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MEASUREMENT OF CONTAGION IN BANKS´ EQUITY PRICES

BY REINT GROPP AND
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Abstract

This paper uses the co-incidence of extreme shocks to banks' risk to examine within country and across country contagion among large EU banks. Banks' risk is measured by the first difference of weekly distances to default and abnormal returns. Using Monte Carlo simulations, the paper examines whether the observed frequency of large shocks experienced by two or more banks simultaneously is consistent with the assumption of a multivariate normal or a student t distribution. Further, the paper proposes a simple metric, which is used to identify contagion from one bank to another and identify "systemically important" banks in the EU.

JEL classification: G21, F36, G15

Keywords: Banking; Contagion; Monte Carlo Simulations

Non-technical Summary

There is a very active debate on the use of market data in the supervision of banks. This paper proposes to use market data, especially the distance to default, to examine bank contagion. The paper builds upon the approach taken in a recent paper by Bae et al. (2003), who considered contagion among stock market returns in emerging markets. The approach is related to the growing conviction that the behaviour of tail observations for financial market data is quite different from the behaviour of other observations (extreme value theory). In this sense, the paper attempts to make a contribution to both the bank contagion and market discipline literatures.

We empirically examine contagion in a sample of 67 EU banks. The banks in the sample are those EU banks, for which we were able to obtain sufficiently long and liquid data series on stock market returns. For these banks we analyse the weekly first difference of the distance to default (and weekly abnormal stock returns). In a recent paper (Gropp et al., 2003), it was shown that the distance to default may be a particularly suitable way to measure bank risk, avoiding problems of other measures, such as subordinated debt spreads. The distance to default combines information on stock price returns with asset volatility and leverage and represents the number of standard deviations away from the default point. The default point is defined as the point at which the liabilities of the bank are just equal to the assets.

We define contagion as one bank being hit by an idiosyncratic shock, which is transmitted to other banks. We will not specify the channel of transmission, but one could imagine money markets, payment systems, equity (ownership) links and “pure” contagion. The paper has two parts. In the first part, we test whether observed patterns in the data are consistent with standard distributional assumptions. In order to do this, we us a concept called “co-exceedance.” A co-exceedance is a period (in this paper: a week) during which two or more banks first difference in the distance to default was in the 5th percentile positive or negative tail. We then test whether the observed co-exceedances are consistent with a multivariate normal distribution or a Student t distribution under different assumptions about its kurtosis. These tests are carried out by using Monte Carlo simulations: Based on the observed variance/covariance matrix we generate co-exceedances based on multivariate normality or student t distributional assumptions and compare the patterns of co-exceedances to those generated by the actual data.

We find that within countries and across countries, multivariate normality can be rejected in all cases. A student t distribution may be consistent with the observed patterns in some cases, but generally we cannot replicate the co-exceedences either under multivariate normality or student t assumptions. The same result is found for simulations across country pairs. This implies that there are non-linearities in the tails of the distribution. In particular, it would suggest that the distribution of the first difference in the distance to default of each individual bank not only exhibits fat tails (a common phenomenon in asset prices), but that the probability of one bank being in the tail is conditional on other banks being in the tail. Economically, this either means that large common shocks are more highly correlated across banks than small common shocks or that idiosyncratic shocks affecting one bank are transmitted to other banks (contagion).

We argue that an appropriate way to address this finding and distinguish common shocks affecting two or more banks from contagion may be a non-parametric approach. This is done in the second part of the paper. We present a simple measure of what we label "net-contagious influence." The measure represents the difference in the conditional probabilities of being in the tail between two banks adjusted for differences in the probabilities of being hit by an idiosyncratic shock. We show that this measure should give an accurate indication of contagious influence between two banks.

Using this method we identify banks, which appear to have been of systemic importance within individual countries and across countries. Overall, the results suggest that there may be relatively few banks with EU-wide systemic importance. The banks consistently identified as systemically important in the EU are Deutsche Bank, Dresdner Bank, Danske Bank, Allied Irish Bank, Bank of Ireland, ING, ABN Amro, HSBC and National Westminster Bank. BNP Paribas, Natexis, BBVA, Banco Santander and a number of large UK banks seem to have some systemic importance, but the evidence is weaker. Finally, the methodology lends itself to identify the strength of the links among banking systems in the EU. This analysis has a number of interesting conclusions: One, the UK and other non-euro countries seem to be no less integrated (by our measure of contagious influence) with euro area countries than euro area countries with each other. Second, there may be significant contagious influence emanating from the banking systems of some of the smaller countries, such as Denmark and Ireland, which may be a reflection of significant exposures of foreign banks in these countries.

The paper has implications for the ongoing debate on how to use market information for supervisory purposes and for monitoring financial stability. In particular, it suggests that a further use of market data, beyond predicting individual bank failures, may be to measure contagion and, ultimately, systemic risk. Market information may also give information on banks, which have systemic importance, and therefor may deserve particular attention from supervisors and central banks. It is also of relevance to a better understanding of the extent to which European banking systems have become interconnected and how banking problems could spread across borders.

1. Introduction

This paper proposes a new methodology, which we believe may be able to identify the direction of contagion from one bank to another, given a relatively non-restrictive set of assumptions about the shocks affecting banks. The paper builds upon the approach taken in a recent paper by Bae et al. (2003), who considered contagion among stock market returns in emerging markets. The approach is related to the growing conviction that the behaviour of tail observations for financial market data is quite different from the behaviour of other observations (extreme value theory).

The previous empirical literature on bank contagion has largely employed three distinct approaches: autocorrelation tests, survival time tests and event studies. Along the lines of the first approach, a number of papers has tested for autocorrelation in bank failures, controlling for macroeconomic conditions (Grossman, 1993; Hasan and Dwyer, 1994; Schoenmaker, 1996). A positive and significant autocorrelation coefficient indicates that bank failures cluster over time, given that all macroeconomic factors have been appropriately controlled for. All authors find evidence in favour of contagion, although the approach suffers from a number of inherent disadvantages. In particular, omitted macro variables, which exhibit autocorrelation would bias the results, the approach is limited by the frequency of the availability of macroeconomic data and third, the implications of the papers for today's banking system may be limited, as all papers have examined contagion in historical periods, in order to avoid problems associated with public safety nets (such as deposit insurance, lender of last resort).[1]

More recently, Calomiris and Mason (2000) examine the question whether fundamentals can explain the survival time of banks during the great depression. They find that micro, regional and national fundamentals indeed can explain a large portion of the probability of survival of banks during the great depression. There is some evidence of contagion, although it appears to have been limited to specific regions of the US.

Somewhat more closely related to the approach taken in this paper is the quite extensive literature examining the reaction of stock prices to news (for a survey see De Bandt and Hartmann, 2001). Overall, the literature suggests that stock price reactions to news vary proportionally to the degree of the news' extent of affecting the bank. Hence, the results tend to be consistent with "information based" contagion, rather than "pure" contagion. Overall, the evidence, however, is limited to the US banking system (an exception is Gay et al. (1991) which examine data for Hong Kong) and the approach is not well suited to distinguishing macro shocks affecting all banks simultaneously and "proper" contagion as defined above. Further, as for example Gropp et al. (2002) argue, the measure employed in these papers, namely cumulative abnormal stock market returns may not be well suited to measure certain types of shocks, such as increases in earnings volatility or leverage. In order to avoid these problems, in this paper we consider the distance to default, which combines information on leverage, asset volatility with information contained in stock returns, in addition to using abnormal returns.

[1] Grossman (1993) looks at US data for 1875-1914, Hasan and Dwyer (1994) consider the US free banking era (1837-1863) and Shoemaker (1996) the years 1880-1936, also in the US.

While this paper is concerned with bank contagion, the approach followed is much more closely related to the empirical literature on financial market contagion and extreme value theory. Financial market contagion (equity markets, foreign exchanges markets and, to a more limited extent, bond markets) up until fairly recently was largely examined by testing whether the correlation between two markets increased in crisis periods (e.g. Bennett and Kelleher, 1988; King and Wadhwani, 1990; Wolf, 2000). However, Boyer et al. (1997) point out that observed increases in asset price correlations during crisis periods may simply be a statistical artefact. They show that for any bivariate normal return distribution, the correlation coefficient of the two marginal distributions conditional on the marginal distributions' standard deviations increases with the conditioning standard deviation. Hence, dividing a sample into crisis periods, which by definition tend to exhibit higher volatilities, and tranquil periods, which show lower volatility, will statistically result in a higher measured correlation during crisis periods, which, however, is not a reflection of contagion. Forbes and Rigobon (2002) correct for the problem and conclude that contagion during the 1987 stock market, the 1994 Mexican and the 1997 Asian crises have been significantly overstated. Virtually all of the observed patterns can be explained by the markets' usual interdependence. Recently Forbes and Rigobon (2002) approach has been criticised as regards to its lack of robustness with respect to omitted variable bias (Corsetti et al., 2002), as well as its choice of time window (Billio et al., 2002). Following this criticism, Ciccarelli and Rebucci (2003) present a Bayesian time-varying coefficient model and show that it provides improvements in the (joint) presence of heteroskedasticity and omitted variables.

Another avenue of research has been the application of extreme value theory, which concentrates on extreme co-movements, rather than examining statistical interdependence for the entire distribution. Examining interdependencies in the tails of the distribution, permits the examination of non-linearities in co-movements, as well as a relaxation of the assumption of multivariate normality of returns, which in case of fat-tailed financial market data tend to be violated (De Bandt and Hartmann, 2001; Straetmans, 2000). Hartmann et al. (2003) apply non-parametric extreme dependency measures to study extreme co-movements between stock, bond and money markets across G5 countries. They find that while the probability of a crash of the size as experienced in 1987 in the US is extremely low, the conditional probability of having a stock market crash of the size of 1987 in a G5 country, given a crash of this size in another G5 country, is significantly higher. In addition, the paper shows that the tails of the distribution exhibit substantial non-linearities relative to the entire distribution of returns. Longin and Solnik (2001) apply extreme value theory to monthly G5 equity returns between 1958 and 1996, assuming a logistic distribution function. They reject normality in the left tail (crashes), but not in the right tail (booms).[2]

In this paper we examine contagion in a sample of 67 EU banks. For these banks we analyse the weekly first difference of the distance to default (and weekly abnormal stock returns). We define contagion as one bank being hit by an idiosyncratic shock, which is transmitted to other banks. We will not specify the

[2] Another strand of literature has advocated the use of GARCH models (Hamao et al., 1990; Lin et al., 1994; Susmel and Engle, 1994). Ramchand and Susmel (1998) extent the approach such that high variance and low variance states are no longer required to be drawn from the same distribution. Hence, they estimate a bivariate switching ARCH model, with the advantage that crisis episodes are endogenously determined by the data.

channel of transmission, but one could imagine money markets, payment systems, equity (ownership) links and "pure" contagion. The approach employed is quite closely related to Longin and Solnik (2001), in the sense that we test whether the observed co-exceedances (i.e. the presence of two or more banks in the tail of the distribution simultaneously) are consistent with a multivariate normal distribution. As in Bae et al. (2003) we also examine, whether a Student t distribution under different assumptions about its kurtosis is consistent with the observed patterns in the data. We find that within countries, multivariate normality can be rejected in all cases. A student t distribution may be consistent with the observed patterns in some countries but generally we cannot replicate the co-exceedences either under multivariate normality or student t assumptions. The same result is found for simulations across country pairs. The findings are strongly suggestive of non-linearities in the tails of the distribution. We argue that an appropriate way to address this finding may be a non-parametric approach. Hence, the paper presents a simple measure of what we label "net-contagious influence." Using this method we identify banks, which appear to have been of systemic importance both for individual countries and across countries. Overall, the results suggest that there may be few banks with EU-wide systemic importance.

The paper has implications for the ongoing debate on how to use market information for supervisory purposes and for monitoring financial stability. It is also of relevance to a better understanding of the extent to which European banking systems have become interconnected and how banking problems could spread across borders. The remainder of the paper is organised as follows: In the next section, the calculation of our measure of bank risk is briefly described. In section 3, the sample and the data used in this paper are described, section 4 discusses the approach to identifying contagion employed and presents the main results. In section 5, we apply the methodology to identifying systemically important banks in the EU and section 6 concludes.

2. Calculation of *ln(Δdd)*

We use the weekly first difference of the distance to default as our measure of bank risk. In Gropp et al. (2002) it was argued that specifically with respect to banks, the distance to default may be a particularly suitable and all-encompassing measure of bank risk. In particular, the measure's ability to measure risk is not affected by the presence of explicit or implicit safety nets (unlike e.g. subordinated debt spreads). Further, it combines information about stock returns with leverage and volatility information, encompassing the most important concepts of risk (unlike e.g. unadjusted stock returns). As we are interested in the transmission of shocks from one bank to another we use the first difference of the distance to default. We calculated the distance to default for each bank in the sample and for each time period, t, using that period's equity market data. The distance to default is derived based on the Black-Scholes model, in which the time path of the market value of assets follows a stochastic process: [3]

$$\ln V_A^T = \ln V_A + \left(r - \frac{\sigma_A^2}{2} \right) T + \sigma_A \sqrt{T} \varepsilon, \tag{1}$$

[3] See KMV Corporation (1999) for a similar derivation and more ample discussions.

which gives the asset value at time T (i.e. maturity of debt), given its current value (V_A). ε is the random component of the firm's return on assets, which the Black-Scholes model assumes is normally distributed, with zero mean and unit variance, N(0,1).

Hence, the current distance d from the default point (where $\ln V_A^T = \ln D$) can be expressed as:

$$d = \ln V_A^T - \ln D = \ln V_A + (r - \frac{\sigma_A^2}{2})T + \sigma_A \sqrt{T}\varepsilon - \ln D <=>$$

$$\frac{d}{\sigma_A \sqrt{T}} = \frac{\ln\left(\frac{V_A}{D}\right) + \left(r - \frac{\sigma_A^2}{2}\right)T}{\sigma_A \sqrt{T}} + \varepsilon. \tag{2}$$

That is, the distance to default, DD

$$DD \equiv \frac{d}{\sigma_A \sqrt{T}} - \varepsilon = \frac{\ln\left(\frac{V_A}{D}\right) + \left(r - \frac{\sigma_A^2}{2}\right)T}{\sigma_A \sqrt{T}} \tag{3}$$

represents the number of standard deviations that the firm is from the default point. The inputs to DD, V_A and σ_A, can be calculated from observable market value of equity capital, V_E, volatility of equity σ_E, and D using the system of equations below:

$$\begin{aligned} V_E &= V_A N(d1) - D e^{-rT} N(d2) \\ \sigma_E &= \left(\frac{V_A}{V_E}\right) N(d1)\sigma_A, \\ d1 &\equiv \frac{\ln\left(\frac{V_A}{D}\right) + \left(r + \frac{\sigma_A^2}{2}\right)T}{\sigma_A \sqrt{T}} \\ d2 &\equiv d1 - \sigma_A \sqrt{T}, \end{aligned} \tag{4}$$

The system of equations (4) was solved by using the generalised reduced gradient method to yield the values for V_A and σ_A, which in turn entered into the calculation of the distance to default. The measure of bank risk used in this paper is then obtained by taking $\ln(dd_t/dd_{t-1})$, using the end of week distance to default which in the following will be denoted as *ln(Δdd)*. Hence, *ln(Δdd)* measures the percentage change in the number of standard deviations away from the default point.[4]

As underlying data we used monthly averages of the equity market capitalisation, V_E from Datastream. The equity volatility, σ_E, was estimated as the standard deviation of the daily absolute equity returns and, as proposed in Marcus and Shaked (1984), we took the 6-month moving average (backwards) to reduce noise. The presumption is that the market participants do not use the very volatile short-term estimates, but more smoothed volatility measures. This is not an efficient procedure as it imposes the volatility to be constant. However, equity volatility is accurately estimated for a specific time interval, as long as leverage does not change substantially over that period (see for example Bongini et al., 2002). The total debt liabilities, V_L, are obtained from published accounts and are interpolated (using a cubic spline) to yield weekly observations. The time to the maturing of the debt, T was set to one year, which is the common benchmark assumption without particular information about the maturity structure. Finally, we used the government bond rates as the risk-free rates, r.

3. Sample selection and characteristics

We started with all EU banks that are listed at a stock exchange and whose stock price and total debt are available from Datastream during January 1991 to January 2003 (92 banks). We deleted all banks that had trading volume below one thousand stocks in more than 30% of all trading days (7 banks). Furthermore, we deleted three additional banks where we had serious concerns about data quality[5] and 15 banks due to data covering less than half of the entire sample period. As will be seen below, completeness of data for each bank remaining in the sample is important, in order to avoid distortions in our measure of contagion due to few (tail) observations. The resulting sample contains 38600 week/bank observations for 67 banks, i.e. on average around 576 observations per bank (Table 1).

