many as 7,652,609 quarterly observations, the computer program used to do the Maximum Likelihood estimation of the logit model (GAUSS version 3.5) cannot handle all observations simultaneously. For Models I and II presented below, we therefore made a random selection of 27 and 21% of the observations such that the aggregate default frequency over time is identical to the one computed using all observations. To check for convergence in parameter values, we decreased the estimation samples to 26 and 20% of the observations and re-estimated the models. Fortunately, we found convergence in parameter at the three-digit level and the estimation results in Table 2 are thus based on the 27/21% sized samples, respectively. For Model III this approach was not feasible because we could not find convergence at the three digit level given the increased number of regressors. For this model, we therefore drew 50 samples of size 10% of the population, and for each parameter we report the mean estimate of the resulting 50 sub-sample estimates. The standard errors are based on the mean inverse Hessian matrix.

[b] See Section 2.1 for exact definition of these variables.

[c] See Section 2.2 for definition and sources. The variables are not scaled so the importance of a variable cannot be interpreted directly from the size of the parameter estimate.

[d] We use Laitila (1993) measure of pseudo R^2. The aggregate R^2 is computed using all 7,652,609 quarterly observations.

quarterly frequency, this assumption could presumably lead to underestimation of the importance of the balance-sheet variables in the default risk model. We examined this by estimating the credit-risk model at the annual frequency instead, and the coefficients for the balance sheets variables were found to be quite similar. In fact, only the coefficients for EBITDA/TA and TL/TS were found to be slightly higher (−1.30/0.27 instead of −1.07/0.19, interest coverage ratio appear to be less important. Turning to the macroeconomic variables, we find that they are significant, with the exception of inflation, and have the correct signs. Note that a higher value of the real exchange rate implies a depreciation, and therefore the negative estimate for this variable suggests that a depreciation on average reduces the risk of default at a given point in time. It should be pointed out that the macroeconomic variables are highly significant and quantitatively important even if we allow for non-linear effects of the balance-sheet variables.[21]

The advantage of using firm-specific data when estimating the default-risk model can be understood as follows. If we estimate Model III without the dummy variables (REMARK1, REMARK2, PAYDIV, and TTLFS are left out because they do not enter significantly) on aggregate/average data using OLS (TSLS give very similar results), we obtain

$$
\begin{aligned}
\mathrm{df}_t = \underset{(0.06)}{-0.23} \underset{(0.13)}{-0.23}\left(\frac{\mathrm{EBITDA}}{\mathrm{TA}}\right)_t + \underset{(0.06)}{0.30}\left(\frac{\mathrm{TL}}{\mathrm{TA}}\right)_t + \underset{(0.03)}{0.09}\left(\frac{\mathrm{LA}}{\mathrm{TL}}\right)_t \cdots \underset{(0.21)}{-0.94}\left(\frac{\mathrm{I}}{\mathrm{TS}}\right)_t \\
+ \underset{(0.08)}{0.19}\left(\frac{\mathrm{TL}}{\mathrm{TS}}\right)_t \underset{(0.12)}{-0.02}\left(\frac{\mathrm{IP}}{\mathrm{IP}+\mathrm{EBITDA}}\right)_t \cdots - \underset{(0.03)}{0.05}\, y_{\mathrm{d,t}} \underset{(0.03)}{-0.05}\, \pi_{\mathrm{d,t}} \\
\underset{(0.03)}{+0.12}\, R_{\mathrm{d,t}} \underset{(0.009)}{+0.002}\, q_t + \hat{u}_{\mathrm{df,t}},
\end{aligned}
$$

$$R^2 = 0.93,\ \mathrm{DW} = 2.10,\ \mathrm{Sample:}\ \ 1990\mathrm{Q}1\text{–}1999\mathrm{Q}2\ (T = 38) \tag{3}$$

If we compare the point estimates in Table 2 with those in (3), we see that they differ substantially. In particular, the balance-sheet variables I/TS and LA/TL account for a lot of the variation in the aggregate default rate, but with the wrong sign. Because the accounting ratios are relatively smooth in the aggregate, which is clear from Fig. 4, it is not surprising that we obtain spurious results when estimating the model on aggregate data rather than at the firm level.

In Figs. 6 and 7, we plot the aggregate default rate together with the average predicted default rates from Model I (Fig. 6) and Model III (Fig. 7) for the whole sample of firms, i.e., using the 7,652,609 observations. Very interestingly and as conjectured previously in the paper, we note in Fig. 6 that the model with firm-specific information only cannot capture the up- and downturns in average default rate over time, whereas the model with both micro- and macro-variables included is indeed able to replicate the high default rate

respectively), whereas the other coefficients were actually found to be smaller in the annual model. Moreover, the decision to lag the accounting data 4 quarters in the estimation in order to make the model "operationable" in real-time could presumably also affects the estimated coefficients. Therefore, we re-estimated the model using contemporaneous data instead, and again, the estimation results were to found to be very similar.

[21] When estimating the model where the balance-sheet variables enter in a non-linear way (interaction dummies), we used the cumulated distributions depicted in Fig. 1 to categorize the balance-sheet variables (three categories for each variable). For instance, we classified EBITDA/TA into the decile-based categories 0–10, 10–90, 90–100, whereas TL/TA was classified into the categories 0–75, 75–90, 90–100. The pseudo R^2 in a non-linear version of Model II is around 0.48, but the aggregate R^2 is still slightly below 0.45. So although this model somewhat better account for the aggregate default frequency, macroeconomic variables are still found to be essential for explaining the absolute level of default risk.

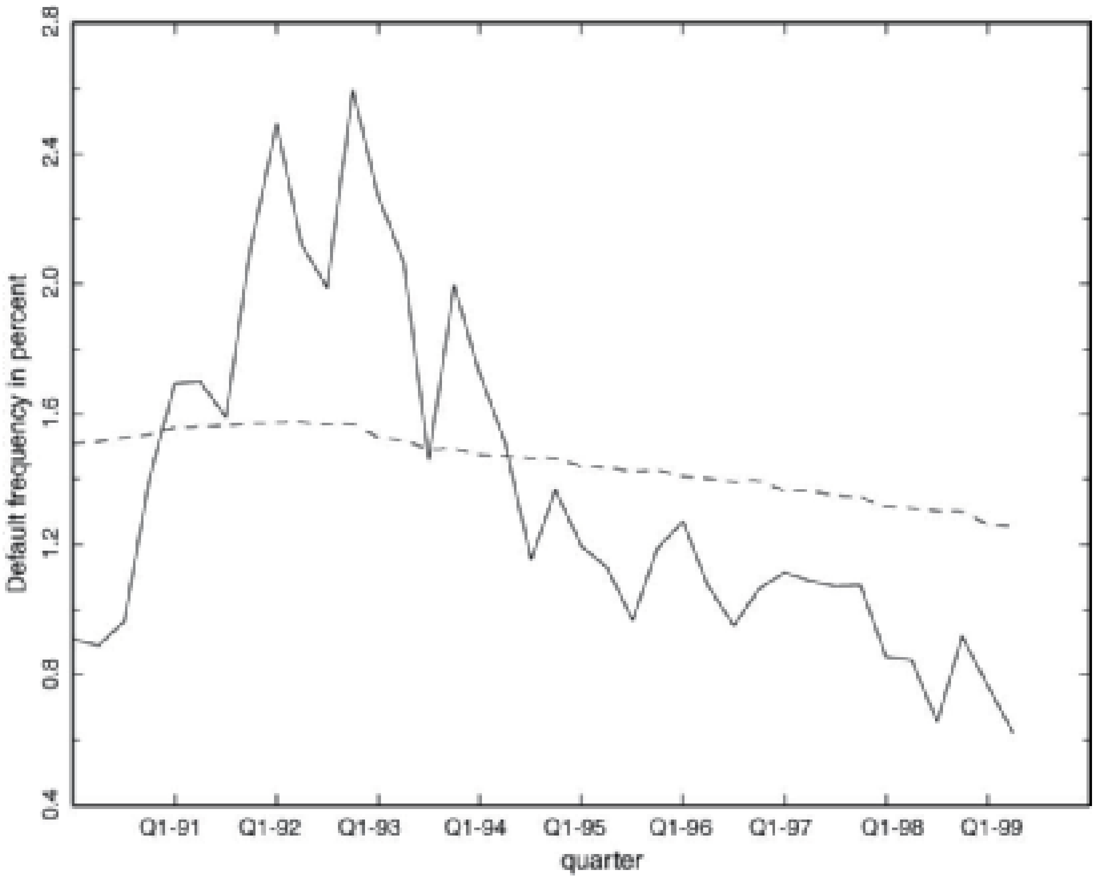

Fig. 6. Actual and projected default rates at the aggregate level in the estimated default-risk model with only balance sheet variables included (Model I).

during the banking crisis, as well as the downturn to very moderate default rates during the latter part of the sample. The explained fraction of variation (R^2) in the model with macro-variables included is 94% at the aggregate level, whereas it is as low as 26% in the model with balance-sheet ratios only.[22] This finding is very interesting for several reasons. First, because it suggests that the high default rates recorded during the banking crisis were not exceptional events that we cannot learn anything useful from, but rather that they were consequences of unusually bad economic outcomes, both domestically and internationally.[23] Second, when the aggregate default rate is included in the VAR-model

[22] The 95% confidence intervals around the fitted values in Figs. 6 and 7 cover the actual values 3/15 number of times out of the 38 periods. Thus, while Model III outperforms Model I in this respect, it seems as though uncertainty around some of the peaks and through is underestimated by the bootstrap procedure that we employ and further development is required here. Our single-bootstrap approach for constructing these confidence intervals (bootstrapping parameters in the logit models using a Cholesky-decomposition of the inverse Hessian) seem to result in underestimation of the confidence intervals. Presumably, by adopting a double-bootstrap procedure one can account for the uncertainty in estimated standard errors and achieve reasonable coverage for the confidence intervals. However, a double-bootstrap is currently not feasible in practice.

[23] Lindé (2002) shows that a significant portion of the variation in the domestic macroeconomic variables are of foreign origin.

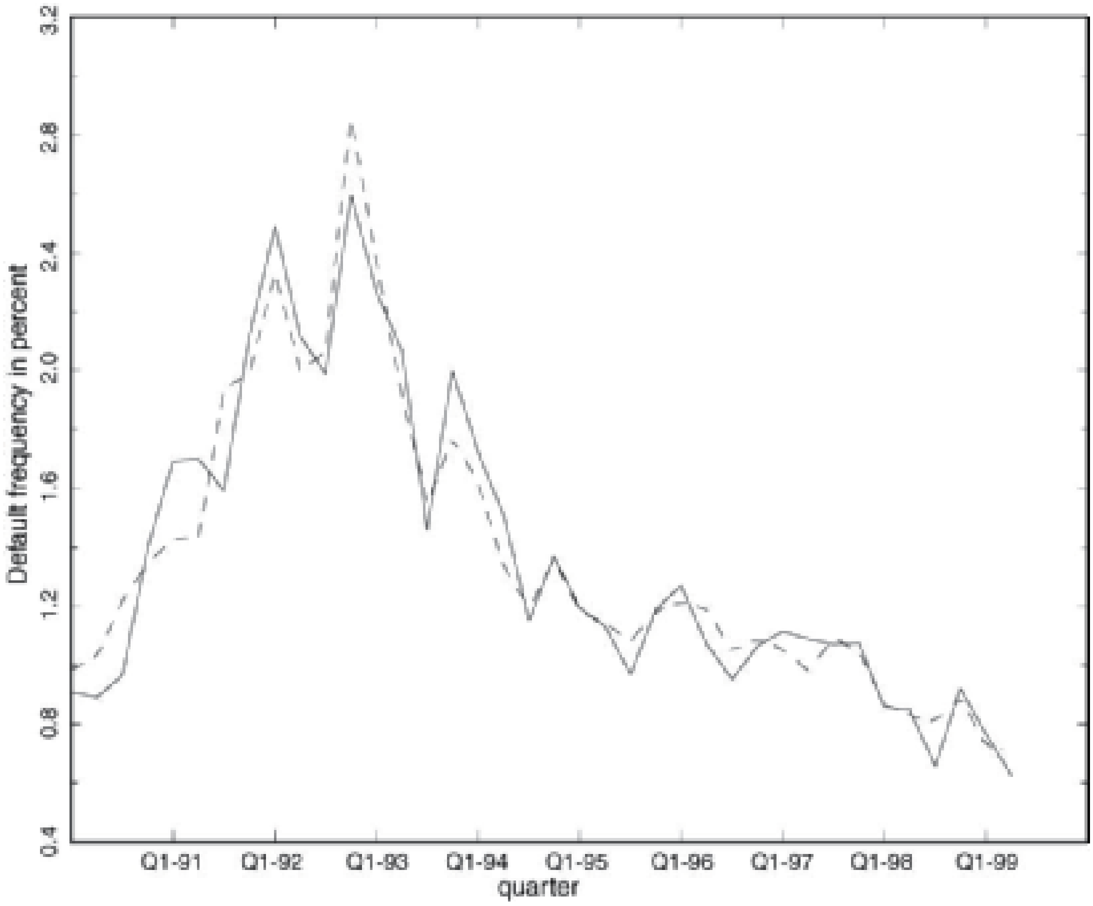

Fig. 7. Actual and projected default rates at the aggregate level in the estimated default-risk model with macro-variables (Model III).

in Eq. (1) as an endogenous variable, the share of the explained variation in the default rate is about 88% and the sum of the two lags for the average default rate is as high as 0.74. Without the lags, the share of the explained variation in the average default rate shrinks considerably to about 82%.[24] One possible interpretation of these results is that the estimated high weight on the lags in the aggregate default rate equation are proxies for missing information at the firm level, since Model III is estimated at the microeconomic level and gives a better fit at the aggregate level without any intrinsic dynamics in the model.

Finally, one way of demonstrating how much is lost by omitting the micro-structure is to regress the average default frequency on the macroeconomic variables included in Model III only.

[24] Note that the numbers for the aggregate default rate are taken from the VAR estimated on a slightly different data sample, 1986Q3–2002Q4. However, when restricting the sample to the same period as used for the default-risk model above, the results are actually even more in favor of the micro-model.

We then obtain

$$\mathrm{df_t} = \underset{(0.11)}{1.00} - \underset{(0.03)}{0.19}\, y_{\mathrm{d},t} + \underset{(0.02)}{0.04}\, \pi_{\mathrm{d},t} + \underset{(0.01)}{0.02}\, R_{\mathrm{d},t} - \underset{(0.007)}{0.002}\, q_t + \hat{u}_{\mathrm{df,t}},$$

$$R_2 = 0.65, \mathrm{DW} = 1.27, \text{Sample}: 1990\text{Q1–}1999\text{Q2}(T = 38) \tag{4}$$

If we compare the results of this regression with the results in Table 2, we see that we loose about 30% of the explanatory power by excluding the balance-sheet variables. This number is in line with the aggregate R^2 reported in Table 2 for Models I and II.

4.2. The dependency of balance-sheet ratios on aggregate shocks

An interesting question is to what extent the balance-sheet ratios are driven by macroeconomic factors and to what extent they live their own lives, i.e., driven by idiosyncratic shocks. There are good reasons to believe that some of the balance-sheet ratios may be more independent of the aggregate state of the economy than others. Consider for example the variable earnings over total assets (EBITDA/TA). In a favorable macroeconomic situation, earnings should improve, as will total assets. Therefore, the net effect on EBITDA/TA is not obvious. However, the coverage ratio $\left(\frac{\mathrm{IP}}{\mathrm{IP+EBITDA}}\right)$, is likely to be more heavily affected by aggregate shocks, because interest payments on debt (IP) should increase after an increase in the nominal interest rate, while earnings (EBITDA) should fall.

Let $Y_{i,t} = \left[\frac{\mathrm{EBITDA}}{\mathrm{TA}_{i,t}} \quad \frac{\mathrm{TL}}{\mathrm{TA}_{i,t}} \quad \frac{\mathrm{LA}}{\mathrm{TL}_{i,t}} \quad \frac{\mathrm{I}}{\mathrm{TS}_{i,t}} \quad \frac{\mathrm{TL}}{\mathrm{TS}_{i,t}} \quad \frac{\mathrm{IP}}{\mathrm{IP} + \mathrm{EBITDAIP}}_{i,t}\right]'$ denote a 6×1 vector with the financial ratios for firm i, and let $Y_t = [Y_{1,t} \cdots Y_{N_t,t}]$ denote a $6 \times N_t$ matrix where N_t is the number of firms in the panel in quarter t. Then the process for the financial ratios can be written

$$Y_t = \Theta_{\mathrm{Y}} Y_{t-1} + \Theta_{\mathrm{X}} X_t + u_t, \mathrm{var}(u_{Y,t}) = \Sigma_u \tag{5}$$

where X_t is defined by (2). Because we want to estimate the model on quarterly data in order to better identify the aggregate shocks, but typically have new information about the financial ratios annually, we use annual moving averages when estimating (5). Each equation in (5) is estimated using the Arellano and Bond (1991) estimator using 1,701,878 observations that are constructed from the original data set of all 7,652,609 observations.[25]

[25] Suppose the true model is given by (5). If we define the variables $\bar{Y}_t = \frac{1}{4}(Y_t + Y_{t-1} + Y_{t-2} + Y_{t-3})$ and $\bar{X}_t = \frac{1}{4}(X_t + X_{t-1} + X_{t-2} + X_{t-3})$, we can write (using (5)):

$$\bar{Y}_t = \Theta_{\mathrm{Y}} \bar{Y}_{t-1} + \Theta_{\mathrm{X}} \bar{X}_t + \bar{u}_t \tag{6}$$

where $\bar{u}_t = \frac{1}{4}(u_t + u_{t-1} + u_{t-2} + u_{t-3})$. This implies that after estimating (6), we can retrieve the parameters of interest Θ_{Y}, Θ_{X} and $\Sigma_u = 4\Sigma_{\bar{u}}$. As valid instruments (i.e., instruments uncorrelated with the shocks $\bar{u}_t$) when estimating (6), we use $\bar{Y}_{t-5}$ and $\bar{X}_{t-4}$, thus allowing for one-period, serially correlated measurement errors in Y_{t}. This procedure implies that in order for a firm to be included in the estimation, it must have reported a financial statement for nine consecutive quarters (3 years). This is why the sample used to estimate (6) is considerably smaller than the total number of observations.

