BANK CONTAGION IN EUROPE

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PRELIMINARY AND INCOMPLETE. COMMENTS WELCOME.

Abstract

This paper analyses contagion in a sample of European banks during 1996-2003. We use a multinomial logit model to estimate the number of banks in a given country that experience a large shock during the same period ("coexceedances") as a function of variables measuring common shocks and lagged coexceedances in other countries. Large shocks are measured by the bottom 95th percentile of the distribution of the first difference in the distance to default of the bank. Common shocks are modelled by extracting common factors from coexceedances, industry sector shocks and standard macro variables. We find significant cross-border contagion in the EU, but also some countries that seem to be completely insulated from contagion. We attribute this insulation to their very low cross-border interbank exposures. We also find some evidence that since the introduction of the euro cross-border contagion has increased and that contagion seems to spread largely through the interbank market. We report some evidence that only large banks are contagious across borders and also only large banks suffer from contagion across borders, which is in line with a tiered interbank market structure.

JEL codes: G21, F36, G15

Keywords: Banking, Contagion, Distance to default

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I. Introduction

The aim of this paper is to estimate the extent of cross-border contagion in the EU banking sector. It is intended to contribute to a better understanding of the extent to which European banking systems have become interconnected and how banking problems could spread across borders. When we use the term "contagion", we mean the transmission of an idiosyncratic shock affecting one bank or possibly a group of banks and how this shock is transmitted to other banks or banking sectors. Defined in this way, contagion is a subset of the broader concept of a systemic crisis, which may be the result of contagion or of a common shock affecting all banks simultaneously. Econometrically, therefore, the identification of contagion crucially depends upon our ability to distinguish common shocks affecting more than one bank from contagion. In this paper, we use a two stage procedure. First we use factor analysis to identify a set of common factors affecting more than one bank. In the second step we combine these factors with a measure of contagion, which is based on banks in other countries experiencing large shocks.

One could imagine a number of channels for contagion. The theoretical banking literature has focussed on contagion among banks via the interbank market. Allen and Gale (2000) show that in a Diamond/Dybvig (1983) liquidity framework an "incomplete" market structure, with only unilateral exposure chains across banks is the most vulnerable to contagion. In contrast, a "complete" structure, with banks transacting with all other banks, contains less risk of contagion.[2] A "tiered structure" of a "money centre" bank (or banks), where all banks have relations with the centre bank, but not with each other, is also susceptible to contagion (Freixas, Parigi and Rochet, 2000). In both papers, contagion arises from unforeseen liquidity shocks, i.e. banks withdrawing interbank deposits at other banks. Alternatively, contagion conceivably could arise from credit risk in the interbank market, namely deposits at other banks not being repaid.

In the financial markets literature, most authors have stressed that there may be contagion in the absence of explicit links. In the presence of asymmetric information difficulties in one market may be perceived as a signal of possible difficulties in others. Equivalent consideration could apply to banks, especially if one thinks that banks' assets may be particularly opaque and balance sheet data and other publicly available information may be particularly uninformative.[3] In Freixas, Parigi and Rochet (2000) if a liquidity shock hits one bank, depositors may run on other banks as well, even if they are perfectly solvent, if they fear of lacking reserves of liquid assets in the banking system.

Other channels of contagion could be the payment system, where difficulties in one bank may lead to credit losses to other banks (in net systems), gridlock in the entire system, or ownership

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2 The intuition is that in the case of an "incomplete" market, the effects of a shock hitting one bank are concentrated, while in the case of "complete" market the shock is distributed among a large number of banks and, thus, it can be more easily absorbed.

3 For recent evidence to the contrary see Flannery et al. (2004).

links among banks. Our empirical approach does not rely on the measurement of any particular link, but uses a comprehensive measure of default risk, the distance to default, which should reflect all potential channels of contagion, also contagion occurring in the absence of explicit links between banks.

The previous empirical literature has followed a number of different avenues to measure contagion and the risk of contagion. First, evidence of contagion has been estimated using autocorrelation and survival time tests using historical data on bank failures. A number of papers have tested for autocorrelation in bank failures, controlling for macroeconomic conditions, generally in historical samples during which bank failures were common occurrences in the US.[4] Most of these studies find some evidence of contagion, i.e. bank failures tend to be autocorrelated controlling for macro variables. Similarly, using survival time tests, Calomiris and Mason (2000) find that bank-level, regional and national fundamentals can explain a large portion of the probability of survival of banks during the Great Depression. They also find some evidence of contagion, which, however, is limited to specific regions of the US. Inherently, both approaches are limited to times of sweeping bank failures. In this paper, we examine the spill over effects during calm times and we hope to uncover information that may still be indicative of the links during times of crisis. In this sense, the second and third avenues of empirical research is more closely related to ours, namely studies examining the reaction of stock prices to news and studies using actual interbank data and simulating the failure of one or more banks. The literature examining the reaction of stock prices to news suggests that stock price reactions vary proportionally to the degree of the news' extent of affecting the bank and banks' share prices react to problems of other banks. However, the findings could also be consistent with no contagion, as the results may be driven by common shocks, rather than contagion.[5]

In the simulation studies, the evidence of contagion is mixed. Furfine (2003) finds limited evidence of contagion via direct interbank exposures using data on individual banks' bilateral exposures in the Federal Funds market. In the worst case scenario of a default of the most significant bank, 2 to 6 other banks fail, accounting for less than 0.8% of total U.S. banking assets. This finding does not mean, however, that widespread contagion is necessarily absent, since the Federal Funds market accounts for only 10 to 20% of total interbank exposures in the U.S. Sheldon and Maurer (1998) build a matrix of bilateral exposures using interbank loans for Swiss banks and find that the structure of the interbank market poses little threat to the stability of the Swiss banking system. In a similar fashion, Upper and Worms (2002) estimate a matrix of interbank loans for German banks and find some evidence of contagion risk. The failure of a single large bank could lead to a breakdown of up to 15% of the German banking system in terms

4 Grossman (1993) looks at U.S. data for 1875-1914, Hasan and Dwyer (1994) consider the U.S. free banking era (1837-1863), and Schoenmaker (1996) the years 1880-1936, again in the U.S.

5 For a survey see De Bandt and Hartmann (2001).

of total assets. Degryse and Nguyen (2004) examine actual interbank exposure data for the Belgian banking system during 1993-2002. They find that the patterns of linkages changed from a structure with complete links among banks to one in which there are multiple money centre banks. Overall, the change in structure suggests a decrease in the risk of contagion, consistent with this paper.

In this paper, in the absence of data on bilateral exposures at the EU level, we attempt to identify contagion among banks using the distance to default. [6] This implies that in the first instance we do not take a specific view on the channel of contagion (such as the interbank market); rather we use weekly innovations in this comprehensive risk measure to examine whether shocks to one bank appear in the distance to default of other banks, controlling for common factors extracted from macroeconomic and other information. Econometrically, our approach builds on recent papers by Bae et al. (2003), which uses a similar methodology to study contagion among stock market returns in emerging markets and Gropp and Moerman (2004), which examines the tail properties of bank's distances to default. Gropp and Moerman (2004) uses the co-incidence of extreme shocks in banks' distance to default to examine contagion. They use Monte Carlo simulations to show that standard distributional assumptions (multivariate Normal, Student t) cannot replicate the patterns of observed in tails of the data. This implies that not only the distribution of distances to default of individual banks exhibit fat tails, but also that the correlation among banks' distances to default is substantially higher for larger shocks. Bae et al. (2003) do the same for emerging market stock returns and conclude, as Gropp and Moerman (2004) that it may be justified to examine the tails of the distribution of returns (in our case of the distance to default) only. Hence, in this paper we estimate the probability of experiencing a large shock (95^{th} percentile of the distribution in the innovations in the distance to default) as a function of domestic common factors, foreign common factors and the number of banks in the tail in another country (number of coexceedances). The latter variable should give us an indication of the degree of contagion from one country to another, as in Bae et al. (2003).

In a sample of (predominately) large EU banks for 1996-2003 that are stock market listed, we find evidence of significant cross border contagion. We find strong evidence that cross-border contagion may have increased in importance after the introduction of the euro. We are able to link the patterns of contagion uncovered in this paper to the existing interbank market structure, but we are unable to distinguish the credit risk approach to contagion, primarily used in the empirical literature, from the liquidity risk approach to contagion, primarily used in the theoretical literature, due to the high correlation between interbank assets and liabilities to the same country.

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6 Gropp et. al. (2004a and b) argue that, specifically with respect to banks, the distance to default may be a particularly suitable and all-encompassing measure of default risk. In particular, its ability to measure risk correctly is not affected by the potential incentives of the stock holders to prefer increased risk taking (unlike e.g. in the case of unadjusted equity returns) or 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, thus encompassing the most important determinants of default risk (unlike e.g. unadjusted stock returns).

The remainder of the paper is organised as follows. In the next Section, our empirical approach to identifying contagion is described. Section III defines the variables used for capturing idiosyncratic and common shocks, and Section IV discusses the sample construction as well as the emerging patterns of negative (and positive) tail events in our sample. Section V presents our econometric results. Section VI discusses the coexceedance response curves, i.e. the marginal effects of the variables and Section VII discusses a few issues related to the robustness of our findings. Finally, Section VIII concludes the paper.

II. Econometric model

We argue that contagion can be identified as associated with negative extreme movements in banks' default risk. These events can be identified from the negative tail of the distribution of the innovations in our preferred market-based indicator of default risk, i.e. distance to default. The calculation of distances to default and the used data sources are presented in Appendix 1. Hence, we aim to estimate whether the number of coexceedances in one country (the number of banks simultaneously in the tail) can be explained by the number of coexceedances in another country, controlling for common shocks.

As we ultimately want to employ a multinomial logit model, we were forced to be as parsimonious as possible in our choice of independent variables. Conceivable, one could imagine a large number of variables related to measuring common shocks across banks. Faced with this problem, we decided to use a factor model in order to extract common components between the number of coexceedances in a country, industry sector shocks that could affect the portfolios of more than one bank and standard macroeconomic variables, such as interest rates, inflation and GDP growth. This procedure gives us explanatory variables, which should capture the correlation of the coexceedances with common shocks and thus allows us to identify banks' tail events which are due to contagion.

Hence, we first estimate for each country c

(1) $$X_c = f_c \Lambda_c^{'} + e_c \, .$$

Suppose we use p variables and q factors. X_c then represents the (*1x p*) dimensional vector of observed variables, Λ represents the factor loading matrix with dimension (*p x q*) and *f* an (*1 x q*) matrix of factors. Under the factor model, the correlation matrix of X_c, called Σ is decomposed as

(2) $$\Sigma_c = \Lambda_c \Lambda_c^{'} + \Psi \, ,$$

where Ψ is a (*p x p*) dimensional diagonal matrix of uniqueness. Ψ is estimated and then the columns of Λ are computed as the eigenvectors, scaled by the square root of the appropriate eigenvalue (see e.g. Harman, 1976).

After having obtained a small number of factors for each country, which should be excellent measures of joint components of coexceedances and common shocks, we estimate a multinomial logit model of the form

(3) $$\Pr[Y = j] = \frac{e^{\left[\beta_j' F_c + \gamma_j C_{dt-1} + \lambda_j F_d\right]}}{\sum_k^J e^{\left[\beta_k' F_c + \gamma_k C_{dt-1} + \lambda_k F_d\right]}} ,$$

where j = 1,2,3…J represents the number of banks in the tail simultaneously ("coexceedances"), F_c the factors measuring common shocks in country *c*, F_d the factors explaining common shocks in country *d* and C_d represents the coexceedances in period *t-1* in country *d*.

In order to remove the indeterminacy associated with the model, we follow the convention and define Y=0 (zero coexceedances) as the base category. All coefficients, hence, are estimated relative to this base. Still, the coefficients from this model are difficult to interpret. Hence, it is useful to also report the marginal effect of the regressors. The marginal effects are obtained from the probability for each outcome j

(4) $$\Pr[Y = j] = \frac{e^{\left[\beta_j' F_c + \gamma_j' C_{dt-1} + \lambda_j' F_d\right]}}{1 + \sum_k^J e^{\left[\beta_k' F_c + \gamma_k' C_{dt-1} + \lambda_k' F_d\right]}} .$$

Differentiating with respect to C_{dt-1} yields

$$\frac{\partial \Pr[Y = j]}{\partial C_{dt-1}} = \Pr[Y = j] * \left[\gamma_j - \sum_{k=1}^{J} P_k \gamma_k \right],$$

which can be computed from the parameter estimates, with the independent variables evaluated at suitable values, along with its standard errors.[7]

III. Definition of the dependent and independent variables

As described above we use a factor model to extract the common components of a number of variables, which we hypothesise are related to common shocks affecting banks in a country simultaneously. We use two sets of variables. First, we focus on sources of credit risk and calculate the percentage changes in the sectoral stock market indexes for a given industry in country *c*. We used the standard NACE classification of two digit industries (in total 18 industries, excluding financials), which are given in Appendix 2. From these 18 sectoral risk variables we extracted one common factor.

7 The computation of the standard errors is exceedingly difficult and most studies do not report them. However, both the significance and even the sign could differ between the coefficients and their marginal effects (Green 2000).

Next we estimated a second factor model in which we combine the credit risk factor with standard macroeconomic variables and the number of coexceedances (see below). For that purpose, we use the difference between the 10 year government bond rate and one year money market rates, CURVE, as a crude measure of the steepness of the yield curve and banks' interest rate risks. We compute weekly averages of daily data. As additional macro variables, we include annualised changes in inflation and real GDP growth, *GDP*, which we imputed to weekly frequency using quarterly data at the country level.[8] From these factor models estimated separately for each country we retained two factors, which explain most of the common variance in the underlying variables. We will examine their performance in measuring common shocks across banks below.

In order to obtain our measure of contagion, which we have labelled, following Bae et al. (2003) and Gropp and Moerman (2004) coexceedances, we calculated the weekly distance to default for each bank in the sample and for each time period, *t*, using that period's equity market data and the prevailing bank's balance sheet data (see Appendix 1). We then fixed extreme events arbitrarily at the negative 95[th] percentiles of the common distribution of ($\Delta dd_{it} / | dd_{it} |$) across all banks. Choosing he bottom 95[th] percentile was a compromise between the need for "large" shocks in the spirit of extreme value theory (Straetmans, 2000) and maintaining adequate sample size for the estimation. Finally, we counted the number of banks in a given country that were simultaneously in the tail (coexceedances). When combining this variable with the credit risk factor and the macro variables in a factor model, we believe we have extracted the common component(s) of the number of coexceedances with credit risk and the overall macroeconomic performance.

IV. Sample and descriptive statistics

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 1996 to January 2003 (70 banks). We deleted all banks that had trading volume below one thousand stocks in more than 30% of all trading days and banks which had less than 100 weeks of stock data available (7 banks). Furthermore, we deleted three additional banks where we had serious concerns about data quality.[9] We matched these banks with the available data on syndicated loans exposures and deleted all banks for which this data is unavailable (14 banks). The resulting sample contains 16619 observations for 46 banks, i.e. on average around 361 weekly observations per bank. The data are complete for 42 banks, i.e. we have the full 368 weekly observations. We left four banks with incomplete data in the sample. Two banks drop out after they merge, namely Dresdner Bank in may of 2002 (340 observations) and Banco di Napoli in December 2001 (295 observations). Further for Credito

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8 The measurement of the macro shocks at the country level is in line with the some recent evidence that most banks' loan exposures are still within their domestic countries in Europe (Cabral et al., 2002) and foreign exposures are mainly acquired through subsidiaries abroad.

