E   NEW QUANTITATIVE MEASURES
OF SYSTEMIC RISK

A host of new quantitative measures of systemic risk have recently been proposed in the academic and central banking literature. The stated purpose of these tools is to support macro-prudential oversight and inform policy decisions. This special feature surveys these measures, focusing primarily on the most recent developments that have not yet been covered in the ECB's Financial Stability Review,[1] and explains what can be learned from them. The strengths and weaknesses of approaches when applied in a macro-prudential context are discussed. Significant research in this area has addressed how to measure the systemic importance of specific financial intermediaries, for example by estimating the externalities they may exert on the financial system. With the rising number of different analytical measures and models it becomes increasingly important to prioritise between them and to construct a system of measures that, overall, covers all dimensions of systemic risk and how they relate to each other.

INTRODUCTION

The financial crisis has raised new challenges for central bank policy, in particular in relation to strengthening the macro-prudential aspects of financial supervision. Such macro-prudential oversight is expected to identify, assess, prioritise and help mitigate systemic risks. As one element in the required macro-prudential analyses, new quantitative measures for systemic risk have recently been proposed in the academic and central banking literature. These measures can serve as tools and indicators for the identification and assessment of systemic risks and events. Systemic events can be understood broadly as financial instabilities spreading to the extent that the financial intermediation process is impaired and economic growth and welfare suffer materially. Systemic risk is the risk of experiencing a systemic event.

This special feature is structured as follows. The first section recalls the main elements of the ECB's conceptual framework for systemic risk, which is then applied to the survey (although other categorisations may be possible). The second section discusses new approaches on how to assess contagion risks and, particularly, the contribution of individual financial intermediaries to the combined risk of all intermediaries.[2] The third section reviews recent contributions that assess the impact of aggregate shocks on financial systems. The fourth section discusses measures of widespread financial imbalances. The last section concludes.

REMINDER ON THE CONCEPT OF SYSTEMIC RISK

The quantitative literature captures different types of systemic events and risks through different modelling frameworks. In the context of the great complexity of systemic risk and the need to formulate well-targeted policy responses, it has proven to be useful to distinguish three main forms of systemic risk, as laid out recently, for example by the President of the ECB and Financial Stability Review special feature articles.[3] First, contagion risk refers to an initially idiosyncratic problem that becomes more widespread in the cross-section, often in a

1   For an overview of the main approaches on how to identify and assess systemic risks for the purposes of macro-prudential supervision, see ECB, "Analytical models and tools for the identification and assessment of systemic risks", *Financial Stability Review,* June 2010. For systemic risk measures regularly used in the Financial Stability Review see, for example, the boxes entitled "Measuring the time-varying risk to banking sector stability" and "A market-based indicator of the probability of adverse systemic events involving large and complex banking groups" in, respectively, the December 2008 and December 2007 issues of the ECB's Financial Stability Review.

2   The order of papers in the survey is not indicative of their relative value for macro-prudential oversight.

3   See J.-C. Trichet, "Systemic risk", *Clare Distinguished Lecture in Economics and Public Policy*, delivered at the University of Cambridge, 10 December 2009; V. Constâncio, "Macro-prudential supervision in Europe", speech delivered at the ECB-CEPR-CFS conference, *Macro-prudential regulation as an approach to containing systemic risk: economic foundations, diagnostic tools and policy instruments*, Frankfurt am Main, 27 September 2010; ECB, "The concept of systemic risk", *Financial Stability Review*, December 2009; ECB, 2010, op. cit.; and O. de Bandt, P. Hartmann and J.-L. Peydró-Alcade, "Systemic risk in banking: An update", in A. Berger, P. Molyneux and J. Wilson (eds.), *Oxford Handbook of Banking*, Oxford University Press, 2009.

sequential fashion. Second, shared exposure to financial market shocks or adverse macroeconomic developments may cause simultaneous problems for a range of financial intermediaries and markets. Third, financial imbalances, such as credit and asset market bubbles that build up gradually over time, may unravel suddenly, with detrimental effects on intermediaries and markets. These forms of systemic risk can also be interrelated. For example, contagion risk may be more pronounced in a business cycle downturn, when financial intermediaries are already weakened. Similarly, in such a situation a relatively small financial shock may be sufficient to unravel a pent-up imbalance. It is important that the set of quantitative measures of systemic risk used in macro-prudential oversight covers all of these phenomena, as well as all systemically important financial intermediaries, markets, infrastructures and instruments.