The estimation results of (5) are

$$\Theta_Y = \begin{bmatrix} 0.807 & 0.025 & -0.0002 & -0.029 & -0.0003 & -0.006 \\ -0.016 & 0.968 & -0.002 & 0.005 & -0.001 & 0.007 \\ 0.007 & -0.062 & 0.938 & -0.011 & -0.0091 & -0.021 \\ -0.004 & -0.001 & -0.0005 & 0.940 & 0.0001 & 0.002 \\ -0.0007 & -0.033 & 0.005 & -0.005 & 0.990 & 0.008 \\ -0.031 & 0.069 & -0.005 & 0.034 & 0.006 & 0.573 \end{bmatrix},$$

$$\Theta_X = 100 \times \begin{bmatrix} -0.039 & 0.060 & -0.010 & 0.031 \\ -0.026 & 0.016 & 0.053 & 0.004 \\ 0.187 & 0.180 & -0.089 & -0.048 \\ 0.033 & 0.007 & 0.039 & -0.008 \\ -0.524 & -0.092 & 0.154 & 0.088 \\ -0.167 & -0.007 & 0.148 & -0.021 \end{bmatrix},$$

$$\Sigma_Y = \begin{bmatrix} 0.15390 & 0.02288 & -0.22309 & 0.04976 & 0.23547 & 0.37508 \\ 0.02288 & 0.03079 & -0.10535 & 0.01890 & 0.12979 & 0.14406 \\ -0.22309 & -0.10535 & 1.35270 & -0.18691 & -1.04964 & -1.45223 \\ 0.04976 & 0.01890 & -0.18691 & 0.07183 & 0.20798 & 0.31972 \\ 0.23547 & 0.12979 & -1.04964 & 0.20798 & 1.24893 & 1.60151 \\ 0.37508 & 0.14406 & -1.45223 & 0.31972 & 1.60151 & 2.78039 \end{bmatrix}.$$

We see that there is considerable persistence in the variables, which is presumably due to the fact that we do not allow for firm or industry specific effects when estimating the model. The macro-parameters are seemingly small, but the p-values for joint Wald-test of all the macro-variables are essentially zero in all the equations. However, given the large number of observations, this might not come as a big surprise. Arguably more interesting is to examine to what extent aggregate shocks account for variation in the financial ratios according to the estimates. We found that the macro-variables account for maximum 0.1% of the fluctuations in the financial ratios included in Y_t, which implies that the accounting ratios are essentially are living lives of their own.[26] By looking at Fig. 4, these results are not

[26] Assuming that the unconditional variance in X_t is unaffected by the variables in Y_t in the long-run, which is a reasonable approximation for reasons discussed in Section 3, we can compute the contribution of the macro-variables to fluctuations in Y_t as follows. Noting that (5) implies that $\Sigma_Y = \Theta_Y \Sigma_Y \Theta'_Y + \Theta_X \Sigma_X \Theta'_X + \Sigma_u$ where Σ_Y, Σ_X and Σ_u are the unconditional covariance matrices for Y_t, X_t and u_t, respectively. Since the VAR is stable, Σ_X and Σ_u known (Σ_X is computed as the covariance matrix for the domestic macro-variables 1986Q3–2002Q4 and an estimate of Σ_u is computed from the residuals in (5), we can compute Σ_Y by iterating on this equation, starting with an arbitrary positive definite matrix as an initial guess. Let Σ_Y^{tot} denote the resulting covariance matrix. The amount of variation due to the idiosyncratic shocks can be found by iterating on $\Sigma_Y = \Theta_Y \Sigma_Y \Theta'_Y + \Sigma_u$, and we let Σ_Y^{mic} denote the resulting covariance matrix. Similarly, the amount of variation in Y_t due to aggregate shocks are found by iterating on $\Sigma_Y = \Theta_Y \Sigma_Y \Theta'_Y + \Theta_X \Sigma_X \Theta'_X$, and we let Σ_Y^{mac} denote the resulting covariance matrix. We can

that surprising given that the balance-sheet ratios do not display a strong degree of cyclical behavior, with the possible exceptions of EBITDA/TA and IP/(IP + EBITDA).

Because the effects of the aggregate shocks were found to be surprisingly low, we also conducted the following experiment. For each balance-sheet ratio, we ran simple OLS regressions

$$Y_{i,t} = c + \sum_{s=0}^{p} b_s X_{t-p} + \varepsilon_{i,t},$$

using both quarterly (setting $p = 4$) and annual data (using $p = 0$). From the OLS results, the share of explained variation in $Y_{i,t}$ due to aggregate shocks is directly given by the R^2 for regression i. In none of the estimated equations, we obtained an R^2 larger than 0.03, again suggesting a very minor role for aggregate shocks in explaining the fluctuations in firms balance-sheet ratios.

However, before drawing too strong conclusions upon these estimation results. The following aspects should be considered. First, the adopted estimation procedure does not allow for firm specific effects, i.e., there is a common intercept in (5) for all firms. However, when we re-estimated allowing for firm-specific effects by including a firm-specific constant, we found the importance of the aggregate shocks to be at most 1.9% (EBITDA/TA), i.e., very similar to the previous results. But surely, the way one models the firm-specific effects can be of importance for the results. Second, the model is linear, and of course non-linear effects can be of important. Third, and perhaps most important, is that we do not allow for different propagation of aggregate shocks in different industries, since we do not have access to a consistent industry classification over time for all firms (industry classification was changed in 1992). But it seems unlikely that the basic message conveyed, namely that idiosyncratic risk is far more important than aggregate shocks, could be overturned.

5. Putting all things together: a simple empirical model of the interaction between the real and the financial economy

In this section, we will briefly describe a simple, but complete model that can be used to study the interaction between the real and financial side of the economy. The model consists of three blocks.

First, we have the VAR-models for the domestic and foreign variables that are estimated on aggregate data. The domestic VAR(2)-model is given by (1) with the terms $\sum_{s=1}^{2} \Lambda_s \, \mathrm{df}_{t-s}$ added. In order to be able to study the dependency of the foreign variables, we follow Lindé (2002) and estimate the following VAR(2)-model for the foreign variables

$$Z_t = C_{\mathrm{f}} + \tau_{\mathrm{f}} T_{\mathrm{t}} + \sum_{i=1}^{2} B_{\mathrm{f},i} Z_{t-i} + u_{\mathrm{f,t}}. \tag{7}$$

then compute the share of fluctuations in the balance sheet ratios due to aggregate shocks as diag $(\Sigma_{\mathrm{Y}}^{\mathrm{mac}} ./ \Sigma_{\mathrm{Y}}^{\mathrm{tot}})$. Notice that $\Sigma_{Y}^{\mathrm{mac}} + \Sigma_{Y}^{\mathrm{mic}} = \Sigma_{\mathrm{Y}}^{\mathrm{tot}}$.

The second block of the model is the default-risk model (Model III in Table 2). This model is used to compute the average default frequency that enters into the estimated VAR-model for the domestic variables, i.e., $\mathrm{df_t} = \frac{1}{N_\mathrm{t}} \sum_{i=1}^{N_\mathrm{t}} \hat{p}_{i,\mathrm{t}}$ where $\hat{p}_{i,t}$ is the estimated default probability for firm i in period t and N_t is the number of firms in the panel in period t. The third block of the empirical model is the panel VAR-model (5) for the financial ratios which enter into the default-risk model. The default-risk model is the crucial link between the "financial" and "real" side of the economy in this empirical model.

6. Policy experiments with the empirical model

In this section, we will discuss how the empirical model can be used to shed light on various policy issues. We will show why we think it is useful for policy makers to use micro-information rather than just aggregated data on default risk. That is, we will examine why we think it is better to include the estimated default-risk model in the empirical model rather than making aggregate default frequency an endogenous variable in the VAR-model given by (1). We will also study how the trade-off regarding stabilizing inflation and the aggregate default rate with monetary policy has changed over time in the estimated empirical model. Finally, we will show how one can use the estimated model to compute model consistent joint forecasts for default-frequency and inflation along with uncertainty bands.

6.1. Computing default frequency distribution percentiles with the model 1991Q1 and 1998Q1

In this subsection, we report the results of computing default frequency distribution percentiles with the estimated empirical model. As initial conditions, we take the portfolio compositions as they were in 1991Q1 and 1998Q1, respectively, along with corresponding macroeconomic stances. Note that computing a default frequency distribution is the same thing as computing a loss distribution under the assumption that all loans are of the same size. Computing the default frequency distribution is done in the following way. First we compute a "trend path" by simulating the economy when no shocks hit the economy, i.e., u_t^d, u_t^f and $u_{i,\mathrm{t}}^\mathrm{y}$ are all zero and using the actual values on the macro-variables {1990Q4, 1991Q1} and {1997Q4, 1998Q1} as starting values (two lags are used in the VARs). Let d_{t+h}^{trend} denote the computed trend default rate at horizon $h = 1, 2, \ldots, 8$. Second, we make an additional simulation using the same initial conditions but this time we allow for shocks hitting the economy (i.e., u_t^d, u_t^f and $u_{i,\mathrm{t}}^\mathrm{y}$ are now non-zero). Let d_{t+h}^{shock} denote the outcome when the shocks are included in the model. Third, we compute $d_{t+h}^{\mathrm{Dfd}} = d_{t+h}^{\mathrm{shock}} - d_{t+h}^{\mathrm{trend}}$, where Dfd is spelled out as Default frequency distribution. Fourth, we generate 1000 realizations of d_{t+h}^{Dfd} and choose the upper $(1 - XX/100)$th percentile for each horizon h of the simulated distribution as our Value-at-Risk-measure of the portfolio of firms in the Swedish corporate sector. We also report the $(1 - XX/100)$th percentile of the distribution for d_{t+h}^{shock}, to ensure that the model is consistent with the fact that default risks were higher in the beginning of the 1990s than during the boom in late 1990s.[27]

[27] Note that we keep REMARK and TTLFS equal to their initial distributions 1991Q1 and 1998Q1 in the simulations because we have no model for the dynamics of these variables.

Table 3
Absolute and relative default frequency distribution percentiles at different horizons h into the future using the empirical model 1991Q1 and 1998Q1

Percentile	Time period 1991Q1				Time period 1998Q1			
	$h=1$	$h=4$	$h=6$	$h=8$	$h=1$	$h=4$	$h=6$	$h=8$
Absolute default frequency percentiles at horizon h (quarters ahead)								
95	2.02	2.73	2.97	2.78	0.99	0.99	0.99	1.01
99	2.17	3.08	3.48	3.46	1.04	1.09	1.06	1.06
Relative default frequency percentiles at horizon h (quarters ahead)								
95	0.30	0.67	0.85	0.82	0.13	0.18	0.19	0.20
99	0.45	1.02	1.36	1.50	0.18	0.28	0.26	0.26

Notes: The absolute default frequency distribution percentiles have been determined from a distribution of 1000 outcomes h periods ahead by simulating the empirical model with shocks added to the domestic and foreign VAR-models, and to the VAR-model of the financial ratios. The relative default frequency percentiles have been determined from a distribution where a "trend-path" for the default frequency level (given by a simulation of the empirical model where no shocks are added to the economy using the same initial conditions) has been subtracted from the absolute default frequency level.

In Table 3, we show the resulting figures for the 1991Q1 portfolio and 1998Q1 portfolio of firms. In the table, the absolute default frequency distribution percentile refers to the $(1-XX/100)$th percentile for the d_{t+h}^{shock}-distribution at horizon h, while the relative default frequency distribution percentile refers to the $(1-XX/100)$th percentile for the d_{t+h}^{Dfd}-distribution at horizon h. It is important to note that using an aggregate approach, i.e., including the aggregate default frequency as an endogenous variable in the VAR-model, would give rise to exactly the same outcome for the $(1-XX/100)$th percentile for the d_{t+h}^{Dfd}-distribution at horizon h (since the VAR-model is linear). So if these number are different, then this constitutes evidence that the non-linearities induced by the default-risk model at the firm level give rise to effects that differ from those in a pure macro-approach. It is harder to say with certainty whether the differences we observe are due to the differences in portfolio compositions of firms, or differences in the initial macroeconomic conditions.

We learn two things from the results in Table 3. First, the empirical model correctly identifies that absolute default risks were substantially higher in 1991 than in 1998. The estimated percentiles cover the actual default frequencies during 1991–1992 and 1998–1999, even though the dummy variables REMARK and TTLFS are kept at their initial values throughout the simulations which tends to yield a downward/upward bias for the first/latter period. Second, and most importantly, we note that the relative default frequency distribution percentiles are at least two times larger for the 1991 portfolio of firms than for the 1998 portfolio of firms. This is a clear indication that the micro-data approach using the non-linear default-risk model differs substantially from a pure macro-approach, because – as mentioned earlier – a pure macro-approach implies that these numbers are the same.

This latter result is quite pronounced, although we have not taken into account in the estimated default-risk model that different industries might display different degrees of sensitivity to the macroeconomic stance. If this is the case, and if the composition of shares of firms in different industries has changed over time, then the results reported in Table 3

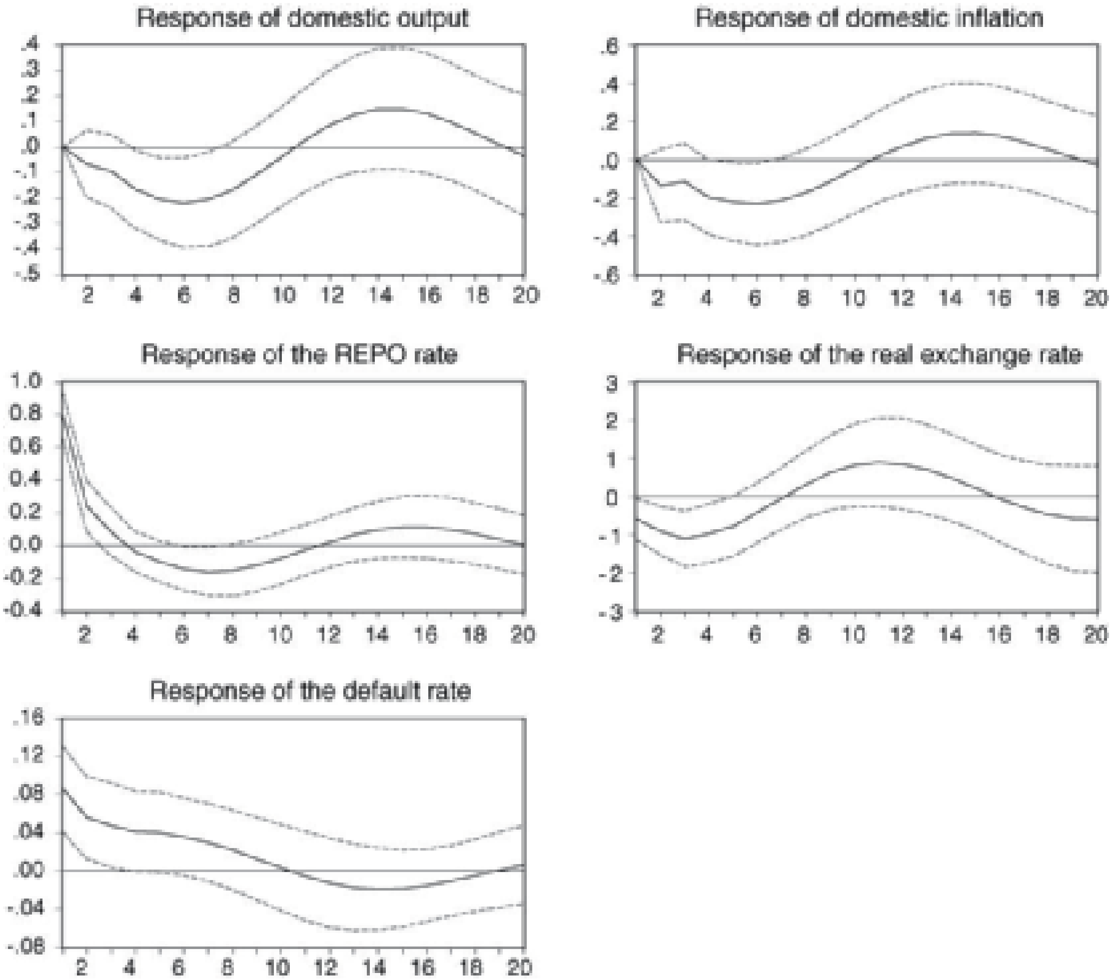

Fig. 8. Impulse response functions to an identified shock to monetary policy in the VAR-model where the default rate is endogenous. Solid line shows point estimates and dashed lines 95% confidence interval.

would be even more pronounced, and the evidence in favor of the micro–macro-based approach even stronger.