The sample contains 39 banks with maximum number of observations, given the time period considered (628) and only three banks with less than 400 observations. The minimum number of observations is 351 (Banco di Desio e della Brianza). On average the banks in the sample are just above four standard deviations away from the default point (a mean distance to default of 4.03). However, this hides substantial variation in the health of banks. Banco di Napoli represents the minimum with a distance of default dipping below zero at -0.29, suggesting that the bank was in default. No other banks exhibit negative distances to default in the sample; Banco Espaniol de Credito (Spain), Bankgesellschaft Berlin (Germany), Sampo Leonia (Finland), SEB (Sweden) all show distances to default below one and all are well known to have experienced significant difficulties during the period under consideration in this paper. At the other end of the spectrum, there were 14 banks with a maximal distance to default of above 10. Interesting the global maximum of 17.11 is attributable to the same bank that also experienced the global minimum: Banca di Napoli. The mean of the first difference in the distance to default is approximately zero, the largest negative change is about –4, which given a mean level of 4 can truly be considered a sizeable weekly shock.

The banks in the sample are generally quite large. On average, total assets amount to EUR 152 billion. The relatively large average size is an outcome of the requirement for the bank to be traded at a stock exchange. Nevertheless, the size variation is considerable within the sample. For example, the largest bank, Deutsche Bank, is 300 times the size of the smallest, Banco Desio e della Brianza. Table 3 gives all banks in the sample, ranked by total assets. The table suggests that in most countries, the largest banks are

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4 Below we will also show results for the absolute first difference in the distance to default, *Δdd,* and abnormal returns.

5 The banks showed zero equity return on a high number of trading days, resulting in extremely volatile distances to default.

covered, although there are some notable exceptions, such as Belgium, where Dexia and Fortis both had to be excluded due to data limitations. This results in an above 50 percent coverage of total banking assets in the EU, despite the fact that in numbers the sample contains less than 1 percent of all EU banks (Table 2). The degree of coverage in each country depends on the number of banks traded at a stock exchange and the structure (especially concentration) of the banking system. The sample contains banks from all EU countries except Luxembourg. The ranking of all banks by total assets (with the largest bank in each country in bold) is also presented, because it permits a check of all results presented subsequently in the paper. Clearly, the naïve approach to determining within country systemically important banks would be to pick the largest bank(s) in each country and for the EU as a whole, the largest banks in the EU.

As a first step we calculated the full correlation matrix of *ln(Δdd)* for all banks in the sample.[6] As expected, within country correlations are higher than across country correlations. For example in Germany, BHVB correlation with Deutsche Bank, Dresdner Bank and Commerzbank are around 0.7, the correlation between Deutsche Bank and Dresdner Bank is 0.86. Similarly, the correlation between the distribution of ING and ABN Amro in the Netherlands is 0.6. The correlation in *ln(Δdd)* among UK banks is also high, in many cases above 0.5. However, in some cases within country correlations among banks are much lower, i.e. in Italy where most correlations cluster around 0.2, as well as in Portugal, Sweden and Austria. In Spain, we have some banks that show quite high correlations, especially involving BBVA , whose Δdd shows a correlation of 0.6 with Banco Santander and 0.5 with Banco Popular Espanol. Most other Spanish banks show correlations that range between just above zero and 0.2.

Again as one would expect, correlations are also generally quite low for cross-country bank pairs. Of the 4489 cross-country correlations, only around 60 (less than 2 percent) are above 0.3. High correlations exist between German and some Spanish banks, between the largest French and Spanish banks, between Dutch and German, as well as Dutch and Irish banks. Interestingly, some banks tend show negative correlations with most banks in the sample. These include Banco di Napoli and Okobank, both of which experienced substantial difficulties during the sample period.[7]

As we have argued above, the study of correlations may be misleading or uninformative in a number of respects. Correlations may not be constant during crisis times, precisely when contagion would be of particular interest. It has been well established that the behaviour of tail observations for financial market data is quite different from the behaviour of other observations. In addition, we are specifically interested in distinguishing contagion, as opposed to common shocks affecting banks simultaneously. We define contagion as one bank being hit by an idiosyncratic shock, which then is transmitted to other banks. Correlations, by definition, will not be able to distinguish the two, unless one attempts to fully control for common (macro) shocks. Related to this, in the case of banks in particular, the <u>direction</u> of contagion is of interest, i.e. which bank may have systemic importance for other banks.

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6 The matrix is not presented due to space limitations, but is available upon request.

7 As we will see below, idiosyncratic shocks facing each bank are crucial in order to identify contagion. This issue will be revisited below.

For these reasons, in this paper we follow Bae et al. (2003) and focus on co-exceedances in the tails of the distribution of *ln(Δdd)*. We count the number of times at least one bank's *ln(Δdd)* is in the tail of the distribution ("exceedance") and, more importantly, the number of times more than one bank is in the tail of the distribution ("co-exceedance"). We arbitrarily define a tail event as one in the 5 percent (positive and negative) tail of the distribution.[8] Figure 1 shows the number of tail events per week: panel A shows the histogram of both tails simultaneously, while panel B and panel C represent the number of tail events in the positive and negative tail respectively. The histograms show that the tail events are not evenly spread over the sample period. The maximum number of co-exceedences is reached in the first week of November 1997, when 49 (out of 67) banks have a big (negative) change in their distance to default.

In table 4 we report the counts of the number of co-exceedances within countries. For the within country exercise to be meaningful, we were limited to countries with at least three banks. Hence, no figures are provided for banks in Austria, Belgium, Denmark, Finland, Greece and Sweden.[9]
For the following, we also limit the sample to banks for which we have at least 500 concurrent observations; this is necessary for the simulations reported below.[10] Let us examine co-exceedances within countries first. The maximum number of co-exceedances is naturally constrained by the number of banks for which we have observations. From this perspective, Germany, Italy, and the UK are the most interesting countries, as we have 8, 10 and 7 banks in the sample, respectively. Considering only these three countries, one is immediately struck by the fact that Germany and Italy have 6 and 8 weeks, during which 5 or more banks were in the bottom tail and 4 and 7 weeks, respectively, in which 5 or more banks were in the top tail. In contrast, the corresponding figures for Spain are 2 and 2 weeks. Recall that the correlations among banks of ln(Δdd) considering the entire distribution were higher in Germany and Spain compared to the Italy.. Next, consider the three countries with three banks (France, Ireland and the Netherlands) together with Portugal, which has 4 banks in the sample. Ireland and Portugal have substantially more weeks, in which all three (or more, in case of Portugal) banks were in the bottom tail compared to the other two countries. Furthermore, there are considerable asymmetries with respect to bottom and top tail co-exceedances. In Ireland, for example, there are seven weeks, in which all three Irish banks experienced a bottom tail event, but only four weeks in which all three banks had a top tail event. Also, in the UK bottom tail co-exceedances are more frequent than top tail co-exceedances, as there is only one week with five banks co-exceeding in the top tail, but six such cases in the bottom tail.

We are also interested in cross-border contagion. Hence, we performed the same exercise of counting co-exceedances for bilateral country pairs of the largest EU countries (Germany, Spain, France, Italy and the UK). The results are reported in Table 5. For ease of presentation, we report co-exceedances if at least one bank from each country is in the tail in a given week. Hence, the category "5 co-exceedances" for the UK-FR country pair contains at least one bank each from the UK and France, but we do not distinguish between whether there are four French banks and one UK bank or four UK banks and one French bank. Overall, there are a substantial number of weeks with more than five banks concurrently in the tail.

8 We check a 10 percent threshold below.

9 Note that the banks in these countries will, however, be considered when we examine systematically important banks below.

10 The requirement will be relaxed in Section IV.2. of the paper.

Excluding the country pairs with France, which given the low number of French banks in the sample are not strictly comparable, this figure varies from 6 (Spain-UK) to 16 (Germany-Spain) for the bottom tails and from 7 (Spain-UK) to 20 (Spain-Italy) for the positive tails. For the country pairs involving France, five or more banks are in the bottom tail 5-7 weeks, in the top tail 3 to 9 weeks. This high variation in itself may suggest that there are differences across country pairs, although clearly this may be due to common shocks hitting banks in the two countries simultaneously as much as to contagion. Looking across the table, one also notices that in some cases the frequency of bottom tail co-exceedances appears to be quite different from the one in the top tail, although no strong patterns emerge.

In summary, both the relatively high number of co-exceedances and the asymmetry in bottom and top tail co-exceedances are suggestive that the correlation among banks may not be constant during "extreme" times. In the following, we compare the observed co-exceedances with those generated by Monte Carlo simulations under standard distributional assumptions.

4. Identification of contagion

4.1. Co-exceedances and Monte Carlo evidence

Suppose that the variance/covariance matrix of ln(*Δdd)* is stationary over the sample period and that the returns follow a multivariate Normal or Student t distribution. Using that variance-covariance matrix, we simulate 1000 random realisations of the time series of weekly realisations of ln(*Δdd)*. In order to limit computations, rather than simulate the joint distribution of all 67 banks, we simulated country by country as a first step. For each realization, we identify the 5 percent tail for the bottom tail and the top tail separately and perform a non-parametric count across banks within countries. This process yields a set of simulated exceedences (one bank in the tail) and co-exceedances (two or more banks in the tail), which we can compare to the number of exceedances and co-exceedances in the actual data.

The distribution of the co-exceedances will depend on the assumptions made about the data generating process. We perform Monte Carlo simulations under three assumptions: The data have been generated by a multivariate normal distribution, by a student t distribution with 5 degrees of freedom or by a student t distribution with 10 degrees of freedom.[11] The results of this exercise are reported in Table 6 for each country separately. We, as before, limited ourselves to countries with three or more banks. We find that the multivariate Normal distribution is unable to replicate the number of co-exceedances in the actual data for any of the banks in the countries we study, regardless of whether we consider positive or negative co-exceedances. Even more striking, in some countries, the student t distribution with 5 degrees of freedom,

[11] The degrees of freedom in a student t distribution equal N+K-1, where N is the number of banks (8 for Germany, 7 for Spain, 3 for France, 3 for Ireland, 10 for Italy, 3 for the Netherlands, 4 for Portugal and 7 for the UK) and where K can be set from 1 (significant positive excess kurtosis) to 25 (little excess kurtosis, approximating Normal). We also explored scenarios with lower values for K, but found them to vastly understate the number of cases with co-exceedances of less than 3 banks. Bae et al. (2003) report also scenario's using a multivariate GARCH approach, but find that it also is unable to generate the number of co-exceedances in their sample of emerging market stock returns.

i.e. under fairly strong assumptions about kurtosis, is unable to generate the number of co-exceedances in the data or if it is, is unable to replicate the number of single exceedances.

Let us consider the countries with at least 7 banks first. The multivariate Normal distribution generates zero weeks with five or more co-exceedances for Spain, the UK, and Italy for both tails, while the actual figures are 2, 6 and 8 weeks for the bottom tail and 2, 1 and 7 weeks for the top tail, respectively. In Germany the Normal distribution, due to the higher correlations among banks, generates 3 weeks with five or more co-exceedances in both tails, which compares to 6 (4) weeks for bottom (top) tails in the data. In general, in the case of Germany, the Normal distribution comes closest of all countries to replicating the actual data. In Ireland, France, and the Netherlands, there are only three banks in the sample. The Normal distribution generates 1.7, 0.9 and 1.1 weeks, respectively, in which all of these banks are simulated to be in the bottom tail. This compares to 7, 2 and 3 weeks in the data. The figures for the top tails look quite similar.

The student t distribution yields simulation results closer to the actual data. For example, the German and Spanish co-exceedances for both tails can largely be replicated assuming a student t distribution with 10 degrees of freedom. In countries with 3 or 4 banks, we find that the student t distribution with 5 degrees of freedom is able to replicate the results for both tails in France and Portugal and for bottom tails in the Netherlands and the top tails in Ireland. Nevertheless, the results overall suggest that in most countries it is exceedingly difficult to replicate the distribution of co-exceedances. Looking at the 95 percent confidence bands of the simulated distributions, we can reject equality for all countries at least for some level of co-exceedance for the Normal distribution and for many in case of the student t distributions.

We wanted to check whether this result would extend to other measures of bank risk. We report the results for the first differenced distance to default in Table 6a. Conceptually, the simple first difference in the distance to default reflects shocks, which are large in absolute terms. This has the consequence, however, that banks, which are already close to the default point, by construction, cannot experience a tail event, as the distribution of the level distance to default is truncated at zero. The log-differenced distance to default highlights percentage changes, which avoids the problem of truncation. However, to the extent that our measure is noisy, for banks close to the default point we may be interpreting noise as tail events.

Table 6a is organised exactly as Table 6 above. Comparing the two tables it turns out that the results are very similar. As before, a multivariate normal distribution is not able to replicate our counts of co-exceedances. The fatter-tailed student t-distribution does a better job in this respect. For example, both measures suggest equal frequencies of weeks in which at least five banks were concurrently in the tail (in countries with at least 5 banks). More formally, we examined whether applying the first-differenced simulation results to the log-differenced actual co-exceedances would have resulted in more or less rejections of the simulated co-exceedances. We found this not to be the case, the only exception being the UK in the case of negative tail co-exceedances. In addition, we checked whether the measures pick up the same exact weeks with a high number of exceedances and whether the banks with an exceedance are the same. Again we found this to be the case.[12]

For the second robustness check we use abnormal returns, which we obtained by using the residuals from the following standard one factor model:

$$R_{it} = \alpha_0 + \alpha_1 M_{ct} + \varepsilon_{1t} \quad (5)$$

where R_{it} denotes the log weekly return of bank i in week t and M_{ct} denotes the weekly log return of the broad market index of the country c, where bank i is headquartered. The estimated residuals $\hat{\varepsilon}_{1t}$ are then the abnormal returns of bank i. Results from estimating equation (5) are given in Appendix A. The estimated coefficient on α_1 ("beta") is of particular interest. On average, it is 0.89, with a maximum of 1.58 (Standard Chartered) and a minimum of 0.22 (Banco Guipuzcoano). In all cases, the coefficient is significant at the one percent level. On average, the market portfolio explains around a third of the total variation in log weekly returns (R^2 = 0.32).

Descriptive statistics for the resulting abnormal returns are given in table 7. Notice that the number of observations is higher (647 versus 576), since some data were lost in the calculation of stock price volatility used as in input in the distance to default and there were missing values for other inputs. The mean for the abnormal returns is equal to zero, as expected. The minimum and maximum are quite high and are caused by exceptional cases: the maximum is due to Banca di Napoli in January 1998 and the minimum is due to Banco Espanol de Credito in February 1994. Note that outliers should not be a problem, given that we consider the presence in the tail rather than the absolute size of returns.

The comparison between the actual abnormal return data and the simulations are reported in Table 6b, which is constructed in the same way as Tables 6 and 6a above. It shows that we observe significantly fewer instances, in which many banks experienced a bottom tail event concurrently, compared to the other two measures. This is not entirely surprising, because we have eliminated at least some macro shocks as a source for the concurrent presence in the tail of the distribution of more than one bank. It is striking, however, to observe that as for the two measures used before, the normal distribution is unable to replicate the observed frequencies of co-exceedances. Further, even when assuming fat tailed distributions such as the student t distribution with 5 and 10 degrees of freedom, in many countries we can reject that such distributions adequately describe the observed patterns. Note one important conceptual difference between the distance to default and abnormal returns. The distance to default is declining in the volatility of the underlying assets, while returns are increasing in asset volatility (see Goh and Ederington, 1993; Gropp et

[12] In most cases the number of extreme observations was approximately the same and deviations were small, i.e. no more than one bank. For example, looking at the negative tail for Italy, during weeks with 6 or more banks in the tail in the first differences of the distance to default distribution (Table 6), there were at least 4 banks in the tail of the log difference distribution. The same holds for the positive tail: the two extra observations in table 6a, had respectively 5 and 4 banks in the tails when the first difference of the distances to default was used.

al., 2003 and Gropp and Richards, 2001), due to the call option characteristic of the stock price.[13] While we examine results for abnormal returns also below, we view this as a major caveat and would place greater emphasis on results obtained using the distance to default as a measure of bank risk.[14]

We reach similar conclusions when considering cross-country co-exceedances. The results for the log-differenced distance to default, the first differenced distance to default and abnormal returns are reported in Tables 8, 8a and 8b, respectively. We performed exactly the same exercise, simulating multivariate Normal and student t distributions with 5 and 10 degrees of freedom, using the historical variance-covariance matrix to replicate the patterns of co-exceedances reported in Table 5. In case of the log-differenced distance to default, neither the multivariate Normal nor the student t distributions can replicate the patterns of co-exceedances observed in the data for any country pair, except for Germany-France. In all cases (aside from Germany-France) we can reject equality based on the 5 percent simulated confidence band at least for some level of co-exceedances. This is true for the bottom as well as for the top tail co-exceedances. Again, patterns are strikingly similar for the log-differenced distance to default (Table 8a), although in this case there is rejection in all cases. Finally, for the abnormal returns, we find that we cannot reject that the simulated patterns coincide with actual patterns for two country pairs: Germany-France and France-Spain. Nevertheless, the difference for the cross-border co-exceedances between the three measures seem even smaller than in the case of within country co-exceedances and the inability of the simulations to replicate the patterns observed in the data even more striking.

Table 9 gives some summery statistics for the Monte Carlo Simulations. Overall, the normal distribution is unable to explain the patterns in the data. There is virtually no country or country pair, in which there is not at least one rejection. The fatter tails student t distributions, especially the student t with 10 degrees of freedom, do slightly better, but for all measures there are only few countries or country pairs, for which there is not at least one rejection. While our simulation difficulties may ultimately concern only a relatively small number of observations, the events that occur “too often” compared to multivariate Normal or student t distributions may be precisely those one would be interested in from the perspective of bank contagion.