CONTAGION RISK AND MEASURES OF SYSTEMIC RISK CONTRIBUTION

The studies discussed in this section focus on the systemic risk contribution of individual firms. Thus, systemic risk is understood as the extent to which an individual firm pollutes the "public good" of overall financial stability. If such measures were accurate, they could in principle be used for Pigouvian taxes, levies or other regulatory interventions aimed at internalising the negative externalities.

Acharya et al.[4] present a simple model of systemic risk and show how each financial institution's contribution to systemic risk can be measured and priced. The extent to which an institution may impose a negative externality on the system is proxied by the *systemic expected shortfall* (SES), measuring an institution's propensity to be undercapitalised when the system as a whole is hit by a financial shock. The nature of the externality, however, is not specified exactly. The SES can be estimated and aggregated. An institution's SES increases in its leverage, equity volatility, equity correlation with a market index, and tail dependence. The last three components

are summarised by an institution's *marginal expected shortfall* (MES), which in turn is defined as the institution's expected shortfall when the market return is below a given low percentile. The authors provide some evidence that leverage and MES are able to capture emerging systemic instability, for example during the financial crisis of 2007-09.

Brownlees and Engle[5] use the set-up of Acharya et al. and provide improved MES estimates. While the latter calculate the MES of each firm using equity returns on the worst 5% of days in a given year according to a market index, Brownlees and Engle employ sophisticated econometric tools to estimate firms' time-varying conditional volatilities, time-varying correlations with a market index, and corresponding joint tail indices. Thus, Brownlees and Engle effectively make use of a small amount of publicly available information to assess the likelihood of a given firm being undercapitalised in adverse conditions. The risk measures can be updated frequently, and are currently published online as the NYU Stern systemic risk rankings. The fact that a small amount of publicly available information yields information about systemic risk externalities is an intriguing prospect. On the other hand, the logical link between a decline in an intermediary's equity market valuation and its institutional failure is quite indirect. A decline in the market value of a firm's equity may be an adverse signal, but it does not necessarily imply a subsequent capital shortage or insolvency. Acharya et al. seek to provide such a link empirically, by comparing ex ante MES and SES measures with the capital shortfalls estimated from the 2009 US bank stress tests and realised equity returns during the crisis. The reported scatter plots have R-squared statistics between 6% and 33%.

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4 V. V. Acharya, L. H. Pedersen T. Philippon and M. Richardson, "Measuring systemic risk", *New York University Working Paper,* May 2010.
5 C. T. Brownlees and R. Engle, "Volatility, correlation, and tails for systemic risk measurement", *New York University Working Paper,* May 2010.

Huang et al.[6] propose a systemic risk measure called the *distress insurance premium*, or DIP. The DIP represents a hypothetical insurance premium against systemic financial distress, defined as total equity losses that exceed a given threshold, say 15%, of total liabilities. Each bank's marginal contribution to systemic risk is a function of its size, default probability, and asset correlation. The last two components need to be estimated from market data. The DIP measure is closely related to Brownlees and Engle's MES, except that credit default swap (CDS) spreads are used as data input instead of equity returns, and that technical difficulties are overcome differently, in particular regarding the calculation of the tail expectation. CDS returns are driven in part by investors' risk appetites and changes in risk liquidity premiums. As a result, an increase in measured risk may not be due to increased physical risk but to a decrease in overall risk appetite. This ambiguity complicates generally the application of indicators based on observed market prices.

Adrian and Brunnermeier[7] suggest *CoVaR* as a measure of systemic risk. It is the Value at Risk (VaR) of the financial system conditional on an individual institution being under stress. An institution's individual contribution to systemic risk is defined as the difference between CoVaR and the unconditional VaR of the financial system. CoVaR is related to the risk measures presented in Acharya et al. and Huang et al. (2009) respectively, but it has drawbacks in that it does not give a bigger weight to larger systemic events, is only bivariate and cannot easily be aggregated. The direction of CoVaR is from individual distress to the system, rather than the other way around. This direction may be more in line with the definition of systemic risk.[8] Neither risk measure – CoVaR nor MES – should be interpreted as a causal effect.