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

Emiliano and Credito Valtellinese data on syndicated loans become available only in January 1998, which means for those banks we have 264 observations. The results are unaffected by dropping these four banks with incomplete data from the sample.

Table 1 shows that the banks in the sample on average are just above four standard deviations away from the default point (mean distance to default of 3.8). However, this hides substantial variation in the health of banks. Banco di Napoli represents the minimum with 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; Bankgesellschaft Berlin (Germany) and SEB (Sweden) show distances to default below one and are known to have experienced significant difficulties during the period under consideration. At the other end of the spectrum, there were a number of banks with a maximal distance to default of above 10. The mean of the first difference in the distance to default is approximately zero, the largest negative change is above 7, which can truly be considered a sizeable weekly shock. The 95th percentile is at –0.03 respectively, which gives us 899 observations. The banks in the sample are generally quite large relative to the population of banks in the EU (see also Table 3). One average, total assets amount to EUR 143 billion. The relatively large average size is an outcome of the requirement that the bank 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, Singer and Friedlander Group, Schroders etc.. The sample contains banks from all EU countries except Luxembourg and Austria. The degree of coverage in each country depends on the number of banks traded at a stock exchange and the structure of the banking system. On average, the sample covers around 40 percent total commercial banking assets in the EU. Table 4 reports a decomposition of the sample by individual countries.

In Table 5, we report the number of times banks are in the tails at the same time (coexceedances), depending on whether the banks are from the same or other countries. This represents the count of the coexceedances of tail events within and across countries (Bae et al., 2003, Gropp and Moerman, 2004). With the 95% critical value, the number of coexceedances ranges from 2 (Finland) to 170 (Italy). The number of cross-country coexceedances from zero (Belgium) to 206 (Italy). The large number of co-incidences with Italian banks is largely explained by the fact that Italy has the largest number of banks in our sample.

V. Estimation results

V.1. Factor models

We report the outcome of the factor models in Appendix 3. In general, note that two factors explain essentially all of the common variance of the variables and that adding further factors tends to not improve this value, meaning that factors beyond two tend to be noise. Given out estimation procedure, these two factors should capture the impact of common shocks on the coexceedances, provided that our underlying macroeconomic and sectoral variables represent well the most important sources of common shocks.

We will refrain from assigning too much economic interpretation to each factor. However, given the correlation of the underlying variables with the factors (factor loadings), the first factor seems to represent the overall macroeconomic conditions as there is a high correlation with GDP growth and inflation, and a rather high correlation with the steepness of the yield curve. The second factor seems to represent the common credit risk components stemming from industry sector conditions and the co-movement in coexceedances. The factor loadings of the individual sectors presented in Appendix 3 provides information of the correlation of the different sectors with the common credit risk component.

V.2. Base model

The results for the basic contagion estimation are given in Table 6. For each country we first report the results for a specification in which the own common factors are the only explanatory variables. Subsequently, we add the one period lagged coexceedances from other countries, always together with the common factors from these countries. Table 7 summarises our findings as regards the contagion variables and the emerging cross-border contagion patterns.

Before we discuss the results in detail, we should stress what we would consider evidence of contagion. In countries with many banks, Gropp and Moerman (2004) had trouble simulating the high number of periods with four or more banks in the tail (four or more coexceedances). Hence, we would be particularly interested if contagion from other countries has explanatory power for explaining a high number of coexceedances. This should be particularly strong evidence for the importance of contagion. It turns out that typically contagion variables are indeed stronger and more significant when the number of coexceedances is higher (there are three or four banks in the tail simultaneously in a country).

Consider the results for Germany first. As in all countries with more than 4 banks, we limited the model to estimating four outcomes: 0, 1, 2, 3 and 4 or more banks in the tail, in order to maintain degrees of freedom. In the base model without contagion variables, the factors alone explain a very high proportion of the variation in coexceedances of German banks (pseudo R^2=0.39).[10] This is generally true except for Italy and Greece, where our model performance in explaining the emergence of coexceedances is significantly lower (pseudo R^2 below 0.10). Both factors are significant at the 1 percent level for all levels of coexceedances. If we introduce the lagged number of coexceedances plus the factors from that country in the estimation, we always find an improvement in fit in the model (pseudo R^2 rises to 0.41-0.51, depending on the countries which are the source of contagion). This suggests that contagion is a relevant factor as well. We also

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[10] As a comparison: in the context of emerging markets, Bae et al. (2003) find pseudo R^2 of around 0.1 in a similar type of model, using three explanatory variables (conditional volatility, exchange rates and interest rates).

generally find that the coefficients of the factors do not change much once the contagion variables are added in the estimations. This gives us confidence that our contagion variables are indeed exogenous to common shocks.

Going across the columns of the table, we find strong evidence of contagion from Spain, Italy, Ireland the UK and Denmark, some contagion from France, the Netherlands and Portugal and no contagion from Belgium, Finland, Greece, with some mixed evidence for Sweden. It is also interesting to examine the effect of including foreign factors in the German model. At least one Dutch, Spanish, Italian, Belgian, Irish, Portuguese, Greek, UK, Danish and Swedish factor is significant in explaining German coexceedances. Intuitively, we would interpret their significance as the result of the exposure of German banks through subsidiaries and branches to those countries, rather than through contagion, where we suspect that the interbank market may be the main channel of contagion. Generally, factor 2 is more significant and important than factor 1, while the latter factor is quite often significant as well. This suggests a larger role for credit risk drivers than general macro factors in explaining tail events in banks' distance to default.

The role of the interbank market in explaining the patterns found here will be explored in more detail below. This, for example, could explain the -possibly surprising- finding that there appears to be not contagion from Belgian banks to Germany; namely that German banks operate largely through subsidiaries in the Belgian market, obtaining their liquidity from the head office in Germany.

While we do not want to discuss the results for each country in detail, we would like to highlight a few interesting findings. One, it appears that larger countries or countries with major banks are more relevant as sources of contagion. German banks are found contagious to four countries, French and Italian to (only) three, Dutch four and Spanish six countries. Irish banks are maybe surprisingly contagious to Germany, Netherlands, Spain and Italy, which could reflect the need for Irish banks to fund their recent heavy lending growth from international markets. Portuguese banks are found contagious to its neighbouring countries (Spain and Italy) and the UK.

Second, we find a significant difference between smaller countries at the periphery, such as Finland and Greece and countries in the centre of the euro area. Generally, we are unable to find any contagion to or from Finland and Greece. A number of interpretations for this finding are possible. One, the banks in these countries are still somewhat outside the integrated interbank money market, due to, say, asymmetric information (Freixas and Holthausen, 2004). Second, as these countries are small, their banks are simply not large enough to result in contagion in other countries. And third, at least for Finland, the interbank exposure of Finish banks is much lower than in other banks in the EU and, hence, their exposures to other banks (both domestic and foreign) is very small.

Third, it is interesting to see whether the contagion patterns from the three countries in the sample, which did not adopt the euro, are different from those that did. Unfortunately, we were unable to estimate the model for contagion to Denmark, as one of the factors from the factor model perfectly predicted the coexceedances of Danish banks. This suggests that Danish banks experienced large shocks only due to some common shock, rather than an idiosyncratic one and it also implies that there was not contagion to Denmark during our sample period. In the UK, we find strong contagion from German and Spanish banks and some contagion from Dutch, Swedish and Portuguese banks. We also find that the foreign factors from euro area countries are highly significant in explaining UK coexceedances, even in countries where we detect no contagion. If we continue with our suspicion that the interbank market lies at the core of these contagion patterns, then it appears that UK banks primarily interact with German and Spanish banks when accessing the euro money market. Why do we also find some contagion from Dutch and Portuguese banks? In the case of Dutch banks, which are known to be particularly internationally oriented, we could imagine that they also are important counterparties to UK banks in the euro area. In the case of Portuguese banks, this seems less likely. But possibly we have found evidence of some second round effects: Portugal and Spain, as expected, have important contagious effects on each other. For Sweden, as the other "out" country, we only find evidence of strong contagion from Germany and some weaker evidence for contagion from Spain, Ireland, Greece and the UK. We interpret that as evidence in favour of German banks being the main conduit of Swedish banks into the euro area money market. It is also interesting that generally foreign factors tend to be insignificant for explaining the coexceedances of Swedish banks, with exception of Belgian, German and Greek factors.

V.3. Effect of the introduction of the euro

One could expect that the entry into the Stage Three of EMU on 1 January 1999 would give rise to further cross-border contagion, since it has led to a single money market for liquid reserves in euro, strengthening the cross-border interbank links among banks. However, the emergence of integrated money market conditions (i.e. single risk-free market rates), which has been evidenced for euro money markets does not necessarily imply the emergence of these links across all banks, for example due to cross border asymmetric information problems (Freixas and Holthausen, 2004). Asymmetric information may give rise to a "tiered" structure at the cross-border level such that large international banks (with better information and lower relative costs) transact with major banks from different countries, and smaller banks only transact with their domestic counterparties.

In order to ascertain the effect of being part of the common currency and sharing an interbank market we split the contagion variables into pre- and a post-euro variables. The results are reported in Table 8. We focus here on the issue of change in contagion patterns after the introduction of the euro. Also for the sake of economising on space, we only report the coefficients of the contagion variables.

For euro area countries, our results are in line with expectations. We find a clear increase in the estimated contagion after the introduction of the euro. The total number of statistically significant coefficients measuring contagion between euro area countries is 57 for the post-euro time period, compared with 24 for the pre-euro period.

Our results also suggest that contagion across euro area country pairs has become more widespread after the introduction of the euro (Table 8). In many cases contagion is significant only for the post-euro time period: From France, Italy and Portugal to Germany; from Netherlands, Spain and Italy to France; from Italy to Netherlands; from France, Netherlands, Italy, Belgium and Portugal to Spain; from Germany, France, Spain and Portugal to Italy; from Netherlands and Spain to Ireland; and from Ireland to Portugal. Moreover, contagion is identified significantly from euro area countries to France and Ireland only after the introduction of the euro. Also, stronger and more significant contagion after the introduction of the euro emerges for other countries, except Netherlands and Belgium.

Almost always, significant contagion identified for the time period before the euro also comes through significantly for the period after. Hence, the introduction of the euro seems to have clearly increased the width of contagion while maintaining the previous contagion patterns in place. Finally, the estimated contagion to a country continues to be stronger and more significant when a larger number of domestic banks are in the tail, also when the coefficients are estimated for the periods after and before the introduction of the euro. As we argued above, our ability to distinguish contagion from the impact of common shocks is strongest when the number of coexceedances is high.

All this evidence suggests that euro area banks have developed a greater variety of significant linkages with banks from other euro area countries in the integrated interbank market denominated in the common currency. This is what could be expected in a unified market (without segmentation due to various local currencies and the transaction costs in trading and hedging in foreign currencies) where effective arbitrage would close pricing anomalies in any parts of the market. However, the increased depth and efficiency of the interbank system seems to have come at the cost of increased risk of cross-border contagion.

For euro area countries, contagion from non-euro area countries has become slightly more prevalent after the introduction of the euro according to our results. For the post-euro time period, there are 26 significant coefficients, while for the pre-euro period 19, measuring contagion from non-euro area countries to euro area countries (Table 8). It seems that contagion from the UK and Sweden to the euro area has become stronger after the euro (the number of significant coefficients increases from 6 to 11 and from 4 to 10 respectively), while it has decreased from Denmark (the number of significant coefficients decreases from 9 to 5). Our results suggest that contagion to the UK from euro area countries has remained largely as important after the euro as before its introduction, while to Sweden it has reduced (contagion to Sweden is no more significant from any euro area country).

All in all, these results suggest that in particular the role of UK and to lesser extent Swedish banks has remained important in the interbank dealings of euro area banks after the introduction of the euro, and even strengthened in terms of potential for contagion. In other words, we do not obtain evidence that the European interbank market has become closed amongst the euro area countries once the euro was introduced and the market switched to euro as its predominant currency. This could reflect the important role of London as a financial centre for also euro-denominated transactions and the recent expansion of Swedish banks into the euro area.

V.4. Interbank links as source of contagion

Banks' exposures against each other in the interbank money market are one source of explicit linkages between banks that could give rise to contagion. The empirical literature (e.g. Degryse and Nguyen, 2004, Upper and Worms, 2002) has concentrated on credit risk exposures, i.e. the risk that a failure of a bank (or a group of banks) leads to losses from interbank assets. As open credit exposures in the foreign exchange markets have been limited through settlement arrangements (such as the establishment of the CLS Bank) in order to mitigate the risks made apparent by the failure of the Herstatt bank and credit exposures in payment systems have been limited though the introduction of Real-Time-Gross-Settlement (RTGS) systems or risk limits in netting systems, most part of the credit exposures would arise from unsecured interbank lending operations. These exposures would be the greater the larger the share of assets lent to a particular entity.

In contrast, the theoretical literature (Allen and Gale, 2000, Freixas et al., 2000, in the tradition of Diamond and Dybwyg (1983), has focused on liquidity risk exposures, i.e. the impact on the availability of interbank funding when a bank (or a group of banks) is forced to reduce its interbank lending and/or general market conditions are tight and one source of funding cannot be easily replaced. These exposures would be the greater the larger the dependency of funding from a particular source, i.e. the larger the share of liabilities accounted for by a particular counterparty.

The first indication that interbank market linkages play an important role in transmitting contagion and explaining our findings of contagion patterns is that there is strong correlation between the importance of the particular interbank asset or liability linkages by country pairs and the estimated statistically significant contagion coefficients. According to the country-level data collected by the ECB, the shares of each EU country in the cross-border interbank assets and liabilities referring to EU counterparties are reported in Tables 9a and b and 10a and b for two points in time December 1997 and December 2002 (i.e. for a period before and after the introduction of the euro). For instance, if significant contagion is at all identified, contagion from Germany and the UK is evidenced by our results. These countries have the highest sharer of the

EU interbank liabilities of around 11% and 31%, respectively at end-2002 and these two countries account for the largest share of the interbank assets of most EU countries.[11]

There is also, in general, significant correlation between the identified contagion and the relevance of the interbank asset and liability shares by country pairs. Closer examination reveals relatively few country pairs where our contagion results would not be supported by the patterns of interbank assets and/or liabilities. However, the results seem to leave space for potential other reasons for the identified contagion. It cannot be concluded that interbank exposures are the only relevant source of contagion.

The fact that EU cross-border interbank assets and liabilities have increased faster than other interbank assets and liabilities is in line with the findings of stronger and wider contagion after the introduction of the euro. Table 11 shows that the average share of EU cross-border interbank assets in total interbank assets (domestic and foreign) has increased from 22% at end-1997 to 28% at end-2002 and the share of EU cross-border liabilities from 33% to 36%.