4.2 Differences in conditional sample frequencies: A measure of net contagious influence

Given this evidence in favour of non-linearities in the tail of the distribution, there are a number of avenues for how to proceed. Bae et al. (2003) propose a multinomial logistic regression model, utilising the fact that the co-presence of observations in the tails can be modelled as a polychotomous variable. Alternatively, GARCH-M models, modelling changing volatilities asymmetrically, may also be a way forward (see e.g. Ang and Chen, 2002). We follow a different approach, refraining from making any

[13] The increase in stock prices in response, say, to an increase in leverage may result in a positive abnormal return, while the distance to default will decline.

[14] We also examined the sensitivity of the results to the choice of the size of the tail. While all calculations in the paper were performed for 5 percent tails, we redid the analysis for 10 percent tails and found virtually identical results for the difference in the distance to default. The results are available upon request.

assumptions about the underlying data generating process. Instead we propose the following simple non-parametric measure of net contagious influence of bank A on bank B

$$\Omega_{A/B} = P(B_T / A_T) - P(A_T / B_T), \tag{6}$$

where $P(B_T / A_T)$ denotes probability that bank B is in the tail of the distribution in some period given that bank A is also in the tail. Expression (6) is simply the difference in the observed conditional sample frequencies of bank A and bank B experiencing a tail event. Under which circumstances does (6) give us an accurate signal regarding the net contagious influence between the two banks? To see this, assume that all shocks are i.i.d. over time. Suppose further that idiosyncratic shocks and the macro shock are jointly distributed. In addition, we need to define some notation:

(i) I_S represents the realisation of bank I's idiosyncratic shock, where $I \ \varepsilon \ (A,B)$.

(ii) I_T represents the event that bank I is in the tail of the distribution.

(iii) M is the realisation of the common shock. A common shock is defined such that upon its realisation both banks are in the tail.

(iv) p_{AB} represents the probability that there is contagious influence from bank A to bank B. We define contagious influence such that bank B is not hit by a shock (either common or idiosyncratic) but is in the tail and A is hit by an idiosyncratic shock, which through contagious influence results in bank B experiencing a tail event.

We claim that there is net contagious influence from bank A to bank B if $p_{AB} > p_{BA}$. Recall that for any two banks A and B, bank A can be in the tail of the distribution if

(i) it is hit by an idiosyncratic shock (A_S) and B is or is not hit by an idiosyncratic shock, or

(ii) if there is a common (macro) shock (M) affecting both banks simultaneously, or

(iii) if bank B is hit by an idiosyncratic shock and there is contagion from bank B to bank A.

We do not assume that the system of the two banks A and B is closed. This means that we do not exclude the possibility of outside contagion. However, if this outside contagion affects either bank individually, this is observationally equivalent to an idiosyncratic shock affecting the bank and, hence, is subsumed under I_S. Similarly, suppose both banks experience contagion from some bank other than A and B. In our framework this would be subsumed under the banks experiencing a common shock. Note that the phrase common shock, as used here, is distinct from a macro shock affecting all banks; rather a common shock is simply a shock affecting both banks, such that they are in the tail of the distance to default or abnormal return distribution. This can, but must not be, a macro shock.

Breaking down the conditional probabilities of being in the tail into their components we obtain:

$$p(B_T \mid A_T) = \frac{pr(A_S, B_S, \neg M) + pr(A_S, \neg B_S, \neg M)p_{AB} + pr(\neg A_S, B_S, \neg M)p_{BA} + pr(M)}{pr(A_S, B_S, \neg M) + pr(A_S, \neg B_S, \neg M) + pr(\neg A_S, B_S, \neg M)p_{BA} + pr(M)}$$

$$p(A_T \mid B_T) = \frac{pr(A_S, B_S, \neg M) + pr(A_S, \neg B_S, \neg M)p_{AB} + pr(\neg A_S, B_S, \neg M)p_{BA} + pr(M)}{pr(A_S, B_S, \neg M) + pr(A_S, \neg B_S, \neg M)p_{AB} + pr(\neg A_S, B_S, \neg M) + pr(M)}$$

A necessary condition for these probabilities to be defined is that the denominator of the two expressions does not become zero. For this we need that each bank has some non-zero probability of experiencing an idiosyncratic shock or that there exists some common shock.

Further, given the decomposition, we immediately see that $p(B_T|A_T)-p(A_T|B_T)>0$ is equivalent to

$$\frac{(1-p_{BA})}{(1-p_{AB})}-\frac{pr(A_S,\neg B_S,\neg M)}{pr(\neg A_S,B_S,\neg M)}>0. \tag{7}$$

Condition (7) gives some idea about when the measure of contagious influence gives an accurate signal. The accuracy of the signal is inversely related to the ratio of the probabilities that that bank A or bank B is hit by an idiosyncratic shock. Put differently, if those probabilities are approximately equal, then the measure identifies contagion accurately. Unfortunately, the measure may also understate or overstate true contagion, if the difference in the probability of experiencing an idiosyncratic shock is large. For example, suppose in reality there is no contagion (i.e. $p_{BA}=p_{AB}=0$), but bank B has a much higher probability of experiencing an idiosyncratic shock compared to bank A (i.e. if $pr(\neg A_S, B_S, \neg M) >> pr(A_S, \neg B_S, \neg M)$). Condition (7) tells us that in this case, the measure may suggest contagion, even though there is none. Conversely, suppose in reality there is contagion. If bank A is very likely to experience an idiosyncratic shock (i.e. if $pr(\neg A_S, B_S, \neg M) << pr(A_S, \neg B_S, \neg M)$), then the measure tends to understate true contagion.[15]

In order to illustrate the intuition behind equation (5) consider the example given in Figure 2. In Case 1, there are five periods. In period 1 we observe that both banks are in the tail of the distribution of *Δdd* and in period 2, we see only bank B in the tail. This means that in period 2 bank B experienced an idiosyncratic shock. If we assume that the probabilities of experiencing an idiosyncratic shock are equal across the two banks then the two banks should have an equal number of realisations of the idiosyncratic shock on average.[16] This means the presence of bank A in the tail in period 1 must be the realisation of an idiosyncratic shock. In turn this implies that there was contagion from bank A to bank B. Hence, the approach uses the information contained both in the realisation of idiosyncratic as well as common shocks. Now consider Case 2. The only change involves period 3, in which both banks again are present in the tail. As before, we observe that Bank B has a realisation of an idiosyncratic shock in period 2. Again, this suggests that bank A must have experienced an idiosyncratic shock either in period 1 or in period 3, which was transmitted through contagion to bank B. Why does $\Omega_{A/B}$ decline from 0.5 in Case 1 to 0.33 in Case 2? The reason is that we have information, which may suggest that the contagious influence from bank A to bank B may be smaller. We know that there is contagion from bank A to bank B either in period 1 or 3. But we do not know what happened in the other period. Suppose there was contagion in period 1.

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[15] In fact, given our assumption that the system is "open", $pr(A_s \neg B_s, \neg M)$ is composed of the probability of being his of an idiosyncratic shock plus the probability of experiencing contagion from some "outside" bank $i \neq B$. Hence, a somewhat less stringent requirement for $\Omega_{A/B}$ to give a correct signal is that the two components be perfectly negatively correlated. If this is violated, holding the probability of experiencing an idiosyncratic shock constant, the measure will understate contagion from banks with a lot of outside contagion to banks with little outside contagion. This means that the measure understates contagion from banks, which themselves experience a lot of contagion to banks which do not and may overstate contagion from banks, which do not experience "outside" contagion to those that do.

[16] Of course this is not necessarily true over five periods as in this example. In the actual data, there are around 600 periods.

In period 3, there was either the realisation of the common shock or each of the banks experienced an idiosyncratic shock. This means that the probability of contagion from A to B may be lower (but must not be lower), hence the lower $\Omega_{A/B}$. In Case 3, bank B experiences one additional realisation of the idiosyncratic shock in period 4. Again this provides additional information. Under the assumption that both banks have an equal number of realisations of the idiosyncratic shock, in the two periods when both banks are in the tail must be due to bank A experiencing an idiosyncratic shock and transmitting it to bank B. The reason is that we know, if bank B shows two realisations of the idiosyncratic shock, bank A must too. In the final Case 4, we cannot distinguish the case of a common shock affecting both banks in periods 1 and 3 from the possibility that in one period bank A transmitting its idiosyncratic shock to bank B and in another the contagion goes the other way. Hence, $\Omega_{A/B}$ shows no "net contagious influence."

This discussion has highlighted that the accurateness of the contagious influence measure proposed depends on the difference between the probability of each bank to be hit by an idiosyncratic shock. The example shows that if this probability is not equal, the signal given by $\Omega_{A/B}$ is not informative. This probability of an idiosyncratic shock is unobservable. One solution to this problem may be to attempt to control for the difference between the two probabilities through some bank characteristic, which may be related to the likelihood of experiencing an idiosyncratic shock. The problem is that the variable should also be orthogonal to the likelihood of being subject to contagion. In this paper, we use the size of the bank as measured in total assets as a candidate variable. We view size as a summary variable of the different business mix of large banks compared to small banks, which in turn tends to expose them to different shocks. For example, large banks may have only very little exposure to the small business sector, while small banks may conduct a majority of their business there. Similarly, large banks exposure to the stock market or to foreign exchange markets may be much larger than the one of small banks.[17] Hence we estimate

$$\Omega_{A/B} = \beta_0 + \beta_1 \left[\frac{S_A}{S_B} \right] + \varepsilon_2 \, , \tag{8}$$

where S_I represents an indicator of the size of bank I (see below). We then calculate the "adjusted" measure of net-contagious influence as the residuals of equation (8), i.e.

$$\Omega^*_{A/B} = \Omega_{A/B} - \hat{\beta}_1 \left[\frac{S_A}{S_B} \right] - \hat{\beta}_0 \, . \tag{9}$$

To calculate S, we assign each bank a quartile ranking for size in each sample year (i.e. a ranking from 1 to 4, with one being "smallest" and four being "largest"). Hence, $\frac{S_A}{S_B}$ can potentially vary from 0.25 to 4.

As $\Omega^*_{A/B}$ is a time invariant measure, we use simple averages over the ten-year sample period of the bank characteristics. Put differently, we assign a quartile ranking in each year and then take an average of this

17 Obviously, larger banks may also be better diversified compared to small banks and, hence, less likely to be subject to contagion.

ranking. As the dependent variable exists for each bank pair in the sample, with 67 banks, the sample size is 67!/(65!-2!)=2211 observations.

Equation (8) is estimated separately for the log-differenced distance to default[18] and the abnormal returns. In addition, we estimate equation (8) separately for negative and positive tails, and for both tails. The estimated coefficients are reported in Table 10. Before we discuss them, we should clarify that we have no particular prior about the sign of $\hat{\beta}_1$. If size is positively correlated with being exposed to idiosyncratic risk, because larger banks have a greater exposure to volatile asset markets (especially if they take significant unhedged positions), we would see a positive coefficient. If the diversification effect dominates, we should see a negative coefficient. Table 10 shows that the estimated $\hat{\beta}_1$ is indeed positive and significant at the 1 percent level in 5 of the 6 specifications. Only for negative tails of abnormal returns, we find no significance. Note also, however, that while we explain between 24 and 35 percent of the variation in $\Omega^*_{A/B}$ for log-differenced distances to default, equation (6) only explains very little of the variation in $\Omega^*_{A/B}$ for abnormal returns.

Next, we examine the obtained results for $\Omega^*_{A/B}$ for the two measures of bank risk. The Spearman rank correlation coefficient is 0.17 for positive tails, 0.09 for negative tails and 0.16 for both tails. Independence can be rejected at any significance level. While this is encouraging, the correlation coefficients are quite low and it may be instructive to examine whether the method yields consistent signals across the measures of bank risk regarding which banks may be of particular systemic importance. We use the term "systemic importance" here in the sense that banks with systemic importance are banks which tend have net-contagious influence on other banks.

5. Systemic banks

5.1 Within country systemic banks

We define a bank *i* as having systemic importance within country y if

$$\Phi_i^{within} = \sum_{j \in Y} \Omega^*_{i/j} > 0$$

This simply suggests that if the sum of the net contagious influence of a bank with respect to its peers in the same country is positive, it may have systemic importance for the banking system as a whole. We report results for Φ_i^{within}>0.1, in order to eliminate contagious influence that is very close to zero[19]. The

[18] We report the results only for the log differences of the distance to default and not the results for the first differences of the distances to default, since we saw in the simulations that both measures yield essentially equivalent patterns of co-exceedances.

[19] See table 11 for the statistics of the measure. The threshold of Φ_i^{within}>0.1 does not imply any claim about significance of the results. Merely, we want to exclude those banks whose contagious influence is very close to zero.

results for this exercise are given in Table 12. Note that we can only identify systemically important banks in countries, where the sample contains more than one bank and that in countries where the sample only contains two very large banks, we tend to not to be able to detect significant contagious influence.[20] This excludes Belgium and in Austria, Denmark, Finland and Greece we are unable to identify systemically important banks. In the table, we rank banks within countries, i.e. the bank listed first has the largest net-contagious influence within a country. A first result is that there seems to be little difference between considering negative versus positive tails or both tails jointly, but noticeable differences across the two measures of bank risk (log-differenced distance to default and abnormal returns). Contagion, as measured here, appears to be symmetric for negative and positive shocks. This finding will largely carry through to cross-border contagion considered below.

Now consider the banks that one would have expected to have systemic importance judging simply from their size in the country. These banks include Deutsche Bank and HVB (DE), and BBVA (ES). In addition, while not the largest banks in the country, it is no surprise to find National Westminster Bank, and HSBC (both UK) in this group, as well as Sanpaolo IMI, Unicredito (both IT), Svenska Handelsbanken (SE) and ING (NL). These results are largely unaffected whether we consider the log-differenced distance to default or abnormal returns. However, there a number of important exceptions to this consistency. One, using the log-differenced distance to default, we identify Dresdner Bank as systemically important in Germany, BNP Paribas in France and a number of UK banks including Bank of Scotland and Abbey National. Using abnormal returns, we no longer identify these banks and instead IKB (DE), Societe Generale (FR) and Royal Bank of Scotland appear. We explain these inconsistencies across the log-differenced distance to default and abnormal returns by their differences. An increase in stock price volatility associated with an increase in the stock price will result in an unambiguously positive abnormal return, while the effect is ambiguous on the distance to default. This is so because the distance to default is declining in asset price volatility. Hence, the observed differences can very likely be explained by differences in the type of shocks (rather than their frequency) that the banks experienced.

There are a number of additional surprises, mainly relating to Portuguese, Italian and Spanish banks. In Portugal, instead of the largest bank in the country, Banco Comercial Portugues, Banco Espirito Santo is identified, which is considerably smaller. The most surprising findings emerge for Italy and Spain. In Spain, while BBVA and Banco Santander do appear in the table, neither is consistently identified as systemically important, although they are by far the largest banks in Spain. Instead, we identify some of the smallest banks in our sample: Banco Popular Espaniol (1/10 the size of Banco Santander), Banco Guipuzcoano (1/60 of Banco Santander) and Banco Zaragozano (1/60 of Banco Santander). Similarly in Italy, while Sanpaolo IMI is consistently identified and somewhat less consistently Unicredito, Banca Intesa, the largest bank in Italy, does not appear at all. Instead, the method identifies a number of very small banks as having contagious influence within Italy.

What can explain these surprising findings? Recall that the measure employed crucially depends on the equality of the probability of being hit by an idiosyncratic shock. We used differences in size to proxy for

[20] Essentially we need at least some banks that are exposed to contagious influence.

this, but it appears from these results that the proxy is insufficient. Hence, below we will also report results limited to the largest banks in the sample.

5.2 Across country systemic banks

Analogously to identifying within country systemically important banks, we can also identify systemically important banks for the sample countries as a whole. We define a bank *i* as systemically important for banks in country *Z* if

$$\Phi_i^{across} = \sum_{k \in Z} \Omega_{i/k}^* > 0 \qquad Z \neq Y$$

Hence, this section attempts to identify banks that can be considered systemically important in the EU as a whole. The results are summarised in Table 13, where we –as before- only report the banks with Φ_i^{across} >0.1.[21] Let us start with the expected. Deutsche Bank (#1 by total assets), Dresdner Bank (#6), ABN Amro (#4), ING (#9), National Westminster Bank (#12), Danske Bank (#19) and HSBC (#15) are all consistently identified as systemically important for the banks in the sample outside of their own country. In addition, there is evidence that HBV (#2), BNP Paribas (#3), Banco Santander (#10) and BBVA (#14) have some systemic importance, but the evidence is less clear. On the other hand, we have surprises among the included as well as the omitted banks. Among the included banks, we find IKB (DE, #42), Allied Irish Banks (#30) and Bank of Ireland (#31, both IE), BPI (PT, #49) and some very small Spanish and Italian banks to have contagious influence. The notable omissions include Barclays (UK, #5), Societe Generale (FR, #7) and Banca Intesa (IT, #11).