The methods surveyed so far rely on market data and are therefore only precise to the extent that market participants are sufficiently well-informed, good at assessing financial risk, and not subject to herding and other behavioural biases. Also, all measures more or less ignore the

important role of financial institutions' specific capital structures. On the other hand, this strand of research indicates what macro-prudential overseers can learn from a limited amount of publicly available and easily observed data.

Segoviano and Goodhart[9] define banking stability measures which capture the distress dependence among financial firms in a system. These measures allow an assessment of common stress, distress between specific groups of banks and distress associated with a specific firm. In this non-parametric approach, a panel of individual banks' time-varying default probabilities is taken as input. In principle, these conditional probabilities can be obtained using various methods and data sources (none of which is perfect). A posterior density is fitted as closely as possible to a proposal density. The multivariate density permits computation of the *joint probability of distress*, i.e. the time-varying probability that all (or a large number of) banks in a system become distressed. Relative changes of stability over time can also be examined. A *Banking Stability Index* (BSI) is calculated, which captures the expected number of banks to become distressed given that at least one bank has become distressed.[10] Naturally, a higher number implies increased instability. The downside of this approach is that the dependence matrix grows quadratically with

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6   X. Huang, H. Zhou and H. Zhu, "A framework for assessing the systemic risk of major financial institutions", *Journal of Banking and Finance*, No 33, 2009 and X. Huang, H. Zhou and H. Zhu, "Systemic risk contributions", *Federal Reserve Board Working Paper*, August 2010.

7   T. Adrian and M. Brunnermeier, "CoVar", *Federal Reserve Bank of New York Staff Reports*, No 348, 2008.

8   The motivation for conditioning individual returns on the systemic event is risk attribution. The SES is the key measure of each bank's expected contribution to a systemic crisis.

9   M. A. Segoviano and C. Goodhart, "Banking stability measures", *IMF Working Paper,* No WP/09/4, January 2009.

10 This measure was developed by X. Huang, "Statistics of bivariate extreme values," Tinbergen Institute Research Series, PhD thesis, No 22, Erasmus University Rotterdam, 1992, and applied in bivariate and multivariate contexts by P. Hartmann, S. Straetmans and C. de Vries in "Asset market linkages in crisis periods", *Review of Economics and Statistics*, Vol. 86, No 1, 2004, and "The breadth of currency crises", presented at the Center for Financial Studies and The Wharton School joint conference on *Liquidity Concepts and Financial Instabilities*, Eltville, 12-14 June 2003.

the number of banks. This suggests a curse of dimensionality. With 100 banks in the system, 10,000 elements of the distress dependence matrix would need to be inferred. The method works best when applied to a smaller number of banks regarded a priori as systemically important.

Billio et al.[11] propose several econometric measures of systemic risk to capture dependence among the monthly returns of hedge funds, banks, brokers and insurance companies. The risk measures capture changes in dependence by means of principal component analysis, and changes in the direction of correlation through predictive (Granger) causality tests. An indicator for systemic risk can be constructed as the total number of financial institutions that are connected, in the sense that their returns causally impact each other at a given significance level. The proposed statistics are relatively easy to compute. Parts of the shadow banking system (hedge funds, broker-dealers, and insurers) can be taken into account provided their returns are observed. Predictive causality, however, is not an entirely straightforward concept. A causal link between financial institutions is neither necessary nor sufficient for one institution's returns to Granger cause another institution's returns. For example, Granger causality tests are vulnerable to common factors (such as the business cycle or term structure) driving returns if the returns load on shared factors at different lags. In that case, predictive ability will be found but it does not imply a causal connection between two institutions. The failure of one would not necessarily affect the other as a result. Conversely, not finding Granger causality does not necessarily mean an absence of dependence. Instead, it might "hide" in the tails where it cannot be detected with measures not focusing on extreme values.

Tarashev et al.[12] suggest a methodology for attributing overall financial system risk to individual institutions. The methodology is based on concepts from cooperative game theory, such as the Core and the Shapley value. Gauthier et al.[13] apply several methodologies,

including the Shapley value, to determine the systemic risk contribution of Canadian financial firms.