In order to obtain more evidence of the relevance of contagion through the interbank market exposures in explaining the contagion patterns, we utilised the country-level data on interbank assets and liabilities. We first calculated the share of each EU country in the total interbank assets and liabilities of a particular country. This share measures the intensity of the interbank market linkages of the banks in this country vis-à-vis the other EU countries, also taking into account the shares of domestic interbank assets and liabilities and the interbank assets and liabilities vis-à-vis the rest of the world. As argued above, these indicators should capture the major part of the explicit financial exposures between banks from different countries, while they exclude ownership links which could transmit contagion as well. As the data are at the country-level, possible concentration of exposures to individual banks cannot be accounted for and thus potentially a major explanatory factor behind bank-level contagion patterns is excluded. Note however that our model is specified at the country level.

We then interacted the contagion variables with the shares of particular countries in total interbank assets and liabilities and replaced the original contagion variables with these new interacted variables. If the interbank market shares do not explain the contagion patterns, we would be just adding noise through this procedure and we would expect the significance of the contagion variables (interacted with the interbank asset or liability shares) to be greatly reduced. We find this not to be the case. Table 12 reports the coefficients of the interacted contagion variables when interbank asset shares are included in the model. Again, other coefficients are omitted in the interest of conserving space. We find that when interbank asset shares are used in the multinomial logit-regressions, the significance of the coefficients measuring contagion improves in 14 cases (from 5% level to 1% level of significance) and decreases in 6 cases. There

[11] The high share of UK banks includes the liabilities of subsidiaries of foreign banks located in London, as the ECB statistics is collected on a locational rather than cross-border consolidated basis.

is also typically a marginal improvement in the model fit as measured by the pseudo R^2. Hence, the precision of estimating contagion links is improved when the information on interbank assets is employed in the estimations. Moreover, three new significant contagion links emerge compared with our base estimations. This evidence suggests that contagion patterns may at least in part be explained by the patterns of trading in interbank money markets.

We also attempted to distinguish between the relevance of credit risk and liquidity risk exposures as sources of contagion, thus possibly contributing to a resolution of the discrepancy between the theoretical and empirical literatures. However, we find that when shares in interbank liabilities (liquidity risk) are used instead of the asset shares (credit risk), the precision of estimating contagion links also improves in 14 cases and deteriorates in 6 cases, while the actual country pairs where this occurs are different (results omitted). The reason for these findings seems to be that, at the country-level, bilateral country links are equally important in terms of interbank assets and liabilities. This is broadly evident from Tables 9a and b and 10a and b. Hence, the correlation of interbank assets and liabilities to the same country is too high to give our test of distinguishing between the credit risk and liquidity risk explanations much power. Nevertheless, when interbank liability shares are interacted with the contagion variables, the number of new significant contagion links increases by seven. This result, together with the findings of improved precision of estimation contagion suggest that contagion due to interbank liabilities could be somewhat more significant from smaller countries.

V.5. Small versus large banks

Closely related, we also examine the question of whether we can detect in contagion among small versus large banks. Ex ante, it is clear that one would not necessarily expect small banks to be contagious at all, especially not to very large banks. Clearly, even if a small bank has a sizeable exposure to a large bank, this exposure will be small for the large bank. There is also a second reason in the context of cross-border contagion and here lies our main interest. In the literature, it has frequently been argued that large banks within countries act as money centre banks. Only these money centre banks have cross-border transactions, while smaller banks only deal domestically. If this is true, we should be unable to detect any contagion from small banks across borders, because their cross-border exposures are going to be small, even relative to their smaller size. The notion of money centre banks for cross-border transactions also means that small banks would not be subject to contagion from large foreign banks, which would be a very interesting finding.

In the context of our sample it is difficult to examine this question, as most of our banks, given our sample selection process and in particular our requirement that consistent stock price data exist for 1996-2003, are by definition relatively large. In addition, for most countries we tend to have only very few banks. Hence, we decided to examine this question for Italy only. We choose Italy, because Italy has the largest number of banks in the sample of all countries (12), many of which are small. In addition, in the previous sections we report that Italian banks tend to be surprisingly immune from contagion and are themselves only relatively infrequently contagious. If we find evidence of contagion, the coefficients tend to be associated with relatively large standard errors. We hypothesise that this finding may be due to the fact that we did not distinguish between large banks, such as Banca Intesa, Unicredito, SanPaolo IMI and Banca di Roma, from small banks such as Banca Popolare di Novarra, BP di Lodi, Banca Lombarda etc (Table 3). Hence, we re-estimated the base model from Section V.2. counting the coexceedances for the four large Italian banks only.

The results are reported in Table 13. We have limited ourselves to estimating contagion among large countries. In the first four columns of the table we are considering contagion from Italy to Germany, France, Spain and the UK. In the remaining four columns the reverse, i.e. contagion from these countries to Italy. The results for contagion to Italy are virtually unchanged from the earlier results; by concentrating on the larger banks, we did not change the fact that these banks tend to be relatively immune to contagion from abroad. However, the results for contagion from Italian banks are different: we find some evidence of strong contagion from Italy to Germany (as before, but now all four contagion variables are significant at least at the five percent level) to France (where we estimate a larger coefficient, which significant at the five percent level, as opposed to insignificant before), to Spain (where the coefficients are larger and significant at the 1 percent level) and to the UK (where before we found not evidence of contagion and now some, albeit mild, effects). Overall, these results seem to support our conjecture about the money centre structure, at least in the case of Italian banks.

VI. Coexceedance response curves

[To be completed]

VII. Robustness

As a first robustness check, we re-estimated the base model with contagion effects (Table 6) with dummies for the week of September 11 (US terror attacks) and the first two weeks of October 1998 (Russia's default). During both time periods, the number of coexceedances was particularly high and we were concerned that our results could in part be driven by the inability of the factors to properly account for either event. The results, however, are unaffected by the inclusion of these dummies (not reported).

Second, we concede that a multinomial logit model is only one way to estimate a model with count data as the dependent variable. Other methods include tobit models, Poisson models, negative binomial models and ordered logit models. A tobit model is clearly inappropriate as it relies on the assumption that the dependent variable is truncated normal, an assumption, which Gropp and Moerman (2004) show to be clearly rejected in the data used in this paper. Poisson models rely on the assumption of equality between mean and variance of the dependent variable, an assumption, which is clearly rejected in our sample. The negative binomial model is essentially a generalised Poisson model, which avoids this restrictive assumption of mean/variance equality. Nevertheless, it still makes the restrictive assumption that the dependent variable was drawn from a mixture of Poisson random variables. Given the evidence and arguments in Gropp and Moerman (2004) and Bae et al. (2003) we do not think that the estimation of this model would be advisable. We did, however, re-estimate a subset (among the main countries) using an ordered logit model. The main difference between a multinomial logit model and an ordered logit model is that the ordered logit restricts the marginal effects at each outcome to the same. This means that the effect of coexceedances in another country on going from 1 to 2 bank coexceedances in the dependent variable is restricted to be the same as going from 3 to 4 banks. Given our results (Table 6), this assumption seems to be frequently violated; however, we do gain degrees of freedom in the ordered logit model, as we have to estimate each covariate only once and not once for each outcome in the dependent variable. We found the patterns of contagion to be robust to using an ordered logit model instead of the multinomial logit model (results not reported).

VIII. Conclusions

In this paper, we analyse cross-border contagion in the EU banking sector using an approach somewhat related to extreme value theory, as we focus on the tail observations in a measure derived from financial market data. Applying this approach to bank contagion, we modelled banks' default risk using the stock market-based distance to default and examined the occurrence of extreme changes in this measure as depicting major shocks in banks' financial condition. We argued that contagion can be identified, when the incidence of such tail events is significantly influenced by a lagged measure of coexceedances of banks from another country. In order to distinguish between common shocks affecting more than one bank and contagion and to maintain degrees of freedom in the multinomial logit model, we use a factor model to extract common factors between coexceedances, sector risk and macro variables.

We feel we are able to present fairly strong evidence in favour cross-border contagion. Cross-border contagion was found to be significant and economically relevant. This suggests an important pan-European dimension in the monitoring of systemic risk. This point becomes event stronger as we found some evidence of increased relevance of cross-border contagion after the introduction of the euro. Interbank market links across borders seem to corroborate with our identified contagion links. Some of our findings are in line with a "tiered" interbank structure at the cross-border level such that small banks only deal with domestic counterparties, leaving foreign operations to major international banks.

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Table 1. Variable definitions and summary statistics [expand]

Variable	Definition	n	Mean	Median	Standard deviation	Minimum	Maximum
dd_{it}	Distance to default of bank i in week t (see Appendix I)	16619	3.84	3.32	1.71	-0.29	17.11
$\Delta dd_{it} / \lvert dd_{it} \rvert$	Percentage change in the distance to default	16619	-0.001	-0.004	0.06	-7.12	0.59
$Tail\_95_{it}$	Binary variable equalling 1 if bank i is in the negative 95th percentile of the $\Delta dd_{it} / \lvert dd_{it} \rvert$ distribution in week t	16619	0.05	0	0.21	0	1
$CURVE_{tc}$	Long term government bond rate-1 year money market rate of country c	16619	1.44	1.39	1.32	-2.85	10.36
$INFL_{tc}$	Weekly change in CPI in country c, year-on-year, based on quarterly data	16619	2.34	2.06	1.18	-1.10	6.56
GDP_{tc} *growth*	Weekly GDP growth rate in country c, year-on-year, based on quarterly data	16619	2.78	2.51	2.31	-1.30	15.24

Table 2. Tail statistics, distance to default [expand for each country**]**

	95% tail
dd	2.07
Δdd	-0.123
$\Delta dd_{it} / \lvert dd_{it} \rvert$	-0.031
Number of tail observations	899

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

Rank	Bank name	Country	Total assets
1	Deutsche Bank AG	DE	900.14
2	BNP Paribas	FR	693.05
3	ABN AMRO Bank N.V.	NL	543.16
4	Royal Bank of Scotland	UK	495.98
5	Barclays	UK	493.04
6	Dresdner Bank. AG	DE	482.57
7	Commerzbank	DE	454.45
8	Banco Santander Central Hispano	ES	347.28
9	Banca Intesa	IT	331.36
10	Abbey National	UK	297.10
11	Banco Bilbao Vizcaya Argentaria	ES	292.55
12	HSBC	UK	291.98
13	Bankgesellschaft Berlin	DE	203.53
14	UniCredito Italiano	IT	202.64
15	Danske Bank	DK	184.09
16	KBC Bank	BE	176.90
17	Sanpaolo IMI	IT	171.04
18	DePfa Group	DE	156.44
19	Banca di Roma	IT	132.72
20	Skandinaviska Enskilda Banken (SEB)	SE	119.71
21	Svenska Handelsbanken	SE	114.19
22	Natexis Banques Populaires	FR	113.13
23	Standard Chartered	UK	109.91
24	Allied Irish Banks	IE	77.93
25	Bank of Ireland	IE	73.85
26	Banco Comercial Portugues	PT	61.85
27	Banco di Napoli	IT	34.36
28	Banca Popolare di Lodi	IT	34.23
29	Banco Espirito Santo	PT	33.86
30	IKB Deutsche Industriebank	DE	32.36
31	Banco Popular Espanol	ES	31.29
32	Alpha Bank	GR	30.18
33	Banca Popolare di Milano	IT	28.28
34	Banca Lombarda	IT	26.82
35	Banca Popolare di Novara	IT	20.96
36	Banca Popolare Commercio e Industria	IT	20.91
37	Jyske Bank	DK	17.19
38	Commercial Bank of Greece	GR	16.16
39	Credito Emiliano	IT	15.15
40	Anglo Irish Bankcorp	IE	11.05
41	Okobank	FI	11.00
42	Banco Pastor	ES	9.40
43	Credito Valtellinese	IT	7.42
44	Singer & Friedlander Group	UK	6.18
45	Banco Zaragozano	ES	5.18
46	Schroders	UK	4.23

Table 4. Description of the sample by countries

	Number of observations	Number of banks	Number of tail events
			95th percentile
Belgium	368	1	17
Denmark	736	2	36
Finland	368	1	11
France	736	2	38
Germany	2180	6	145
Greece	736	2	42
Ireland	1104	3	46
Italy	4135	12	215
Netherlands	368	1	29
Portugal	736	2	48
Spain	1840	5	106
Sweden	736	2	27
UK	2576	7	139
Total	16619	46	899

Table 5. Total number of coexceedances by countries, January 1996 – January 2003

	Lower 95 % critical value	
	Number of “co-incidences ” with banks from the same country	Number of “co-incidences ” with banks from the other countries
Germany	92	139
France	19	37
Netherlands	14	29
UK	95	134
Spain	68	102
Italy	170	206
Denmark	14	31
Belgium	0	16
Sweden	10	26
Ireland	25	43
Portugal	26	42
Finland	2	8
Greece	20	39

Table 6. Contagion test results of the basic multinomial logit model for weekly coexceedances of the first differenced distance to default, January 1996-January 2003

*Dependent variable: number of domestic banks) simultaneously in the tail. *, ** indicate statistical significance at the 5% and 1% levels, respectively .All models estimated with 367 weekly observations.*

Germany	Base	from FR	from NL	from ES	from IT	from BE	from IE	from PT	from FI	from GR	from UK	from DK	from SE
Constant_1	-1.41**	-1.45**	-1.59**	-1.85**	-1.73**	-1.51**	-1.78**	-1.66**	-1.45**	-1.45**	-1.77**	-1.48**	-1.62**
Constant_2	-4.04**	-4.17**	-5.04**	-6.23**	-4.63**	-5.32**	-5.06**	-5.25**	-4.19**	-4.38**	-6.12**	-5.16**	-5.44**
Constant_3	-6.00**	-7.53**	-6.04**	-10.05**	-7.61**	-8.33**	-7.47**	-7.91**	-6.07**	-6.96**	-9.60**	-8.16**	-8.92**
Constant_4	-9.30**	-11.61**	-14.23**	-15.26**	-13.01**	-16.79**	-12.68**	-17.19**	-10.87**	-12.10**	-14.26**	-14.01**	-13.73**
Own1 Factor_1	0.92**	1.04**	1.16**	1.49**	0.92**	0.44	1.95**	1.55**	1.09**	0.86**	1.58**	0.92**	1.59**
Own1 Factor_2	1.99**	1.11	2.51**	3.71**	0.93	0.67	3.42**	3.43**	2.49**	1.68**	2.95**	2.12**	3.16**
Own1 Factor_3	2.15**	-0.00	1.62	5.20**	1.71	-0.46	3.79**	3.78**	2.48**	1.75*	3.09*	2.58**	2.95*
Own1 Factor_4	3.69**	1.82	5.94*	5.26**	4.25*	3.59	6.60**	6.55**	4.82**	3.26*	6.63**	4.93**	7.11**
Own2 Factor_1	-4.62**	-4.47**	-5.87**	-6.64**	-5.76**	-7.87**	-8.76**	-7.39**	-4.82**	-6.63**	-6.93**	-5.20**	-7.46**
Own2 Factor_2	-7.51**	-7.69**	-11.72**	-14.18**	-9.17**	-15.46**	-13.23**	-13.59**	-7.82**	-10.48**	-13.52**	-10.64**	-13.51**
Own2 Factor_3	-9.89**	-11.10**	-11.45**	-19.17**	-11.92**	-19.89**	-16.34**	-16.50**	-10.05**	-13.88**	16.93**	-14.05**	-17.00**
Own2 Factor_4	-12.54**	-14.64**	-19.94*	-23.09**	-15.33**	-26.12**	-20.87**	-24.15**	-14.32**	-18.24**	-20.65**	-18.49**	-21.25**
Foreign1 Factor_1		-0.15	0.605	-0.16	0.03	-0.31	-0.61*	-0.04	0.30	0.28	0.08	0.23	-0.19
Foreign1 Factor_2		0.95	1.88*	-0.23	-1.30	-0.54	-0.70	-0.62	0.89*	0.18	1.10	1.89**	0.43
Foreign1 Factor_3		2.02	-0.22	-1.26	-0.92	-2.06	-0.64	0.25	0.71	-0.24	1.97	2.09**	1.37
Foreign1 Factor_4		2.03	4.16*	-0.28	-0.57	1.20	-1.40	-0.78	1.40*	0.12	0.58	2.40*	-0.54
Foreign2 Factor_1		0.20	1.29**	2.44**	1.39*	4.79**	4.88**	3.28**	-0.28	2.29**	2.20**	-0.99*	4.03**
Foreign2 Factor_2		0.51	4.66**	7.80**	1.82**	11.00**	6.41**	8.31**	0.16	3.73**	5.41**	-2.73**	6.87**
Foreign2 Factor_3		0.18	2.59*	12.45**	2.16*	16.76**	7.20**	9.31**	0.55	5.81**	6.43**	-3.63**	6.52**
Foreign2 Factor_4		-1.45	4.53**	12.76**	3.48**	18.10**	8.79**	13.20**	-1.68	8.25**	7.60**	-4.89**	8.42**
Contagion_1		0.31	1.19*	1.08**	0.43*	1.29	1.87**	1.02**	0.49	0.02	0.68**	0.98	1.50*
Contagion_2		0.21	0.50	2.11**	0.56	0.89	2.87**	0.31	-0.54	0.28	1.52**	2.44*	2.69
Contagion_3		3.09**	2.14*	2.65**	1.20**	-34.81	3.41**	1.69	-0.56	-36.77	2.32**	3.84**	6.68**
Contagion_4		3.18*	3.59*	4.04**	1.66**	5.41	3.81**	4.45*	-0.33	0.71	1.93**	5.89**	3.84
Pseudo R2	0.39	0.41	0.46	0.50	0.45	0.51	0.49	0.50	0.41	0.46	0.49	0.45	0.50
Log-likelihood	-200.81	-192.33	-178.22	-164.29	-179.13	-159.89	-166.21	-164.66	-192.31	-177.49	-166.08	-180.55	-164.23