In order to ascertain to which extent this is due to insufficiently controlling for the likelihood of idiosyncratic shocks, we redid the analysis, considering only banks above EUR 50 billion in total assets (the 33 largest banks of the sample, see Table 3). The idea is that these banks may be more similar in terms of their probability of experiencing an idiosyncratic shock. This exercise also addresses the question of how sensitive the results are to the sample composition, i.e. whether or not a specific bank is included. In addition, of course, the limitation gives an idea of contagion among the largest banks only, which may be of independent interest. Table 14 shows that the results are quite robust. By definition, the smallest banks no longer appear in the table, but those that do appear tend to be identical to those when using the full sample.

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[21] The list of banks would have been longer, of course, if we had reported all banks with Φ_i^{across} > 0 (for the statistics on this measure, see Table 11). While we do not make any claims about statistical significance, by using this nonzero threshold, we exclude banks whose contagious influence is essentially zero. Note that the number of banks differs somewhat, as banks in the same country do not enter Φ_i^{across}. Hence for KBC the sum

$\sum_{k \in Z} \Omega_{i/k}$ contains 66 items (KBC is the only Belgian bank in the sample), while for Italian banks it contains 50 items, i.e. 67 total – 17 Italian banks.

It is clear that even banks with small or even negative Φ_i^{across} may exercise some net contagious influence on some banks. We will examine this in more detail below.

The approach summarised here, which consists of unweighted sums, may hide considerable bilateral links among banks. For example, a bank would be found not to have any contagious influence based on Φ_i^{within} and Φ_i^{across}, if, for example, it had a strong contagious influence on one bank, but was subject to an equally strong contagious influence from another bank. In order to address this issue, we prepared Table 15, which lists the number of banks that have contagious influence on at least three other banks. We are considering "strong" contagious influence only; that is the upper 10 percent tail of the distribution of $\Omega^*_{A/B}$. We report the results for cross-border contagion only. Comparing these results to those in Table 13, the main finding is that there is somewhat more consistency across the rows of the table. Fundamentally, however, Tables 13 and 15 exhibit surprising consistency.

Finally, the data easily lend themselves to the preparation of "contagion charts", in which the links among the banking systems in different countries are graphically represented (Figures 3-7). We have limited ourselves to showing the map for the largest five European countries. A thin arrow on the figure indicates that there is some contagious influence from the banks in one country to another. A thick arrow indicates that there is some contagious influence from the banks in one country on a bank that was identified as systemically important within its own country in Table 12. The figures show how closely linked banking systems of different countries are. For example, the link between German and UK banks seems to be quite strong, as the banks in each country tend to have contagious influence on the systemically important banks in the other. But there are also unidirectional links among countries. Considering the German chart once more, Danish and Irish banks have contagious influence upon German banks, but not vice versa. How should this be interpreted? Clearly the converse of contagious influence as described in this paper must be some sort of exposure to risks in the other banking system (abstracting from pure contagion). Hence, the thick arrow from Ireland to Germany in Figure 3 suggests that German banks are substantially exposed to the Irish banking system. This exposure could manifest itself through direct exposures, i.e. in the money market, in exposures through the payment system, ownership links and potential direct exposures to non-financial sectors in the country. It would go beyond the scope of this paper to explore the exact nature of these links, however; rather, we view these maps as a basis for further research into the underlying fundamentals for these links.

6. Conclusions

This paper analyses bank contagion in a sample of 67 EU banks for the period 1991-2003. The methodology employed builds upon previous work on financial market contagion (Bae et al., 2003). First, we analyse the properties of three weekly indicators: the simple first difference of the distance to default (measuring absolute shocks), the log-differenced distance to default (percentage shocks) and, as a robustness check, abnormal returns. Monte Carlo simulations show that the patterns observed in the tails of the data, regardless of the measure used, are inconsistent with standard multivariate Normal or student t distributions, suggesting substantial non-linearities. Based on this finding the paper proposes a simple non-parametric measure of what is labelled "net contagious influence". We show that this measure may be able to accurately measure contagion among any bank pair, as long as the probabilities of an idiosyncratic shock hitting the two banks are quite similar. We control for differences in these probabilities by adjusting our measure for bank size, arguing that bank size may pick up important differences in the business mix of banks.

We use the measure to identify banks, which have systemic importance within countries and across countries. While the results seem quite sensible for most countries, in Italy and Spain, the measure seems to suggest that an unreasonable number of very small banks have systemic importance. We argue that the reason for this uncomfortable finding may be that Italian and Spanish small banks have a particularly low probability of experiencing an idiosyncratic shock and hence our measure overstates contagion of these banks with respect to other banks. Overall, the paper shows that there may be tight links among banks within countries, as well as links connecting the major banking systems in Europe. We do not detect a major difference between the strength of links among euro area versus non-euro area countries.

We view the paper as a first step towards devising market based indicators of how vulnerable banks and banking systems may be to contagion. The measure of contagion suggested in this paper has the advantage of being able to identify the direction of contagious influence among banks, although only on a "net" basis. The results presented in the paper may provide a basis to obtain a better understanding of the extent to which European banking systems have become interconnected and how banking problems could spread across borders. The paper, however, is a purely statistical exercise and to explain the patterns obtained in this paper with fundamentals remains an important avenue for future research.

Appendix A. Results from a one factor market model

Results from estimating equation (4) in the text. Dependent variable is the log return of bank *i* in week *t*, the independent variable is the log return of the market portfolio (broad market indices) of country c, in which the bank has its headquarters.

	$\alpha 0$		$\alpha 1$			R-squared
	Coefficient	Standard error	Coefficient	Standard error	T-value	
1 Bank Austria	0.093	0.187	0.867	0.095	9.135	0.164
2 Creditanstalt	-0.065	0.172	1.095	0.066	16.687	0.402
3 KBC Bank	0.078	0.102	1.194	0.045	26.274	0.504
4 Bankgesellschaft Berlin	-0.249	0.177	0.727	0.066	11.021	0.152
5 Bayerische Hypo- und Vereinsbank	-0.090	0.138	1.208	0.051	23.474	0.448
6 BHF-BANK	0.109	0.127	0.563	0.049	11.489	0.168
7 Commerzbank	-0.148	0.123	1.191	0.046	26.057	0.500
8 DePfa Group	0.096	0.149	0.601	0.056	10.761	0.158
9 Deutsche Bank AG	-0.046	0.100	1.194	0.037	32.197	0.604
10 Dresdner Bank, AG	0.045	0.119	0.903	0.047	19.231	0.362
11 IKB Deutsche Industriebank	-0.010	0.086	0.417	0.032	13.099	0.202
12 Danske Bank	0.068	0.103	0.952	0.045	21.132	0.397
13 Jyske Bank	0.068	0.110	0.632	0.048	13.193	0.204
14 Banco Bilbao Vizcaya Argentaria	0.022	0.101	1.337	0.034	38.805	0.689
15 Banco Espanol de Credito	-0.249	0.219	0.781	0.075	10.477	0.139
16 Banco Guipuzcoano	0.101	0.088	0.221	0.030	7.381	0.074
17 Banco Pastor	0.131	0.115	0.426	0.039	10.840	0.148
18 Banco Popular Espanol	0.154	0.111	0.821	0.038	21.751	0.411
19 Banco Santander Central Hispano	-0.016	0.110	1.335	0.038	35.501	0.650
20 Banco Zaragozano	0.044	0.126	0.465	0.043	10.814	0.147
21 Okobank	0.046	0.164	0.184	0.034	5.345	0.042
22 Sampo Leonia	-0.021	0.233	0.581	0.050	11.617	0.166
23 BNP Paribas	-0.008	0.169	1.209	0.059	20.665	0.470
24 CPR	-0.139	0.181	0.618	0.071	8.750	0.116
25 Natexis Banques Populaires	-0.068	0.143	0.659	0.052	12.692	0.192
26 Societe Generale	0.035	0.141	1.276	0.051	24.916	0.478
27 Alpha Bank	0.059	0.124	1.024	0.026	40.083	0.703
28 Commercial Bank of Greece	-0.028	0.156	1.258	0.032	38.989	0.691
29 Allied Irish Banks	0.052	0.106	1.172	0.041	28.707	0.548
30 Anglo Irish Bankcorp	0.183	0.147	0.805	0.057	14.231	0.230
31 Bank of Ireland	0.122	0.102	1.181	0.039	29.910	0.569
32 Banca Agricola Mantovana	0.081	0.104	0.325	0.031	10.408	0.138
33 Banca Intesa	0.048	0.172	0.998	0.051	19.435	0.357
34 Banca di Roma	-0.249	0.172	1.203	0.051	23.392	0.446
35 Banca Lombarda	0.121	0.118	0.342	0.035	9.739	0.123
36 Banca Pop Bergamo	0.063	0.112	0.498	0.033	14.882	0.246
37 Banca Popolare Commercio e Industria	-0.046	0.133	0.533	0.040	13.347	0.208
38 Banca Popolare di Intra	0.125	0.118	0.410	0.035	11.596	0.165
39 Banca Popolare di Lodi	-0.028	0.134	0.502	0.040	12.492	0.187
40 Banca Popolare di Milano	-0.066	0.150	0.782	0.045	17.438	0.309
41 Banca Popolare di Verona	-0.018	0.157	0.610	0.047	12.987	0.199
42 Banco di Desio e della Brianza	0.134	0.197	0.455	0.058	7.841	0.133
43 Banco di Napoli	-0.160	0.311	0.697	0.091	7.638	0.101
44 Credito Emiliano	-0.068	0.202	0.724	0.061	11.961	0.174
45 Credito Valtellinese	0.014	0.100	0.400	0.030	13.425	0.210
46 Rolo Banca 1473	0.128	0.165	0.763	0.048	15.865	0.307
47 Sanpaolo IMI	-0.106	0.157	0.986	0.046	21.590	0.454
48 UniCredito Italiano	0.086	0.151	1.142	0.045	25.315	0.486
49 ABN AMRO Bank N.V.	0.027	0.110	1.259	0.044	28.923	0.565
50 ING Bank NV	-0.003	0.110	1.455	0.043	33.668	0.647
51 Kas-Associatie N.V.	0.148	0.141	0.512	0.057	8.990	0.106
52 Banco Comercial Portugues	-0.010	0.104	1.008	0.044	22.723	0.432
53 Banco Espirito Santo	0.090	0.112	0.903	0.046	19.688	0.420
54 Banco Totta e Acores	0.080	0.124	0.675	0.053	12.846	0.196
55 BPI-SGPS	-0.015	0.150	1.259	0.064	19.780	0.366
56 Skandinaviska Enskilda Banken	-0.033	0.259	0.897	0.075	11.979	0.174
57 Svenska Handelsbanken	0.149	0.190	0.653	0.055	11.936	0.173
58 Abbey National plc	0.051	0.136	1.150	0.062	18.592	0.337
59 Bank of Scotland	0.115	0.154	1.421	0.075	18.995	0.384
60 Barclays	0.070	0.132	1.423	0.060	23.639	0.451
61 Close Brothers	0.166	0.159	0.798	0.072	11.018	0.152
62 National Westminster Bank	-0.063	0.161	1.531	0.080	19.180	0.415
63 Schroders	0.103	0.159	1.081	0.072	15.002	0.249
64 Singer & Friedlander Group	0.060	0.155	0.622	0.071	8.827	0.103
65 Standard Chartered	0.116	0.164	1.575	0.075	21.079	0.396
66 HSBC	0.190	0.142	1.487	0.064	23.300	0.498
67 Royal Bank of Scotland	0.174	0.143	1.445	0.065	22.237	0.421
Average	**0.028**	**0.145**	**0.887**	**0.052**	**18.015**	**0.320**

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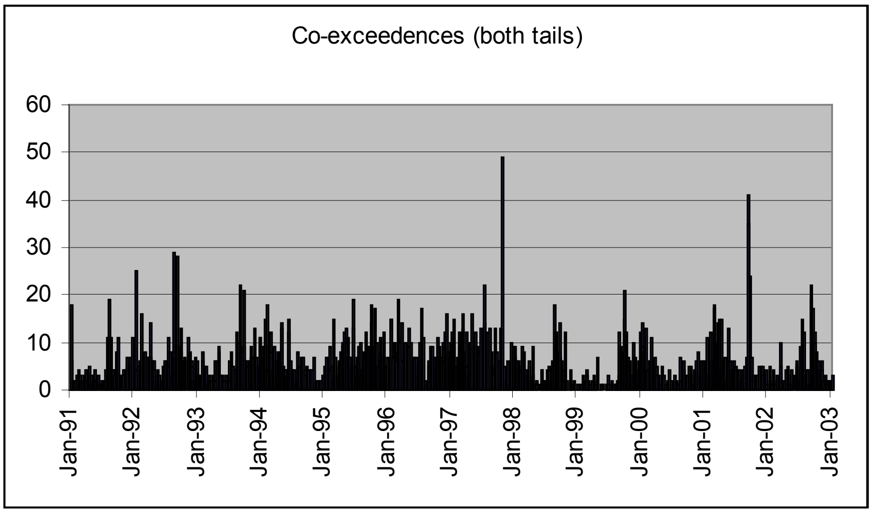
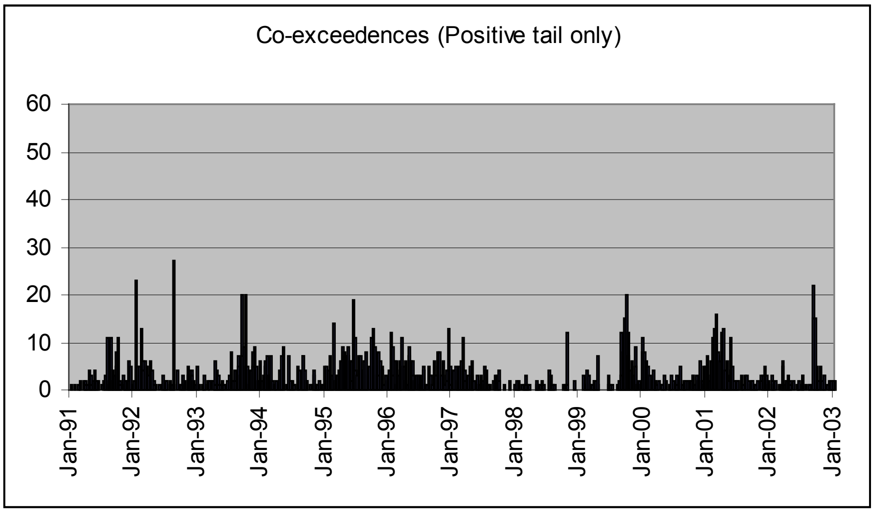
Figure 1. Histogram of the tail events

This figure shows the number of tail events per week in *ln(Δdd)*. The tail is defined as the 5% largest (positive tail) and smallest (negative tail) observations of the distribution of *ln(Δdd)*. Panel A shows the histogram of both tails simultaneously. Panel B and panel C represent the number of tail events in the positive and negative tail respectively.

Panel A



Panel B



Panel C

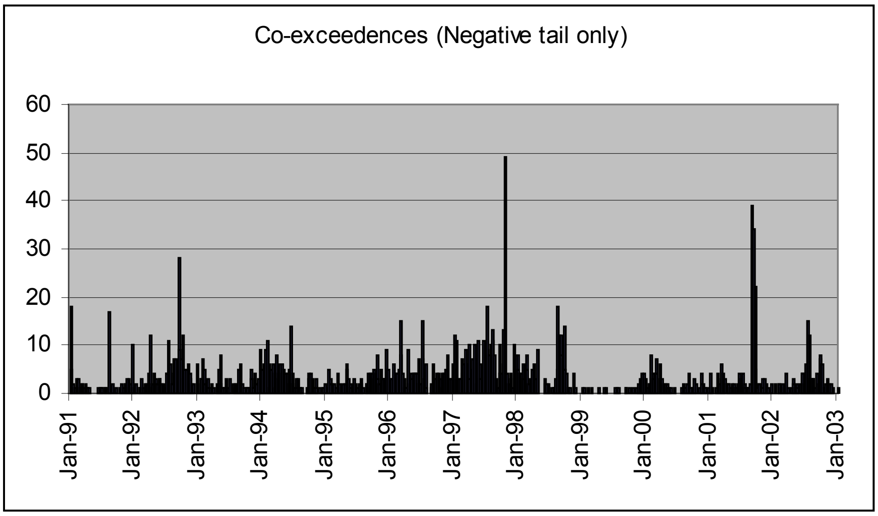


Figure 2. A simple example

Case 1

Period	Bank A		Bank B
1	*	→	*
2			*
3			
4			
5			

	Bank A	Bank B
Pr(x in tail)	0.20	0.40
Pr(A and B in tail)	0.20	0.20

Omega 0.50

Case 2

Period	Bank A		Bank B
1	*	→	*
2			*
3	*		*
4			
5			

	Bank A	Bank B
Pr(x in tail)	0.40	0.60
Pr(A and B in tail)	0.40	0.40

Omega 0.33

Case 3

Period	Bank A		Bank B
1	*	→	*
2			*
3	*		*
4			*
5			

	Bank A	Bank B
Pr(x in tail)	0.40	0.80
Pr(A and B in tail)	0.40	0.40

Omega 0.50

Case 4

Period	Bank A		Bank B
1	*	←	*
2			*
3	*	→	*
4	*		
5			

	Bank A	Bank B
Pr(x in tail)	0.60	0.60
Pr(A and B in tail)	0.40	0.40

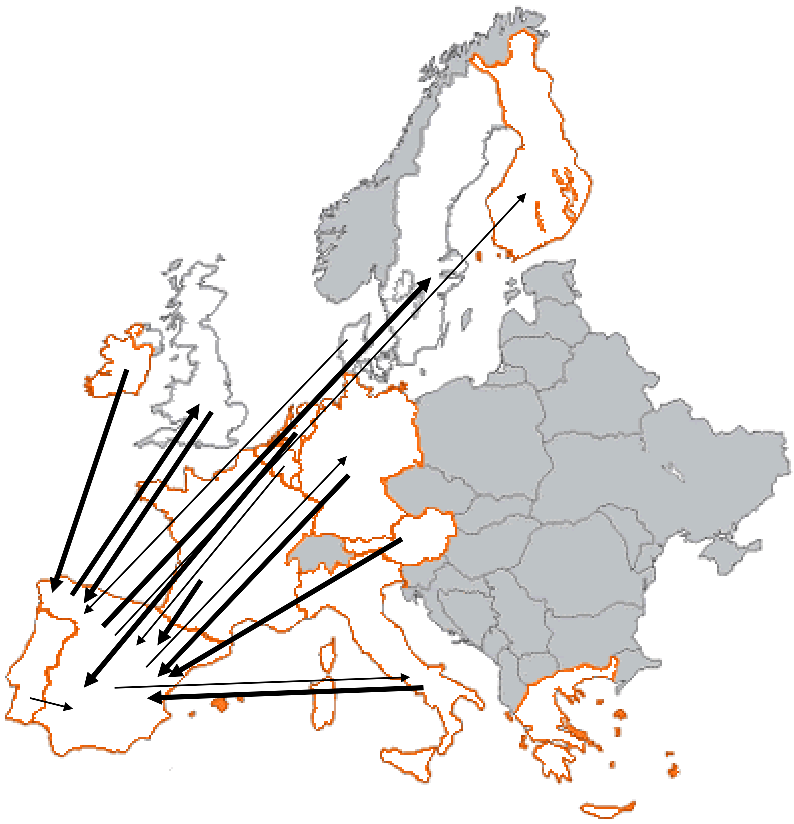
Omega 0.00

* denotes a tail event. x=A,B.