Castren and Kavonius[14] seek to identify aggregate counterparty risk exposures between the different financial and macroeconomic sectors based on euro area financial accounts (flow of funds) data. Local shocks are propagated in a sector-level network of bilateral balance sheet exposures. Contingent claims (option pricing) theory is used to extend the accounting-based information into a risk-based network of exposures. Not surprisingly, high financial leverage and high asset value volatility increase the financial sector's vulnerability to the transmission of shocks. Correlations among sector-level risk indicators are elevated during the outbreak of the recent financial crisis. CoVaR measures of sector risk contribution can also be defined.

Hartmann et al.[15] are the first to apply extreme value theory to banking system risk, deriving indicators of the severity and structure of banking system risk from asymptotic interdependencies between banks' equity prices. A semi-parametric estimation approach is applied to estimate

11 M. Billio, M. Getmansky, A. W. Lo and L. Pelizzon, "Econometric measures of systemic risk in the finance and insurance sectors", *NBER Working Paper,* No 16223, July 2010.

12 N. Tarashev, C. Borio, and K. Tsatsaronis, "Attributing systemic risk to individual institutions", *BIS Working Paper*, No 308, May 2010.

13 C. Gauthier, A. Lehar and M. Souissi, "Macroprudential Regulation and Systemic Capital Requirements", *Bank of Canada Working Paper*, No 4, 2010. As regards the systemic risk contribution of individual institutions, see also Bank of England, "The Role of Macroprudential Policy – Discussion Paper", 21 November 2009.

14 O. Castrén and I. K. Kavonius, "Balance sheet interlinkages and macro-financial risk analysis in the euro area", *ECB Working Paper Series,* No 1124, December 2009, and Box 13 in ECB, *Financial Stability Review*, June 2010. Earlier studies applying a contingent claim analysis to the financial sector include A. Lehar, "Measuring systemic risk: A risk management approach", *Journal of Banking and Finance*, Vol. 29, 2005, and D. Gray, R. Merton and Z. Bodie, "New framework for measuring and managing macro-financial risk and financial stability", *NBER Working Paper*, No 13607, 2007.

15 P. Hartmann, S. Straetmans and C. de Vries, "Banking system stability: A cross-Atlantic perspective", *NBER Working Paper,* No 11698, 2005.

extreme spillover risk among multiple banks, as well as extreme systematic risk that is due to shared exposure to a common observed factor (tail-beta). The authors provide evidence that tail dependencies are time-varying. A particular challenge in estimating tail dependencies is the limited number of jointly extreme observations. One contribution of the extreme value literature is to derive the optimal number of tail observations to be used in the estimators. A relatively low number of low frequency data could lead to imprecise estimates. Using too high a number of observations could lead to biased estimates.

RISK OF AGGREGATE SHOCKS

This section reviews studies that focus on the impact of macroeconomic shocks (such as the adverse macroeconomic scenarios used in stress testing) on the financial system. Some of the most recent macro-financial studies have started to integrate other forms of systemic risk, such as cross-sectional contagion dynamics.

A systematic worsening of credit risk conditions is a dominant source of bank risk. Macroeconomic shocks matter for financial stability inter alia because they tend to affect all firms in an economy, financial and non-financial, at least to some extent. A macro shock causes an increase in correlated default losses, with detrimental effects on financial stability.

Stress-testing models are designed to map adverse macro-financial scenarios into losses in shared credit and asset exposures. As such, they are an important tool for financial systemic risk assessment. The practical stress-testing literature is too extensive to be reviewed here. Sorge, Segoviano and Padilla; Castren et al.; Borio and Drehmann; and Breuer et al., among many others, are relevant contributions to this literature.[16] The remainder of this section focuses on a few key examples that help to assess the evolution of systemic risk over time.

Aikman et al.[17] propose a "Risk Assessment Model for Systemic Institutions" (RAMSI) to assess the impact of macroeconomic and financial shocks on both individual banks, as well as the banking system. RAMSI is a suite of smaller models which are combined in a larger framework that allows for some feedback loops between its parts. Systemic risks stem from the connectedness of bank balance sheets via interbank exposures, "fire sale" interactions between balance sheets and asset prices, and confidence effects that may affect institutions' funding conditions. Importantly, RAMSI can aid the assessment of the impact of potential policy measures. This is not the case for many other macro-financial frameworks. As a suite of reduced form models, RAMSI is as reliable as its individual parts and the behavioural "rules of thumb" that connect them. The model structure is not derived from micro foundations, and the model's risk predictions may be different from, e.g. markets' assessments of risk. The latter feature is not necessarily a disadvantage.