Table 6 continued

France	**Base**	**from DE**	**from NL**	**from ES**	**from IT**	**from BE**	**from IE**	**from PT**	**from FI**	**from GR**	**from UK**	**from DK**	**from SE**
Constant_1	-3.75**	-4.07**	-4.87**	-4.37**	-4.59**	-4.77**	-3.94**	-4.02**	-3.81**	-4.77**	-3.91**	-4.39**	-3.82**
Own1 Factor_1	0.34	0.85	-1.11	0.06	-1.63**	-1.15*	0.24	-0.59	0.42	-0.18	0.11	-1.17**	0.08
Own2 Factor_1	10.27**	10.61**	13.37**	11.72**	14.04**	18.16**	10.58**	12.78**	11.11**	17.06**	10.44**	15.62**	10.46**
Foreign1 Factor_1		-1.12	-1.79*	0.39	-3.18**	0.89	0.12	1.64**	0.42	-0.24	0.47	2.38**	0.46
Foreign2 Factor_1		-0.02	3.17**	1.93*	0.19	9.61**	1.09	2.96**	-0.77	4.50**	0.14	-1.10	0.29
Contagion_1		0.39	1.51*	0.77**	0.48	0.68	0.89	-0.59	0.36	-0.34	0.31	-0.47	0.96
Pseudo R2	0.54	0.56	0.61	0.58	0.63	0.69	0.56	0.61	0.56	0.66	0.55	0.66	0.55
Log-likelihood	-67.73	-64.82	-57.01	-61.42	-55.46	-46.54	-64.52	-58.44	-64.92	-50.37	-66.45	-49.89	-66.22
Netherlands	**Base**	**from DE**	**from FR**	**from ES**	**from IT**	**from BE**	**from IE**	**from PT**	**from FI**	**from GR**	**from UK**	**from DK**	**from SE**
Constant_1	-3.05**	-4.26**	-3.57**	-4.32**	-4.23**	-5.54**	-4.69**	-3.67**	-3.41**	-4.91**	-3.88**	-3.89**	-5.13**
Own1 Factor_1	-2.98**	-4.75**	-2.81**	-4.23**	-4.60**	-6.80**	-6.63**	-4.37**	-4.03**	-6.23**	-4.29**	-3.33**	-8.24**
Own2 Factor_1	-5.05**	-8.13**	-5.90**	-9.42**	-6.38**	-16.12**	-8.74**	-7.75**	-5.56**	-10.85**	-6.47**	-7.86**	-8.50**
Foreign1 Factor_1		-0.36	0.23	0.26	0.37	2.22*	-1.92**	0.21	1.12**	1.62*	-0.06	1.74**	-1.70**
Foreign2 Factor_1		4.43**	-0.92	5.75**	3.21**	15.75**	5.65**	4.98**	-0.86	6.71**	2.47**	-2.72**	6.84**
Contagion_1		0.92**	2.05**	1.28**	0.45	2.52	1.86**	0.60	0.82	0.13	0.65**	1.93**	2.97**
Pseudo R2	0.59	0.71	0.63	0.71	0.69	0.85	0.76	0.68	0.64	0.79	0.66	0.70	0.78
Log-likelihood	-64.85	-46.24	-58.52	-46.75	-48.93	-23.70	-37.38	-50.28	-56.54	-33.67	-53.24	-47.38	-35.36

Table 6 continued													
Spain	**Base**	**from DE**	**from FR**	**from NL**	**from IT**	**from BE**	**from IE**	**from PT**	**from FI**	**from GR**	**from UK**	**from DK**	**from SE**
Constant_1	-1.62**	-1.92**	-1.62**	-2.31**	-1.79**	-1.80**	-1.89**	-1.94**	-1.61**	-1.66**	-1.99**	-1.67**	-1.63**
Constant_2	-5.44**	-7.68**	-6.01**	-6.86**	-6.23**	-9.53**	-7.61**	-6.95**	-6.47**	-6.60**	-6.48**	-7.76**	-8.93**
Constant_3	-7.37**	-11.11**	-8.34**	-13.62**	-8.91**	-21.49**	-10.46**	-10.04**	-8.03**	-10.24**	-8.75**	-10.41**	-11.36**
Own1 Factor_1	0.10	0.24	-0.57	-1.70**	-0.06	-1.74**	-0.59	0.21	0.19	-0.48	-0.18	-0.42	-0.24
Own1 Factor_2	-0.27	-0.48	-1.22	-2.64**	-0.23	-4.30**	-1.74*	-0.45	0.02	-0.94	-0.30	-1.52**	0.10
Own1 Factor_3	-0.52	-0.44	-1.22	-4.96**	0.05	-9.07**	-3.08**	1.17	-0.62	-1.98**	-1.71	-1.75*	-1.74
Own2 Factor_1	-7.02**	-10.57**	-7.87**	-14.39**	-7.19**	-13.49**	-12.09**	-10.22**	-7.04**	-9.20**	-9.83**	-9.81**	-9.24**
Own2 Factor_2	13.75**	-21.70**	-15.20**	-22.47**	-14.35**	-31.09**	-23.57**	-19.62**	-14.19**	-18.81**	-18.12**	-21.72**	-24.03**
Own2 Factor_3	-15.57**	-26.21**	-17.92**	-30.39**	-16.28**	-47.90**	-27.05**	-23.20**	-15.68**	-22.98**	-20.57**	-24.41**	27.04**
Foreign1 Factor_1		-0.68**	0.67*	-0.95	-0.28	-0.21	0.58*	-0.30	0.23	-0.33	0.73	1.23**	0.53
Foreign1 Factor_2		-0.90	0.98	-1.92	-0.24	-0.43	1.24	0.03	1.07*	-0.12	0.48	2.51**	-0.61
Foreign1 Factor_3		-1.34	0.73	-3.88	0.25	-2.72	2.54**	0.83	0.54	-1.03	2.54	3.41**	1.71
Foreign2 Factor_1		2.85**	-1.25*	6.08**	0.18	8.33**	6.00**	4.51**	-0.15	2.46**	2.14**	-1.62**	2.19**
Foreign2 Factor_2		6.40**	-1.41	7.54**	0.76	18.99**	10.92**	7.31**	1.90*	4.43**	3.55**	-4.43**	6.73**
Foreign2 Factor_3		7.75**	-2.45*	12.32**	0.33	44.06**	12.22**	8.67**	2.01	8.95**	3.98**	-4.45**	8.43**
Contagion_1		0.45*	-0.35	0.21	0.27	0.83	1.18*	0.81*	-0.27	-0.68	0.53**	-0.66	-0.38
Contagion_2		1.27**	1.10	0.82	0.73*	0.85	3.29**	1.38*	0.11	-0.79	0.75	1.88	5.53**
Contagion_3		1.36**	1.14	3.34*	1.21**	-1.26	3.59**	2.01**	-0.92	-1.04	1.20**	2.45	6.08**
Pseudo R2	0.42	0.51	0.44	0.58	0.43	0.62	0.53	0.50	0.43	0.50	0.48	0.51	0.52
Log-likelihood	-176.67	-147.61	-168.05	-126.58	-170.63	-114.09	-141.92	-149.51	-170.73	-151.31	-156.81	-148.22	-145.90

Table 6 continued

Italy	Base	from DE	from FR	from NL	from ES	from BE	from IE	from PT	from FI	from GR	from UK	from DK	from SE
Constant_1	-1.09**	-1.19**	-1.12**	-1.15**	-1.20**	-1.07**	-1.13**	-1.12**	-1.08**	-1.08**	-1.22**	-1.12**	-1.09**
Constant_2	-2.56**	-2.90**	-2.73**	-2.82**	-2.78**	-2.64**	-2.87**	-2.71**	-2.78**	-2.67**	-2.60**	-2.67**	-2.83**
Constant_3	-2.39**	-3.07**	-2.66**	-3.09**	-2.82**	-2.70**	-2.98**	-3.00**	-2.67**	-2.47**	-3.09**	-2.55**	-2.84**
Own1 Factor_1	-0.20	0.43	0.68	0.35	-0.04	0.24	0.24	0.93*	-0.06	0.15	0.55	-0.14	0.72*
Own1 Factor_2	0.66*	1.29**	1.03	1.00**	0.58	1.29**	1.32**	1.54*	0.65	1.56**	1.40*	0.71*	1.56**
Own1 Factor_3	1.45**	2.71**	2.03**	2.59**	1.34**	2.67**	2.22**	2.59**	1.61**	2.22**	3.08**	1.30**	3.15**
Own2 Factor_1	0.20	0.03	-0.18	0.17	0.10	0.23	0.72*	-0.43	0.76*	0.53	0.29	0.19	0.59*
Own2 Factor_2	1.56**	1.21*	1.28*	1.44**	1.65**	1.50**	2.38**	1.20*	2.55**	1.87**	1.71**	1.51*	2.11**
Own2 Factor_3	1.10*	0.96	0.39	1.32*	1.15*	0.72	2.42**	0.80	2.01**	1.27*	1.36**	0.89*	1.82**
Foreign1 Factor_1		0.74**	0.81**	-1.05**	0.25	-0.57*	0.65**	1.27**	-0.43*	-0.49*	0.92*	0.04	1.08**
Foreign1 Factor_2		0.65	0.45	-0.50	-0.10	0.71	0.99*	1.07	-0.49	-0.89*	0.86	0.09	1.09*
Foreign1 Factor_3		1.17*	0.64	-2.57**	-0.06	-1.27**	1.16**	1.20	-0.60*	-0.79*	1.63**	0.38	1.83**
Foreign2 Factor_1		0.05	-0.44	0.38	-0.46	0.72	0.20	0.27	0.37	0.26	-0.11	-0.43	-0.40
Foreign2 Factor_2		0.35	0.36	0.61	1.09	1.28	0.40	-0.45	1.00	1.52*	-0.47	-0.36	-0.55
Foreign2 Factor_3		-1.18**	1.20	0.24	-1.48**	1.42	-1.53**	-1.71**	1.26*	1.05	-1.49**	0.40	-1.59**
Contagion_1		0.23	0.15	0.19	0.27	-0.62	0.45	-0.06	-0.31	-0.09	0.29	0.38	-0.33
Contagion_2		0.56**	1.01	1.16*	0.36	0.90	1.43**	0.47	1.25*	-0.54	0.13	1.14	2.25**
Contagion_3		0.43*	0.97**	0.58	0.50*	1.58*	1.38**	0.91**	1.30*	0.01	0.65**	1.43**	2.08**
Pseudo R2	0.06	0.13	0.09	0.13	0.10	0.10	0.14	0.13	0.10	0.09	0.12	0.08	0.13
Log-likelihood	-349.32	-324.13	-337.93	-323.47	-335.71	-337.19	-320.45	-326.19	-335.97	-338.37	-327.88	-341.92	-326.07

Belgium	Base	from DE	from FR	from NL	from ES	from IT	from IE	from PT	from FI	from GR	from UK	from DK	from SE
Constant_1	-3.37**	-3.61**	-3.87**	-3.79**	-3.82**	-4.63**	-4.41**	-3.53**	-5.22**	-4.62**	-3.98**	-4.02**	-3.97**
Own1 Factor_1	-1.22**	-1.12*	-1.45**	-1.78**	-2.02**	-2.87**	-4.33**	-1.26*	-6.95**	-5.05**	-2.27**	-2.21**	-3.40**
Own2 Factor_1	-0.71	0.64	2.56*	2.56	2.77*	2.24*	1.83	-0.02	-1.86	-3.28*	1.60	-1.53	3.10*
Foreign1 Factor_1		-0.07	-0.48	0.56	-1.11*	0.14	-2.28**	-0.26	3.68**	2.68**	1.52	1.45	-2.58**
Foreign2 Factor_1		0.91	3.51**	-2.03**	-1.86**	3.03**	-1.12*	-0.46	-1.62**	2.26*	-0.20	0.44	-0.97
Contagion_1		0.30	-0.11	0.54	0.20	0.34	0.14	0.55	-0.18	0.17	0.41	1.92**	0.33
Pseudo R2	0.09	0.14	0.21	0.18	0.20	0.22	0.29	0.10	0.29	0.31	0.20	0.19	0.19

Log-likelihood	-62.90	-59.14	-54.19	-56.36	-55.20	-53.61	-48.71	-61.69	-48.58	-47.22	-55.29	-55.68	-56.03