6.2. Is there a trade-off between real and financial stability?

In this subsection, we compute the impulse response functions to an identified monetary policy shock, and examine if there is a potential trade-off between stabilizing inflation and output and the default frequency. Following Lindé (2002), the monetary policy shock is identified using the so-called recursiveness assumption adopted by Christiano et al. (1999, 2005). The assumption being that goods market clear before and financial markets after the central bank sets the interest rate. In our empirical model, this implies that output and inflation do not react contemporaneously to a policy shock, whereas the real exchange rate and the default rate do react contemporaneously.

In Fig. 8, we show the impulse response functions to a shock to monetary policy in the estimated VAR-model where the default rate is included as an endogenous variable. There are several features worth noting in this graph. According to the VAR, output and inflation

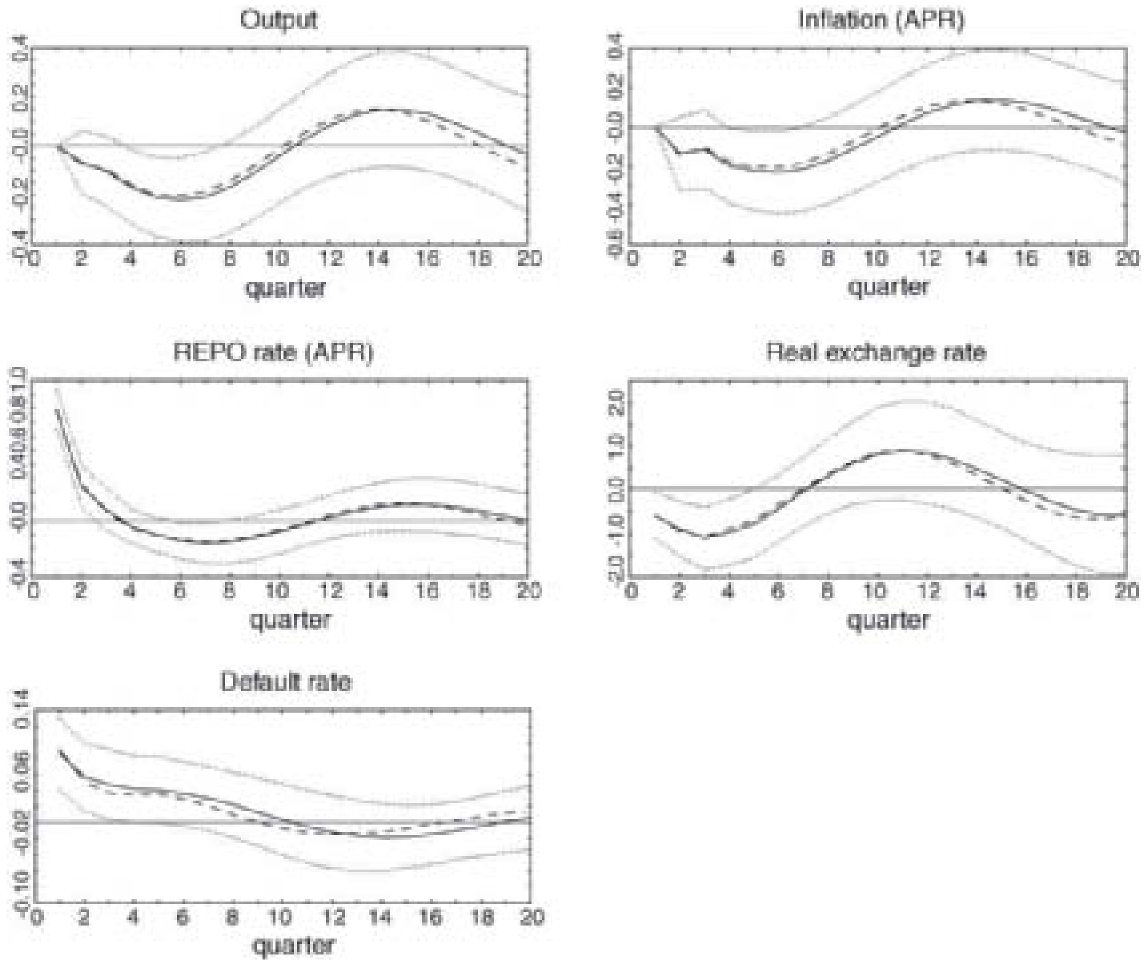

Fig. 9. Impulse response functions in the estimated VAR-model with the default rate endogenous (point estimates – solid line, dotted lines shows 95% confidence interval) and in the empirical micro–macro-model (dashed line) for 1991Q1.

fall after an increase in the interest rate, whereas the real exchange appreciates.[28] As in many other studies (see e.g. Christiano et al., 2005), the maximum effects are quite delayed in time with peak effects after 1–2 years. Simultaneously, there is a significant and persistent rise in the average default rate. Consequently, the results in Fig. 8 suggest that there is a trade-off between stabilizing the inflation rate and the default rate for monetary policy. If the Riksbank at a given point in time would like to fight inflation more aggressively than prescribed by the rule normally followed, thereby injecting a positive policy shock (i.e., an unanticipated increase in the REPO rate), this would lead to increasing default frequencies according to the VAR.

However, if we do the same experiment in the empirical micro–macro-model outlined in Section 4, the picture changes substantially. According to the micro–macro-model, the potential trade-off between stabilizing the real economy (i.e., output and inflation) and financial stability (approximated by the default rate) is highly time-dependent. In Figs. 9 and 10,

[28] Note that the real exchange rate q_t is defined as $s_t + p_t^f - p_t$, implying that a decrease in q_t is an appreciation.

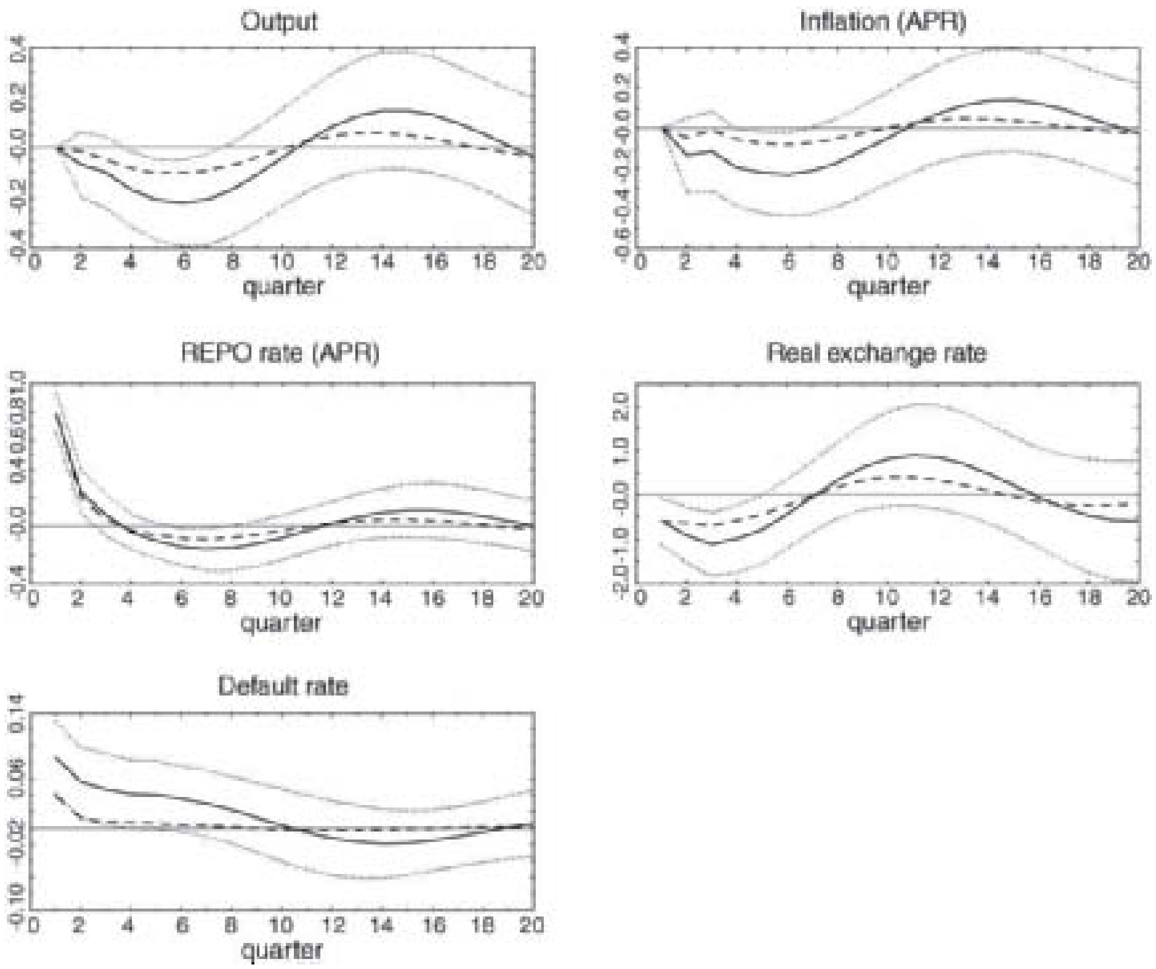

Fig. 10. Impulse response functions in the estimated VAR-model with the default rate endogenous (point estimates – solid line, dotted lines shows 95% confidence interval) and in the empirical micro–macro-model (dashed line) for 1998Q1.

we plot, for the portfolio of firms in 1991Q1 and 1998Q1, the impulse response functions for an identical policy shock as in Fig. 8 along with the impulse response functions in the estimated VAR-model where the default rate is endogenous.[29] As can be seen from Figs. 9 and 10, the point estimates for output, inflation and the default rate are quite different in the micro–macro-model compared with the aggregate VAR-approach. For 1991Q1, the

[29] The impulse response functions in the micro–macro-model have been computed as follows. As initial conditions, we use how the portfolio look like in 1991Q4 and 1998Q1, along with the macroeconomic stance. We then compute a "trend path" by doing a dynamic simulation of the model when no shocks are hitting the economy, i.e. u_t^{d}, u_t^{f} and $u_{i,t}^{\mathrm{y}}$ are all zero and we use actual values on the macro-variables {1990Q3, 1990Q4} and {1997Q3, 1997Q4} are used as starting values (two lags are used in the VARs). Let X_{t+h}^{trend} denote the computed trend default rate at horizon $h = 1,2,\ldots,20$. Second, we make an additional simulation using exactly the same initial conditions but this time we allow for the policy shock hitting the economy (i.e. u_t^{d} is non-zero). Let X_{t+h}^{shock} denote the computed default rate at horizon $h = 1,2,\ldots, 20$ in this case. The impulse responses are then computed as $X_{t+h}^{\mathrm{shock}} - X_{t+h}^{\mathrm{trend}}$ for each variable in X.

impulse response functions are roughly the same as in the aggregate VAR-model, although the persistence in the default rate is somewhat lower due to the fact that there is a substantial amount of intrinsic persistence for that variable in the VAR, but none in the default-risk model. Turning to 1998Q1, however, we see that the point estimates of the same sized policy shock are rather different in the micro–macro-model compared with the aggregate VAR-model. The effects on the aggregate default frequency are considerably less pronounced according to the micro–macro-model than in the aggregate VAR. Moreover, the different response of the default rate implies that the impulse response functions for output and inflation are very different. In the 1998Q1-period, effects on inflation are less than half compared with those in the estimated VAR.

Given that the uncertainty about the parameters in the VAR-model (1) is rather high, we cannot claim that the point estimates for the micro–macro-model reported in Figs. 9 and 10 are significantly different from the ones in the aggregate VAR in a statistical sense. But if the micro–macro-model is a more realistic model than the aggregate VAR-model (we will discuss this issue in greater detail the next subsection), then the effects of monetary policy on the economy are state-dependent. This possibility has interesting implications for policy from an economic point of view. In this case, monetary policy is a potent tool for stabilizing the economy in recessions in the sense that small unexpected movements in the interest rate have relatively large effects on the economy. But in booms, when macroeconomic conditions are favorable and firms' balance sheets strong, monetary policy is a less potent tool for stabilizing the economy, i.e., the central bank must inject much larger policy shocks in order to fight inflation (at the cost of driving up the default frequency). An interesting question, of course, is whether most of these effects come from differences in macroeconomic stance rather than changes in the balance-sheet variables of the firms in the portfolio. Unfortunately, we cannot provide a clear-cut answer to this question. The reason being that the formation of the population of existing firms in a given period is most likely dependent on the stance of the macroeconomy. Nevertheless, the estimation results for the default-risk Models I and III suggest that the macroeconomic stance might play a larger role than firms' balance sheets.

6.3. Joint forecasts of default-frequency and inflation

In this last subsection, we use the micro–macro-model to produce joint forecasts of the default-frequency and inflation rate. We use the same initial conditions as in the previous sections and for the same two quarters, 1991Q1 and 1998Q1, i.e., the beginning of a recession and the beginning of a boom in the economy. To produce these forecasts and associated uncertainty bands, we perform 1000 dynamic simulations with the estimated model eight quarters into the future. This produces 1000 projections in periods $t+1,\ldots,$ $t+8$ for the aggregated default frequency and inflation rate. The resulting forecasts and uncertainty bands are shown in the left-hand panels of Figs. 11 and 12. The right-hand panels display corresponding results for the VAR-model (1). The dashed lines are the median forecasts and the dotted lines represent the 2.5 and 97.5% in the simulated distributions. The solid lines show the actual outcomes for 1991Q2–1993Q1 and for 1998Q2–2000Q1. There are a couple of interesting features worth noting. First, the micro–macro-model appears to forecast actual inflation and default frequency quite well, although for the forecasts

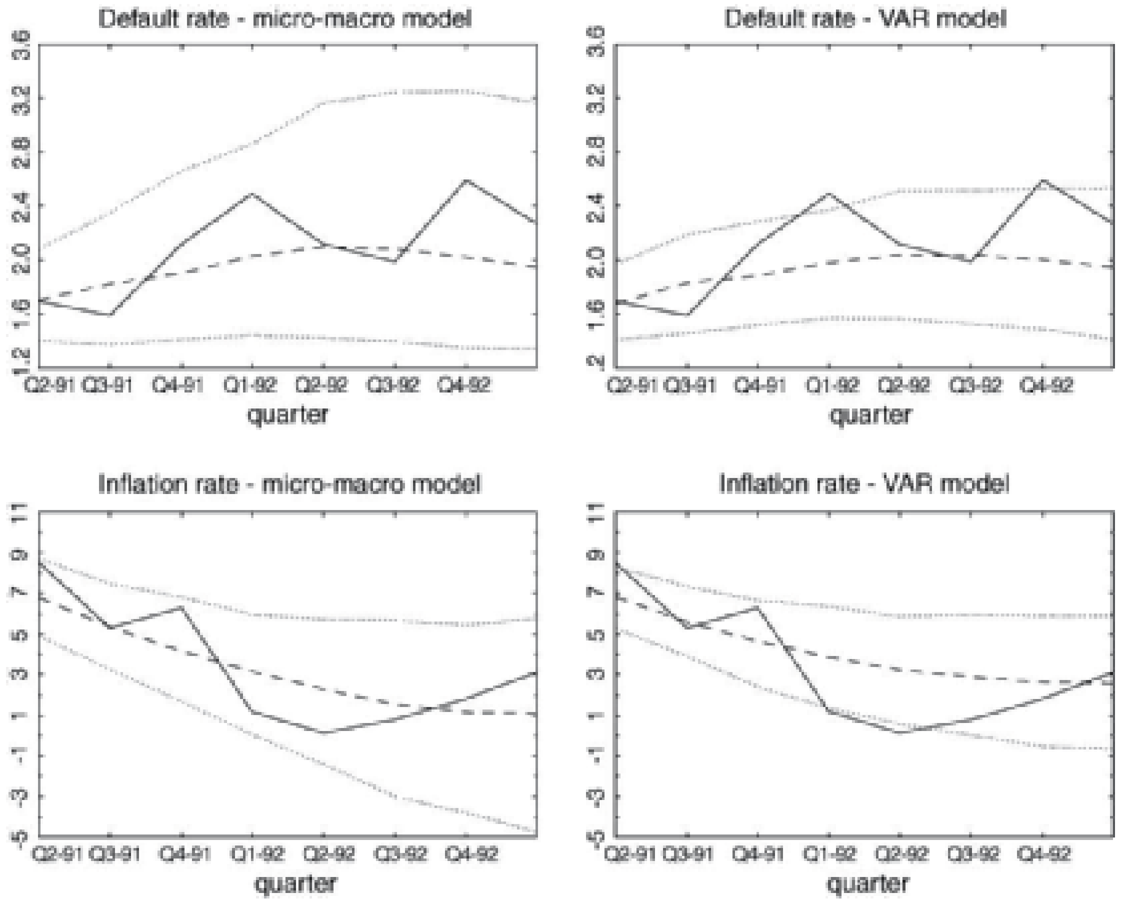

Fig. 11. Joint dynamic forecasts of the default frequency and inflation eight quarters ahead starting 1991Q1. The left panel shows the results for the micro–macro-model, and the right panel the results for the VAR-model where the aggregate default rate is included as an endogenous variable. The dashed line is the median forecast, and the dotted lines indicate the 95% confidence interval. The solid line shows the actual outcome.