Figure 3. Cross-border contagious influence: Germany

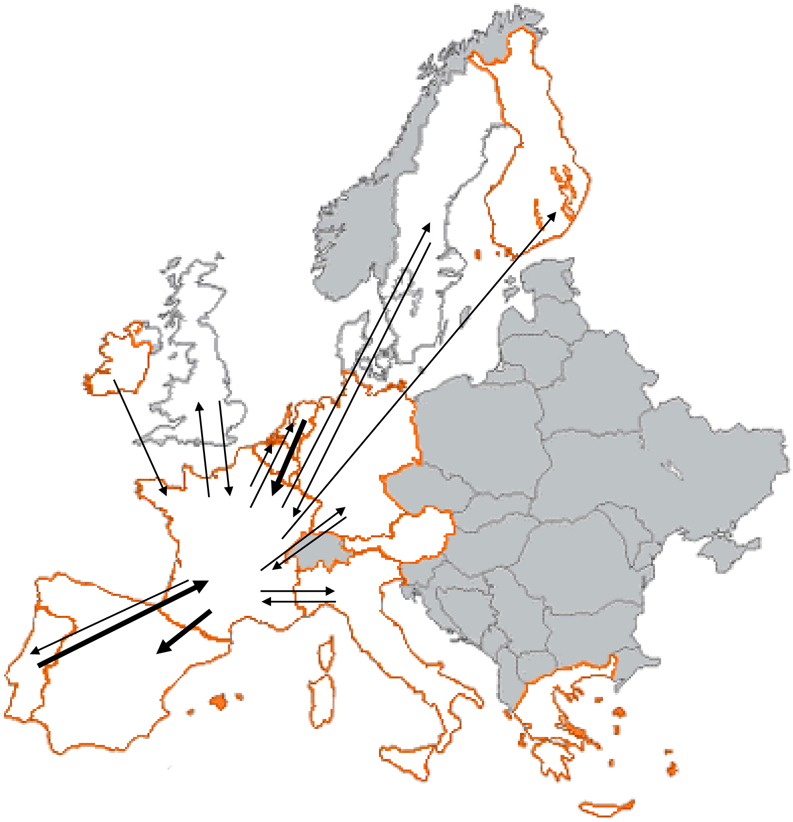
Thin arrow: Banks in country A have some contagious influence to at least one bank in country B.
Thick arrow: Banks in country A have contagious influence to a bank in country B with within country systemic importance.

Figure 4. Cross-border contagious influence: Spain



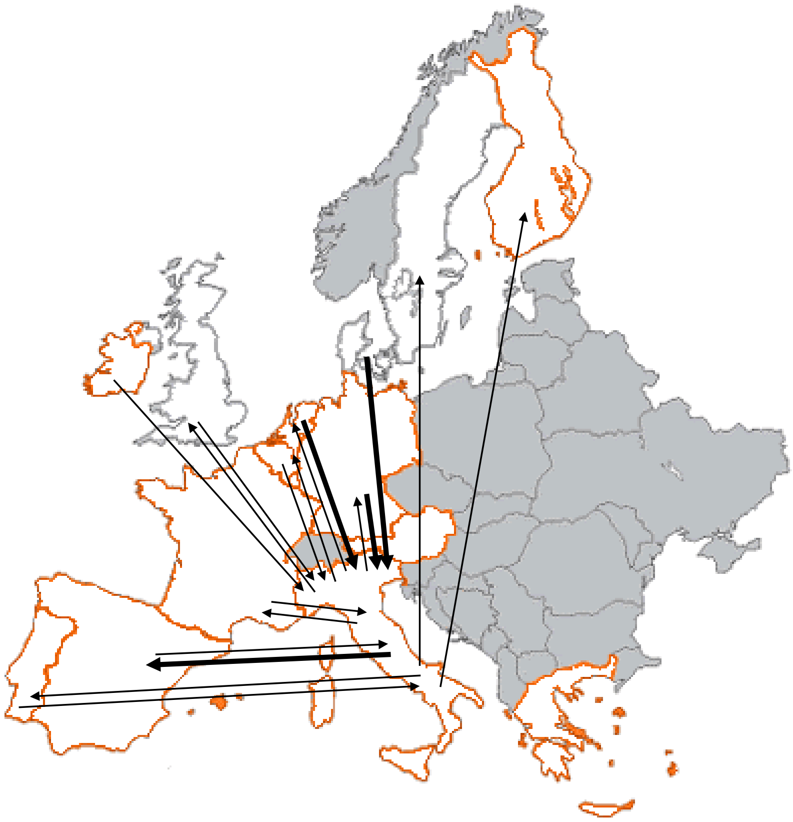
Thin arrow: Banks in country A have some contagious influence to at least one bank in country B.
Thick arrow: Banks in country A have contagious influence to a bank in country B with within country systemic importance.

Figure 5. Cross-border contagious influence: France



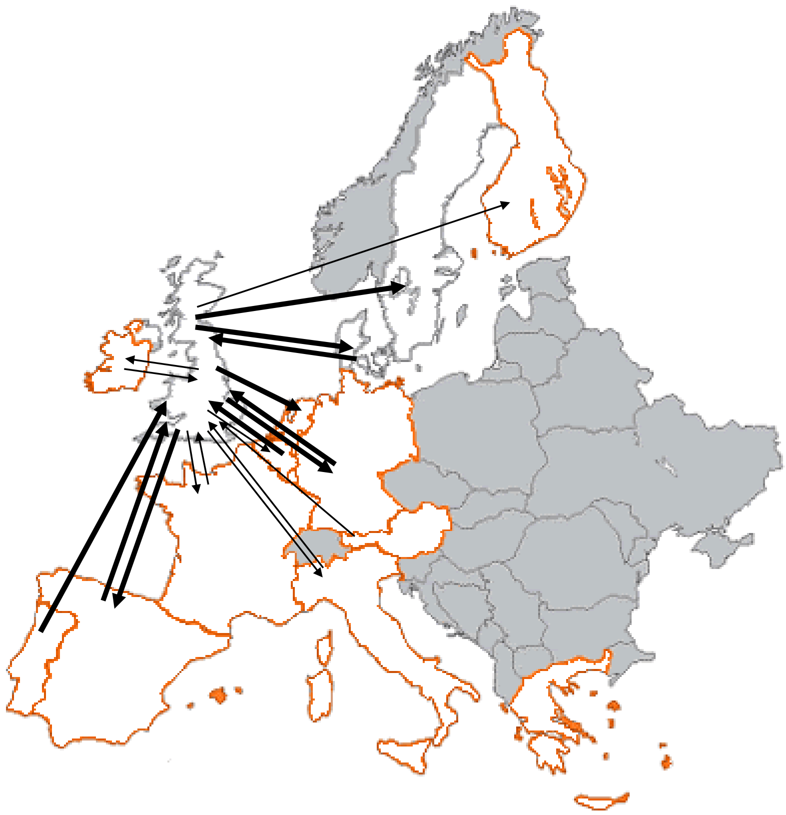
Thin arrow: Banks in country A have some contagious influence to at least one bank in country B.
Thick arrow: Banks in country A have contagious influence to a bank in country B with within country systemic importance.

Figure 6. Cross-border contagious influence: Italy



Thin arrow: Banks in country A have some contagious influence to at least one bank in country B.
Thick arrow: Banks in country A have contagious influence to a bank in country B with within country systemic importance.

Figure 7. Cross-border contagious influence: UK



Thin arrow: Banks in country A have some contagious influence to at least one bank in country B.
Thick arrow: Banks in country A have contagious influence to a bank in country B with within country systemic importance.

Table 1. Descriptive statistics of the distances to default

	Mean	Minimum	Maximum	Standard deviation
Distance to default	4.03	-0.29	17.11	1.88
Log-differenced DD	-0.0003	-1.47	1.25	0.031
Total assets (in billions of euro)	152.0	2.8	927.9	198.5
Number of observations	576	351	628	77.0
Number of tail observations	60.1	20	125	28.6

Table 2. Sample composition and coverage by country

Country	Number of banks	Percentage of total assets of commercial banks
Austria	2	35.3%
Belgium	1	22.7%
Germany	8	55.4%
Denmark	2	85.3%
Spain	7	68.3%
Finland	2	43.5%
France	4	36.2%
Greece	2	33.4%
Ireland	3	44.0%
Italy	17	59.5%
The Netherlands	3	58.9%
Portugal	4	53.7%
Sweden	2	79.2%
United Kingdom	10	72.8%
Total	67	53.9% 1/

1/ Total assets of banks in the sample divided by total assets of commercial banks of all countries.

Table 3. Sample banks (sorted by total assets in 2000, millions of euro)

1	**Deutsche Bank AG**	**DE**	**927,900**
2	Bayerische Hypo- und Vereinsbank		694,300
3	**BNP Paribas**	**FR**	**693,053**
4	**ABN AMRO Bank N.V.**	**NL**	**543,200**
5	**Barclays**	**UK**	**486,936**
6	Dresdner Bank, AG		482,600
7	Societe Generale		455,881
8	Commerzbank		454,500
9	ING Bank NV		406,393
10	**Banco Santander Central Hispano**	**ES**	**347,288**
11	**Banca Intesa**	**IT**	**331,364**
12	National Westminster Bank		294,695
13	Abbey National		293,395
14	Banco Bilbao Vizcaya Argentaria		292,557
15	HSBC		288,339
16	Royal Bank of Scotland		206,176
17	Bankgesellschaft Berlin		203,534
18	UniCredito Italiano		202,649
19	**Danske Bank**	**DK**	**182,520**
20	**KBC Bank**	**BE**	**176,909**
21	Sanpaolo IMI		171,046
22	**Bank Austria**	**AT**	**164,669**
23	Standard Chartered		161,964
24	DePfa Group		156,446
25	Bank of Scotland		136,288
26	Banca di Roma		132,729
27	**Skandinaviska Enskilda Banken (SEB)**	**SE**	**118,261**
28	Natexis Banques Populaires		113,131
29	Svenska Handelsbanken		112,804
30	**Allied Irish Banks**	**IE**	**77,932**
31	Bank of Ireland		73,859
32	**Banco Comercial Portugues**	**PT**	**61,850**
33	BHF-BANK		53,863
34	Rolo Banca 1473		47,044
35	Banco Espanol de Credito		44,381
36	Banca Pop Bergamo		37,670
37	Banco di Napoli		34,361
38	Banca Popolare di Lodi		34,223
39	Creditanstalt		34,040
40	Banco Espirito Santo		33,862
41	**Sampo Leonia**	**FI**	**32,795**
42	IKB Deutsche Industriebank		32,359
43	Banco Popular Espanol		31,288
44	**Alpha Bank**	**GR**	**30,183**
45	Banca Popolare di Milano		28,282
46	Okobank		27,086
47	Banca Lombarda		26,816
48	Banco Totta e Acores		23,166
49	BPI-SGPS		21,906
50	Banca Popolare di Novara		20,959
51	Banca Popolare Commercio e Industria		20,911
52	Jyske Bank		17,044
53	Commercial Bank of Greece		16,164
54	Credito Emiliano		15,148
55	Anglo Irish Bankcorp		11,047
56	Banca Agricola Mantovana		10,190
57	Banco Pastor		9,404
58	CPR		8,616
59	Credito Valtellinese		7,416
60	Banco Guipuzcoano		5,518
61	Kas-Associatie N.V.		5,417
62	Banco Zaragozano		5,175
63	Schroders		4,180
64	Banca Popolare di Intra		3,929
65	Close Brothers		3,241
66	Singer & Friedlander Group		2,792
67	Banco di Desio e della Brianza		2,776

Table 4. Summary statistics of (co-) exceedances for weekly log-differenced distance to defaults for EU banks

	Number of (co-) exceedances in the bottom tails							Number of (co-) exceedances in the top tails						
	>6	5	4	3	2	1	0	0	1	2	3	4	5	>6
DE (8 banks)	3	3	8	9	20	79	416	407	83	29	9	6	3	1
ES (7 banks)	1	1	5	11	29	98	483	483	102	22	12	7	2	0
FR (3 banks)	-	-	-	2	15	29	384	382	34	11	3	-	-	-
IE (3 banks)	-	-	-	7	15	43	563	555	56	13	4	-	-	-
IT (10 banks)	5	3	5	10	36	114	403	411	105	27	18	8	2	5
NL (3 banks)	-	-	-	3	11	40	418	417	46	2	7	-	-	-
PT (4 banks)	-	-	3	7	9	46	420	412	56	11	5	1	-	-
UK (7 banks)	0	6	1	6	33	102	480	477	109	25	10	6	0	1

Table 5. Summary statistics of (co-) exceedances for weekly log-differenced distance defaults for EU banks, cross country evidence

In parenthesis the number of banks in each country. Co-exceedances are defined such that at least one bank from each country is in the tail. Hence zero co-exceedances means that many banks in one country can be in the tail simultaneously. The Number of observations may differ across country groups, as they are determined by the bank with the least number of observations available. Only concurrent samples for banks were used.

	Number of (co-) exceedances in the bottom tails							Number of (co-) exceedances in the top tails						
	>6	5	4	3	2	1	0	0	1	2	3	4	5	>6
ES-UK (7,7)	5	1	6	10	30		576	581		24	11	5	7	0
ES-DE (7,8)	10	6	9	8	7		498	494		11	10	9	4	10
ES-FR (7,3)	3	3	4	5	7		408	412		7	2	4	02	3
ES-IT (7,10)	8	2	4	18	24		520	512		24	12	8	9	11
DE-UK (8,7)	9	2	9	6	8		504	489		16	14	9	6	4
DE-FR (8,3)	5	2	2	4	5		384	380		9	5	2	5	1
DE-IT (8,10)	10	3	8	9	15		493	483		22	12	5	5	11
FR-UK (3,7)	4	1	4	3	4		414	410		7	7	3	2	1
FR-IT (3,10)	5	1	4	6	6		408	406		11	1	3	4	5
UK-IT (7,10)	10	3	6	12	19		526	522		22	7	11	5	9

Table 6. Monte Carlo Simulations of co-exceedances of weekly logdifferenced distance to defaults for EU banks

Reported are the mean number of co-exceedances under the different distributional assumptions, given the actual covariance matrix. Figures in bold denote that equality can be rejected at the 5 percent confidence level.