Ireland	**Base**	**from DE**	**from FR**	**from NL**	**from ES**	**from IT**	**from BE**	**from PT**	**from FI**	**from GR**	**from UK**	**from DK**	**from SE**
Constant_1	-5.66**		-6.02**	-6.23**	-8.71**	-6.75**	-8.21**		-6.04**	-9.54**	-6.30**	-7.77**	-7.73**
Constant_2	-10.49**		-12.24**	-15.70**	-24.72**	-21.23**	-25.66**		-9.88**	-18.02**	-17.50**	-13.22**	-13.89**
Own1 Factor_1	-0.14		0.15	-0.28	0.59	0.67	1.30		1.62	2.99	0.83	-0.82	0.66
Own1 Factor_2	-0.22		-0.36	0.53	2.62	5.06*	0.04		-0.42	-1.75	0.63	-0.59	0.24
Own2 Factor_1	-11.48**		-12.41**	-15.57**	-23.46**	-12.85**	-21.33**		-12.32**	-22.92**	-15.02**	-16.86**	-18.72**
Own2 Factor_2	-15.05**		-17.34**	-24.94**	-39.11**	-25.32**	-36.22		-15.30**	-29.44**	-25.08**	-21.38**	-24.31**
Foreign1 Factor_1			-0.44	0.30	-0.70	1.04	3.89		1.76	3.86	-0.52	2.78*	0.41
Foreign1 Factor_2			0.41	1.96	-1.35	4.78*	-2.12		-0.31	-2.16	1.53	3.21	1.20
Foreign2 Factor_1			-1.32	4.51**	12.56**	1.13	12.98**		-1.68*	9.66**	3.71*	-3.92*	9.67**
Foreign2 Factor_2			-2.28	7.97**	21.49**	10.76*	27.68*		-0.24	16.36**	7.03**	-4.40*	11.03**
Contagion_1			0.18	1.08	1.58	0.51	2.15		0.60	-6.36	0.14	1.83	1.82*
Contagion_2			2.12	4.25	3.96*	-0.21	-0.47		-0.47	-5.28	1.89	2.90	2.35
Pseudo R2	0.70		0.73	0.79	0.87	0.77	0.90		0.72	0.85	0.78	0.79	0.81
Log-likelihood	-39.14		-35.51	-26.61	-16.38	-29.28	-12.34		-35.56	-19.27	-28.23	-27.04	-24.04

Portugal	**Base**	**from DE**	**from FR**	**from NL**	**from ES**	**from IT**	**from BE**	**from IE**	**from FI**	**from GR**	**from UK**	**from DK**	**from SE**
Constant_1	-2.97**	-4.06**	-2.92**	-4.07**	-3.56**	-4.05**	-11.35**	-4.50**	-3.45**	-3.78**	-3.62**	-3.61**	-4.53**
Constant_2	-6.35**	-16.48**	-7.27**	-8.36**	-12.56**	-9.02**	-46.31**	-10.10**	-7.11**	-10.30**	-10.47**	-9.24**	-12.04**
Own1 Factor_1	0.33	1.36*	-0.29	1.30*	1.05	0.12	-4.27	2.35**	0.97*	0.66	1.41*	-0.20	2.38**
Own1 Factor_2	-0.90	2.39	-2.85*	0.13	-1.33	-0.53	-24.03	1.79	0.43	-0.78	1.65	-2.17*	1.92
Own2 Factor_1	-6.63**	-13.09**	-7.15**	-13.25**	-9.39**	-11.70**	-70.87**	-16.86**	-10.50**	-12.09**	-10.18**	-10.76**	-15.12**
Own2 Factor_2	-11.36**	-31.08**	-12.68**	-18.65**	-21.94**	-18.46**	-130.64**	-25.11**	-15.68**	-22.30**	-18.85**	-19.13**	-26.78**
Foreign1 Factor_1		-2.17**	0.59	3.63**	-0.93	-0.30	9.58	-2.87**	1.57**	1.51**	-0.87	2.68**	-1.61*
Foreign1 Factor_2		-2.29	1.74	3.91**	-0.49	-0.25	3.60	-3.54**	2.19**	1.97*	-1.57	3.01**	-2.39
Foreign2 Factor_1		5.12**	-0.68	4.05**	3.75**	4.11**	5.32*	9.24**	-1.08*	3.82**	3.26**	-1.86*	7.95**
Foreign2 Factor_2		9.76**	-0.09	4.43**	9.76**	6.32**	11.95*	10.79**	1.12	8.19**	6.24**	-5.04**	11.78**
Contagion_1		0.17	-1.17	0.30	0.59*	-0.05	-0.99	-0.21	-2.66	0.06	0.07	0.56	-2.78*
Contagion_2		2.66**	0.76	2.53*	3.08**	0.03	-6.63	1.79	-35.45	0.44	1.41**	3.11*	1.03
Pseudo R2	0.45	0.67	0.48	0.61	0.57	0.60	0.92	0.71	0.56	0.63	0.58	0.59	0.70

Log-likelihood	-104.72	-62.36	-99.24	-73.46	-81.60	-75.21	-14.97	-55.04	-83.00	-70.02	-80.27	-78.15	-57.38

Finland	**Base**	**from DE**	**from FR**	**from NL**	**from ES**	**from IT**	**from BE**	**from IE**	**from PT**	**from GR**	**from UK**	**from DK**	**from SE**
Constant_1	-3.83**	-5.18**	-6.82**	-4.89**	-5.38**	-5.72**	-6.34**	-4.65**	-7.19**	-4.57**	-6.24**	-4.06**	-5.23**
Own1 Factor_1	0.28	-0.79	-1.84*	-0.16	-1.36*	-0.87*	-2.58**	-1.67**	-2.27**	-2.02**	-2.57**	0.49	-1.79**
Own2 Factor_1	4.05**	6.94**	7.78**	6.04**	6.02**	6.35**	9.08**	5.28**	7.47**	5.55**	7.61**	4.13**	5.91**
Foreign1 Factor_1		-2.33**	-3.52**	2.14**	-2.63**	3.04**	4.89**	-2.51**	-5.77**	3.11**	-4.58**	-0.52	-3.13**
Foreign2 Factor_1		-0.00	-0.61	-0.89	0.26	-0.72	-2.40	0.03	-0.66	0.41	1.69*	0.16	0.35
Contagion_1		-0.08	0.07	0.26	-0.06	0.11	0.83	0.08	0.36	-0.08	-0.47	0.67	0.08
Pseudo R2	0.28	0.42	0.48	0.41	0.46	0.42	0.52	0.40	0.52	0.41	0.46	0.29	0.43
Log-likelihood	-65.93	-52.62	-47.73	-54.29	-49.45	-53.19	-44.10	-55.06	-43.95	-53.86	-49.45	-64.42	-52.31

Greece	**Base**	**from DE**	**from FR**	**from NL**	**from ES**	**from IT**	**from BE**	**from IE**	**from PT**	**from FI**	**from UK**	**from DK**	**from SE**
Constant_1	-2.64**	-2.64**	-2.63**	-2.66**	-2.80**	-2.63**	-3.00**	-3.02**	-2.83**	-2.69**	-2.73**	-2.76**	-2.87**
Own1 Factor_1	0.40	0.28	0.36	0.33	0.12	0.13	0.84	-3.40**	0.51	0.08	0.02	0.48	-0.03
Own2 Factor_1	1.80**	2.75**	2.14**	2.43**	2.82**	2.14**	4.74**	3.61**	2.70**	2.13**	2.87**	2.54**	3.49**
Foreign1 Factor_1		-0.27	-0.09	0.04	-0.54*	0.52	-0.68	-3.78**	-0.27	0.36	-1.03**	-0.55	-1.06**
Foreign2 Factor_1		-1.23**	1.07	-1.05**	-1.56**	0.34	5.39**	-1.38**	-1.63**	0.59	-0.89*	0.54	-1.71**
Contagion_1		-0.31	-0.38	-0.46	-0.12	-0.09	-1.84	-0.53	0.30	-0.54	-0.24	0.62	-1.17
Pseudo R2	0.09	0.13	0.11	0.12	0.14	0.10	0.22	0.20	0.14	0.11	0.15	0.12	0.17
Log-likelihood	-98.98	-94.26	-97.08	-95.37	-92.97	-97.47	-84.30	-87.09	-93.70	-96.93	-92.16	-96.10	-89.88

United Kingdom	Base	from DE	from FR	from NL	from ES	from IT	from BE	from IE	from PT	from FI	from GR	from DK	from SE
Constant_1	-1.23**	-1.78**	-1.35**	-1.56**	-1.41**	-1.36**	-1.47**	-1.41**	-1.59**	-1.38**	-1.38**	-1.30**	-1.33**
Constant_2	-4.15**	-6.10**	-4.57**	-5.05**	-4.81**	-4.89**	-6.35**	-5.00**	-4.77**	-4.58**	-4.95**	-4.55**	-5.50**
Constant_3	-5.24**	-9.90**	-6.17**	-6.87**	-6.76**	-6.44**	-7.88**	-7.79**	-5.92**	-6.48**	-5.92**	-6.94**	-11.72**
Constant_4	-11.03**	-16.41**	-11.84**	-20.11**	-22.59**	-30.52**	-18.93**	-13.72**	-18.35**	-18.66**	-18.50**	-15.05**	-19.78**
Own1 Factor_1	-1.13**	-2.48**	-2.31**	-2.48**	-2.11**	-1.20**	-5.70**	-1.38**	-2.48**	-0.76**	-2.03**	-1.78**	-8.73**
Own1 Factor_2	-2.50**	-4.47**	-4.80**	-4.67**	-4.19**	-2.95**	-10.52**	-2.94**	-4.44**	-1.86**	-3.63**	-3.46**	-17.92**
Own1 Factor_3	-2.52**	-4.84**	-1.95	-4.76**	-3.27**	-2.91*	-10.40**	-3.72*	-4.29**	-4.59**	-3.61**	-4.17**	-34.29**
Own1 Factor_4	-4.49**	-7.86**	-7.66**	-9.79**	-8.99**	-0.64	-18.23**	-2.07	-7.27*	-5.16*	-6.18	-6.62**	-42.91**
Own2 Factor_1	-3.86**	-6.86**	-4.07**	-6.31**	-4.33**	-4.83**	-7.80**	-6.59**	-5.86**	-4.22**	-5.32**	-4.69**	-5.34**
Own2 Factor_2	-7.62**	-13.16**	-8.06**	-11.26**	-8.96**	-9.52**	-14.93**	-12.50**	-9.81**	-8.33**	-10.37**	-9.09**	-9.59**
Own2 Factor_3	-7.82**	-15.95**	-7.65**	-11.76**	-10.22**	-9.92**	-15.06**	-13.51**	-9.98**	-6.55**	-10.00**	-9.86**	-9.76**
Own2 Factor_4	11.89**	-18.27**	-12.15**	-21.24**	-20.28**	-26.85**	-22.12**	-18.23**	-19.99**	-19.06**	-19.86**	-16.34**	-13.18**
Foreign1 Factor_1		0.28	1.01	0.26	0.83*	0.15	-1.66**	-0.51	0.92**	0.68**	0.27	0.82**	6.94**
Foreign1 Factor_2		0.49	1.93**	-0.63	1.42	-0.12	-3.14**	-0.64	1.62	1.38*	0.57	1.41**	14.44**
Foreign1 Factor_3		-0.24	-0.44	-0.16	0.59	-0.13	-3.03**	0.19	1.43	-2.43	0.18	0.61	28.62**
Foreign1 Factor_4		3.26	3.24*	-2.15	1.34	3.56	-8.32**	-2.94	1.20	3.35	2.38	4.34*	34.73**
Foreign2 Factor_1		3.50**	-0.63	3.51**	1.11	1.48**	10.77**	3.72**	3.69**	-0.09	2.89**	-1.06*	3.90**
Foreign2 Factor_2		5.55**	-1.18	5.27**	3.21**	2.62**	19.43**	6.30**	3.70**	0.50	4.61**	-2.00*	5.09**
Foreign2 Factor_3		7.15**	0.85	5.01**	4.13**	2.62*	19.31**	6.25**	3.53*	1.28	3.67**	-5.89**	6.58**
Foreign2 Factor_4		6.22**	-0.09	9.86**	8.02**	13.33	32.61**	4.49*	8.63*	-3.83	10.46**	-2.89	6.18**
Contagion_1		0.79**	0.47	0.87	0.45	0.04	-0.64	0.16	0.88*	0.72	-0.51	0.08	0.91
Contagion_2		1.44**	0.58	0.69	0.90*	0.29	1.66	-0.20	1.36*	-0.06	-0.44	0.64	2.99**
Contagion_3		2.32**	2.99**	2.57*	1.45**	0.68	1.25	2.48**	1.70*	1.33	0.65	2.32*	5.08**
Contagion_4		2.45**	-0.30	5.83*	3.15**	4.17	-2.67	1.87	2.72*	1.26	0.86	2.93	5.78*
Pseudo R2	0.38	0.51	0.42	0.48	0.43	0.44	0.59	0.48	0.46	0.42	0.48	0.44	0.53
Log-likelihood	-208.22	-163.25	-192.53	-174.86	-190.35	-186.66	-137.17	-173.74	-179.24	-192.43	-173.39	-188.22	-157.64

Sweden	Base	from DE	from FR	from NL	from ES	from IT	from BE	from IE	from PT	from FI	from GR	from UK	from DK
Constant_1	-4.18**	-5.73**	-4.39**	-4.44**	-5.21**	-4.63**	-5.66**	-4.48**	-4.37**	-4.32**	-5.57**	-4.64**	-4.36**
Own1 Factor_1	-0.64	-2.11**	-1.09	-0.15	0.95	-0.81	-5.12**	-0.11	-0.71	-0.36	-1.15	-2.70	-0.94*
Own2 Factor_1	-5.09**	-7.88**	-4.71**	-6.27**	-7.91**	-6.04**	-11.08**	-5.97**	-6.11**	-5.10**	-9.34**	-6.06**	-5.87**
Foreign1 Factor_1		0.93	0.49	1.15	-2.19*	0.67	-2.98**	-0.58	0.15	0.47	-0.14	2.55	0.64
Foreign2 Factor_1		2.58**	0.81	0.28	2.83**	1.57	13.27**	0.92	1.51	0.37	5.59**	0.49	-0.94
Contagion_1		0.90**	0.75	0.77	0.70*	0.32	1.26	1.09*	0.29	0.66	1.22*	0.67*	0.73
Pseudo R2	0.42	0.54	0.44	0.44	0.52	0.46	0.64	0.45	0.44	0.43	0.60	0.47	0.45
Log-likelihood	-48.61	-38.48	-46.84	-46.71	-40.20	-45.05	-29.96	-45.61	-46.58	-47.70	-33.08	-44.03	-45.72

Table 7. Summary matrix of contagion patterns based on base model estimated in Table 6.