starting in 1998Q1, actual default frequency is outside the 95% confidence interval in one quarter. It should be noted that since the default risk model is only estimated on data up to 1999Q2, this forecast is to some extent out-of-sample. Second, confirming the results reported in Table 3, we see that the uncertainty is much lower in the 1998Q1 forecast. The 95% confidence interval for the predicted default frequency in 1993Q1 is between 1.3 and 3.2%, whereas the interval for 2000Q1 is roughly between 0.6 and 1.0%. The confidence intervals for VAR-model forecasts are of equal width in both period, suggesting an under-estimation of uncertainty in the first period and an over-estimation in the latter period. In comparison with the aggregate VAR-model, the micro–macro-model produce a much more plausible picture in that default risk is more severe in the beginning of the 1990s, whereas the band width is very tight in the late 1990s, suggesting a very low risk of financial distress. As noted by Christoffersen (1998), this is a desirable property of a forecasting model. A similar, but less pronounced, interpretation can be done for the inflation rate forecasts. Given an extended data set it would, of course, be very interesting to compare the genuine out-of-sample forecasts properties of the micro–macro-model

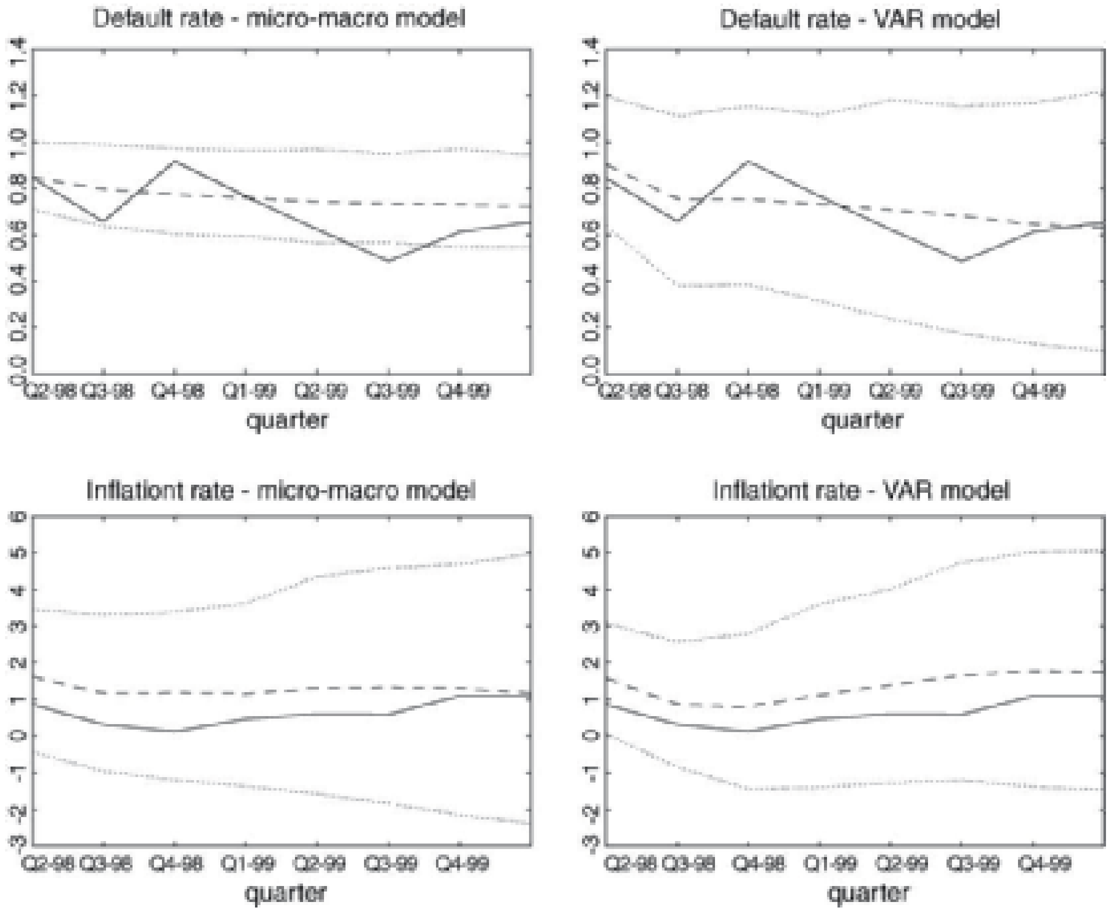

Fig. 12. Joint dynamic forecasts of the default frequency and inflation eight quarters ahead starting 1998Q1. The left panel shows the results for the micro–macro-model, and the right panel the results for the VAR-model where the aggregate default rate is included as an endogenous variable. The dashed line is the median forecast, and the dotted lines indicate the 95% confidence interval. The solid line shows the actual outcome.

and the VAR-model (comparing RMSE and forecasting distributions, see Christoffersen, 1998).

7. Conclusions

In this paper, we have studied the interaction between real economic activity and the financial stance of the economy using reduced form methods. To this end we have acquired a large panel data set for the Swedish economy during 1990–1999. A period covering a banking crises episode and associated deep recession in the early 1990s, as well as a boom in the latter part of the 1990s.

Our empirical results provide support for the idea that the financial stance of the economy matters for real economic activity. We argue on empirical grounds that the aggregate default frequency is a good proxy for measuring the financial stance, at least this seems to be case for Sweden. Other financial indicator variables such as stock prices, term structure or the supply loans do not carry information for aggregate quantities and prices, whereas on the other hand housing prices do. We leave for future research to examine the role of housing prices. Moreover, we find that a simple logit model for default at the firm level using both firm-specific and macroeconomic variables as explanatory variables can explain the extremely high default frequencies during the banking crisis in the beginning of the 1990s, and also the considerably lower default frequencies in the late 1990s. Furthermore, we find strong evidence that most of the variation in balance-sheet variables are due to idiosyncratic shocks. Finally, we show that augmenting a standard macroeconomic model with predicted aggregated default-frequencies from the logit model and a simple dynamic panel for the balance-sheet variables will produce state-dependent effects of monetary policy that are quantitatively important. According to our model, monetary policy is a more potent tool for stabilizing the economy during recessions than in booms, when the effects of monetary policy are rather limited. These latter results provide some implicit empirical support for the existence of a so-called credit channel of monetary policy.

In our view, the results in the paper suggest that central banks should consider integration of the analyses of financial stability and economic activity. The empirical micro–macro-model developed in the paper is an example of a simple empirical model, which can be used for such a purpose.

The analysis conducted in the paper should be improved and expanded in a variety of ways. First, it would be of interest to examine the out-of-sample forecasting performance of the estimated logit model, i.e., whether the estimated model can accurately predict the default frequency rates for the year 2000 and onwards. Another promising research direction is to condition on firms' industry-classification, both in the default-risk model and in the dynamic panel VAR for the balance-sheet variables. Presumably, one reason why the macroeconomic variables come out as very important in the estimated logit model is that they capture systematic industry differences in firm-specific variables. Estimating the logit model on industry data would be a stronger test of whether the empirically important role for the macroeconomic variables is spurious or not. Conditioning on industry would also be a natural way to examine the robustness of the results pertaining to the role of aggregate versus idiosyncratic shocks for the balance-sheet variables. Third, we need to think about the theoretical arguments for macroeconomic factors to enter as separate regressors in the default-risk model.

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SELECTED INDICATORS OF FINANCIAL STABILITY

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1. Introduction

The stability of the financial system, as evidenced by markets that are functioning well, by key institutions that are operating without major difficulty, and by asset prices that are not significantly removed from fundamental values, is vital if an economy is to achieve the objectives of sustained growth and low inflation. A financial system that is stable will also be resilient and will be able to withstand normal fluctuations in asset prices that result from dynamic demand and supply conditions, as well as substantial increases in uncertainty. Financial instability, on the other hand, can impede economic activity and reduce economic welfare. If financial markets become dysfunctional or the condition of key institutions becomes severely strained, the attendant pressures on businesses and households may have adverse effects on the real economy as capital may be prevented from flowing to worthy investments and credit crunches may develop. To the extent that those pressures are judged to be sufficiently acute, policymakers may want to respond by altering the stance of monetary policy. Conversely, economic and monetary policy surprises can trigger financial instability and compromise the effectiveness of the

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monetary policy transmission mechanism. As markets react to the new information, large and sudden price movements may occur that may lead to substantial losses and to heightened uncertainty and unwillingness to take on risk. Because of the interdependency between the financial system, the state of the economy, and monetary policy, monitoring financial markets and appropriately assessing their stability are tasks of great importance to policymakers. Indeed, the staff of the Federal Reserve Board devotes a significant amount of time and resources to assess the overall health of the financial system and, when financial disturbances occur, to judge the implications of those disturbances for the nonfinancial sector.

The rapid pace of financial innovation that has taken place over the course of the last decade has brought about a proliferation of new and increasingly sophisticated financial products, has led to the appearance of new types of institutions, and has created new and expanded roles for existing institutions. Against this backdrop of increased complexity, key goals of the Board s staff are to understand financial markets as well as possible and to be able to identify in a timely fashion the potential consequences of any new developments. In pursuit of those objectives, the staff relies on its expertise and judgment, on market intelligence, and on a broad range of financial indicators. Many of those indicators are measures of financial strength, that is, measures of the ability of households or businesses to weather shocks without greatly contracting their spending. Other measures focus on market participants assessments of, and appetite for, risk. Individual indicators are also combined into aggregate measures that give a synthetic picture of overall financial conditions and thus summarize the general stability of the financial system. While notable efforts have been made in the academic literature as well as at other institutions to develop indicators that could be predictive of adverse developments, all indicators in use at the Board are contemporaneous in nature and are used purely as tools to help interpret current conditions.[1] And importantly, neither the

[1] Reviews and discussions of the predictive ability of various types of indicators, as applied to different types of crises, are contained, for example, in Berg, A. and Pattillo, C., Are Currency Crises Predictable? A Test, IMF Staff Papers vol. 46, no. 2, June 1999, and Kumar, M.S. and Persaud, A., Pure Contagion and Investors Shifting Risk Appetite: Analytical Issues and Empirical Evidence, IMF Working Paper no. 134, 2001.

individual nor the aggregate measures are used as black boxes to determ ine policy actions; rather, they are just a few among a host of instruments that the Board s staff draws on to inform policy makers of the current state of financial markets.

The individual measures of financial stability used by the Board s staff are taken from a variety of sources, and are available at a wide range of frequencies. Some, such as asset prices, are market-based and can be calculated daily, if not even more frequently. Others, such as financial stocks and flows, are aggregated from individual institutions at a weekly, monthly, or quarterly basis. Finally, some measures are based on surveys, both formal and informal, of market participants, and are gathered on an ongoing basis. The Board of Governors is provided updates about financial market developments often (at least weekly and sometimes more frequently). The Federal Open Market Committee, which sets the overnight interbank (federal funds) rate in the United States, is provided with information on financial conditions before each FOMC meeting, although many measures are also provided to Committee members on a more frequent basis. Reports on the functioning of U.S. financial markets are prepared at regular intervals in advance of international meetings on financial stability. Several Divisions at the Federal Reserve Board, including the Divisions of Monetary Affairs, Research and Statistics, International Finance, Bank Supervision and Regulation, and Reserve Bank Operations and Payment Systems, contribute to the compilation and interpretation of this information.

While the focus of this paper is on quantitative gauges of financial stability, we should note that qualitative information also figures prominently in the set of tools Board economists use to assess the state of the financial system. Formal surveys of investors and bank senior loan officers are conducted regularly and provide timely information on the respondents views on current developments and their likely future unfolding. More informal contacts with market participants, either direct or through the Open Market Desk of the Federal Reserve Bank of New York, are instrumental in the interpretation of the vast amount of information that is received on any given day. Market contacts are especially valuable when events are unfolding rapidly and there is no time to wait for responses to formal surveys. Of course, qualitative information that is received from market participants needs to be evaluated, put in context, and possibly filtered, but has nonetheless repeatedly proved useful in the past.

Sections 2 to 6 of this paper summarize some of the individual and aggregate indicators that are monitored by the authors and other members of the Board s staff.[2] Section 7 briefly discusses how some of those indicators were used to assess the impact of the turmoil in the credit markets in the spring of 2005 that was induced by the credit quality deterioration of two large U.S. automobile manufacturers, and section 8 contains some conclusive thoughts.

2. Measures based on interest rates and asset prices

Asset prices and interest rates are determined by the supplies and demands of forward-looking investors and savers; as such, they react nearly instantaneously to investors judgments about financial conditions. Because many prices and rates are available virtually instantaneously and continuously, Board staff members monitor a broad range of them for prompt information on market liquidity and market participants attitudes toward risk.[3]

Measures of market liquidity provide information on the ability of financial markets to absorb large transactions without large changes in prices, and on the premiums investors are willing to pay to hold more liquid assets. The Board s staff assesses the liquidity of the market for U.S. Treasury securities, in part, by looking at bid-ask spreads and volumes. As an example, the top two panels of exhibit 1 plot these measures for the

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[2] The authors are part of the Monetary and Financial Stability section (MFST) of the Division of Monetary Affairs (MA). MFST is responsible for analyzing a variety of issues related to financial stability and the operation of financial institutions and markets. Key areas of specialization include the collection and evaluation of information on financial institutions, methods for assessing stress in financial markets, and assisting in the formulation and implementation of policies regarding Reserve Banks' credit and risk management. Section economists analyze financial developments for the Board of Governors and the FOMC and engage in a broad range of longer-term research projects. Not all the measures discussed in this paper are produced by MFST or MA.

[3] This paper draws, in part, from Prag matic Monitoring of Financial Stability, b y William R. Nelson and Wayne Passmore, in *Marrying the Macro- and Micro-Prudential Dimensions of Financial Stability*, BIS Papers, No.1, March 2001. That paper contains, among other things, a more detailed description of some of the individual indicators of financial stability in use at the time at the Federal Reserve Board.

ten-year on-the-run Treasury security in April and early May, 2005.[4] The Treasury market is an over-the-counter (OTC) market, and consequently bid-ask spreads and volume data for Treasury securities are more difficult to obtain than for exchange-traded securities, such as stocks or most futures. The Board s staff currently relies on intraday data collected by electronic brokers, such as BrokerTec for the interdealer market and TradeWeb for the dealer-to-customer market. While those electronic brokers do not represent the whole market, they appear to account for substantial and growing percentages of the total daily trading volumes in Treasury securities.

[Exhibit 1 about here]

Members of the Board s staff also follow liquidity premiums, defined as the yield on a less liquid security minus the yield on a highly liquid but otherwise similar security. Highly liquid securities, generally, can be sold rapidly and at a known price. The amount investors are willing to pay for that comfort, in the form of higher prices or lower yields with respect to less liquid securities, may rise rapidly during periods of financial market difficulties, particularly when the source of such difficulties is heightened investor uncertainty. Because these spreads may react rapidly to financial difficulties, and are available at high frequencies, the Board s staff reviews them often. The middle-left panel of exhibit 1 plots the liquidity premium for the two- and ten-year on-the-run Treasury securities relative to the corresponding first-off-the-run securities in recent months, adjusted for the auction cycle. Yield data on Treasury securities are readily available from a variety of sources.

As suggested by economic theory, expected yields on risky debt instruments and equities relative to those on riskless assets vary with investors assessments of risk and willingness to bear risk. The spreads between the yields on riskier and less risky securities widen when investors judge their relative risks to have increased, and also

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[4] Corporate credit markets were under stress at that time because of the problems at Ford and General Motors. The Treasury market, however, was functioning properly, as evidenced by the minimal bid-ask spreads and the substantial volumes.

when investors demand a higher premium for a given amount of risk. Thus, these spreads will increase when investor uncertainty increases or financial conditions worsen; a sharp widening of these spreads has often been a component of financial turmoil. Examples of such spreads are the differences between investment-grade and speculative-grade corporate yields and comparable-maturity Treasury yields, plotted in the middle-right panel of exhibit 1. The Federal Reserve Board receives yields on several thousand outstanding corporate bonds every day; those data are then used to compute a variety of indexes, such as those shown in the exhibit. Other spreads over Treasury securities that are regularly monitored are swap spreads, which can provide information on the credit quality of the banking sector as well as market liquidity conditions; agency spreads (also relative to swaps and high-grade corporate debt), which are proxies for the housing government-sponsored enterprises (or GSEs) cost of funds; and money market spreads, such as commercial paper spreads (an indicator of the costs of short-term corporate funding).

Equity prices vary with changes in investors appetite for risk; in investors expectations for, and uncertainty about, future macroeconomic and firm-specific outcomes; and in the clarity of information available to investors. To invest in equities, investors demand a premium over bond yields because the return on bonds is generally more predictable. The Board s staff assesses the equity premium in a number of ways, including by comparing the earnings-price ratio of the S&P 500 to the real level of the ten-year Treasury rate the lower-left panel in exhibit 1. The earnings-price ratio is calculated using analysts expectations for earnings during the upcoming year and is adjusted to remove the effect of cyclical changes in earnings. For this purpose, the real ten-year interest rate is calculated by subtracting a survey-based measure of long-term inflation expectations from a nominal long-run Treasury rate. Unfortunately, interpreting changes in this measure of the equity premium is difficult. For example, a decline in the earnings-price ratio relative to the real interest rate may reflect new economic information that raises investors expectations of future earnings growth; or it may indicate that investors have better information or greater certainty about economic outcomes, or an enhanced appetite for risk. Comparisons of analysts expectations about longer-term earnings growth to the staff s forecast of earnings permit some judgments about reasons for changes in the earnings-price ratio, but such analysis embodies a great degree of uncertainty.