	Number of (co-) exceedances in the bottom tails							Number of (co-) exceedances in the top tails						
	>6	5	4	3	2	1	0	0	1	2	3	4	5	>6
DE (8 banks)	*3*	*3*	*8*	*9*	*20*	*79*	*416*	*407*	*83*	*29*	*9*	*6*	*3*	*1*
Normal	**0.70**	1.48	**3.52**	7.93	26.29	**112.78**	**385.29**	**385.62**	**112.32**	26.43	7.85	3.50	1.60	0.69
Student t(5)	3.31	4.26	7.26	11.43	22.66	**63.94**	425.14	**424.97**	**64.21**	22.56	11.53	7.17	4.22	3.34
Student t(10)	2.22	3.63	6.57	11.52	24.14	73.71	416.21	416.32	73.63	24.06	11.59	6.51	3.63	2.27
ES (7 banks)	*1*	*1*	*5*	*11*	*29*	*98*	*483*	*483*	*102*	*22*	*12*	*7*	*2*	*0*
Normal	**0.00**	**0.01**	**0.08**	**0.95**	**16.68**	**183.43**	**426.85**	**426.04**	**184.84**	16.25	**0.81**	**0.05**	**0.00**	0.00
Student t(5)	0.55	1.64	4.93	12.35	30.33	91.00	487.20	487.14	90.99	**30.50**	12.29	4.86	1.68	0.54
Student t(10)	0.23	0.99	3.72	10.91	30.68	104.67	476.80	477.10	104.16	**30.90**	10.86	3.67	1.07	0.24
FR (3 banks)	-	-	-	*2*	*15*	*29*	*384*	*382*	*34*	*11*	*3*	-	-	-
Normal				0.94	11.22	**39.72**	**378.11**	377.69	41.68	9.57	1.06			
Student t(5)				2.32	11.07	35.90	380.71	381.34	35.56	10.85	2.25			
Student t(10)				1.74	10.45	**38.90**	**378.92**	379.71	38.24	10.41	1.65			
IE (3 banks)	-	-	-	*7*	*15*	*43*	*563*	*555*	*56*	*13*	*4*	-	-	-
Normal				**1.66**	11.76	**65.51**	**549.08**	**549.17**	65.43	11.65	1.76			
Student t(5)				**3.41**	14.91	**53.96**	**555.73**	555.54	54.28	14.82	3.36			
Student t(10)				**2.44**	14.02	**58.62**	**552.91**	553.16	58.26	14.01	2.57			
IT (10 banks)	*5*	*3*	*5*	*10*	*36*	*114*	*403*	*411*	*105*	*27*	*18*	*8*	*2*	*5*
Normal	**0.16**	**0.54**	2.21	9.40	41.15	**164.97**	**357.59**	**356.62**	**166.14**	**41.32**	**9.22**	**2.09**	0.48	**0.13**
Student t(5)	2.90	3.85	7.99	**16.62**	36.28	**95.47**	412.89	413.26	95.10	**36.25**	16.53	8.06	3.87	2.93
Student t(10)	**1.54**	2.79	6.73	15.82	38.92	111.97	398.24	**397.78**	112.62	**39.04**	15.51	6.70	2.78	**1.58**
NL (3 banks)	-	-	-	*3*	*11*	*40*	*418*	*417*	*46*	*2*	*7*			
Normal				1.05	6.89	**54.06**	**410.00**	**407.57**	**58.58**	5.11	**0.73**			
Student t(5)				2.58	11.81	39.63	417.98	418.06	39.37	**12.06**	**2.5**			
Student t(10)				1.78	11.32	43.04	415.87	415.90	43.03	**11.25**	**1.82**			
PT (4 banks)	-	-	*3*	*7*	*9*	*46*	*420*	*412*	*56*	*11*	*5*	*1*	-	-
Normal			0.11	**1.08**	7.41	**78.51**	**397.89**	**396.83**	**80.48**	**6.66**	**0.94**	0.10		
Student t(5)			**0.77**	4.17	14.10	53.21	**412.75**	413.04	52.79	14.11	4.24	0.82		
Student t(10)			**0.49**	**3.34**	13.44	**58.14**	**409.59**	409.69	57.97	13.48	3.40	0.47		
UK (8 banks)	*0*	*6*	*1*	*6*	*33*	*102*	*480*	*477*	*109*	*25*	*10*	*6*	*0*	*1*
Normal	0.04	**0.18**	0.85	4.40	28.79	**144.69**	**449.05**	**450.86**	**142.12**	28.77	**4.96**	**1.00**	0.24	**0.04**
Student t(5)	0.84	**2.28**	**5.78**	**12.43**	28.96	**85.19**	**492.54**	**492.31**	**85.42**	28.97	12.62	5.60	2.25	0.83
Student t(10)	0.39	**1.52**	4.54	**11.32**	29.87	98.14	482.22	482.90	97.14	30.00	11.40	4.62	1.50	0.43

Table 6a. Monte Carlo Simulations of co-exceedances of weekly first differenced distance to defaults for EU banks

Reported are the mean number of co-exceedances under the different distributional assumptions, given the actual covariance matrix. Figures in bold denote that equality can be rejected at the 5 percent confidence level.

	Number of (co-) exceedances in the bottom tails							Number of (co-) exceedances in the top tails						
	>6	5	4	3	2	1	0	0	1	2	3	4	5	>6
DE (8 banks)	*4*	*1*	*5*	*18*	*17*	*77*	*416*	*402*	*93*	*26*	*8*	*4*	*2*	*3*
Normal	**0.78**	2.29	5.09	**10.82**	**24.88**	**96.20**	**397.95**	395.78	99.45	24.47	10.47	4.89	2.13	**0.81**
Student t(5)	3.74	**4.51**	7.34	**11.24**	21.47	**62.55**	**427.15**	**427.78**	**61.92**	21.41	11.14	7.32	4.54	3.89
Student t(10)	2.72	4.02	7.00	**11.24**	22.70	70.57	419.75	**419.70**	**70.63**	22.69	11.22	7.06	4.00	2.71
ES (7 banks)	*1*	*0*	*3*	*9*	*26*	*123*	*466*	*478*	*107*	*26*	*8*	*8*	*1*	*0*
Normal	**0.00**	0.00	**0.01**	**0.67**	**18.91**	**180.15**	**428.27**	**428.40**	**179.90**	**19.02**	**0.67**	**0.02**	**0.00**	0.00
Student t(5)	0.35	1.47	4.51	11.91	30.55	**95.85**	**483.46**	483.30	96.12	30.48	11.69	4.61	1.44	0.36
Student t(10)	0.12	0.81	3.17	10.39	30.50	110.40	472.61	472.38	110.78	30.44	10.24	**3.30**	0.73	0.13
FR (3 banks)	-	-	-	*3*	*9*	*38*	*380*	*378*	*40*	*11*	*1*	-	-	-
Normal				0.97	7.21	**47.67**	**374.15**	**372.95**	**50.89**	**5.38**	0.79			
Student t(5)				1.99	10.76	37.51	379.74	380.29	37.38	10.36	1.97			
Student t(10)				1.50	10.04	40.42	378.04	378.67	40.16	9.69	1.49			
IE (3 banks)	-	-	-	*7*	*14*	*45*	*562*	*553*	*59*	*13*	*3*	-	-	-
Normal				**1.40**	14.96	**59.87**	**551.77**	551.82	59.80	14.94	1.44			
Student t(5)				3.63	15.03	53.07	556.58	556.49	52.74	15.04	3.73			
Student t(10)				**2.89**	14.23	**56.86**	**554.02**	553.77	57.24	14.21	2.78			
IT (10 banks)	*4*	*4*	*3*	*12*	*39*	*114*	*400*	*398*	*115*	*38*	*12*	*7*	*3*	*3*
Normal	**0.00**	**0.00**	**0.05**	**2.66**	38.78	**202.24**	**332.26**	**332.88**	**201.02**	39.38	**2.68**	**0.05**	**0.00**	**0.00**
Student t(5)	2.49	3.76	**7.94**	16.50	37.00	**97.69**	410.60	**410.42**	**98.06**	36.91	16.49	7.83	3.71	2.58
Student t(10)	**1.30**	2.53	6.27	15.61	39.59	115.99	394.71	394.88	115.77	39.62	15.54	6.35	2.56	1.28
NL (3 banks)	-	-	-	*1*	*13*	*42*	*416*	*417*	*44*	*6*	*5*	-	-	-
Normal				0.56	**4.76**	**59.81**	**406.87**	**405.093**	**63.22**	3.28	**0.41**			
Student t(5)				1.99	11.28	42.47	416.26	416.21	42.60	**11.17**	**2.02**			
Student t(10)				1.47	10.66	45.30	414.59	414.29	45.85	**10.44**	**1.43**			
PT (4 banks)	-	-	*2*	*5*	*11*	*52*	*415*	*409*	*61*	*10*	*4*	*1*	-	-
Normal			**0.08**	**1.13**	9.59	**74.12**	**400.08**	**399.58**	**74.96**	9.40	**0.99**	0.07		
Student t(5)			0.62	3.87	14.07	54.80	411.65	411.47	55.10	14.04	3.78	0.62		
Student t(10)			0.37	2.81	13.22	60.65	**407.95**	407.98	60.65	13.15	2.85	0.38		
UK (8 banks)	*1*	*1*	*5*	*2*	*29*	*125*	*465*	*467*	*124*	*24*	*8*	*3*	*1*	*1*
Normal	**0.00**	**0.00**	**0.02**	1.12	22.69	**171.21**	**432.97**	**433.61**	**170.06**	23.07	**1.25**	**0.01**	**0.00**	**0.00**
Student t(5)	0.66	1.96	5.37	**12.32**	29.47	**88.79**	**489.44**	**489.88**	**88.15**	29.49	12.46	5.39	1.99	0.66
Student t(10)	0.32	1.28	4.10	**11.19**	30.13	**101.41**	**479.57**	**479.51**	**101.55**	30.02	11.20	4.17	1.24	0.32

Table 6b. Monte Carlo Simulations of co-exceedances of weekly abnormal returns for EU banks

Reported are the mean number of co-exceedances under the different distributional assumptions, given the actual covariance matrix. Figures in bold denote that equality can be rejected at the 5 percent confidence level.

	Number of (co-) exceedances in the bottom tails							Number of (co-) exceedances in the top tails						
	>6	5	4	3	2	1	0	0	1	2	3	4	5	>6
DE (8 banks)	*0*	*2*	*2*	*13*	*32*	*115*	*426*	*428*	*107*	*43*	*7*	*4*	*0*	*1*
Normal	0.02	**0.21**	1.21	**6.48**	32.30	**145.95**	**403.83**	**404.40**	**144.84**	**32.82**	6.50	**1.22**	0.20	**0.03**
Student t(5)	0.70	1.78	4.94	12.89	33.34	**97.63**	**438.72**	**439.24**	96.85	**33.55**	**12.78**	5.04	1.88	0.67
Student t(10)	0.25	0.97	3.48	11.05	34.14	114.24	425.87	426.41	113.38	34.34	11.11	3.52	0.99	0.26
ES (7 banks)	*0*	*0*	*3*	*9*	*41*	*117*	*511*	*504*	*125*	*44*	*7*	*1*	*0*	*0*
Normal	0.00	0.02	**0.27**	**3.18**	**27.81**	**171.71**	**478.03**	**477.58**	**172.36**	**27.81**	**2.99**	0.24	0.02	0.00
Student t(5)	0.13	0.73	3.05	10.99	35.64	117.11	513.35	513.39	116.92	35.79	11.05	3.05	0.68	0.13
Student t(10)	0.03	0.28	1.62	8.18	35.02	**135.34**	**500.52**	500.04	136.12	**34.91**	8.02	1.61	0.28	0.03
FR (3 banks)	-	-	-	*1*	*14*	*41*	*427*	*429*	*39*	*12*	*3*	-	-	-
Normal				0.64	9.50	**51.07**	**421.79**	**422.13**	50.46	9.69	**0.72**			
Student t(5)				1.80	11.05	44.50	425.65	426.17	43.51	11.48	1.85			
Student t(10)				1.30	10.34	47.42	423.94	424.06	47.10	10.61	1.23			
IE (3 banks)	-	-	-	*0*	*13*	*76*	*592*	*588*	*85*	*7*	*1*	-	-	-
Normal				0.37	**6.40**	**88.11**	**586.13**	586.28	87.83	6.51	0.39			
Student t(5)				1.59	12.78	71.67	594.96	**594.93**	**71.67**	**12.88**	1.52			
Student t(10)				0.96	11.00	77.13	591.92	591.71	77.50	10.88	0.91			
IT (10 banks)	*4*	*5*	*4*	*6*	*48*	*161*	*453*	*455*	*164*	*34*	*16*	*5*	*3*	*4*
Normal	**0.10**	**0.55**	2.75	**13.04**	52.88	**181.78**	**429.91**	**430.42**	181.12	**52.76**	13.20	2.90	**0.51**	**0.11**
Student t(5)	2.60	4.02	**8.93**	**19.99**	45.36	**117.58**	**482.52**	**482.68**	**117.15**	**45.68**	19.88	9.03	4.00	2.58
Student t(10)	**1.19**	2.48	7.02	**18.64**	48.81	**139.50**	463.38	463.26	**139.48**	**49.15**	18.51	6.93	2.49	**1.18**
NL (3 banks)	-	-	-	*1*	*15*	*60*	*544*	*533*	*82*	*4*	*1*	-	-	-
Normal				0.20	**5.43**	**81.54**	**532.83**	532.65	81.91	5.24	0.20			
Student t(5)				1.04	11.30	67.29	540.37	**540.26**	**67.50**	**11.22**	1.02			
Student t(10)				0.55	**9.70**	**71.94**	537.81	537.52	**72.52**	**9.41**	0.56			
PT (4 banks)	-	-	*0*	*0*	*10*	*61*	*332*	*337*	*54*	*9*	*3*	*0*	-	-
Normal			0.01	0.36	6.53	66.83	329.27	**329.28**	**66.79**	6.60	**0.33**	0.01		
Student t(5)			0.12	1.41	10.17	55.93	335.36	335.62	55.52	10.25	1.47	0.14		
Student t(10)			0.05	0.84	8.60	61.08	332.43	332.35	61.27	8.47	0.87	0.05		
UK (8 banks)	*0*	*0*	*3*	*13*	*31*	*125*	*509*	*507*	*128*	*33*	*9*	*3*	*1*	*0*
Normal	0.01	0.08	0.77	**5.51**	32.93	**152.08**	**489.62**	**489.85**	**151.71**	32.96	5.63	**0.76**	0.08	0.01
Student t(5)	0.21	0.98	3.61	11.78	35.53	110.95	517.94	**517.65**	**111.53**	35.53	11.74	3.52	0.98	0.22
Student t(10)	0.06	0.46	2.09	9.27	35.07	128.99	505.06	504.99	129.03	35.08	9.31	2.12	0.41	0.06

Table 7. Descriptive Statistics for first differenced distance to default and abnormal returns

	Mean	Minimum	Maximum	Standard deviation
Δ Distance to default	-0.001	-3.97	6.69	0.15
Abnormal returns	0.000	-94.20	131.94	3.75
Number of observations	647	402	681	69.73
Number of tail observations	65	20	153	30.7

Table 8. Monte Carlo Simulations of co-exceedances of weekly logdifferenced distance to defaults for EU banks, cross–country evidence

Reported are the mean number of co-exceedances under the different distributional assumptions, given the actual covariance matrix. In parenthesis the number of banks in each country simulated. Co-exceedances are defined such that at least one bank from each country is in the tail. Hence zero co-exceedances means that many banks in one country can be in the tail simultaneously. The Number of observations may differ across country groups, as they are determined by the bank with the least number of observations available. Only concurrent samples for banks were used. Figures in bold denote that equality can be rejected at the 5 percent confidence level.