++ denotes contagion variables significant at the 1 percent level, + contagion variables significant at the five percent level. 0 denotes no contagion.

from to	DE	FR	NL	ES	IT	BE	IE	PT	FI	GR	UK	DK	SE
DE	/	+	+	++	++	0	++	0	0	0	++	++	+
FR	0	/	+	++	0	0	0	0	0	0	0	0	0
NL	++	++	/	++	0	0	++	0	0	0	++	++	++
ES	++	0	0	/	+	0	++	+	0	0	+	0	++
IT	+	+	0	0	/	0	++	+	+	0	+	+	++
BE	0	0	0	0	0	/	0	0	0	0	0	++	0
IE	0	0	0	+	0	0	/	0	0	0	0	0	0
PT	++	0	+	++	0	0	0	/	0	0	++	+	0
FI	0	0	0	0	0	0	0	0	/	0	0	0	0
GR	0	0	0	0	0	0	0	0	0	/	0	0	0
UK	++	0	+	++	0	0	0	+	0	0	/	0	+
DK	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	/	N/A
SE	++	0	0	+	0	0	+	0	0	+	+	0	/

Table 8. Multinomial regression results – coefficients for periods before and after the introduction of the euro

*Dependent variable: number of domestic banks simultaneously in the tail. *, ** indicate statistical significance at the 5% and 1% levels, respectively. Number of observations 367.*

Germany	**From DE**	**From FR**	**From NL**	**From ES**	**From IT**	**From BE**	**From IE**	**From PT**	**From FI**	**From GR**	**From UK**	**From DK**	**From SE**
Contagion1 after the euro		-1.39	0.82	0.65*	0.30	1.70	1.52	1.26**	0.23	1.29	0.74*	0.28	-39.16
Contagion1 before the euro		1.19	1.38*	1.65**	-1.72	1.12	1.83**	0.82	1.20	0.33	0.58*	5.28**	2.08*
Contagion2 after the euro		0.21	0.75	1.71**	1.33*	n.a.	5.41**	2.00	n.a.	n.a.	2.00**	n.a.	5.36**
Contagion2 before the euro		0.42	0.08	2.68**	0.20	1.25	2.33*	n.a.	-0.12	0.84	1.13*	n.a.	n.a.
Contagion3 after the euro		3.86**	2.63*	3.11**	4.97**	n.a.	6.59**	3.35**	n.a.	n.a.	3.18**	6.45**	10.24**
Contagion3 before the euro		1.93	0.98	2.47*	-0.29	n.a.	2.68*	n.a.	n.a.	n.a.	1.88*	9.75**	1.35
Contagion4 after the euro		3.34*	4.26*	4.29**	6.07**	9.19	10.55**	5.98**	n.a.	n.a.	3.03**	n.a.	8.51**
Contagion4 before the euro		3.43	2.82	4.02**	0.14	4.40	0.44	2.00	-0.02	n.a.	-0.44	11.41**	-1.51
Log likelihood		-186.91	-177.11	-160.21	-166.74	-159.09	-158.22	-161.94	-191.26	-173.36	-161.25	-168.29	-156.52
Pseudo R^2		0.42	0.45	0.51	0.49	0.51	0.51	0.50	0.41	0.47	0.50	0.48	0.52
France													
Contagion1 after the euro	0.56		1.85**	1.52**	0.86*	2.98[1]	2.33*	-1.26	1.36	-0.74	0.40	1.64	1.27
Contagion1 before the euro	0.31		1.04	-0.42	0.19	-3.45	0.28	0.29	-1.28	-0.44	0.20	-0.83	0.54
Log likelihood	-64.60		-56.71	-55.12	-54.57	-44.23	-62.69	-57.10	-63.58	-49.88	-66.32	-49.42	-66.10
Pseudo R^2	0.56		0.61	0.62	0.63	0.70	0.57	0.61	0.57	0.66	0.55	0.66	0.55
The Netherlands													
Contagion1 after the euro	0.68*	1.82**		0.94*	0.77*	2.44	1.51	0.90	1.61[1]	0.48	0.29	2.45*	3.77**
Contagion1 before the euro	1.23**	2.33**		1.73**	0.23	2.52	1.96*	0.33	1.19	0.27	1.20**	10.09**	1.94
Log likelihood	-45.46	-58.39		-45.92	-48.32	-23.69	-37.31	-50.01	-55.51	-33.54	-51.17	-39.22	-34.77
Pseudo R^2	0.71	0.63		0.71	0.69	0.85	0.77	0.68	0.64	0.78	0.67	0.75	0.78

Table 8. Multinomial logit-regression results – coefficients for periods before and after the introduction of the euro (continued)

*Dependent variable: number of domestic banks simultaneously in the tail. *, ** indicate statistical significance at the 5% and 1% levels, respectively. Number of observations 367.*

Spain	**From DE**	**From FR**	**From NL**	**From ES**	**From IT**	**From BE**	**From IE**	**From PT**	**From FI**	**From GR**	**From UK**	**From DK**	**From SE**
Contagion1 after the euro	0.45	-0.45	0.77		0.88**	3.43*	2.48**	1.20*	0.05	-0.25	0.66*	-0.04	n.a.
Contagion1 before the euro	0.43*	-0.28	-0.28		-0.11	-0.14	0.20	0.44	0.98	-0.57	0.40	1.72	n.a.
Contagion2 after the euro	1.78**	1.63	1.78		0.87	8.78**	5.53**	n.a.	0.95	0.09	0.88	2.47	5.36*
Contagion2 before the euro	1.05*	0.51	-0.049		0.38	-7.60	2.04*	1.10	-0.06	-0.65	0.34	9.42**	4.10
Contagion3 after the euro	2.54**	3.66*	6.57**		3.05**	11.26	6.81**	4.03**	0.67	n.a.	2.23**	5.49*	10.02**
Contagion3 before the euro	-0.60	-1.38	0.82		0.20	n.a.	1.78	1.04	0.90	-0.90	0.37	12.96**	2.27
Log likelihood	-141.95	-164.74	-122.63		-161.25	-106.14	-136.70	-145.93	-170.31	-151.50	-152.52	-140.30	-142.77
Pseudo R^2	0.52	0.45	0.59		0.46	0.64	0.54	0.51	0.43	0.49	0.49	0.53	0.52
Italy													
Contagion1 after the euro	0.48*	-0.18	0.54	0.59*		0.13	0.63	0.12	-0.03	0.10	0.56**	-0.89	0.17
Contagion1 before the euro	0.02	0.45	-0.16	-0.16		-1.02	0.27	-0.19	0.24	-0.01	-0.07	1.76	n.a.
Contagion2 after the euro	0.93**	1.67*	0.35	0.63		2.36	1.40	0.41	0.48	n.a.	-0.478	1.28	2.20*
Contagion2 before the euro	0.35	0.49	1.38*	0.13		0.02	1.38**	0.48	n.a.	-0.30	0.19	1.78	2.30*
Contagion3 after the euro	0.86**	1.66**	0.24	0.77*		2.41*	1.57*	1.33**	1.43*	n.a.	0.75**	0.67	2.00*
Contagion3 before the euro	0.19	0.31	0.84	0.28		1.10	1.25*	0.60	2.35*	0.31	0.57*	2.37**	2.21*
Log likelihood	-321.47	-335.70	-322.03	-333.13		-336.16	-320.30	-325.32	-333.55	-336.75	-324.85	-340.50	-325.12
Pseudo R^2	0.13	0.10	0.13	0.11		0.01	0.14	0.13	0.11	0.10	0.12	0.09	0.13
Belgium													
Contagion1 after the euro	0.10	-0.47	-0.15	-0.11	0.30		0.24	-0.12	0.70	n.a.	0.27	1.12	0.42
Contagion1 before the euro	0.44	0.27	1.03	0.40	0.35		0.10	1.06*	-5.28	0.33	0.53*	1.35	0.21
Log likelihood	-58.72	-54.01	-55.70	-54.64	-53.59		-48.70	-60.33	-48.01	-46.77	-55.01	-58.51	-56.02
Pseudo R^2	0.15	0.21	0.19	0.21	0.22		0.29	0.12	0.29	0.32	0.20	0.15	0.19

Table 8. Multinomial logit-regression results – coefficients for periods before and after the introduction of the euro (continued)

*Dependent variable: number of domestic banks simultaneously in the tail. *, ** indicate statistical significance at the 5% and 1% levels, respectively. Number of observations 367.*

Ireland	**From DE**	**From FR**	**From NL**	**From ES**	**From IT**	**From BE**	**From IE**	**From PT**	**From FI**	**From GR**	**From UK**	**From DK**	**From SE**
Contagion1 after the euro	n.a.	0.76	3.02*	2.45[1]	0.02	4.94		n.a.	1.39	n.a	1.33*	n.a.	5.27**
Contagion1 before the euro	n.a.	-0.59	-4.41	0.37	n.a.	0.52		n.a.	n.a.	-6.27	-0.49	n.a.	n.a.
Contagion2 after the euro	n.a.	3.12	12.70*	5.39*	n.a.	n.a.		n.a.	n.a.	-5.18	4.58*	n.a.	9.01*
Contagion2 before the euro	n.a.	1.18	-1.46	2.34	n.a.	-1.27		n.a.	-1.90	n.a.	0.34	n.a.	n.a.
Log likelihood	n.a.	-35.10	-21.48	-15.56	-22.78	-11.93		n.a.	-34.70	-19.12	-25.08	n.a.	-21.45
Pseudo R^2	n.a.	0.72	0.83	0.88	0.82	0.91		n.a.	0.73	0.85	0.80	n.a.	0.83
Portugal													
Contagion1 after the euro	0.06	-1.46	0.35	-0.05	0.64	n.a.	4.04**		n.a.	1.08	0.08	n.a.	-1.67
Contagion1 before the euro	0.57	-0.85	0.14	1.01**	-0.29	n.a.	-3.69		0.86	-0.34	0.04	7.40**	n.a.
Contagion2 after the euro	2.72*	-0.07	1.17	3.22**	2.31*	n.a.	9.78**		n.a.	n.a	1.25*	2.23	2.41
Contagion2 before the euro	2.81*	1.53	3.12*	3.15**	-0.58	n.a.	-0.23		0.35	0.26	1.57**	10.24*	-0.50
Log likelihood	-62.06	-98.81	-72.74	-79.41	-70.69	n.a.	-44.93		-84.58	-67.98	-80.11	-69.53	-56.26
Pseudo R^2	0.67	0.48	0.61	0.60	0.62	n.a.	0.76		0.55	0.64	0.57	0.63	0.70
Finland													
Contagion1 after the euro	-0.34	-0.90	0.58	-0.012	-0.13	n.a	0.45	0.77		n.a.	-0.66	-0.19	0.98
Contagion1 before the euro	0.34	1.51	0.01	-0.10	0.29	1.614	-0.05	-0.028		-0.19	-0.37	0.89	-0.69
Log likelihood	-51.96	-46.14	-54.18	-49.43	-52.81	-43.14	-54.95	-43.65		-53.49	-49.29	-63.85	-51.84
Pseudo R^2	0.43	0.49	0.41	0.46	0.42	0.52	0.39	0.52		0.41	0.46	0.29	0.43
Greece													
Contagion1 after the euro	-0.52	n.a	-0.28	-0.19	-0.25	n.a	-0.05	0.33	n.a		-1.28	0.58	n.a
Contagion1 before the euro	-0.25	0.07	-0.51	-0.08	-0.04	-1.76	-0.65	0.28	1.25		-0.13	-1.01	-0.81
Log likelihood	-94.15	-95.75	-95.35	-92.94	-97.35	-84.26	-86.95	-93.69	-95.16		-91.05	-96.04	-89.58
Pseudo R^2	0.13	0.09	0.12	0.14	0.10	0.22	0.20	0.13	0.12		0.16	0.12	0.17

Table 8. Multinomial logit-regression results – coefficients for periods before and after the introduction of the euro (continued)

*Dependent variable: number of domestic banks simultaneously in the tail. *, ** indicate statistical significance at the 5% and 1% levels, respectively. Number of observations 367.*

The United Kingdom	**From DE**	**From FR**	**From NL**	**From ES**	**From IT**	**From BE**	**From IE**	**From PT**	**From FI**	**From GR**	**From UK**	**From DK**	**From SE**
Contagion1 after the euro	0.51	0.74	0.03	0.52	0.58*	n.a.	0.83	0.78	1.02	-0.91		0.17	1.35
Contagion1 before the euro	0.92**	0.24	1.32**	0.37	-0.19	-0.55	0.06	0.89[1]	n.a.	-0.61		3.48**	0.56
Contagion2 after the euro	1.61**	0.95	-37.36	0.91	0.50	n.a.	1.78	1.41	0.82	n.a.		0.95	4.29**
Contagion2 before the euro	1.37**	0.24	2.16*	0.85[1]	0.20	-2.04	n.a.	1.23	3.37	0.07		8.50**	1.84
Contagion3 after the euro	2.78**	3.18*	1.80	1.93**	1.27*	3.48	4.88**	3.07**	2.75*	n.a.		2.91*	6.41**
Contagion3 before the euro	2.03**	2.87*	2.56[1]	1.24*	0.48	0.39	2.09*	n.a.	4.60	1.38		n.a.	4.37
Contagion4 after the euro	2.37	3.18*	-4.52	-0.12	0.72	0.67	4.21	0.98	n.a.	-0.90		n.a.	4.08
Contagion4 before the euro	2.48**	2.87*	16.06[1]	4.84*	3.73[1]	-3.31	1.55	2.57*	5.34	1.41		16.77**	7.41
Log likelihood	-160.65	-191.62	-167.26	-187.51	-183.44	-136.53	-171.77	-175.58	-187.36	-171.19		-178.25	-156.37
Pseudo R^2	0.51	0.42	0.49	0.43	0.44	0.59	0.48	0.47	0.43	0.48		0.46	0.53
Sweden													
Contagion1 after the euro	0.67	-0.02	0.41	0.05	-0.01	0.82	0.36	0.66	0.65	n.a.	0.27	-0.24	
Contagion1 before the euro	1.07**	1.89*	1.45	1.35**	0.48	1.38	1.41*	-1.12	1.78	1.34	1.06**	1.26	
Log likelihood	-38.12	-45.64	-46.36	-38.14	-44.64	-29.93	-45.06	-45.97	-47.13	-32.03	-42.48	-45.91	
Pseudo R^2	0.54	0.45	0.44	0.54	0.46	0.64	0.46	0.44	0.43	0.61	0.49	0.45	

Full results available from authors. [1] significant at 6% level n.a.: coefficient was not identifiable. The model did not converge for Denmark.

Table 9a. Breakdown of EU cross-border interbank assets 12/1997

	Borrowing country													
Creditor country	**DE**	**FR**	**NL**	**ES**	**IT**	**BE**	**IE**	**PT**	**FI**	**GR**	**UK**	**DK**	**SE**	**SUM**
Germany		13.0%	6.3%	2.1%	6.0%	5.2%	4.9%	0.7%	0.5%	0.6%	58.0%	1.6%	1.1%	100.0%
France	7.3%		5.9%	6.2%	9.5%	7.4%	1.4%	1.6%	1.4%	0.9%	53.9%	1.8%	2.6%	100.0%
Netherlands	11.5%	12.4%		2.0%	5.6%	14.3%	8.2%	1.4%	0.5%	0.3%	40.2%	2.1%	1.6%	100.0%
Spain	7.5%	28.6%	3.1%		9.0%	6.3%	1.5%	5.7%	0.1%	0.3%	37.3%	0.3%	0.4%	100.0%
Italy	9.4%	18.7%	2.3%	3.9%		4.9%	0.4%	1.2%	0.2%	0.5%	57.9%	0.4%	0.3%	100.0%
Belgium	10.0%	15.1%	9.7%	3.0%	7.7%		2.6%	1.4%	0.5%	0.2%	45.3%	2.4%	2.0%	100.0%
Ireland	18.7%	5.7%	9.2%	13.7%	3.1%	2.0%		0.2%	0.3%	0.5%	43.0%	2.6%	1.1%	100.0%
Portugal	4.7%	10.4%	2.8%	20.8%	37.3%	2.7%	0.6%		0.0%	0.6%	19.3%	0.2%	0.5%	100.0%
Finland	4.7%	8.7%	1.3%	0.5%	1.1%	3.4%	0.2%	0.0%		0.1%	39.8%	15.3%	24.8%	100.0%
Greece	1.7%	14.8%	1.1%	0.0%	1.0%	4.4%	1.2%	0.6%	0.1%		74.7%	0.2%	0.1%	100.0%
UK	34.1%	18.7%	11.4%	4.2%	12.0%	5.1%	6.5%	1.8%	0.6%	1.4%		1.8%	2.4%	100.0%
Denmark	19.7%	2.1%	1.7%	1.1%	1.6%	4.0%	1.3%	0.5%	10.5%	0.1%	32.0%		25.5%	100.0%
Sweden	13.8%	3.3%	4.1%	1.0%	0.6%	3.2%	2.3%	0.9%	8.6%	0.3%	46.0%	15.8%		100.0%
Average	11.9%	12.6%	4.9%	4.9%	7.9%	5.2%	2.6%	1.3%	1.9%	0.5%	45.6%	3.7%	5.2%	100.0%

Source: ECB.