The Board s staff uses option prices to measure investors assessment of the likely volatility of interest rates and equity prices. These measures have proven to be useful and timely indicators of investor uncertainty and can also be used to construct the probability distribution of underlying economic outcomes. For example, options on Eurodollar futures provide a measure of the expected volatility of very short-term rates, which rises when investors become more uncertain about the future path of near-term monetary policy (the black line in the lower-right panel of exhibit 1). Equity options (the red line) provide information on investors uncertainty about equity prices. Those options can also be used to construct the risk-neutral probability distribution of the returns on underlying contract (such as the S&P 500 index): A distribution with a long left tail would presumably indicate elevated market participants concerns about, or aversion to the possibility of, large losses before the options expiration.

Those described above are but a small sample of the indicators based on interest rates and asset prices that members of the Board s staff regularly monitor. A rough count of the number of the basic, individual indicators in daily (or more frequent) production easily exceeds one hundred. Large amounts of data are necessary to construct those indicators and use them in daily reports. In addition, the data, which are provided by a large number of different sources, in different formats, and often at different frequencies, need to be stored in a convenient and easily-accessible database. Significant resources are devoted to the maintenance of such a database, in terms of software, storage space, network accessibility, and personnel.

3. A financial fragility indicator

The information contained in an array of financial variables such as those described above can be condensed into a financial fragility indicator which estimates the probability that the U.S. financial system is currently under severe stress. In our view, two episodes in recent U.S. financial history can unambiguously be called financial crises the weeks surrounding the Russian default and the recapitalization of Long Term Capital Management in the fall of 1998, and the aftermath of September 11, 2001. While the causes of those crises were entirely different, several key financial variables behaved in a very similar way during both of those episodes. In particular, risk, liquidity, and term spreads and implied volatilities all moved significantly higher at those times; moreover, they did so at a rapid pace and largely at the same time. Based on these observations, the construction of the indicator follows a two-step process. First, the information contained in the twelve individual variables listed in the top panel of exhibit 2 is reduced to three summary statistics that capture their level, their rate of change, and their correlation.[5] And second, a logit model is estimated to obtain the probability that, at any given time and based on the three summary statistics, the behavior of financial markets is analogous to that of the fall of 1998, and the aftermath of the terrorist attacks of 2001.

[Exhibit 2 about here]

Perhaps the most straightforward summary statistic, plotted in the middle-left panel, is an arithmetic average of the values of the individual indicators, normalized by their standard deviations, over the entire sample period from 1994 to the present. As noted by the gray-shaded regions, the index is quite elevated during times of acute stress.[6] As shown in the middle-center panel, the percentage change in the level indicator computed over rolling eight-week intervals gives a sense of the speed of the movements in the underlying financial market variables. One might expect that financial markets would be more fragile during episodes when risk spreads, liquidity premiums, and volatility indicators are moving sharply higher. Conversely, even when the level of those indicators remains high, sharp declines in many or all of them might signal the end of a period of acute financial distress. This rate-of-change indicator again singles out the fall

[5] Those indicators are quoted so that higher values would be associated with greater market strains.

[6] A third episode during which financial markets where under heavy strain, in addition to the two noted earlier, was the summer and fall of 2002, when risk spreads widened sharply in response to corporate scandals and credit quality problems at several large institutions.

of 1998, the weeks following the terrorist attacks, and the late summer of 2002 as particularly noteworthy periods.

As shown in the middle-right panel, a time-varying measure of the comovement in the individual stress variables can be defined as the percentage of the total variation of the individual variables that can be explained by a single, common factor. This measure was highest at the time of the global financial crisis of 1998, but the months in the run-up to Y2K and following the September 11th attacks were also characterized by elevated correlation among the key financial variables. The shaded region corresponding to the late summer and fall of 2002 does not stand out as a period of high comovement. Even though risk spreads widened dramatically at that time, changes in other measures of market stress were mixed.

The three summary statistics discussed above can be combined into a single measure of financial fragility and used to model the probability that, at any given time, the U.S. financial system is in a situation similar to that of the periods identified as crises. This can be accomplished by fitting a logit model with the three statistics as explanatory variables and a binary variable which identifies crises on the left-hand-side:

$$p_t = L(\beta_0 + \beta_1\lambda_t + \beta_2\delta_t + \beta_3\rho_t)$$

In the formula above λ denotes the level indicator, δ represents the rate-of-change indicator, and ρ is the comovement indicator.

The model is estimated using weekly data from June 1994 to June 2002, with the episodes of 1998 and 2001 defined as crises, and then extended out-of-sample until the present.[7] The fitted probability of being in a crisis at each date in the sample is shown in the bottom panel of exhibit 2. As expected, the period of August to October 1998 emerges as the most severe episode of financial fragility in the recent past. The model does show an increase in the probability of crisis or financial fragility at other points in time that were not defined as crises. For example, there is a notable uptick in early 1999

[7] The summer and fall of 2002 seems to have been, in retrospect, a time of less virulent strain in U.S. markets, and thus was not classified as a crisis period and was not included in the estimation. A robustness check showed that results would be qualitatively similar if it had been defined as a period of crisis and if the estimation period had been extended to the end of 2002.

coincident with market concerns about developments in Brazil. The summer and fall of 2002 also stand out, although not at levels as high as the two major crises. The last notable but minor peak occurred in the spring of 2004, when there was some unease in financial markets about the onset of monetary policy tightening and uncertainty about the pace at which it would proceed after it was started. The measure has remained at quite low levels in the spring of 2005, suggesting that the turmoil in credit markets that was sparked by credit problems at the large automobile manufacturers has not affected other markets to a significant extent.

4. Mortgage market indicators

In recent years, the U.S. mortgage market has grown rapidly. At the end of 2004, the total value of mortgages outstanding exceeded $10 trillion, of which $8 trillion were single-family residential mortgages; of those mortgages, about $4.5 trillion were pooled into MBS, or mortgage-backed securities. The MBS market is larger than the Treasury market, the nonfinancial corporate bond market, and the agency market. Virtually all mortgages pooled into U.S. MBS can be prepaid with no penalty; the prepayment option induces what is known as negative convexity, which implies that duration decreases when yields decrease and increases when yields increase. Because of the size of the market, MBS investors who desire to hedge the prepayment risk of those securities are now, in the aggregate, required to buy or sell substantial amounts of other financial instruments; the volumes involved have the potential to reinforce existing market trends. Such effects can arise under a variety of hedging strategies, but they are perhaps best understood in a simple example of dynamic hedging. A decline in market interest rates, say, causes an increase in prepayment risk that reduces the duration of outstanding MBS. Holders of those securities who wish to maintain the duration of their portfolios at a constant target would then have to purchase other longer-term fixed-income securities to add duration, potentially causing yields to fall further. Similar effects tend to amplify increases in market interest rates as well. Thus, mortgage-related hedging flows have the potential, at least for a while, to push interest rates significantly above or below the level that would be justified by macroeconomic conditions and expectations, and to increase the volatility of fixed-income markets. Quantifying the extent to which interest rates may at times misaligned with economic fundamentals is thus important both from a financial stability and from a monetary policy perspective.

Several indicators are useful to monitor the impact that mortgage market conditions have on long-term interest rates. One is the average duration of all fixed-rate mortgages included in outstanding MBS securities, plotted in the top-left panel of exhibit 3. Periods of time when duration is increasing or decreasing rapidly could be associated with large hedging flows, as investors buy or sell other fixed-income securities in order to maintain an approximately constant duration target for their portfolios. A rough estimate of the size of those flows can be obtained by assuming that investors have a duration target of 4.5 years and that all MBS investors hedge in the same way.[8] The amount of ten-year equivalent securities that investors would need to hold in their portfolio to achieve their hypothetical target is plotted in the top-right panel of the exhibit. A rapid increase or decrease in the amount plotted indicates a corresponding potential increase in the demand or the supply of ten-year equivalent securities. For example, in July and early August of 2003, when long-term rates rose rapidly as investors sensed that the Federal Reserve s easing cycle had ended, up to $2 trillion of ten-year equivalent securities may have been sold in the market, likely amplifying the upward move in rates that was already taking place.[9]

[Exhibit 3 about here]

Perhaps more interesting than duration is convexity (which can be interpreted roughly as the amount by which duration would change following a 100 basis points change in yields). MBS convexity depends mostly on how likely mortgage holders are to prepay their mortgage; that likelihood, in turn, depends on the distance between the

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[8] The hypothetical 4.5 years target matches the historical average duration of MBS at times when little refinancing activity was taking place.

[9] That estimate is conditional on all mortgage investors fully hedging their portfolios, and as such it provides an upper limit to the actual flows.

current mortgage rate and the rates of outstanding mortgages. The middle-left panel of exhibit 3 shows the percentage of mortgages in outstanding MBS that are economically refinanceable at a given mortgage rate.[10] The steeper the cumulative distribution is at the current mortgage rate, the higher (more negative) is the convexity of the MBS market. A time series of convexity itself is plotted at the right; for example, in mid 2005, convexity was as negative as it had been in recent years, suggesting that the potential risk of increased volatility in the Treasury and related markets was high.[11]

The information contained in MBS duration and convexity can be used to estimate by how much long-term interest rates shocks are likely to be amplified by mortgage-related hedging flows. Following Perli and Sack (2003), the amplification factor can be obtained by fitting a GARCH model to the volatility of interest rates, under the assumption that hedging flows are determined by either the duration, or the convexity, or the actual amount of refinancing activity currently taking place in the market.[12] The amplification factor is plotted in the last panel of the exhibit: According to our estimates, up to 20 percent of the downward move in ten-year yields that took place earlier in 2005 can be attributed to hedging-related flows. While the confidence interval around that point estimate is fairly wide, it is clear that mortgage hedging could have significant effects on the fixed-income markets that should be monitored carefully. It is important to note that hedging activities, at least in our framework, are never the factor that set off moves in interest rates; they can only amplify, albeit substantially, moves that are already in place.

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[10] We assume that the current mortgage rate should be 50 basis points below the existing rate to make it worthwhile to refinance a mortgage due to the various fees associated with extinguishing an old mortgage and starting a new one. The data in the chart are as of the end of May 2005.

[11] Duration and convexity help inform judgments of the likelihood that substantial mortgage prepayments will take place. It is also useful to monitor the actual pace of refinancing activity; that measure is shown in the bottom-left panel of exhibit 3.

[12] See Perli, R. and Sack, B., Does Mortgage Hedging Amplify Movements in Long-Term Interest Rates?, *The Journal of Fixed Income*, vol. 13, December 2003, pp. 7-17.

5. Measures of conditions of individual institutions

Banks can act as transmission mechanisms of crises because they may sharply contract credit in response to depositor demands for early and quick redemption of funds. Or, with deposit insurance, depository institution liabilities may rise with heightened demand for safety and liquidity. The Federal Reserve collects weekly data on bank credit and the monetary aggregates which, to some extent, can be used to monitor financial problems. For example, rapid growth in bank business loans may indicate substitution away from unreceptive capital markets. Similarly, the monetary aggregates may grow more rapidly when investors shift funds out of bond and stock mutual funds and into safer and more liquid bank deposits or money funds.

In the past, both aggressive lending practices and the contraction of lending at banks have been cited as the transmission mechanism of financial problems to nonfinancial businesses and households. The Board collects information from commercial banks four times per year be fore every other FOMC meeting on the standards and terms on, and demand for, loans to businesses and households in its Senior Loan Officer Survey on Bank Lending Practices. The Senior Loan Officer Survey poses a broad range of questions to loan officers at approximately sixty large domestic banks and twenty-four U.S. branches of foreign banks. On the topic of banks tolerance for risk, the survey asks about changes in risk premiums on business loans, and about changes in business loan standards. Although these surveys are not frequent enough to use for monitoring a quickly unfolding financial crisis, the Federal Reserve has authority to conduct up to six surveys a year, and has done special surveys when warranted by financial conditions, most recently in March of 2001.

The Federal Reserve is the umbrella regulator for financial services holding companies, the primary regulator of bank holding companies, U.S. branches of foreign banks, and state-chartered banks that are members of the Federal Reserve System; other institutions have other primary regulators, with whom Federal Reserve regulatory staff maintains close contacts. Through its supervisory role, the Federal Reserve learns about the condition and behavior of commercial banks, and acts to maintain the soundness of these institutions. During periods of financial turmoil, the familiarity with these intermediaries deepens the Federal Reserve s understanding of developing conditions. Communication between the regulatory and policy functions occurs regularly and is institutionalized at various levels.

Not all financial institutions are depositories; indeed many large ones, such as insurance companies, the financial subsidiaries of large nonfinancial corporations, the housing GSEs, etc., are not. In addition, many nonfinancial corporations are heavy participants in financial markets through their comm ercial paper and bond issuance programs and often have large lines of cred it with banks. While the Federal Reserve does not regulate most nondepository financial and nonfinancial institutions, the Board s staff does monitor information that bears on financial conditions to be able to assess the impact of difficulties at one or more of those institutions on the financial system. The monitoring takes place primarily through market-based indicators, such as commercial paper, corporate bond, and credit default swap (CDS) spreads.

An example of nonfinancial institutions monitoring is presented in the top two panels of exhibit 4. Two large U.S. automobile manufacturers have experienced some difficulties in the spring of 2005; the top-left panel of the exhibit plots five-year CDS spreads for the two institutions, as well as the average spread for CCC-rated institutions.[13] While the rating agencies downgraded the obligations of one or both automakers to junk status beginning in early May, judging from the CDS spreads plotted in the charts market participants anticipated the rating action by many months. The chart at the top-right shows the term structure of default probabilities for the two automakers obtained from CDS spreads as of the end of May 2005. The term structure for another large nonfinancial institution is shown for comparison purposes.

[Exhibit 4 about here]

The Board s staff monitors CDS on a large number of institutions, both financial and nonfinancial. As of this writing, CDS data is available on about a thousand U.S.

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[13] Our data source, Markit, does not report CDS quotes for firms rated below CCC.

firms, of which roughly two-thirds are rated investment-grade and the remainder are rated speculative-grade. With such a large amount of data, it is useful and convenient to calculate indexes. The investment-grade and speculative-grade indexes computed by weighting each individual CDS spread by the outstanding liabilities of the corresponding firm are plotted in the middle panels of exhibit 4. The panels also show the corresponding market-traded indexes, which are constructed as equally-weighted averages of the CDS spreads of the component firms. Those indexes can serve as an alternative to the corporate bond spreads shown in exhibit 1. For several firms CDS are reported to be more liquid than corporate bonds, so CDS indexes may actually be more representative of current market conditions than corporate bond spread indexes.[14]

Credit default swaps give an idea of investors perception of the riskiness of an institution, but the probabilities of default derived from those instruments are risk-neutral probabilities, i.e., they incorporate investors attitude toward risk. Obtaining good measures of actual default probabilities is not easy. One option is to use KMV Corp. s expected default frequencies (EDF). Those are derived by first computing distances to default for all publicly traded firms in the U.S. based on Merton s model, and then by mapping those distances to default into actual defaults using a large historical database.[15] Actual default probabilities are typically lower than risk-neutral probabilities since the latter include a risk premium. Indeed, as shown in the bottom-left panel of exhibit 4, the EDF for General Motors, as estimated by KMV, has been substantially lower than the corresponding risk-neutral default probability since 2002; the risk-neutral probability has surged in March and April of 2005 following the much-publicized problems and the consequent credit rating downgrades, while the EDF has only edged up. The difference

[14] This is especially true at times when individual institutions are experiencing difficulties. At those times many investors would want to sell short the trouble institutions bonds, but those bonds may be hard to obtain in the repo market. Many corporate bonds are typically held by money-managing firms, such as pension funds or mutual funds, that already have plenty of cash and don t need to finance the purchase of the bonds. Those institutions, thus, may not make the bonds available in the repo market, since by doing so they would effectively pay to obtain even more cash. A more detailed analysis of the deviations between CDS and corporate bond spreads is contained in A. Levin, R. Perli, and E. Zakraj ek (2005), The Determinants of Market Frictions in the Corporate Market, manuscript, Federal Reserve Board.

[15] For the details see R.C. Merton (1973), A Rational Theory of Option Pricing, *Bell Journal of Economics and Management Science*, 4, pp. 141 183 and KMV Corp., Modeling Default Risk, January 2002, available at www.moodyskmv.com.

between the two provides a rough estimate of the risk premium that investors demand to provide credit protection on General Motors obligations.

Before backing up in coincidence with the problems at Ford and General Motors, credit spreads declined to levels near or below those that prevailed before the crisis of 1998, and some observers have expressed concern that investors are not pricing risk properly. The difference between risk-neutral probabilities and the EDFs can be taken for all firms for which data are available, and the average or median of that difference across all firms is a measure of the corporate risk premium.[16] This measure is plotted in the bottom-right panel of exhibit 4 for both investment-grade and speculative-grade reference entities. While it is true that the risk premium fell to very low levels (virtually zero, indeed) in the early part of 2005, it backed up noticeably in March and April, especially for speculative-grade credits.