Aspachs-Bracons et al.[18] propose a measure of financial stability that is based on the general equilibrium model of Goodhart et al.[19] The model comprises a household sector, a small number of heterogeneous banks, a regulator,

16 M. Sorge, "Stress testing financial systems: an overview of current methodologies", *BIS Working Paper*, No 165, December 2004; M. A. Segoviano and P. Padilla, "Portfolio credit risk and macroeconomic shocks: Applications to stress testing under data-restricted environments, *IMF Working Paper*, WP/06/283, 2006; O. Castrén, S. Dées and F. Zaher, "Global macro-financial shocks and expected default frequencies in the euro area", *ECB Working Paper Series*, No 875, February 2008; C. Borio and M. Drehmann, "Towards an operational framework for financial stability: "fuzzy" measurement and its consequences", *BIS Working Paper*, No 284, June 2009; T. Breuer, M. Jandačka, J. Mencía and M. Summer, "A systematic approach to multi-period stress testing of portfolio credit risk", *Banco de España Working Paper*, No 1018, 2010.

17 D. Aikman, P. Alessandri, B. Eklund, P. Gai, S. Kapadia, E. Martin, N. Mora, G. Sterne and M. Wilson, "Funding liquidity risk in a quantitative model of systemic stability", *Bank of England Working Paper*, No 372, 2009. The work on RAMSI was based on earlier work at the Oesterreichische Nationalbank, see M. Boss, G. Krenn, C. Puhr and M. Summer, "Systemic Risk Monitor: A model for Systemic Risk Analysis and Stress Testing of Banking Systems", *Financial Stability Report*, No 11, Oesterreichische Nationalbank, 2006.

18 O. Aspachs-Bracons, C. A. E. Goodhart, D. P. Tsomocos and L. Zicchino, "Towards a measure of financial fragility", *Annals of Finance*, Vol. 3(1), January 2007.

19 C. A. E. Goodhart, P. Sunirand, and D. P. Tsomocos, "A model to analyse financial fragility", *Economic Theory*, Vol. 27, 2006.

incomplete markets and endogenous default on debt. Financial instability can arise as an equilibrium phenomenon either through systematic shocks, contagion after idiosyncratic shocks, or a combination of both. The proposed measure of financial instability is a combination of intermediaries' default probabilities and profitability. Introducing the possibility of defaulting intermediaries is a very important advance in the theoretical systemic risk literature. Naturally, financial instability is increasing in institutions' default probabilities and decreasing in profits. In another paper, Goodhart et al.[20] calibrate an extended version of the model to the UK banking sector. The calibration effort is enormous. For example, even if only three banks are considered, a system of 56 equations needs to be solved numerically for 56 endogenous variables, given values for 87 exogenous parameters. At present, the framework is theoretically appealing but may be regarded as less operational for practical systemic risk measurement.

Giesecke and Kim[21] define systemic risk as the conditional probability of failure of a large number of financial institutions. This failure probability can be plotted against time, and is based on a dynamic hazard rate model. The model captures the influence of observed macroeconomic and sector-specific risk factors, as well as the impact of spillovers related to network effects and unobserved risk factors. In and out-of-sample tests demonstrate that point-in-time risk measures are relatively accurate. A similar study based on a large number of macroeconomic and financial covariates is Koopman et al.[22] In either case, however, the model-implied estimates of financial distress are based on actual default experience. Such data are naturally sparse, in particular with respect to financial defaults (the authors report 83 US financial defaults over the last 21 years, and 12 European ones). The reported results are therefore subject to substantial estimation uncertainty.

The probability of simultaneous failure of multiple financial intermediaries can also be inferred from the market prices of traded credit derivatives. This approach is used for one of the ECB's indicators that is regularly reported in the Financial Stability Review, which gives the probability of two or more bank failures over different time horizons.[23] Avesani et al.[24] determine these default probabilities using credit derivative prices on large financial institutions. Since these probabilities are based on market perceptions, they could in principle give a valuable forward-looking assessment of joint risk. Whether this is the case in practice is arguable. The modelling output may also be sensitive to the precise modelling choices (such as the copula and factor structure), most of which need to be inferred from stock market returns.