Table 9b. Breakdown of EU cross-border interbank assets 12/2002

	Borrowing country													
Creditor country	**DE**	**FR**	**NL**	**ES**	**IT**	**BE**	**IE**	**PT**	**FI**	**GR**	**UK**	**DK**	**SE**	**SUM**
Germany		12.0%	5.4%	6.2%	8.3%	5.8%	5.3%	2.0%	0.3%	0.5%	50.4%	2.4%	1.4%	100.0%
France	15.2%		5.3%	11.0%	10.3%	6.9%	2.2%	3.9%	0.5%	0.6%	43.0%	0.2%	0.9%	100.0%
Netherlands	5.1%	9.4%		1.1%	4.1%	5.6%	6.7%	0.4%	0.0%	0.3%	66.0%	0.7%	0.7%	100.0%
Spain	13.9%	13.3%	11.8%		6.0%	8.0%	1.2%	10.6%	0.1%	0.1%	34.2%	0.7%	0.1%	100.0%
Italy	18.8%	13.9%	6.3%	9.1%		7.9%	2.6%	0.9%	0.0%	0.5%	39.1%	0.6%	0.1%	100.0%
Belgium	10.8%	15.8%	15.1%	5.4%	1.8%		8.5%	1.1%	0.3%	0.7%	39.7%	0.6%	0.1%	100.0%
Ireland	17.2%	7.2%	5.0%	6.9%	6.9%	1.8%		0.8%	0.3%	0.0%	51.9%	1.4%	0.6%	100.0%
Portugal	15.8%	10.9%	0.5%	12.6%	30.9%	2.0%	5.3%		0.9%	0.6%	19.5%	1.0%	0.0%	100.0%
Finland	0.2%	0.1%	2.7%	0.0%	0.0%	1.0%	0.1%	0.0%		0.0%	3.5%	41.1%	51.3%	100.0%
Greece	11.3%	13.6%	2.0%	2.6%	6.2%	5.1%	1.4%	0.3%	0.0%		56.1%	0.4%	1.0%	100.0%
UK	34.1%	18.7%	11.4%	4.2%	12.0%	5.1%	6.5%	1.8%	0.6%	1.4%		1.8%	2.4%	100.0%
Denmark	19.7%	2.1%	1.7%	1.1%	1.6%	4.0%	1.3%	0.5%	10.5%	0.1%	32.0%		25.5%	100.0%
Sweden	13.8%	3.3%	4.1%	1.0%	0.6%	3.2%	2.3%	0.9%	8.6%	0.3%	46.0%	15.8%		100.0%
Average	14.7%	10.0%	5.9%	5.1%	7.4%	4.7%	3.6%	1.9%	1.8%	0.4%	40.1%	5.6%	7.0%	100.0%

Source: ECB.

Table 10a. Breakdown of EU cross-border interbank liabilities 12/1997

	Creditor country													
Borrowing country	**DE**	**FR**	**NL**	**ES**	**IT**	**BE**	**IE**	**PT**	**FI**	**GR**	**UK**	**DK**	**SE**	**SUM**
Germany		9.2%	10.0%	1.8%	4.4%	2.5%	2.7%	1.0%	0.3%	0.5%	66.0%	1.5%	0.5%	100.0%
France	8.9%		4.3%	5.7%	8.1%	6.4%	1.3%	1.7%	5.1%	0.9%	53.1%	2.1%	2.2%	100.0%
Netherlands	15.0%	16.9%		2.1%	4.9%	14.2%	1.3%	1.3%	0.9%	1.4%	38.5%	3.1%	0.4%	100.0%
Spain	9.4%	18.8%	3.4%		5.4%	5.4%	4.3%	7.9%	0.2%	0.5%	44.1%	0.3%	0.4%	100.0%
Italy	11.6%	13.8%	5.2%	3.0%		6.1%	0.7%	9.3%	0.2%	0.4%	49.3%	0.1%	0.2%	100.0%
Belgium	9.3%	19.6%	12.0%	4.2%	5.8%		0.9%	0.5%	0.8%	1.4%	43.6%	1.6%	0.3%	100.0%
Ireland	10.9%	5.1%	18.4%	2.5%	4.0%	8.7%		0.1%	0.1%	0.0%	49.7%	0.2%	0.1%	100.0%
Portugal	7.1%	23.1%	8.4%	20.3%	4.1%	8.5%	0.6%		0.0%	0.7%	26.4%	0.4%	0.4%	100.0%
Finland	12.0%	3.7%	4.0%	1.8%	2.8%	4.7%	0.2%	0.0%		0.3%	32.5%	12.7%	25.2%	100.0%
Greece	10.3%	11.5%	2.1%	0.0%	5.2%	5.5%	1.1%	1.5%	0.1%		62.1%	0.3%	0.5%	100.0%
UK	5.9%	3.4%	3.6%	0.7%	2.0%	1.5%	1.2%	0.2%	0.1%	80.3%		0.7%	0.6%	100.0%
Denmark	12.9%	2.6%	4.8%	1.8%	1.4%	4.5%	1.5%	0.2%	25.2%	0.2%	30.5%		14.4%	100.0%
Sweden	8.2%	6.2%	3.3%	0.8%	0.5%	1.9%	0.8%	0.1%	28.7%	0.0%	34.8%	14.7%		100.0%
Average	10.1%	11.2%	6.6%	3.7%	4.1%	5.8%	1.4%	2.0%	5.1%	7.2%	44.2%	3.1%	3.8%	100.0%

Source: ECB.

Table 10b. Breakdown of EU cross-border interbank liabilities 12/2002

	Creditor country													
Borrowing country	**DE**	**FR**	**NL**	**ES**	**IT**	**BE**	**IE**	**PT**	**FI**	**GR**	**UK**	**DK**	**SE**	**SUM**
Germany		13.3%	3.2%	3.4%	7.0%	4.5%	3.0%	1.3%	0.0%	0.8%	60.5%	1.2%	1.8%	100.0%
France	19.9%		7.1%	4.0%	5.6%	8.6%	2.3%	1.3%	0.0%	1.2%	49.6%	0.2%	0.2%	100.0%
Netherlands	8.4%	6.4%		5.4%	3.4%	12.8%	1.7%	0.1%	0.4%	0.8%	59.6%	0.7%	0.2%	100.0%
Spain	23.0%	27.1%	2.2%		10.0%	5.3%	3.7%	2.6%	0.1%	0.1%	25.3%	0.3%	0.4%	100.0%
Italy	21.5%	17.2%	5.5%	3.0%		1.8%	3.0%	5.9%	0.0%	0.3%	41.2%	0.3%	0.2%	100.0%
Belgium	18.8%	12.5%	9.2%	5.5%	8.4%		0.9%	0.6%	0.3%	2.7%	38.9%	2.2%	0.1%	100.0%
Ireland	15.7%	4.8%	9.9%	0.4%	2.1%	10.5%		0.9%	0.0%	0.3%	54.7%	0.3%	0.3%	100.0%
Portugal	22.0%	22.2%	3.5%	16.0%	2.3%	3.2%	1.6%		0.0%	0.2%	28.4%	0.3%	0.3%	100%
Finland	6.6%	1.0%	0.5%	0.3%	0.0%	2.4%	1.0%	1.6%	0.0%		51.6%	5.7%	29.2%	100.0%
Greece	12.6%	6.7%	3.7%	0.5%	4.2%	5.8%	0.3%	1.0%	0.0%		65.0%	0.0%	0.1%	100.0%
UK	5.9%	3.4%	3.6%	0.7%	2.0%	1.5%	1.2%	0.2%	0.1%	80.3%		0.7%	0.6%	100.0%
Denmark	12.9%	2.6%	4.8%	1.8%	1.4%	4.5%	1.5%	0.2%	25.2%	0.2%	30.5%		14.4%	100.0%
Sweden	8.2%	6.2%	3.3%	0.8%	0.5%	1.9%	0.8%	0.1%	28.7%	0.0%	34.8%	14.7%		100.0%
Average	14.6%	10.3%	4.7%	3.5%	3.9%	5.2%	1.8%	1.3%	4.2%	7.9%	45.0%	2.2%	4.0%	100.0%

Source: ECB.

Table 11. EU cross-border interbank operations

	Share in total EU cross-border interbank assets 12/97	Share in total EU cross-border interbank assets 12/02	Share in total EU cross-border interbank liabilities 12/97	Share in total EU cross-border interbank liabilities 12/02	Growth in EU cross-border interbank assets 12/97-12/02	Growth in EU cross-border interbank liabilities 12/97-12/02	Share of EU cross-border assets in total interbank assets 12/97	Share of EU cross-border assets in total interbank assets 12/02	Share of EU cross-border liabilities in total interbank liabilities 12/97	Share of EU cross-border liabilities in total interbank liabilities 12/97
Germany	16.5%	24.1%	8.7%	11.0%	141%	92%	13%	22%	13%	18%
France	20.0%	15.7%	10.4%	8.7%	30%	27%	17%	19%	18%	17%
Netherlands	7.9%	11.1%	3.1%	5.6%	134%	174%	37%	45%	25%	36%
Spain	5.0%	4.7%	2.6%	3.7%	57%	114%	20%	29%	20%	35%
Italy	8.3%	6.8%	5.7%	4.8%	36%	28%	29%	26%	35%	28%
Belgium	9.0%	9.5%	4.1%	3.8%	73%	40%	40%	82%	29%	48%
Ireland	3.0%	3.6%	2.8%	4.0%	96%	116%	41%	52%	49%	60%
Portugal	2.1%	1.7%	0.7%	1.6%	33%	237%	35%	39%	25%	40%
Finland	1.1%	1.3%	0.3%	0.5%	99%	193%	51%	47%	36%	36%
Greece	1.4%	1.1%	0.4%	0.6%	32%	126%	26%	45%	30%	46%
UK	21.2%	16.8%	34.4%	31.3%	31%	38%	30%	30%	92%	92%
Denmark	2.4%	2.0%	14.1%	12.8%	35%	38%	32%	32%	38%	38%
Sweden	2.1%	1.7%	12.8%	11.6%	35%	38%	27%	27%	34%	34%
SUM / Average	100.0%	100.0%	100.0%	100.0%	65%	52%	22%	28%	33%	36%

Source: ECB.

Table 12. Multinomial logit-regression results – explaining contagion with interbank assets

*Dependent variable: number of domestic banks simultaneously in the tail. *, ** indicate statistical significance at the 5% and 1% levels, respectively. Number of observations 367.*

Germany	**From DE**	**From FR**	**From NL**	**From ES**	**From IT**	**From BE**	**From IE**	**From PT**	**From FI**	**From GR**	**From UK**	**From DK**	**From SE**
Contagion1*Interbank asset share		0.00	0.13**	0.09**	0.04**	0.12	0.34**	0.49**	0.69	-0.18	0.01**	0.20	0.44
Contagion2*Interbank asset share		0.01	0.08	0.19**	0.07*	0.03	0.57**	0.63	-1.79	0.17	0.02**	0.54	1.37*
Contagion3*Interbank asset share		0.14**	0.26**	0.27**	0.15**	-5.37	0.64**	1.32**	-1.91	-0.00	0.03**	1.41**	3.31**
Contagion4*Interbank asset share		0.12*	0.41**	0.37**	0.19**	0.62	0.72**	2.30**	0.00	1.00	0.03**	1.76**	2.35*
Log likelihood		-191.83	-176.56	-173.56	-174.36	-159.63	-161.54	-163.63	-192.16	-177.22	-165.45	-180.10	-163.23
Pseudo R^2		0.41	0.46	0.47	0.47	0.51	0.51	0.49	0.41	0.45	0.49	0.45	0.50
France													
Contagion1*Interbank asset share	0.16		0.14*	0.64**	0.025	0.06	0.28*	-0.15	-0.85	-0.30	0.003		0.21
Log likelihood	-177.22		-57.42	-59.09	-55.54	-46.43	-63.68	-57.75	-64.50	-50.26	-66.58		-66.79
Pseudo R^2	0.45		0.61	0.60	0.62	0.68	0.56	0.60	0.56	0.66	0.54		0.54
The Netherlands													
Contagion1*Interbank asset share	0.02**	0.05**		0.19**	0.017	0.02	0.05**	0.06	0.22	-0.006	0.002*	0.28**	0.35**
Log likelihood	-46.06	-58.21		-46.7	-49.09	-24.53	-38.2	-50.70	-56.92	-33.69	-53.74	-47.62	-37.00
Pseudo R^2	0.71	0.63		0.70	0.69	0.82	0.76	0.68	0.64	0.79	0.66	0.70	0.77
Spain													
Contagion1*Interbank asset share	0.01	-0.004	0.048		0.013	0.07	0.55**	0.04**	-0.39	-1.89	0.005*	-0.18	-114.80
Contagion2*Interbank asset share	0.04**	0.02	0.19*		0.04*	0.14	1.01**	0.07*	0.88	-2.21	0.01*	1.23*	3.02*
Contagion3*Interbank asset share	0.54**	0.08	0.50**		0.06**	0.02	1.04**	0.13**	-2.16	-2.49	0.014**	1.56*	3.03*
Log likelihood	-145.64	-168.60	-121.92		-170.53	-113.02	-139.51	-147.66	-170.94	-150.23	-156.78	-149.01	-149.10
Pseudo R^2	0.51	0.44	0.59		0.43	0.62	0.53	0.51	0.43	0.50	0.48	0.50	0.51

Table 12. Multinomial logit-regression results – explaining contagion with interbank assets (continued)

*Dependent variable: number of domestic banks simultaneously in the tail. *, ** indicate statistical significance at the 5% and 1% levels, respectively. Number of observations 367.*