6. Probabilities of multiple defaults

Corporate spreads or credit default swap spreads and KMV s EDF can be used to assess the probability that an individual institution will default within a given time interval. However, from a systemic risk perspective, the likelihood that more than one institution will default within a short time period is arguably more interesting than the probability of an individual default. An estimate of that likelihood can be computed using a Merton/KMV methodology, modified to take into account the correlation among a group of financial institutions. According to Merton s work, an institution s probability of default is a function of three major factors: the market value of the firm s assets (a measure of the present value of the future free cash flows produced by the firm s assets); the asset risk, or asset volatility (which measures the uncertainty surrounding the market value of the firm s assets); and the degree of implied leverage (i.e., the ratio of the book value of liabilities to the market value of assets). A firm s probability of default

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[16] See also Berndt, A., Douglas, R., Duffie, D, Ferguson, M., and Schranz, D. (2004), Measuring Default Risk Premia from Default Swap Rates and EDFs, available at www.orie.cornell.edu/aberndt/papers.html. The authors take the ratio of the two probabilities as a measure of the corporate risk premium.

increases as the value of assets approaches (from above) the value of liabilities; in theory, when the two cross, the firm should be assumed to be in default, as future incoming cash flows will not be sufficient to cover the firm s commitments. At any given time, the probability of multiple simultaneous defaults can be assessed by simulating the market value of assets of a number of firms in a certain sample, based on the volatility of those assets and their correlation. Since market value of assets, asset volatility, and asset correlation are not directly observable, they first have to be estimated from available information.

Estimates of the market value of assets and its volatility can be obtained by using the Black-Scholes methodology and interpreting a firm s market value of equity as a call option on the firm s asset value struck at the book value of liabilities. The asset correlation matrix, which is assumed to be time-varying, can be estimated by using rolling windows or by way of an exponentially-weighted moving average model (EWMA).

Given current estimates for the market value of assets, asset volatility, and asset correlation for a sample of firms, the market value of assets of each firm can be simulated a large number of times for a period of, say, one year, according to a standard Brownian motion model. The probability of multiple defaults among the institutions in the sample can be computed as the relative frequency of the event that the market value of assets will fall below the book value of liabilities for at least two institutions.

That probability, and the probability of at least one default (which is computed similarly), are plotted in exhibit 5 for a group of about 50 large financial institutions that includes banks, broker-dealers, and other financial institutions. Over the time period considered August 1993 to May 2005 the most stressful periods for the institutions in our sample were, according to those measures, the fall of 1998 and the summer and fall of 2002. The spring of 2000, when the equity bubble began to burst, also stands out prominently, although concerns about the viability of financial institutions at that time appear to have been short-lived. Interestingly, the probabilities of default in the aftermath of September 11, 2001 were not as high as those in the other periods. Evidently, while financial markets were under substantial stress, investors did not perceive that the solvency of large financial institutions was threatened at the time. The credit problems at large automobile manufacturers in the spring of 2005 generated only a minor uptick in both probabilities, indicating that investors perceived those problems as well contained.

[Exhibit 5 about here]

The probabilities of defaults plotted in exhibit 5 may seem somewhat high, given that there were relatively few actual defaults of financial institutions since 1994. Several factors, though, should be taken into account when interpreting those probabilities:

- The probability of multiple defaults depends on the sample of institutions that is considered, and it may well be larger than the probability that any given institution will default individually. For example, for a sample of 100 firms all independent of each other and with probability of default of 1 percent within a given time period, the probability that two or more of them will default within the same period is 26 percent. For a sample of ten firms, that same probability is just 0.4 percent.
- The default probabilities obtained from Merton s model are risk-neutral probabilities, since it is assumed that the expected return on any firm s asset is the risk-free rate. Risk-neutral probabilities are typically higher than actual default probabilities, and possibly much higher at times of intense risk aversion. No attempt is made to empirically map the risk-neutral default probabilities into actual defaults, as KMV does.
- Actual defaults may not occur as soon as the market value of assets equals the book value of liabilities; indeed, KMV found empirically that the market value of assets dips further below that theoretical threshold before a default actually occurs. If a lower default threshold had been used, the probabilities would have been correspondingly lower.

These observations suggest that the probabilities shown in exhibit 5 may be most informative when looked at in relation to their own values at different points in time. For example, while it could be useful to know that the estimated probability of multiple defaults was about 5 percent after the terrorist attacks of 2001, it may be preferable to focus on the fact that at that time it was about four times smaller than in the fall of 1998.

7. An example of market monitoring: hedge fund losses induced by difficulties at Ford and General Motors

News reports surfaced in early May 2005 indicating that some hedge funds may have incurred significant losses as a result of the widening of corporate credit spreads that started in mid-March on the heels of the difficulties reported by the two largest U.S. automobile manufacturers. This section presents some data on hedge fund performance over that period and describes two of the trades that allegedly resulted in significant losses. While those trades were quite unprofitable and several funds indeed reported substantial losses in April and May, the impact on financial markets appears to have been contained.

Several funds that were mentioned in press reports publicly denied experiencing particular difficulties. The available data, however, indicate unusually poor hedge fund returns for the month of April, as shown in the top panel of exhibit 6. Quite a few large funds reported losses between 5 and 8 percent in that month, and many other smaller funds performed significantly worse.[17]

[Exhibit 6 about here]

The known hedge fund losses, and fears of losses as yet unknown, sparked concerns that some banks and investment banks that have provided prime brokerage services to hedge funds may have large exposures to troubled funds.[18] Most of the major

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[17] While hedge funds are not required to publish their performance statistics, many voluntarily choose to do so. The source of our data is Bloomberg, which collects data for several thousands hedge funds and funds of hedge funds with a total of more than $800 billion of assets under management. However, the very largest funds, including some of those mentioned in press reports, are not well represented in the database.

[18] Prime brokers provide a variety of services to hedge funds, including financing, trade execution, and performance reporting.

prime brokers stated publicly that most or all of their hedge fund exposures were fully collateralized and that their capital positions were strong; still, as shown in the bottom panels, these firms stock prices dropped, and their credit spreads widened notably in mid May, although from low levels.

While the hedge fund losses that were reported were not dramatic, some of the funds that did not publicly report their performance may have fared significantly worse. To better understand the losses that some funds may have suffered as a consequence of the turmoil in the auto sector, we discuss two types of trades that reportedly were popular among some funds in the months preceding the roiling of credit markets. One such trade involved simply selling protection on auto-sector reference entities in the CDS market. Some funds reportedly believed that Ford and GM spreads already discounted the possibility of a downgrade to junk back in March, before the actual downgrade and even before GM warned about poor earnings on March 16. Indeed, both firms CDS spreads were already comparable to those of low-quality speculative-grade issuers at that time. GM spreads, however, widened dramatically after its preannouncement and, as shown in the top panel of exhibit 7, a fund that sold five-year protection on a notional amount of $10 million of GM debt on March 15 would have sustained a mark-to-market loss of more than $2 million as of the market close on May 15, or more than 20 percent of the notional exposure.[19] Losses would have been comparable if protection of Ford debt had been sold instead.[20] Hedge funds, of course, could have exited the trade earlier, but they still would have suffered substantial losses, especially after taking transaction costs into

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[19] A trade size of $10 million is common among investors. Note that a notional exposure of $10 million does not imply an investment of $10 million: Usually the amount tied up in the trade, as margin or collateral, is much smaller.

[20] Hedge funds would have performed marginally better if they had bought a $10 million GM bond, since bond spreads widened a bit less than those on CDS; however, funds would have had to finance the bond purchase. Press reports indicated that some funds may have hedged the CDS position by selling GM stock short or by purchasing equity put options. Given that GM s stock price declined only 8 percent since mid-March, that hedge would have been largely ineffective. For example, investing the entire CDS premium in GM at-the-money put options would have reduced the net loss by less than $0.5 million as of c.o.b. May 15.

account.[21] Those funds that were willing or able to hold on to their position have seen a partial reversal of their losses, as GM spreads tightened significantly starting in June.

[Exhibit 7 about here]

A second type of trade that is said to have been popular among hedge funds in the months leading to the credit market turmoil involved buying and selling protection in tranches of CDS indexes. Many funds have reportedly sold protection on the equity tranche of the benchmark investment-grade CDS index, and at the same time bought protection on an appropriately-scaled notional amount of the mezzanine tranche of the same index.[22] This trade has been dubbed the co rrelation trade because its profitability depends on investors assessment of the likelihood that defaults among the components of the index will be clustered in time the def ault correlation.[23] As shown in the bottom-left panel of exhibit 7, spreads on the index equity tranche surged in April and May especially after Standard and Poor s downgraded Ford s and General Motors debt to junk status while th ose on the mezzanine tranche rose only moderately. As a consequence, a correlation trade on a $10 million notional amount entered into on March 15 would have been somewhat profitable until early May the bot tom-right panel but would have lost between $1 and $2 million after May 7.

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[21] Bid-ask spreads on Ford and GM CDS reportedly widened in March and April.

[22] The index is the average of the spreads of 125 CDS of equal notional amount written on large and liquid reference entities. The equity tranche is designed to absorb the first 3 percent of losses generated by defaults of those reference entities, while the mezzanine tranche absorbs subsequent losses up to 7 percent (further losses are absorbed by more senior tranches).

[23] A high default correlation can be interpreted as a sign that investors perceive that the components of the index are vulnerable to systemic shocks. A low default correlation is instead an indication that investors are more concerned about idiosyncratic risk. Default correlation has been low and trending down since the inception of the CDS index in late 2003. The problems and consequent downgrades of Ford and GM evidently exacerbated investors concern about idiosyncratic risk, and default correlation dropped sharply in early May. While the mezzanine tranche is relatively insensitive to changes in default correlation, the value of the equity tranche is directly proportional to it. Intuitively, if defaults are clustered together in time o r highly correlated th e likelihood of a few defaults is lower than if defaults are randomly distributed or uncorrelated. Since a few defaults are all it takes for investors to lose 100 percent of their investment in the equity tranche, the value of that tranche diminishes when default correlation declines.

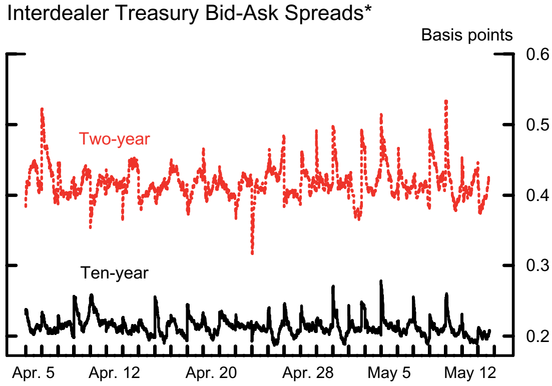
The trades examined here were clearly unprofitable, but the magnitude of actual hedge fund losses depends on several factors, such as the extent of their involvement in these and similar trades and their degree of leverage. The available data, including readings from many of the indicators mentioned in this paper and conversations with market participants, were instrumental in forming the opinion that the situation, while by no means inconsequential, was not likely to cause major market disruptions and to spread throughout the financial system. While some strains could obviously be noticed in the CDS market, where spreads jumped appreciably and index tranches were repriced sharply, liquidity conditions remained close to normal in most markets throughout the whole episode, implied volatilities stayed low, there were no signs that markets were behaving as if a significant crisis was under way, and key financial and nonfinancial institutions, with the exception of those in the automobile sector, did not show signs of any particular stress. In the event, a number of hedge funds suffered severe losses, a few ceased to exist, presumably some prime brokers loans to hedge funds became impaired, and dealers posted poor trading results that affected their second-quarter profitability. Overall, however, the financial system proved resilient and absorbed the shock well and conditions in credit markets returned close to normal by June, with the exception that implied default correlation remained low; as a consequence, mark-to-market losses suffered in the correlation trade remain large as of this writing.

8. Conclusions

We have discussed a number of financial indicators that the Board s staff uses as aids in the interpretation of the conditions of the financial system. Some of those indicators are simple and readily available, while others are more complex in nature and require access to substantial amount of data. None are obviously perfect, in the sense that they are certainly not capable of consistently and correctly gauging the health of financial markets and institutions at any give time. Moreover, the construction of some of them is not solidly grounded in economic or financial theory, and as a consequence they perhaps could be improved. Indeed, all indicators presented here, and certainly their interpretation, are to be considered as work in progress. However, we believe that, when used in conjunction with staff expertise, solid market intelligence, and good judgment, they are valuable tools in assessing the state of financial conditions, in pointing out potential vulnerabilities, and in gauging the severity of crises when they occur.

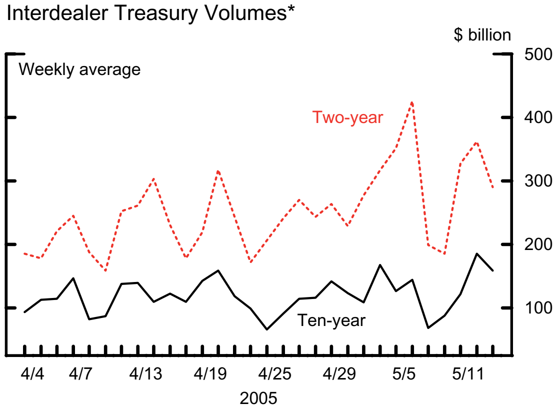
Exhibit 1
Measures Based on Interest Rates and Asset Prices

Interdealer Treasury Bid-Ask Spreads*



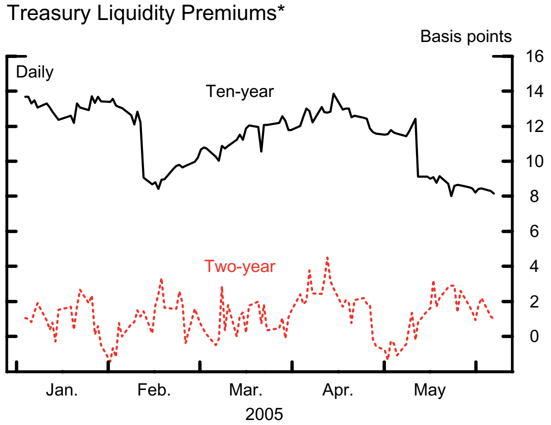
*Intraday four-hour moving average. Source: BrokerTec.

Interdealer Treasury Volumes*



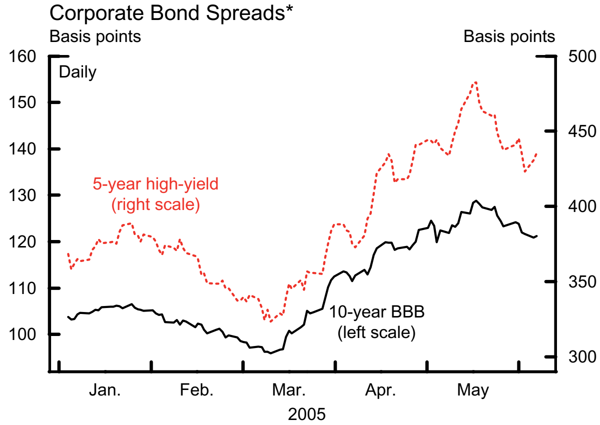
*Source: BrokerTec.

Treasury Liquidity Premiums*



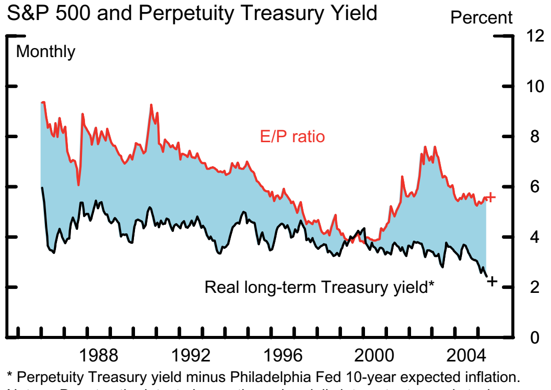
*Computed as the spread of the yield read from an estimated off-the-run yield curve over the on-the-run Treasury yield.

Corporate Bond Spreads*



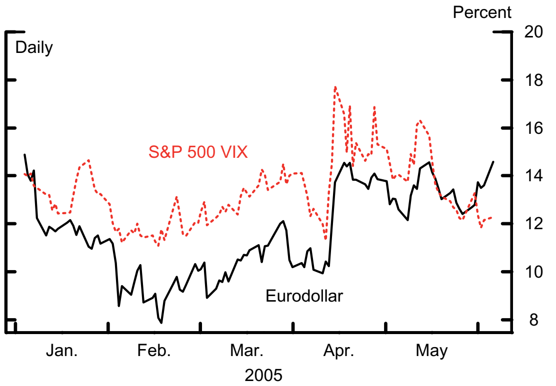
*Based on yield curves estimated using Merrill Lynch bond data.

12-Month Forward Trend Earnings-Price Ratio for S&P 500 and Perpetuity Treasury Yield



* Perpetuity Treasury yield minus Philadelphia Fed 10-year expected inflation.
Note. + Denotes the latest observation using daily interest rates and stock prices and latest earnings data from I/B/E/S.

Implied Volatilities*



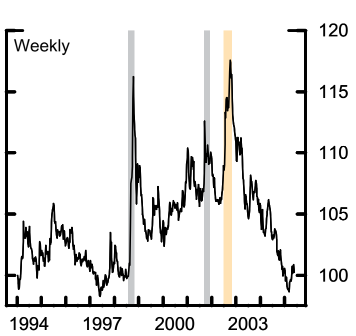
*Calculated from options on the underlying contract.