	Number of (co-) exceedances in the bottom tails							Number of (co-) exceedances in the top tails						
	>6	5	4	3	2	1	0	0	1	2	3	4	5	>6
ES-UK (7,7)	*5*	*1*	*6*	*10*	*30*	-	*576*	*581*	-	*24*	*11*	*5*	*7*	*0*
Normal	**0.22**	**0.72**	**2.92**	11.95	**34.72**		577.47	580.29		**32.48**	**11.48**	**2.84**	**0.67**	**0.23**
Student t(5)	9.80	7.32	11.21	16.21	20.35		**563.11**	**563.45**		20.25	**16.05**	11.17	7.33	9.76
Student t (10)	6.40	5.92	10.21	16.35	22.71		566.42	**566.23**		22.89	**16.35**	10.09	6.00	6.45
ES-DE (7,8)	*10*	*6*	*9*	*8*	*7*	-	*498*	*494*	-	*11*	*10*	*9*	*4*	*10*
Normal	**1.80**	**2.14**	**4.79**	12.96	**34.54**		**481.78**	**482.45**		**34.41**	13.03	**4.48**	2.01	**1.63**
Student t(5)	13.04	6.63	9.17	12.63	**15.50**		**481.04**	**480.75**		15.78	12.65	9.07	6.65	13.10
Student t (10)	9.76	5.96	8.96	13.02	**17.55**		**482.75**	**482.51**		17.68	13.11	8.80	6.06	9.86
ES-FR (7,3)	*3*	*3*	*4*	*5*	*7*	-	*408*	*412*	-	*7*	*2*	*4*	*2*	*3*
Normal	**0.14**	**0.33**	**0.77**	**1.50**	**2.50**		**424.76**	**426.48**		**1.84**	0.94	**0.52**	**0.17**	**0.06**
Student t(5)	2.86	3.18	5.28	7.53	9.17		401.98	**402.12**		9.16	**7.48**	5.24	3.18	2.82
Student t (10)	1.77	2.56	4.63	7.45	9.70		403.89	**403.72**		9.94	**7.44**	4.64	2.48	1.77
ES-IT (7,10)	*8*	*2*	*4*	*18*	*24*		*520*	*512*		*24*	*12*	*8*	*9*	*11*
Normal	**0.63**	1.58	5.48	19.35	**50.26**		**498.71**	**498.78**		**50.59**	**19.17**	5.46	**1.45**	**0.55**
Student t(5)	**13.60**	**8.27**	**12.27**	17.43	21.46		**502.97**	**502.67**		21.51	17.71	12.51	8.18	13.41
Student t (10)	8.97	**7.17**	**11.81**	18.45	24.72		**504.88**	504.68		24.65	18.80	11.78	7.25	8.84
DE-UK (8,7)	*9*	*2*	*9*	*6*	*8*		*504*	*489*		*16*	*14*	*9*	*6*	*4*
Normal	**2.20**	2.49	4.83	**12.39**	**25.77**		**490.32**	492.15		**24.45**	11.58	4.99	**2.53**	2.31
Student t(5)	11.54	**6.33**	8.45	11.42	14.37		**485.89**	486.29		14.27	11.41	8.30	6.01	**11.74**
Student t (10)	8.25	5.40	8.01	**11.83**	**15.76**		**488.76**	488.56		16.05	11.72	8.03	5.33	**8.31**
DE-FR (8,3)	*5*	*2*	*2*	*4*	*5*		*384*	*380*		*9*	*5*	*2*	*5*	*1*
Normal	**0.29**	**0.35**	0.71	1.42	2.12		**397.11**	**396.04**		**2.87**	**1.66**	0.82	**0.37**	0.26
Student t(5)	3.72	2.74	4.27	6.35	8.03		**376.90**	376.76		8.12	6.40	4.31	2.77	3.63
Student t (10)	2.48	2.29	3.76	6.21	8.54		378.71	378.76		8.58	6.09	3.77	2.31	2.49
DE-IT (8,10)	*10*	*3*	*8*	*9*	*15*		*493*	*483*		*22*	*12*	*5*	*5*	*11*
Normal	**3.95**	3.86	7.95	**17.51**	**34.30**		**470.44**	**470.76**		**33.71**	17.89	7.93	3.87	3.84
Student t(5)	**16.63**	**7.60**	10.26	13.85	16.25		**473.41**	**473.57**		16.17	13.76	10.21	7.68	**16.61**
Student t (10)	12.61	7.03	10.07	14.59	18.89		**474.83**	474.64		18.85	14.95	10.16	7.12	12.28
FR-UK (3,7)	*4*	*1*	*4*	*3*	*4*		*414*	*410*		*7*	*7*	*3*	*2*	*1*
Normal	**0.27**	0.67	1.88	4.65	7.44		415.09	**416.08**		7.33	4.13	1.63	0.59	0.26
Student t(5)	2.88	2.82	4.62	7.21	8.51		**403.96**	403.91		8.67	7.03	4.65	2.82	2.91
Student t (10)	1.74	2.14	4.14	6.95	8.99		**406.04**	405.94		9.10	6.92	4.13	2.22	1.70
FR-IT (3,10)	*5*	*1*	*4*	*6*	*6*		*408*	*406*		*11*	*1*	*3*	*4*	*5*
Normal	**0.23**	0.39	**0.82**	**1.89**	2.93		**423.74**	**414.94**		**2.53**	1.44	**0.62**	**0.27**	**0.20**
Student t(5)	4.78	3.33	5.11	7.42	8.86		**400.49**	400.73		8.69	**7.43**	5.01	3.48	4.67
Student t (10)	2.92	2.68	4.52	7.61	9.88		402.40	402.56		9.63	**7.62**	4.58	2.69	2.92
UK-IT (7,10)	*10*	*3*	*6*	*12*	*19*		*526*	*522*		*22*	*7*	*11*	*5*	*9*
Normal	**1.22**	2.30	6.28	17.00	**34.04**		**515.16**	517.70		**32.33**	**16.26**	**6.23**	2.26	**1.23**
Student t(5)	14.26	**8.31**	**12.15**	16.80	20.32		**504.17**	**504.17**		20.41	**16.91**	12.17	8.29	**14.05**
Student t (10)	9.76	7.34	11.83	18.18	23.50		**505.40**	**505.83**		23.42	**18.08**	11.66	7.51	9.50

Table 8a. Monte Carlo Simulations of co-exceedances of weekly first differenced distance to defaults for EU banks, cross–country evidence

Reported are the mean number of co-exceedances under the different distributional assumptions, given the actual covariance matrix. In parenthesis the number of banks in each country simulated. Co-exceedances are defined such that at least one bank from each country is in the tail. Hence zero co-exceedances means that many banks in one country can be in the tail simultaneously. The Number of observations may differ across country groups, as they are determined by the bank with the least number of observations available. Only concurrent samples for banks were used. Figures in bold denote that equality can be rejected at the 5 percent confidence level.

	Number of (co-) exceedances in the bottom tails							Number of (co-) exceedances in the top tails						
	>6	5	4	3	2	1	0	0	1	2	3	4	5	>6
ES-UK (7,7)	*5*	*1*	*6*	*10*	*30*	-	*576*	*581*	-	*24*	*11*	*5*	*7*	*0*
Normal	**0.01**	0.13	**1.42**	11.59	**46.36**		568.50	**570.61**		**44.42**	11.36	**1.46**	**0.13**	0.02
Student t(5)	8.88	**7.12**	11.07	**16.73**	21.88		**562.31**	**562.03**		22.00	16.95	**11.18**	6.96	**8.88**
Student t (10)	5.40	**5.63**	9.93	**16.79**	24.65		**565.60**	**565.62**		24.55	16.98	10.01	5.56	**5.28**
ES-DE (7,8)	*7*	*2*	*14*	*6*	*12*	-	*497*	*492*	-	*17*	*9*	*6*	*7*	*7*
Normal	**1.96**	2.59	**5.19**	**11.80**	**28.39**		488.08	487.29		**30.25**	11.70	4.85	**2.35**	**1.56**
Student t(5)	**12.52**	**6.38**	8.78	**12.39**	15.53		**482.41**	**482.67**		15.61	12.16	8.79	6.29	**12.47**
Student t (10)	9.36	5.69	**8.44**	**12.27**	17.52		**484.73**	484.86		17.34	12.55	8.32	5.66	9.27
ES-FR (7,3)	*2*	*1*	*1*	*3*	*14*	-	*409*	*420*	-	*5*	*2*	*1*	*0*	*2*
Normal	**0.00**	**0.00**	**0.01**	**0.04**	**0.19**		**429.76**	**429.69**		**0.24**	**0.06**	**0.01**	0.00	**0.00**
Student t(5)	2.04	2.69	**4.84**	**7.62**	9.96		**402.84**	**402.91**		10.01	**7.62**	**4.82**	2.59	2.04
Student t (10)	1.14	1.98	4.13	7.38	10.43		404.94	**405.17**		**10.44**	**7.28**	4.08	1.90	1.13
ES-IT (7,10)	*5*	*2*	*11*	*19*	*25*	-	*514*	*507*	-	*32*	*17*	*5*	*7*	*8*
Normal	**0.02**	**0.21**	**2.47**	17.95	**59.05**		**496.32**	**495.98**		**59.14**	18.18	2.48	**0.21**	**0.01**
Student t(5)	**12.48**	**8.19**	12.52	18.44	22.91		**501.46**	501.16		**22.98**	18.47	**12.80**	8.01	12.58
Student t (10)	7.95	**6.63**	11.82	19.29	26.55		**503.78**	503.36		26.51	19.43	**11.87**	6.98	7.85
DE-UK (8,7)	*6*	*4*	*5*	*11*	*11*	-	*501*	*489*	-	*22*	*13*	*7*	*4*	*3*
Normal	**2.10**	2.58	5.05	11.07	**24.70**		492.50	495.30		22.93	10.47	4.72	2.44	2.14
Student t(5)	**11.05**	5.80	7.97	11.00	13.84		**488.34**	488.48		**13.94**	10.93	7.89	5.86	**10.91**
Student t (10)	7.64	5.07	7.35	11.02	15.42		**491.49**	491.32		15.54	10.95	7.51	4.98	**7.71**
DE-FR (8,3)	*4*	*1*	*3*	*2*	*3*	-	*389*	*387*	-	*7*	*5*	*3*	*0*	*0*
Normal	**0.02**	**0.02**	**0.08**	**0.20**	**0.51**		**401.17**	**400.60**		**0.94**	**0.33**	**0.09**	0.03	0.02
Student t(5)	2.84	2.44	4.06	**6.35**	**8.45**		**377.86**	**377.91**		8.34	6.38	4.09	2.44	**2.84**
Student t (10)	1.65	1.90	3.42	5.98	**8.83**		**380.23**	**380.01**		9.02	5.97	3.44	1.89	1.68
DE-IT (8,10)	*9*	*2*	*7*	*12*	*11*	-	*497*	*483*	-	*23*	*9*	*12*	*4*	*7*
Normal	**2.03**	2.95	6.79	16.43	**33.21**		**476.59**	474.68		**34.61**	**17.00**	**6.84**	2.92	**1.96**
Student t(5)	**16.04**	**7.33**	9.86	13.18	15.59		**476.00**	475.94		15.78	12.94	9.99	7.18	**16.16**
Student t (10)	11.86	**6.69**	9.62	13.85	18.28		**477.71**	478.00		18.13	13.75	9.42	6.77	**11.93**
FR-UK (3,7)	*3*	*1*	*1*	*1*	*9*	-	*415*	*408*	-	*11*	*9*	*2*	*0*	*0*
Normal	**0.01**	0.06	0.34	1.64	**4.45**		**423.50**	**422.64**		**5.16**	**1.76**	**0.38**	0.05	0.01
Student t(5)	2.16	2.47	4.34	**7.18**	8.93		**404.92**	404.86		8.98	7.14	4.38	2.48	2.15
Student t (10)	1.12	1.74	3.65	**6.71**	9.68		**407.09**	407.34		9.57	6.66	3.50	1.73	1.21
FR-IT (3,10)	*4*	*0*	*4*	*4*	*11*	-	*407*	*410*	-	*8*	*3*	*3*	*3*	*3*
Normal	**0.00**	0.00	**0.02**	**0.10**	**0.31**		**429.57**	**429.50**		**0.36**	**0.11**	**0.02**	**0.00**	**0.00**
Student t(5)	4.26	**3.14**	5.16	7.79	9.42		400.23	**400.78**		9.36	7.47	5.17	3.10	4.12
Student t (10)	2.45	2.42	4.40	7.68	10.42		402.64	**402.75**		10.27	**7.64**	4.44	2.44	2.46
UK-IT (7,10)	*6*	*4*	*8*	*15*	*29*	-	*514*	*514*	-	*27*	*22*	*5*	*4*	*4*
Normal	**0.03**	**0.27**	**2.82**	15.93	**42.28**		514.67	520.01		**38.03**	**14.87**	2.76	**0.29**	**0.04**
Student t(5)	**12.84**	8.12	12.08	17.45	**20.98**		**504.54**	**504.56**		21.12	17.21	**12.18**	8.07	**12.87**
Student t (10)	8.28	6.99	11.44	18.24	24.63		506.43	506.67		24.55	18.26	**11.53**	6.88	8.11

Table 8b. Monte Carlo Simulations of co-exceedances of weekly abnormal returns for EU banks, cross–country evidence

Reported are the mean number of co-exceedances under the different distributional assumptions, given the actual covariance matrix. In parenthesis the number of banks in each country simulated. Co-exceedances are defined such that at least one bank from each country is in the tail. Hence zero co-exceedances means that many banks in one country can be in the tail simultaneously. The Number of observations may differ across country groups, as they are determined by the bank with the least number of observations available. Only concurrent samples for banks were used. Figures in bold denote that equality can be rejected at the 5 percent confidence level.

	Number of (co-) exceedances in the bottom tails							Number of (co-) exceedances in the top tails						
	>6	5	4	3	2	1	0	0	1	2	3	4	5	>6
ES-UK (7,7)	*5*	*1*	*6*	*10*	*30*	-	*576*	*581*	-	*24*	*11*	*5*	*7*	*0*
Normal	**0.18**	**0.83**	3.74	14.03	**36.38**		625.84	**625.55**		**36.64**	14.17	**3.71**	**0.78**	0.17
Student t(5)	5.31	6.48	**12.39**	21.57	28.51		**606.74**	**606.76**		**28.58**	21.45	12.31	6.62	**5.29**
Student t (10)	2.16	4.09	9.83	20.42	**32.51**		**611.99**	**611.68**		**32.73**	20.66	9.80	3.94	2.19
ES-DE (7,8)	*5*	*5*	*5*	*16*	*19*	-	*540*	*542*	-	*18*	*18*	*7*	*1*	*4*
Normal	**0.29**	**1.17**	4.74	16.21	**37.77**		**529.83**	**529.82**		**37.83**	16.14	4.70	1.17	**0.35**
Student t(5)	6.49	6.57	**11.52**	18.86	24.74		**521.83**	**522.32**		24.26	18.86	11.50	**6.59**	6.48
Student t (10)	3.03	4.33	9.57	18.69	**28.02**		**526.37**	**526.21**		**27.99**	18.74	9.57	4.50	3.01
ES-FR (7,3)	*2*	*2*	*2*	*9*	*10*	-	*458*	*457*	-	*11*	*11*	*3*	*1*	*0*
Normal	**0.03**	**0.21**	1.46	6.85	**17.41**		457.04	457.79		16.79	6.79	1.44	0.19	0.02
Student t(5)	1.11	2.00	4.67	9.28	12.45		453.49	455.39		11.58	8.40	4.52	2.02	1.09
Student t (10)	0.47	1.12	3.38	8.09	13.26		456.69	458.50		12.09	7.76	3.17	1.05	0.42
ES-IT (7,10)	*7*	*2*	*8*	*19*	*26*	-	*619*	*622*	-	*30*	*14*	*7*	*5*	*3*
Normal	**0.42**	1.52	5.77	18.41	**41.15**		613.73	614.05		**40.83**	18.29	5.84	**1.52**	**0.48**
Student t(5)	10.22	**8.65**	**14.62**	22.67	28.19		**596.66**	**596.72**		27.88	**22.63**	**14.75**	8.70	**10.33**
Student t (10)	4.94	**6.08**	12.40	23.05	33.24		**601.29**	**601.19**		33.54	**22.69**	12.41	6.18	4.98
DE-UK (8,7)	*4*	*9*	*9*	*15*	*36*		*517*	*535*	-	*25*	*15*	*8*	*4*	*3*
Normal	**0.56**	**1.68**	5.61	16.34	33.62		**532.19**	532.60		33.18	16.30	5.61	1.75	**0.57**
Student t(5)	7.16	6.82	11.88	18.71	**23.91**		521.52	**521.68**		23.42	18.93	11.93	6.79	7.25
Student t (10)	3.73	**4.92**	10.00	18.59	27.60		525.17	**525.20**		27.23	18.82	10.07	4.99	3.68
DE-FR (8,3)	*1*	*2*	*3*	*9*	*10*	-	*430*	*425*	-	*10*	*12*	*4*	*2*	*2*
Normal	0.23	0.73	2.51	7.67	15.49		428.37	427.998		15.44	7.92	2.59	0.82	**0.25**
Student t(5)	2.34	2.75	5.13	8.74	11.41		424.64	423.86		11.44	8.94	5.41	2.94	2.40
Student t (10)	1.20	1.92	4.12	8.05	12.50		427.21	426.55		12.32	8.43	4.45	2.01	1.24
DE-IT (8,10)	*10*	*2*	*3*	*21*	*27*	-	*527*	*531*	-	*28*	*12*	*5*	*6*	*8*
Normal	**1.05**	2.85	**7.61**	20.01	**37.15**		521.71	520.70		**37.75**	**19.96**	7.88	**2.66**	**1.06**
Student t(5)	12.25	**8.68**	**13.44**	19.48	23.43		**512.71**	**512.25**		23.76	**19.68**	**13.67**	8.68	11.96
Student t (10)	6.58	**6.92**	**12.35**	20.74	28.05		**515.37**	515.01		28.10	**20.80**	**12.56**	6.83	6.70
FR-UK (3,7)	*2*	*1*	*2*	*7*	*9*	-	*462*	*460*	-	*11*	*5*	*2*	*5*	*0*
Normal	**0.10**	0.45	1.85	5.95	12.26		462.39	462.58		12.09	5.93	1.85	**0.45**	0.10
Student t(5)	1.48	2.36	4.95	9.11	12.27		**452.82**	**452.95**		12.01	9.14	5.03	2.35	1.54
Student t (10)	0.67	1.42	3.70	8.18	13.39		455.63	456.03		12.79	8.28	3.74	**1.45**	0.71
FR-IT (3,10)	*4*	*1*	*2*	*6*	*8*	-	*462*	*459*	-	*4*	*12*	*2*	*3*	*3*
Normal	**0.38**	0.95	3.04	7.76	14.00		456.88	457.62		**13.37**	7.81	2.95	0.90	**0.36**
Student t(5)	3.72	3.40	5.76	9.02	11.24		**449.85**	451.76		**10.54**	8.51	5.32	3.26	3.61
Student t (10)	1.93	2.32	4.82	9.04	12.75		**452.15**	455.25		**11.25**	8.02	4.36	2.25	1.87
UK-IT (7,10)	*9*	*8*	*6*	*21*	*28*	-	*609*	*611*	-	*41*	*13*	*4*	*5*	*7*
Normal	**0.96**	**2.73**	8.76	23.82	**43.43**		601.29	601.33		43.54	**23.57**	8.76	2.84	**0.96**
Student t(5)	11.59	9.22	**14.78**	22.22	27.50		**595.69**	**595.78**		**27.41**	**22.68**	**14.69**	9.20	11.23
Student t (10)	5.95	6.76	**13.21**	23.53	32.25		599.30	**599.73**		32.32	**22.96**	**13.02**	6.90	6.06