RISK OF WIDESPREAD FINANCIAL IMBALANCES

The studies reviewed in this section relate to the build-up of financial imbalances over time. For example, bubbles in asset and credit markets can have severe adverse effects on income and employment if they burst suddenly. Financial imbalances are not easily characterised and are difficult to quantify. Inference on the extent of financial misalignments can be based on observed covariates, such as current and past credit-to-GDP ratios, total lending and money growth, changes in property and asset prices, bank leverage, maturity mismatch, capital adequacy, and sector-level flow of funds. For studies relating observed covariates to financial stress, see, for example, Borio and Lowe, Misina and Tkacz, Alessi and Detken, and Barrell

20 C. A. E. Goodhart, P. Sunirand, and D. P. Tsomocos, "A time series analysis of financial fragility in the UK banking system", *Annals of Finance,* Vol. 2(1), January 2006.

21 K. Giesecke and B. Kim, "Systemic risk: What defaults are telling us", *Stanford University Working Paper*, September 2009, revised March 2010.

22 S. J. Koopman, A. Lucas, and B. Schwaab, "Forecasting Cross-Sections of Frailty-Correlated Default", *Tinbergen Institute Discussion Paper*, 029/04, 2008.

23 See Box 16 in ECB, *Financial Stability Review*, December 2007.

24 R. G. Avesani, A. G. Pascual and J. Li, "A new risk indicator and stress testing tool: A multifactor nth-to-default CDS basket", *IMF Working Paper*, WP/06/105, 2006. Related studies include R. G. Avesani, "FIRST: A market-based approach to evaluate financial system risk and stability", *IMF Working Paper*, WP/05/232, 2005.

et al.[25] Recent progress has significantly improved such early-warning indicators and models. At the same time major challenges remain in that they may still not predict new crises well and exhibit great uncertainty about when instability may strike.

In a later paper Koopman et al.[26] investigate the sources of default clustering in a setting where credit and macroeconomic developments are assumed to be driven by latent dynamic factors. These risk factors can be estimated from observed data, and permit an assessment of both the current state of the credit cycle, as well as financial industry distress. Shared variation in defaults and macroeconomic conditions need not coincide at all times. The authors argue that a persistent and significant decoupling of the two processes is possible and may indicate a widespread imbalance in credit markets.

CONCLUDING REMARKS

A host of new quantitative measures of systemic risk have been proposed in the literature. This feature surveyed the most recent developments in this area. The main results of the survey could be summarised as follows. There is currently no widely accepted single indicator or model capturing systemic risks and instabilities comprehensively. Most developments rather cover one or a few specific aspects of systemic risk. Recently, the literature has focused particularly on the systemic risk contribution of individual large and complex financial intermediaries.

Each of these risk measures has strengths and weaknesses if applied in a macro-prudential context. Policy-makers need therefore to rely on a wide range of measures and tools, covering different parts of financial systems, different shocks and transmission mechanisms of instability. The challenges are therefore to prioritise among the increasing number of measures; to ensure that the recent focus on risk contributions of individual intermediaries using market data does not distract attention from other forms of systemic risk and from the

risk that market data in tranquil times may not reflect crisis relationships very well; to establish how to construct a comprehensive systemic risk surveillance and assessment system using the measures and tools; and to make progress in combining a wider range of risks in more comprehensive models.

25 C. E. V. Borio and P. W. Lowe, "Asset prices, financial and monetary stability: Exploring the nexus", *BIS Working Paper,* No 114, 2002; M. Misina and G. Tkacz, "Credit, asset prices, and financial stress in Canada", *Bank of Canada Working Paper*, 2008-10; L. Alessi and C. Detken, "'Real time' early warning indicators for costly asset price boom/bust cycles: a role for global liquidity", *ECB Working Paper Series,* No 1039, March 2009; R. Barrell, E. P. Davis, D. Karim and I. Liadze, "Bank regulation, property prices and early warning systems for banking crises in OECD countries", *Journal of Banking and Finance,* Vol. 34, Issue 9, pp. 2255-2264, September 2010.
26 S. J. Koopman, A. Lucas and B. Schwaab, "Macro, frailty, and contagion effects in defaults: Lessons from the 2008 credit crisis", *Tinbergen Institute Discussion Paper*, No 004/2, August 2010.