Exhibit 2
Financial Fragility Indicators

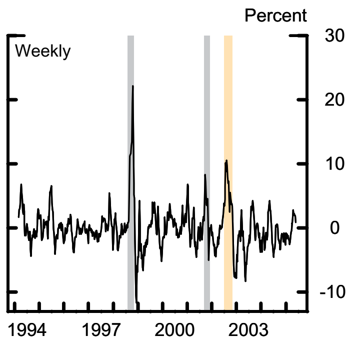
List of Financial Variables Summarized

- 2-year liquidity premium
- 10-year liquidity premium
- BBB risk spreads
- AA risk spreads
- High-yield risk spreads (7-year)
- 3-month Eurodollar confidence interval 1-year ahead
- Long bond implied volatility
- Eurodollar implied volatility
- 10-year Treasury implied volatility
- SP100 implied volatility (VXO)
- Federal funds target - 2-year Treasury
- (12-month ahead earnings/SP500) - (10-year Treasury)

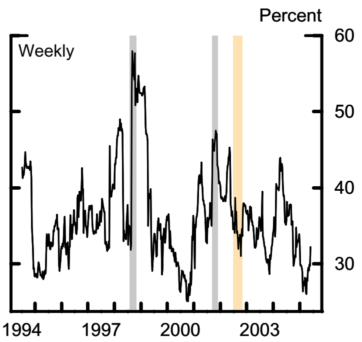
Index of Normalized Variables, January 1994 = 100



Rolling Eight-week Changes, Index of Normalized Variables



Comovement Indicator*



*Percent of total variation in individual stress variables explained by the first factor in a rolling 26-week window.

Financial Fragility Indicator (Probability of Crisis)

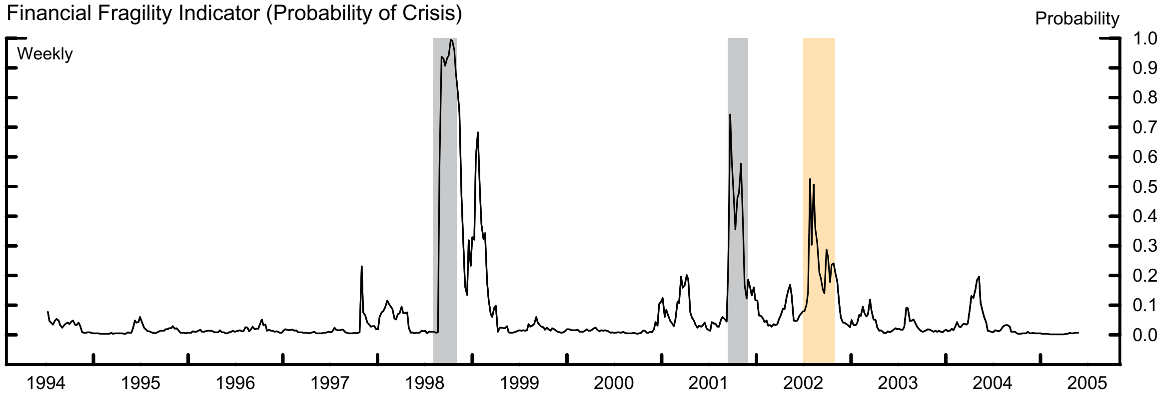
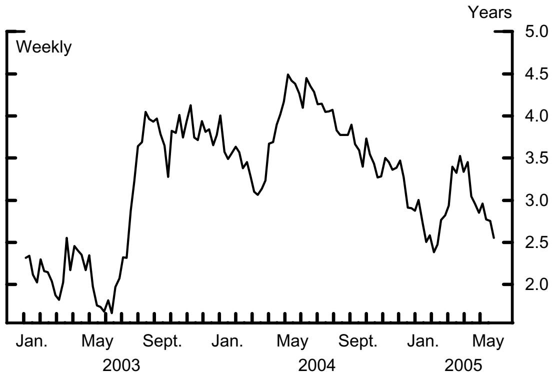


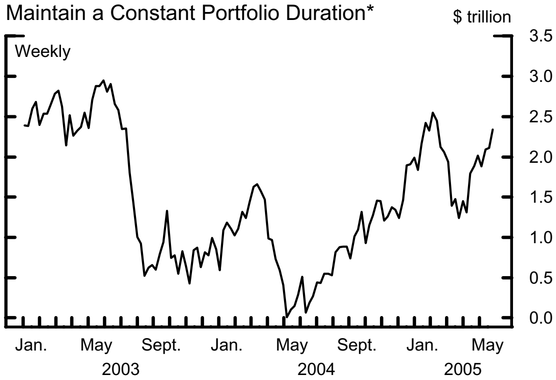
Exhibit 3
Mortgage Market Indicators

Mortgage Duration*



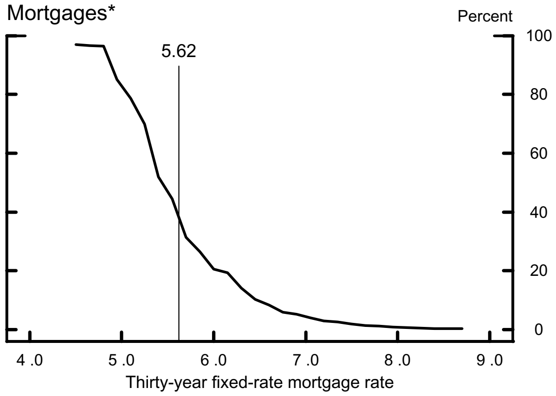
*Based on a large pool of fixed-rate mortgages included in outstanding mortgage-backed securities. Source: Merrill Lynch.

Amount of 10-Year Equivalent Securities Needed to Maintain a Constant Portfolio Duration*



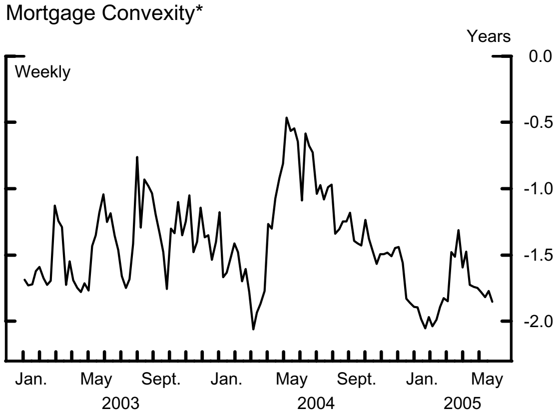
*Staff estimate based on a duration target of 4.5 years.

Percentage of Economically Refinanceable Mortgages*



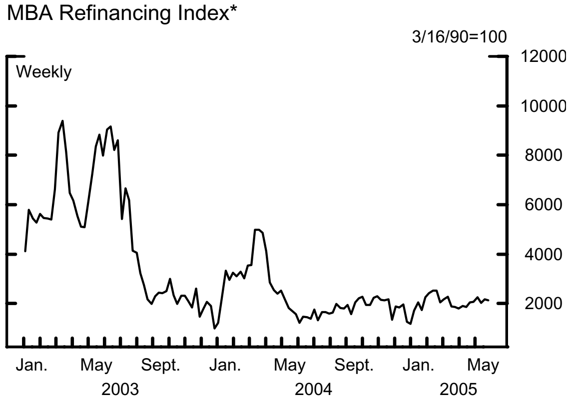
*Cumulative percentage of fixed-rate mortgages included in Fannie Mae's, Freddie Mac's, and Ginnie Mae's outstanding MBS that would be economically refinanceable for any given mortgage rate. Source: Bloomberg.

Mortgage Convexity*



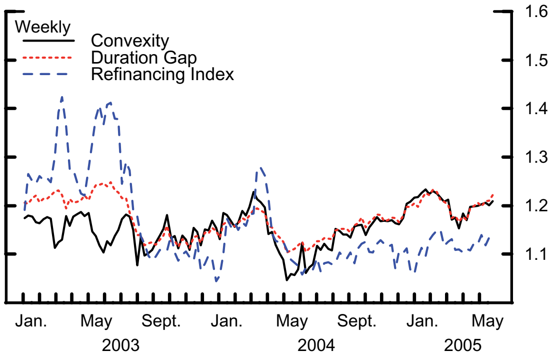
*Based on a large pool of fixed-rate mortgages included in outstanding mortgage-backed securities. Source: Merrill Lynch.

MBA Refinancing Index*



*Source: MBA.

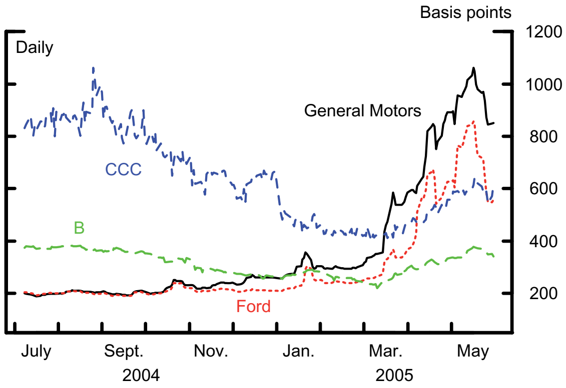
Amplification of Interest Rate Shocks According to Three Hedging Measures*



*Based on Perli and Sack (2003)

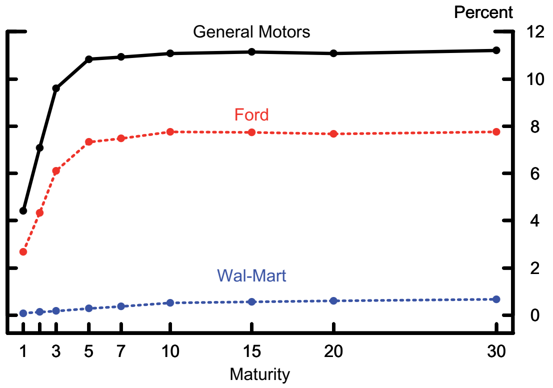
Exhibit 4
Measures of Conditions of Individual Institutions

Credit Default Swap Spreads*



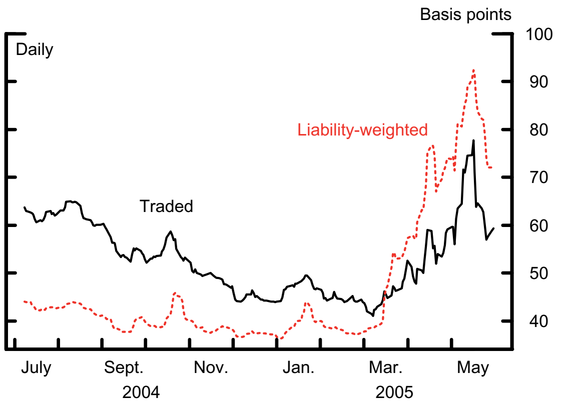
*Source: Markit.

Risk-Neutral Probabilities of Default*



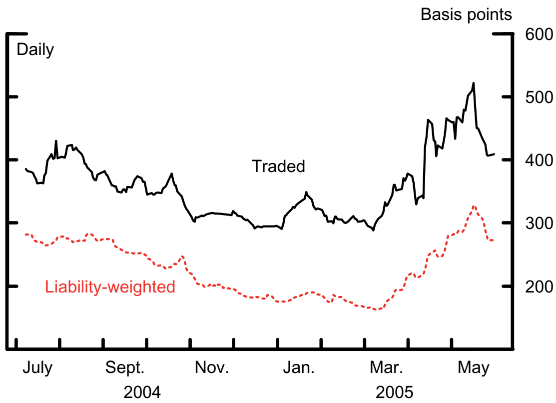
*As of May 31, 2005. Source: MFST staff calculations.

Investment-grade CDS Indexes*



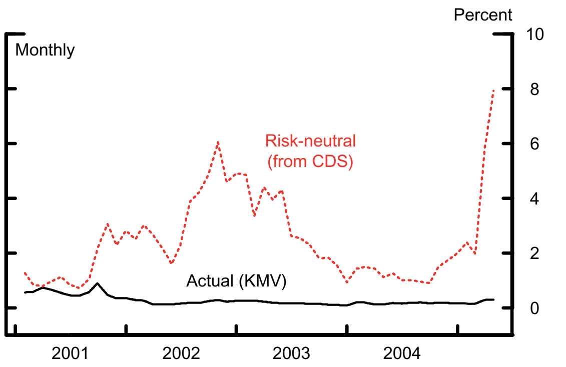
*Source: Markit.

High-yield CDS Indexes*



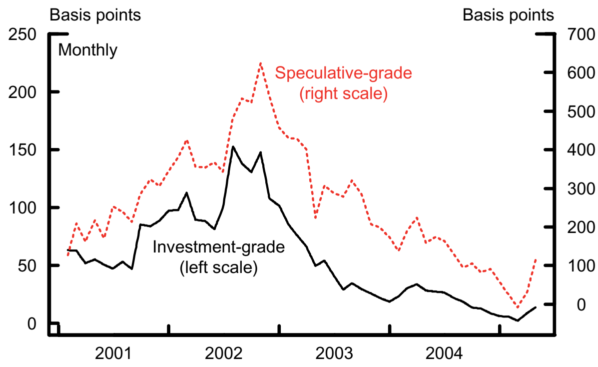
*Source: Markit.

General Motors' One-year Probabilities of Default*



*Source: Moody's KMV and MFST staff calculations.

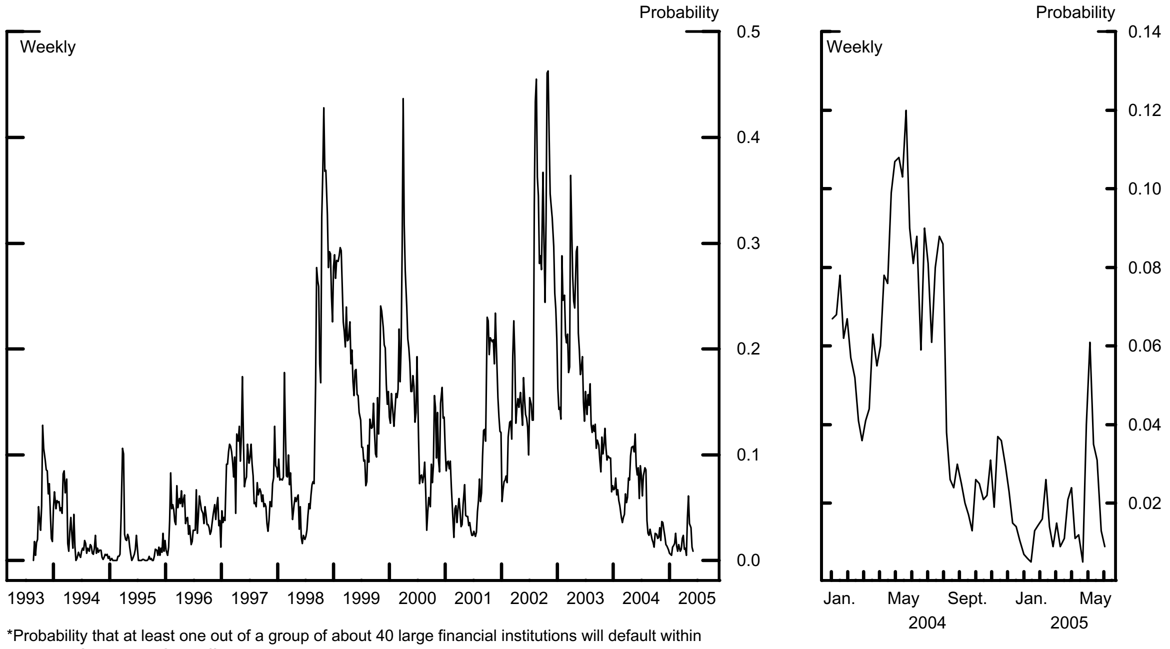
Corporate Risk Premium*



*Source: MFST staff calculations.

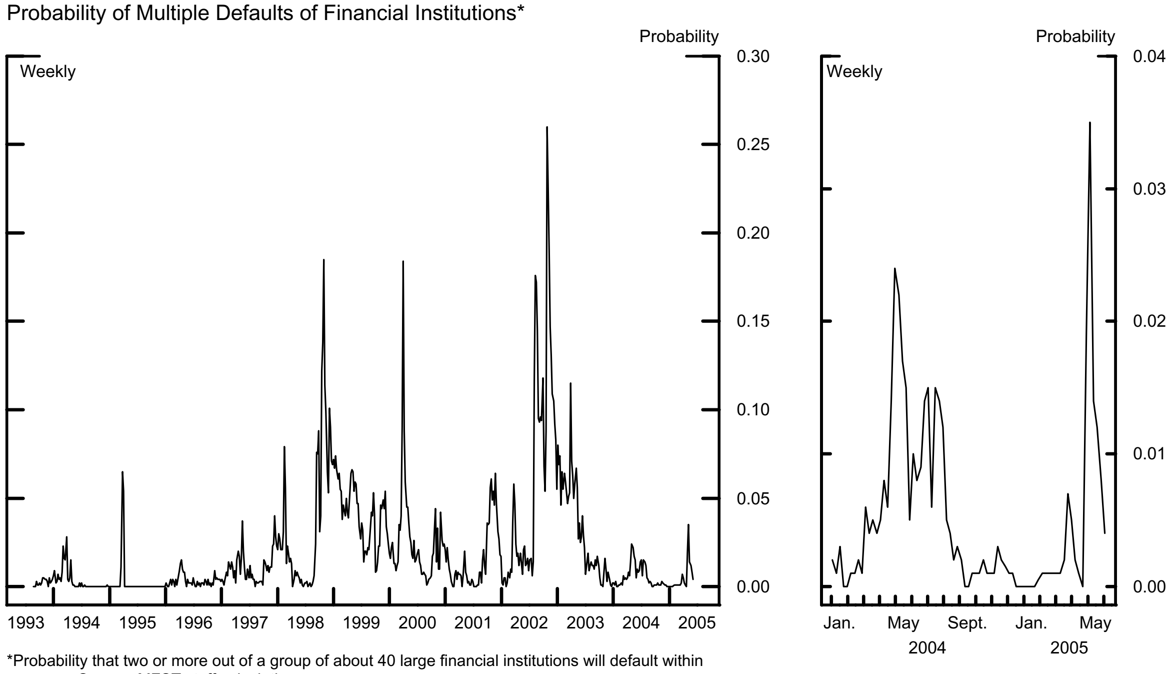
Exhibit 5
Probabilities of Default of Financial Institutions

Probability of at Least One Default of Financial Institutions*



*Probability that at least one out of a group of about 40 large financial institutions will default within one year. Source: MFST staff calculations.