Italy	**From DE**	**From FR**	**From NL**	**From ES**	**From IT**	**From BE**	**From IE**	**From PT**	**From FI**	**From GR**	**From UK**	**From DK**	**From SE**
Contagion1*Interbank asset share	0.005	0.002	0.02	0.02*		-0.02	0.11	-0.04	-0.79	-0.02	0.001	0.13	-0.94
Contagion2*Interbank asset share	0.015**	0.015	0.10*	0.02		0.07	0.19*	0.14	4.35*	-0.50	0.0009	0.50	2.20**
Contagion3*Interbank asset share	0.012**	0.017*	0.07	0.03*		0.10**	0.23**	0.25**	3.39	-0.10	0.003**	0.88*	2.48**
Log likelihood	-322.10	-337.78	-322.81	-334.20		-336.16	-321.94	-326.05	-336.61	-337.83	-328.73	-343.11	-324.69
Pseudo R^2	0.13	0.09	0.13	0.10		0.09	0.13	0.12	0.09	0.09	0.11	0.07	0.12
Belgium													
Contagion1*Interbank asset share	0.004	-0.002	0.005	0.005	0.01		0.06	0.08	0.01	0.073	0.001	0.23**	0.08
Log likelihood	-59.62	-54.12	-56.59	-55.37	-53.24		-48.72	-61.81	-48.59	-47.24	-55.85	-56.40	-55.97
Pseudo R^2	0.13	0.21	0.18	0.20	0.22		0.29	0.10	0.29	0.31	0.19	0.18	0.18
Portugal													
Contagion1*Interbank asset share	0.0007	-0.02	-0.11	0.01**	-0.0003	-0.08	-0.35		n.a.	0.15	0.001	0.11	-3.66
Contagion2*Interbank asset share	0.04**	0.02	-0.03	0.05**	-0.0005	-1.33	0.45**		n.a.	0.12	0.02**	0.66	-0.34
Log likelihood	-64.17	-99.32	-76.49	-80.08	-75.22	-14.95	-52.38		-82.56	-69.79	-80.02	-79.58	-57.97
Pseudo R^2	0.66	0.47	0.59	0.57	0.60	0.92	0.72		0.56	0.63	0.57	0.57	0.69
Finland													
Contagion1*Interbank asset share	-0.002	0.01	-0.03	0.04	0.01	0.03	0.18	0.63		-0.22	-0.001	0.0009	0.003
Log likelihood	-52.61	-47.41	-54.22	-49.40	-53.02	-44.13	-54.92	-43.71		-53.85	-50.26	-64.84	-52.05
Pseudo R^2	0.42	0.48	0.40	0.45	0.41	0.51	0.39	0.52		0.41	0.44	0.28	0.42

Table 12. Multinomial logit-regression results – explaining contagion with interbank assets (continued)

*Dependent variable: number of domestic banks simultaneously in the tail. *, ** indicate statistical significance at the 5% and 1% levels, respectively. Number of observations 367.*

Greece	**From DE**	**From FR**	**From NL**	**From ES**	**From IT**	**From BE**	**From IE**	**From PT**	**From FI**	**From GR**	**From UK**	**From DK**	**From SE**
Contagion1*Interbank asset share	-0.03	-0.002	-0.04	-4.11	0.006	-0.14	-0.49	0.22	-1.22		-0.001	0.32	-1.87
Log likelihood	94.26	97.27	-95.53	-6.63	-97.43	-84.31	-85.63	-92.40	-97.05		-92.22	-96.35	-90.30
Pseudo R^2	0.13	0.10	0.12	0.36	0.10	0.22	0.21	0.14	0.10		0.15	0.11	0.16
The United Kingdom													
Contagion1*Interbank asset share	0.007**	0.008	0.03	0.03	0.001	-0.04	0.008	0.16*	0.42	-0.12		0.01	0.12
Contagion2*Interbank asset share	0.01**	0.01	0.02	0.07*	0.008	-0.10	-0.01	0.25*	-0.03	-0.10		0.11	0.41**
Contagion3*Interbank asset share	0.02**	0.05**	0.08*	0.11**	0.02	0.08	0.12**	0.32*	0.78	0.15		0.42*	0.75**
Contagion4*Interbank asset share	0.02**	-0.005	0.17*	0.24**	0.11	-0.17	0.09	0.51*	0.73	0.21		0.54	0.80*
Log likelihood	-163.24	-192.52	-174.86	-190.34	-186.66	-137.16	-173.74	-179.23	-192.43	-173.38		-188.21	-157.64
Pseudo R^2	0.51	0.42	0.47	0.42	0.44	0.58	0.47	0.46	0.42	0.47		0.43	0.52
Sweden													
Contagion1*Interbank asset share	0.02**	0.08	0.06	0.25*	0.20	0.14	0.17*	0.11	0.02	1.35*	0.005**	0.016	
Log likelihood	-38.5	-46.83	-46.70	-40.20	-45.04	-29.95	-45.61	-46.58	-47.70	-33.08	-44.02	-45.72	
Pseudo R^2	0.53	0.43	0.43	0.51	0.45	0.64	0.45	0.44	0.46	0.60	0.47	0.45	

Full results available from authors. n.a.: coefficient was not identifiable. The model did not converge for Ireland and Denmark.

Table 13. Small versus large banks: Multinomial logit model estimating contagion to and from Italy

*Dependent variable: number of domestic banks simultaneously in the tail. *, ** indicate statistical significance at the 5% and 1% levels, respectively.*

Italy	from DE	from FR	from ES	from UK	to DE	to FR	to ES	to UK
Constant_1	-0.99**	-0.95**	-0.95**	-1.01**	-1.71**	-4.62**	-1.80**	-1.40**
Constant_2	-3.85**	-3.39**	-3.58**	-3.43**	-4.76**		-6.44**	-4.93**
Constant_3	-4.66**	-.3.92**	-4.45**	-4.32**	-7.66**		-8.98**	-6.67**
Constant_4					-12.22**			-30.45**
Own1 Factor_1	0.71**	0.97**	0.25	0.92**	0.91**	-1.69**	-0.10	-1.20**
Own1 Factor_2	1.72*	2.56**	1.66*	2.85**	0.80		-0.27	-2.97**
Own1 Factor_3	3.59**	0.80	0.39	1.39	1.59		-0.04	-2.95**
Own1 Factor_4					4.15*			-0.82
Own2 Factor_1	0.32	0.12	0.43	0.54*	-5.86**	14.04**	-7.28**	-4.83**
Own2 Factor_2	0.80	0.12	0.68	0.52	-9.32**		-14.62**	-9.57**
Own2 Factor_3	0.74	0.94	1.58*	2.28**	-12.01**		-16.48**	-10.05**
Own2 Factor_4					-15.03**			-26.80**
Foreign1 Factor_1	0.66**	0.74**	0.15	0.94**	0.04	-3.22**	-0.30	0.14
Foreign1 Factor_2	-0.11	1.00	0.23	1.62	-1.47		-0.25	-0.13
Foreign1 Factor_3	3.14**	0.18	-0.42	0.35	-1.04		0.29	-0.16
Foreign Factor_4					-0.27			3.41
Foreign2 Factor_1	-0.04	-0.48	-0.31	-0.03	1.48**	0.19	0.19	1.47**
Foreign2 Factor_2	-0.15	-1.25	1.77	-0.15	1.90*		0.84	2.66**
Foreign2 Factor_3	-1.35*	3.66**	-3.31**	-2.16**	2.28**		0.46	2.59*
Foreign2 Factor_4					3.61**			13.24
Contagion_1	0.21	0.29	0.16	0.22	0.48*	0.63*	0.33	0.12
Contagion_2	0.83**	1.17	0.60*	0.42	0.86*		1.04**	0.37
Contagion_3	0.42	0.94	0.78*	0.74**	1.46**		1.47**	0.96*
Contagion_4					1.66**			4.28
Pseudo R2	0.14	0.10	0.12	0.12	0.45	0.63	0.44	0.44
Log-likelihood	-286.64	-297.57	-292.50	-292.70	-179.19	-54.96	-169.30	-185.78

Appendix 1. Calculation of distances to default

The distance of default is derived by starting with the Black-Scholes model, in which the time path of the market value of assets follows a stochastic process: [12]

$$\ln V^{T} = \ln V + \left(r - \frac{\sigma^2}{2}\right)T + \sigma\sqrt{T}\varepsilon, \tag{A1}$$

which gives the asset value at time T (i.e. maturity of debt), given its current value (V). 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 $\ln V = \ln D$) can be expressed as:

$$d = \ln V^{d} - \ln D = \ln V + (r - \frac{\sigma^2}{2})T + \sigma\sqrt{T}\varepsilon - \ln D \Leftrightarrow$$

$$\frac{d}{\sigma\sqrt{T}} = \frac{\ln\left(\frac{V}{D}\right) + \left(r - \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}} + \varepsilon. \tag{A2}$$

That is, the distance to default, *dd*

$$dd \equiv \frac{d}{\sigma\sqrt{T}} - \varepsilon = \frac{\ln\left(\frac{V}{D}\right) + \left(r - \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}} \tag{A3}$$

represents the number of asset value standard deviations (σ) that the firm is from the default point. The inputs to *dd, V* and σ, can be calculated from observable market value of equity capital (V_E), volatility of equity σ_E , and D (total debt liabilities) using the system of equations below:

$$\begin{aligned}
\mathrm{V_E} &= \mathrm{VN(d1)} - \mathrm{D}\,e^{-\mathrm{rT}}\mathrm{N(d2)} \\
\sigma_{\mathrm{E}} &= \left(\frac{\mathrm{V}}{\mathrm{V_E}}\right)\mathrm{N(d1)}\sigma, \\
\mathrm{d1} &\equiv \frac{\ln\left(\frac{\mathrm{V}}{\mathrm{D}}\right) + \left(\mathrm{r} + \frac{\sigma^2}{2}\right)\mathrm{T}}{\sigma\sqrt{\mathrm{T}}} \\
\mathrm{d2} &\equiv \mathrm{d1} - \sigma\sqrt{\mathrm{T}},
\end{aligned} \tag{A4}$$

The system of equations was solved by using the generalised reduced gradient method to yield the values for V and σ, which in turn entered into the calculation of the distance to default. The results were found robust with respect to the choice of starting values. The measure of bank risk used in this paper is then obtained by first differencing (A3), yielding the change in the number of standard deviations away from the default point, which is denoted as Δdd.

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.

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

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., 2001). The total debt liabilities, D, 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*.

Appendix 2. Industry classification[13]

Code	Label	Broad (NACE) industries included
1	Basic resources & industry	Agribusiness
		Fertilizers & Phosphates
		Forest products/packaging
		Glass manufacturer
		Mining & natural resources
		Steel and aluminium
2	Energy	Oil & gas
		Petrochemicals
3	Utilities	Electricity/energy utility
		Water & sewage
4	Construction	Cement, aggregates & building materials
		Construction/heavy engineering
5	Aerospace & defence	Aerospace & defence
		Airline
		Airport
6	General industries (capital goods)	Chemicals, plastics & rubber
		Electronics & electrical
		Manufacturing - other
7	Automobile	Automotive
		Tyre maker
		Vehicle manufacturer
8	Leisure & tourism	Hotels & leisure
9	Media	Broadcasting
		Printing/publishing/media
10	Transport	Motorway operator
		Shipping
		Transportation
11	Other cyclical goods and services	Engineering Co
		Retailing & distribution
		Textiles & clothing
12	Food & beverages	Brewing & distilling
		Foodstuffs, drink & tobacco
13	Health products & services	Healthcare/Pharmaceuticals
14	Telecommunications	Telecommunications
		Cable TV
		Telecom equipment
15	Other non-cyclical goods and services	Education
		Services - other
16	Technology	Computer/software Co

[13] We thank Ivan Alves for developing this useful classification.

Appendix 3. Factor model results

Scoring coefficients for the first stage variable extracting the common variance of the 16 main sectors, as measured by weekly returns of sectoral stock indices.

	DE	FR	NL	UK	ES	IT	DK	BE	SE	IE	PT	FI	GR
Sector 1	0.06	0.03	0.06	0.38	0.05	0.07	0.15	0.05	0.11	0.05	0.05	0.01	0.05
Sector 2	0.11	0.11	0.03	-0.11	0.05	0.08	0.12	0.05	0.04	0.05	0.05	0.04	0.05
Sector 3	0.04	0.02	0.08	0.01	0.07	0.14	0.03	0.07	0.02	0.07	0.07	0.01	0.08
Sector 4	0.07	0.18	0.06	0.07	0.11	0.08	0.05	0.12	0.12	0.12	0.12	0.13	0.04
Sector 5	0.29	0.10	-0.82	0.05	0.14	0.39	0.27	0.14	0.10	0.14	0.14	0.02	0.16
Sector 6	0.05	0.16	1.32	0.05	0.10	0.09	0.15	0.10	0.06	0.10	0.10	0.08	0.06
Sector 7	0.15	0.00	0.01	0.09	0.11	0.07	0.02	0.11	0.21	0.11	0.11	0.02	0.12
Sector 8	0.05	0.02	0.03	0.01	0.03	0.00	0.05	0.03	0.06	0.03	0.03	0.01	0.04
Sector 9	0.04	0.05	0.07	-0.07	0.05	0.04	0.05	0.05	0.08	0.05	0.05	0.01	0.06
Sector 10	0.10	0.01	0.05	0.05	0.05	0.00	0.11	0.05	0.07	0.05	0.05	0.29	0.06
Sector 11	0.06	0.14	0.06	0.03	0.17	0.09	0.05	0.17	0.09	0.17	0.17	0.33	0.20
Sector 12	0.05	0.11	0.07	0.05	0.07	0.06	0.07	0.07	0.03	0.07	0.07	0.05	0.08
Sector 13	0.10	0.03	0.01	0.02	0.04	0.04	0.11	0.04	0.05	0.04	0.04	0.00	0.05
Sector 14	0.04	0.03	0.04	0.03	0.08	0.08	0.08	0.08	0.14	0.08	0.08	0.03	0.09
Sector 15	0.06	0.06	0.24	0.60	0.09	0.06	0.16	0.09	0.09	0.09	0.09	0.05	0.11
Sector 16	0.06	0.05	0.13	0.02	0.06	0.06	0.16	0.06	0.18	0.06	0.06	0.07	0.07

Scoring coefficients for the second stage variables, yielding two factors per country. Coexceedances denotes the number of banks in the tail in week t, risk the factor extracted from the sector stock market shocks in the first stage.

	DE	FR	NL	UK	ES	IT	DK	BE	SE	IE	PT	FI	GR
Factor 1													
Coexceedances	0.09	0.00	-0.18	-0.11	-0.02	0.09	-0.02	-0.06	-0.01	-0.00	0.01	-0.00	0.01
Risk	-0.04	-0.02	0.15	0.04	-0.01	0.02	0.10	0.08	0.02	-0.02	-0.01	0.00	0.04
Curve	0.16	0.10	0.07	0.38	0.05	-0.17	0.36	0.02	0.39	0.16	0.14	0.00	0.08
GDP growth	-0.37	-0.54	0.37	-0.36	-0.46	0.47	0.13	0.39	-0.42	-0.33	-0.45	0.48	0.36
Inflation	0.42	0.36	-0.27	0.13	0.44	-0.28	-0.44	-0.40	0.09	0.51	0.37	-0.47	-0.52
Factor 2													
Coexceedances	-0.29	0.19	-0.27	-0.30	-0.24	0.07	0.30	-0.01	-0.18	-0.27	-0.22	0.14	0.07
Risk	0.30	-0.14	0.27	0.31	0.23	0.12	-0.15	0.16	0.25	0.25	0.20	-0.12	0.16
Curve	0.03	-0.12	-0.06	-0.05	0.11	-0.32	-0.07	0.20	0.01	0.08	0.16	0.26	0.27
GDP growth	-0.05	0.22	-0.08	0.10	-0.03	0.03	0.21	-0.09	0.08	0.06	0.06	0.43	-0.32
Inflation	0.08	0.30	0.23	-0.01	-0.07	0.31	-0.04	-0.03	0.17	0.02	-0.01	0.43	-0.16