Table 9. Summary statistics for Monte Carlo simulations

	Log-differenced distance to default	First differenced distance to default	Abnormal returns
Within country			
% rejections			
Bottom tails (total 45)			
Multivariate normal	62.2%	73.3%	55.5%
Student t (5)	28.9%	24.4%	13.3%
Student t (10)	26.7%	20.0%	15.6%
Top tails (total 45)			
Multivariate normal	57.7%	62.2%	44.4%
Student t (5)	17.8%	17.8%	31.1%
Student t (10)	13.3%	15.6%	13.3%
No rejection: # of countries (total 8)			
Bottom tails			
Multivariate normal	0	0	1
Student t (5)	3	4	6
Student t (10)	3	3	5
Top tails			
Multivariate normal	1	1	2
Student t (5)	3	4	3
Student t (10)	5	4	5
Both tails			
Multivariate normal	0	0	0
Student t (5)	1	3	3
Student t (10)	1	1	5
Across country pairs			
% rejections			
Bottom tails (total 60)			
Multivariate normal	61.7%	63.4%	36.7%
Student t (5)	30.0%	43.3%	25.0%
Student t (10)	18.3%	25.0%	20.0%
Top tails (total 60)			
Multivariate normal	61.7%	63.4%	35.0%
Student t (5)	21.7%	30.0%	30.0%
Student t (10)	15.0%	20.0%	23.3%
No rejection: # of country pairs (total 10)			
Bottom tails			
Multivariate normal	0	0	1
Student t (5)	1	0	2
Student t (10)	4	3	3
Top tails			
Multivariate normal	0	1	1
Student t (5)	2	2	2
Student t (10)	4	3	2
Both tails			
Multivariate normal	0	0	0
Student t (5)	0	0	2
Student t (10)	1	0	2

Table 10. Results from the estimation of equation (7): Adjusted net-contagious influence

Dependent variable	β_0	β_1	R^2	n
Log-differenced distance to default				
Positive tail	0.01*	0.03***	0.24	2211
	(0.006)	(0.001)		
Negative tail	0.076***	0.023***	0.28	2211
	(0.006)	(0.001)		
Both tails	0.043***	0.028***	0.35	2211
	(0.005)	(0.001)		
Abnormal returns				
Positive tail	0.023***	0.007***	0.02	2211
	(0.007)	(0.002)		
Negative tail	0.024**	0.002	0.01	2211
	(0.009)	(0.002)		
Both tails	0.02**	0.005***	0.01	2211
	(0.002)	(0.002)		

*,**, *** denotes significance at the 10, 5 and 1 percent levels, respectively. Coefficients for differences in sample size not reported.

Table 11. Statistics of the measure $\Omega^*_{i/j}$, Ω_i^{within} and Ω_i^{across}

This table presents the statistics for our measure used. For sake of brevity we only mention the statistics for the both tails simultaneously. The results for the negative and positive tail are similar for each measure.

Variable		mean	Standard deviation	minimum	maximum	Obs.	10% tail	5% tail
$\Omega^*_{i/j}$	ln(Δdd)	0.000	0.042	-0.292	0.172	2211	0.047	0.068
$\Omega^*_{i/j}$	abnormal returns	0.000	0.059	-0.303	0.239	2211	0.069	0.097
Ω_i^{within}	ln(Δdd)	0.000	0.309	-0.904	0.877	67	0.322	0.498
Ω_i^{within}	abnormal returns	0.000	0.549	-2.055	1.866	67	1.693	2.101
Ω_i^{across}	ln(Δdd)	0.000	1.488	-5.830	3.741	67	0.491	0.710
Ω_i^{across}	abnormal returns	0.000	2.177	-7.126	5.429	67	2.58	2.94

Table 12. Within country contagious influence

All banks with $\Phi_i^{within} > 0.1$. Within countries banks are ranked by the size of Φ_i^{within}.

Country	Log-differenced distance to default			Abnormal returns		
	Positive tail	**Negative tail**	**Both tails**	**Positive tail**	**Negative tail**	**Both tails**
Austria	None	None	None	None	None	None
Belgium	n.a. 1/	n.a. 1/	n.a. 1/	n.a. 1/	n.a. 1/	n.a. 1/
Germany	HVB Deutsche Bank Dresdner Bank	IKB Deutsche Bank	Deutsche Bank HVB Dresdner Bank	Deutsche Bank IKB	Deutsche Bank IKB BHF	Deutsche Bank IKB BHF
Denmark	None	None	None	None	None	None
Spain	Banco Zaragozano Banco Santander BBVA Banco Guipuzcoano	Banco Popular Espaniol Banco Pastor	Banco Popular Espaniol Banco Zaragozano Banco Guipuzcoano	Banco Guipuzcoano	Banco Guipuzcoano BBVA	Banco Guipuzcoano
Finland	None	None	None	None	None	None
France	BNP Paribas	CPR	BNP Paribas	None	Societe Generale	Societe Generale
Greece	None	None	None	None	None	None
Ireland	None	None	None	Bank of Ireland	Bank of Ireland	Bank of Ireland
Italy	Sanpaolo IMI Unicredito Banca Populare di Milano Banco Desio d. Br. Rolo Banca Banca Pop. Com. e Ind.	Sanpaolo IMI Rolo Banca Banca di Roma Banca Pop. D'Intra Banca Populare Bergamo Banco Desio d. Br.	Sanpaolo IMI Rolo Banca Unicredito Banca Pop. Di Milano Banco Desio d. Br. Banca di Roma Banca Populare Bergamo	Credito Valtellinese Banca Populare Bergamo Banco Desio d. Br. Banca Pop. Com. e Ind. Banca Agricola Mantovana Unicredito Sanpaolo IMI Banca Lombarda Rolo Banca	Credito Valtellinese Banca Agricola Mantovana Banca Lombarda Banca Populare Bergamo Banca Pop. Com. e Ind. Banco Desio d. Br. Sanpaolo IMI Rolo Banca Banca Pop. D'Intra	Credito Valtellinese Banca Populare Bergamo Banca Agricola Mantovana Banco Desio d. Br. Banca Pop. Com. e Ind. Banca Lombarda Sanpaolo IMI Rolo Banca
The Netherlands	ING	None	ING	None	ING	None
Portugal	None	Banco Espirito Santo BPI	None	Banco Espirito Santo	Banco Espirito Santo	Banco Espirito Santo
Sweden	Svenska Handelsbanken	Svenska Handelsbanken	Svenska Handelsbanken	None	Svenska Handelsbanken	Svenska Handelsbanken
United Kingdom	National Westminster Bank of Scotland Abbey National HSBC	National Westminster Bank of Scotland Abbey National HSBC Standard Chartered Royal Bank of Scotland	National Westminster Bank of Scotland Abbey National HSBC	National Westminster HSBC	HSBC National Westminster Royal Bank of Scotland	HSBC National Westminster

1/ There is only one bank from Belgium in the sample.

Table 13. Cross-country contagious influence

Only banks with Φ_i^{across} >0.1 listed.

Country	Log-differenced distance to default			Abnormal returns		
	Positive tail	Negative tail	Both tails	Positive tail	Negative tail	Both tails
Austria	None	Creditanstalt	None	None	Bank Austria	None
Belgium	None	None	None	KBC	KBC	KBC
Germany	Deutsche Bank HBV Dresdner Bank IKB	IKB Deutsche Bank	Deutsche Bank IKB HBV Dresdner Bank	Deutsche Bank IKB BHF Dresdner Bank	Deutsche Bank IKB BHF Dresdner Bank Commerzbank	Deutsche Bank IKB BHF Dresdner Bank Commerzbank
Denmark	Danske Bank Jyske Bank	Jyske Bank Danske Bank	Jyske Bank Danske Bank	Danske Bank Jyske Bank	Danske Bank Jyske Bank	Danske Bank Jyske Bank
Spain	Banco Guipuzcoano Banco Zaragozano	Banco Pop. Esp. Banco Pastor Banco Zaragozano Banco Guipuzcoano	Banco Pop. Esp. Banco Pastor Banco Zaragozano Banco Guipuzcoano	Banco Guipuzcoano BBVA Banco Santander Banco Pop. Esp. Banco Santander Banco Zaragozano Banco Pastor	BBVA Banco Guipuzcoano Banco Pastor Banco Pop. Esp. Banco Santander Banco Zaragozano	BBVA Banco Guipuzcoano Banco Pastor Banco Pop. Esp. Banco Santander Banco Zaragozano
Finland	Okobank	Okobank Sampo Leonia	Okobank	None	None	None
France	BNP Paribas CPR Natexis Banque Populaire	CPR Natexis Banque Populaire	CPR Natexis Banque Populaire BNP Paribas	None	None	None
Greece	None	Alpha Bank	None	Alpha Bank	None	Alpha Bank
Ireland	Allied Irish Bank Anglo Irish Bank Bank of Ireland	Allied Irish Bank Anglo Irish Bank Bank of Ireland	Allied Irish Bank Anglo Irish Bank Bank of Ireland	Allied Irish Bank Bank of Ireland	Allied Irish Bank Bank of Ireland	Allied Irish Bank Bank of Ireland
Italy	Banco Pop. Di Milano Sanpaolo IMI Unicredito Banca Agricola Mantovana	Rolo Banca Sanpaolo IMI Banca di Roma	Sanpaolo IMI Banca Pop. Di Milano Rolo Banca Credito Valtellinese	Credito Valtellinese Banca Agricola Mantovana Banca Pop. Bergamo Banca Com. E Indust. Banco Desio e della Brianza Banca Lombarda	Credito Valtellinese Banca Agricola Mantovana Banca Lombarda Banca Pop. Bergamo Banco Desio d. Br. Banca Pop. D'Intra	Credito Valtellinese Banca Agricola Mantovana Banca Lombarda Banca Pop. Bergamo Banco Desio d. Br. Banca Pop. D'Intra
The Netherlands	ING Kas Associatie ABN Amro	None	ING	ING ABN Amro	ING ABN Amro Kas Associatie	ING ABN Amro
Portugal	None	BPI Banco Espirito Santo	BPI	B. Comercial Port. Banco Espirito Santo BPI Banco Totta e Acor.	B. Comercial Port. Banco Espirito Santo BPI Banco Totta e Acor.	B. Comercial Port. Banco Espirito Santo BPI Banco Totta e Acor.
Sweden	Svenska Handelsbanken	Svenska Handelsbanken	Svenska Handelsbanken	None	None	None
United Kingdom	Abbey National Bank of Scotland National Westminster HSBC Royal Bank of Scotland Barclays Standard Chartered	Abbey National Royal Bank of Scotland National Westminster Barclays Standard Chartered HSBC Bank of Scotland	Abbey National HSBC Barclays Bank of Scotland Royal Bank of Scotland National Westminster Standard Chartered	National Westminster HSBC	National Westminster HSBC	HSBC National Westminster

Table 14. Cross country contagious influence
Banks with total assets of EUR 50 billion or more

Only banks with Φ_i^{across} >0.1 listed.

Country	Log-differenced distance to default			Abnormal returns		
	Positive tail	Negative tail	Both tails	Positive tail	Negative tail	Both tails
Austria (1)	None	None	None	None	Bank Austria	None
Belgium (1)	None	None	None	KBC	KBC	KBC
Germany (7)	Deutsche Bank Dresdner Bank HBV	Deutsche Bank	Deutsche Bank HBV Dresdner Bank	Deutsche Bank Dresdner Bank BHF	Deutsche Bank Dresdner Bank BHF Commerzbank	Deutsche Bank Dresdner Bank BHF
Denmark (1)	Danske Bank	Danske Bank	Danske Bank	Danske Bank	Danske Bank	Danske Bank
Spain (2)	None	None	None	BBVA Banco Santander	BBVA Banco Santander	BBVA Banco Santander
Finland (-)	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
France (3)	BNP Paribas Natexis Banque Populaire	Natexis Banque Populaire	Natexis Banque Populaire BNP Paribas	None	None	None
Greece (-)	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Ireland (2)	Allied Irish Bank Bank of Ireland	Allied Irish Bank Bank of Ireland	Allied Irish Bank Bank of Ireland	Allied Irish Bank Bank of Ireland	Allied Irish Bank Bank of Ireland	Allied Irish Bank Bank of Ireland
Italy (4)	Sanpaolo IMI Unicredito	Sanpaolo IMI Banca di Roma	Sanpaolo IMI	None	None	None
The Netherlands (2)	ING ABN Amro	None	ING	ING ABN Amro	ING ABN Amro	ING ABN Amro
Portugal (1)	None	None	None	B. Comercial Port.	B. Comercial Port.	B. Comercial Port.
Sweden (2)	Svenska Handelsbanken	None	Svenska Handelsbanken	None	None	None
United Kingdom (7)	Abbey National Bank of Scotland Barclays HSBC National Westminster Bank Royal Bank of Scotland	Abbey National Bank of Scotland Barclays HSBC National Westminster Bank Royal Bank of Scotland Standard Chartered	Abbey National Bank of Scotland Barclays HSBC National Westminster Bank Royal Bank of Scotland Standard Chartered	HSBC National Westminster B	HSBC National Westminster	HSBC National Westminster

Table 15. Cross country contagious influence

In parenthesis: Number of banks on which bank exercises "strong" contagious influence. "Strong" is defined as the upper 10 percent tail of $\Omega^*_{A/B}$. Only banks with contagious influence to at least three other banks are reported.

Country	Log-differenced distance to default			Abnormal returns		
	Positive tail	Negative tail	Both tails	Positive tail	Negative tail	Both tails
Austria		Creditanstalt (3)				
Belgium				KBC (10)		KBC (4)
Germany	HBV (11) Deutsche Bank (15) Dresdner Bank (7)	Deutsche Bank (4) IKB (6)	HBV (4) Deutsche Bank (10) Dresdner Bank (4)	Deutsche Bank (16) IKB (3)	BHF (3) Commerzbank (6) Deutsche Bank (10) Dresdner Bank (4) IKB (10)	BHF (3) Commerzbank (5) Deutsche Bank (14) Dresdner Bank (3) IKB (5)
Denmark		Jyske Bank (4)	Jyske Bank (3)	Danske Bank (11)	Danske Bank (12) Jyske Bank (9)	Danske Bank (12) Jyske Bank (4)
Spain	BBVA (3) Banco Pop. Espaniol (3) Banco Santander (3) Banco Zaragozano (3)	Banco Pastor (3) Banco Pop. Espaniol (8)	Banco Pop. Espaniol (3)	BBVA (5) Banco Guipuzcoano (6) Banco Pop. Espaniol (5) Banco Santander (4) Banco Zaragozano (4)	BBVA (8) Banco Pastor (3) Banco Santander (3)	BBVA (9) Banco Guipuzcoano (4) Banco Pastor (3) Banco Pop. Espaniol (3) Banco Santander (3)
Finland		Sampo Leonia (7)				
France	BNP Paribas (12) Natexis (3)		BNP Paribas (5)	BNP Paribas (3)		
Greece						
Ireland	Allied Irish Banks (6) Anglo Irish Bank (3) Bank of Ireland (4)	Allied Irish Banks (22) Anglo Irish Bank (7) Bank of Ireland (18)	Allied Irish Banks (20) Anglo Irish Bank (9) Bank of Ireland (8)	Allied Irish Banks (14) Bank of Ireland (6)		Allied Irish Banks (5)
Italy	Banca Intesa (3) Banca di Roma (3) Banca Pop. Di Milano (6) Banca Desio (6) Sanpaolo IMI (9) Unicredito (7)	Banca di Roma (6) Rolo Banca (8) Sanpaolo IMI (11) Unicredito (3)	Banca Desio (3) Rolo Banca (4) Sanpaolo IMI (12)	Banca Agricola Mantovana (7 Banca Pop. Bergamo (7) Banca Pop. Com. E Indust. (4 Banca Desio (6) Credito Valtellinese (12) Unicredito (3)	Banca Agricola Mantovana (9 Banca Lombarda (9) Banca Pop. Bergamo (10) Credito Valtellinese (17) Banca Desio (5) Sanpaolo IMI (3)	Banca Agricola Mantovana (6 Banca Pop. Bergamo (9) Banca Pop. Com. E Indust. (4 Banca Desio (6) Credito Valtellinese (16) Sanpaolo IMI (4)
The Netherlands	ING (8)	ING (4)	ING (7)	ABN Amro (3) ING (20)	ABN Amro (13) ING (24)	ABN Amro (7) ING (26)
Portugal		Banco Espirito Santo (7) BPI (7)	BPI (4)	Banco Com. Port. (16) Banco Espirito Santo (10)	Banco Com. Port. (10) Banco Espirito Santo (22)	Banco Com. Port. (12) Banco Espirito Santo (16)
Sweden						
United Kingdom	Abbey National (23) Bank of Scotland (16) Barclays (9) National Westminster (11) HSBC (10)	Abbey National (21) Bank of Scotland (7) Barclays (9) National Westminster (10) HSBC (8) Standard Chartered (5) Royal Bank of Scotland (16)	Abbey National (31) Bank of Scotland (15) Barclays (11) National Westminster (12) HSBC (10) Royal Bank of Scotland (7)	National Westminster (3) HSBC (14)		HSBC (6)

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