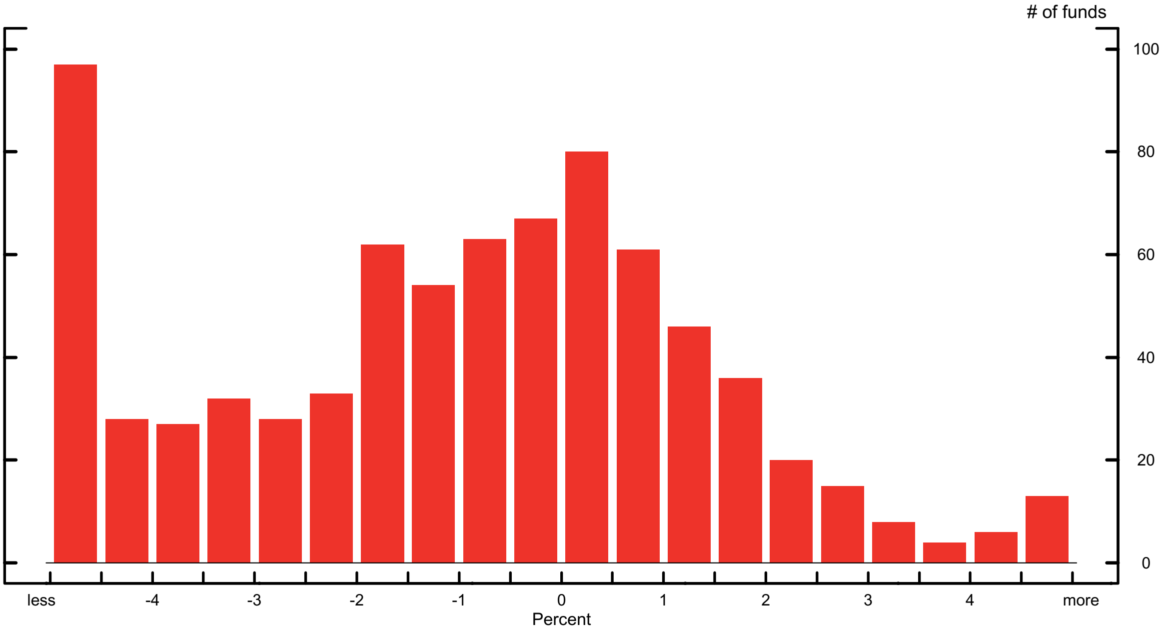
Probability of Multiple Defaults of Financial Institutions*



*Probability that two or more out of a group of about 40 large financial institutions will default within one year. Source: MFST staff calculations.

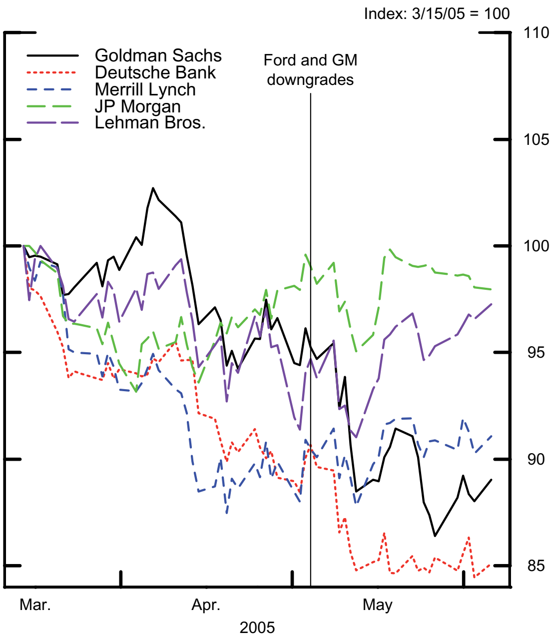
Exhibit 6
Hedge Fund Performance

Distribution of Hedge Fund Returns for April 2005*

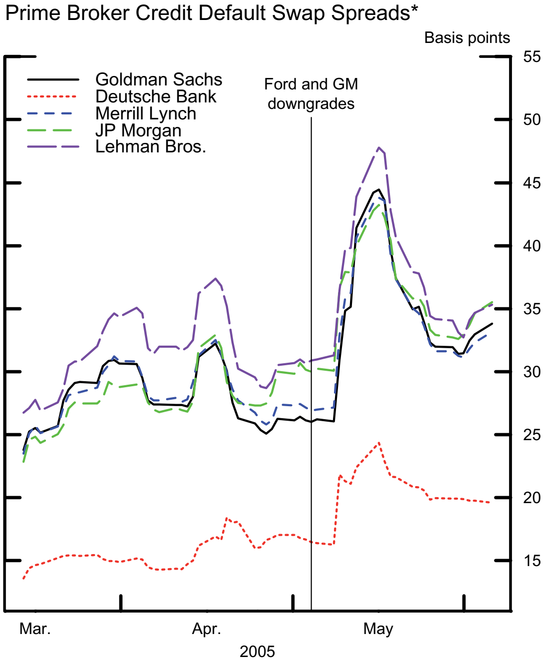


*Includes only funds with assets in excess of $50 million. Source: Bloomberg.

Prime Broker Stock Prices



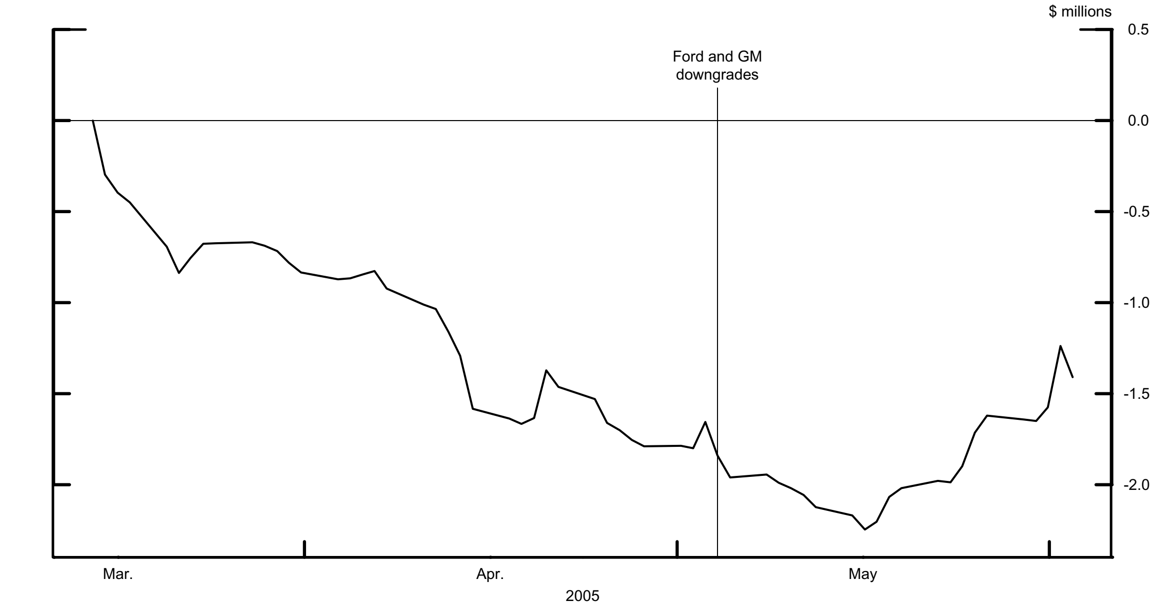
Prime Broker Credit Default Swap Spreads*



*Source: Markit.

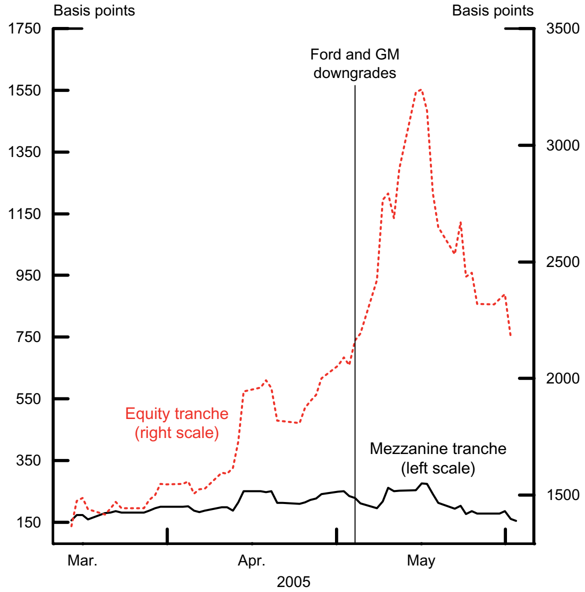
Exhibit 7
Trade Analysis

Profit/Loss from Selling CDS Protection on GM on March 15*



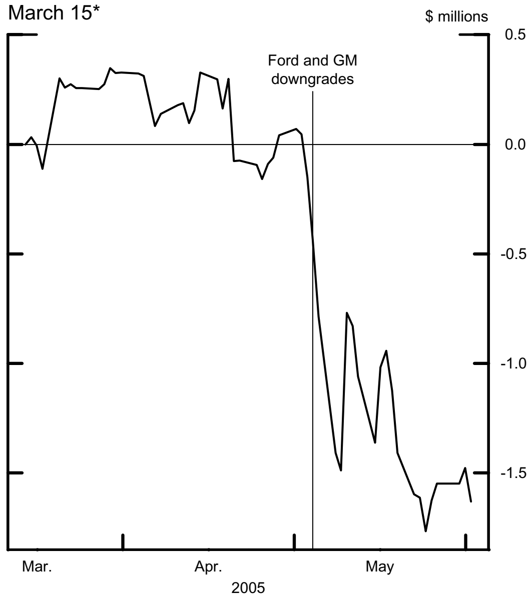
*Based on $10 million notional amount.

Equity and Mezzanine CDS Index Tranche Spreads*



*Equity tranche spread converted from upfront payment to running spread.

Profit/Loss from "Correlation Trade" Entered on March 15*



*Based on selling equity tranche protection on $10 million notional amount and buying mezzanine tranche protection on $42.5 million notional amount (optimal hedge ratio).

ANNEXES

In co-operation with the
Committee on the Global Financial System

4th Joint Central Bank Research Conference on Risk Measurement and Systemic Risk

Tuesday, 8 to Wednesday, 9 November 2005
Frankfurt am Main

programme

日本銀行 BANK OF JAPAN

EUROPEAN CENTRAL BANK

This "Central Bank Research Conference on Risk Measurement and Systemic Risk" is the fourth in a series of conferences focusing on issues related to risk measurement and systemic risks from a central bank perspective. It is organised under the auspices of the Committee on the Global Financial System, a Bank for International Settlements (BIS)-based Committee of senior central bank officials monitoring financial market functioning for the central bank governors of the G10 countries, and is co-organised by the Bank of Japan, the Federal Reserve Board, the European Central Bank and the CGFS Secretariat. The three earlier conferences were hosted by the Federal Reserve Board, the Bank of Japan, and the BIS in 1995, 1998, and 2002, respectively. The conference aims at supporting dialogue among academics, public sector officials, industry professionals involved in trading and risk management as well as central bank staff.

Tuesday, 8 November 2005

8:00 - 8:30	Registration and Coffee
8:30 - 9:00	Opening Remarks: **Otmar Issing** (European Central Bank)
9:00 - 10:55	**Session I: Non-bank Financial Institutions and Systemic Risk** Chair: **José Viñals** (Banco de Espana)
	Systemic Risk and Hedge Funds Nicholas Chan (Alpha Simplex Group), **Mila Getmansky-Sherman**[1] (University of Massachusetts), Shane Haas (Alpha Simplex Group) and Andrew Lo (Massachusetts Institute of Technology)
	Managerial Incentives and Financial Contagion **Sujit Chakravorti** (Federal Reserve Bank of Chicago) and Subir Lall ((International Monetary Fund)
	Liquidity Coinsurance, Moral Hazard and Financial Contagion Sandro Brusco (State University of New York and University Carlos III) and **Fabio Castiglionesi** (University Autonoma de Barcelona)
	Discussant: **Konstantinos E. Tsatsaronis** (Bank for International Settlements)
	General Discussion
10:55 - 11:15	Coffee
11:15 - 13:10	**Session II: Liquidity Risk and Contagion** Chair: **Randall S. Kroszner** (University of Chicago)
	Illiquidity in the Interbank Payment System Following Wide-Scale Disruptions **Morten L. Bech** (Federal Reserve Bank of New York) and Rod Garratt (University of California, Santa Barbara)
	Liquidity Risk in Securities Settlement **Johan Devriese** (National Bank of Belgium) and Janet Mitchell (National Bank of Belgium)
	Interbank Contagion: Evidence from Real Transactions **Rajkamal Iyer** (INSEAD) and José Luis Peydró-Alcalde (European Central Bank)
	Discussant: **Rafael Repullo** (Centro de Estudios Monetarios y Financieros)
	General Discussion
13:10 - 14:15	Lunch
14:15 - 16:10	**Session III: Credit Risk Transfer and Trading in Credit Markets** Chair: **Peter Praet** (National Bank of Belgium)
	Explaining Credit Default Swap Spreads with Equity Volatility and Jump Risks of Individual Firms **Benjamin Yibin Zhang** (Moody's KMV), Hao Zhou (Board of Governors of the Federal Reserve System) and Haibin Zhu (Bank for International Settlements
	Insider Trading in Credit Derivatives Viral V. Acharya (London Business School) and **Timothy Johnson** (London Business School)
	The Determinants of Market Frictions in the Corporate Market Andrew Levin (Board of Governors of the Federal Reserve System), Roberto Perli (Board of Governors of the Federal Reserve System) and **Egon Zakrajsek** (Board of Governors of the Federal Reserve System)
	Discussant: **Reint Gropp** (European Central Ban)
	General Discussion
16:10 - 16:30	Coffee

[1] *The name of the presenter is formatted in bold.*

16:30 - 18:30	**Panel Discussion "The Policy Implications of the Developments in Credit Derivatives and Structured Finance"** **Lucas Papademos** (European Central Bank, Chair) **Sean Kavanagh** (Deutsche Bank) **Eiji Hirano** (Bank of Japan) **Michael Alix** (Bear Stearns) **Roger Ferguson** (Board of Governors of the Federal Reserve System)
20:00	Dinner speech: **André Icard** (Bank for International Settlements)

Wednesday, 9 November 2005

8:45 - 9:00	Coffee
9:00 - 10:55	**Session IV: Systemic Risk Across Countries** Chair: **Fabio Panetta** (Banca d'Italia) Banking System Stability: A Cross-Atlantic Perspective **Philipp Hartmann** (European Central Bank), Stefan Straetmans (Maastricht University) and Casper de Vries (Erasmus University Rotterdam) Estimating Systemic Risk in the International Financial System **Söhnke M. Bartram** (Lancaster University) Gregory W. Brown (University of North Carolina), and John E. Hund (University of Texas) A Large Speculator in Contagious Currency Crises: A Single "George Soros" Makes Countries more Vulnerable to Crises, but Mitigates Contagion **Kenshi Taketa** (Bank of Japan) Discussant: **Hans Degryse** (Leuven University) General Discussion
10:55 - 11:15	Coffee
11:15 - 13:10	**Session V: Risk Measurement and Market Dynamics** Chair: **Hung Tran** (International Monetary Fund) Bank Credit Risk, Common Factors, and Interdependence of Credit Risk in Money Markets: Observed vs. Fundamental Prices of Bank Credit Risk **Naohiko Baba** (Bank of Japan) and Shinichi Nishioka (Bank of Japan) Firm Heterogeneity and Credit Risk Diversification Samuel Hanson (Federal Reserve Bank of New York), **M. Hashem Pesaran** (University of Cambridge) and Til Schuermann (Federal Reserve Bank of New York) Evaluating Value-at-Risk Models with Desk-Level Data Jeremy Berkowitz (University of Houston), **Peter Christoffersen** (McGill University) and Denis Pelletier (North Carolina State University) Discussant: **Joachim Coche** (European Central Bank) General Discussion
13:10 - 14:35	Lunch
14:35 - 16:30	**Session VI: Stress Testing and Financial Stability Policies** Chair: **Hiroshi Nakaso** (Bank of Japan) Corporate Defaults and Large Macroeconomic Shocks **Mathias Drehmann** (Bank of England), Andrew J. Patton (Bank of England) and Steffen Sorensen (Bank of England) Exploring Interactions between Real Activity and the Financial Stance Tor Jacobson (Sveriges Riksbank), Jesper Lindé (Sveriges Riksbank) and **Kasper Roszbach** (Sveriges Riksbank) Selected Indicators of Financial Stability Bill Nelson (Board of Governors of the Federal Reserve System) and **Roberto Perli** (Board of Governors of the Federal Reserve System) Discussant: **Mark Flannery** (University of Florida) General Discussion
16:30 - 17:00	Concluding Remarks: **Lucrezia Reichlin** (European Central Bank)

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ISBN 978-928990048-5