Cross-Border Bank Contagion in Europe*

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We analyze cross-border contagion among European banks in the period from January 1994 to January 2003. We use a multinomial logit model to estimate, in a given country, the number of banks that experience a large shock on the same day ("coexceedances") as a function of common shocks and lagged coexceedances in other countries. Large shocks are measured by the bottom 95th percentile of the distribution of the daily percentage change in distance to default of banks. We find evidence of significant cross-border contagion among large European banks, which is consistent with a tiered cross-border interbank structure. The results also suggest that contagion increased after the introduction of the euro.

JEL Codes: G21, F36, G15.

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1. Introduction

Contagion is widely perceived to be an important element of banking crises and systemic risk. For example, the private-sector rescue operation of LTCM in 1998, coordinated by the Federal Reserve Bank of New York, was justified by the risk of contagion among financial institutions and to markets. Similarly, contagion transmitted through the interbank market played a major role in the failure of a number of Japanese securities houses in the early 1990s (Padoa-Schioppa 2004). Most recently, the crisis that originated with the subprime mortgage market in the United States quickly spread to European banks.

In this paper, we use the distance to default (KMV Corporation 2002) as a measure of the soundness of a bank. Similar to Bae, Karolyi, and Stulz (2003) and Gropp and Moermann (2004), we focus on the behavior of the tail of the distribution of the change in the distance to default. For each country, we construct "coexceedances" by counting the number of banks that experience a large shock in the distance to default on a given day. Large shocks are measured by large negative percentage changes in the daily distance to default of a bank. We then estimate the probability of several banks simultaneously experiencing a large shock in one country as a function of lagged coexceedances in other countries, controlling for common shocks.

We find evidence of significant cross-border contagion for large listed banks during the period of January 1994 to January 2003. There is no evidence of cross-border contagion for smaller banks. Finally, the estimates suggest that the prevalence of cross-border contagion may have increased since the introduction of the euro in 1999.

What are the mechanisms of contagion consistent with these findings? Because the distance to default is derived from equity price data, our approach captures contagion as perceived by banks' equity holders. Market-price-based indicators of bank fragility, such as the distance to default, summarize all available information about a given bank. Hence, our measurement of contagion could be viewed as covering all possible transmission channels of contagion. It does not rely on accurately measuring one particular channel. We consider this to be an advantage.

Nevertheless, the results do suggest that some channels are more likely than others. First, we can exclude "domino effects" due to a chain of bank defaults as an explanation of our findings, as no bank in our sample defaulted on any of its obligations.[1] Second, we find that only large banks exhibit cross-border contagion. This would suggest that cross-border interbank exposures among large banks ("money-center banks") may be important, since small banks tend to only operate in a very limited way across borders in the tiered interbank market structure in the euro area, in which only large banks are active in cross-border interbank markets (Degryse and Nguyen 2007; Freixas and Holthausen 2005). The evidence is consistent with Allen and Gale (2000), who show that, in a Diamond and Dybvig (1983) liquidity framework, an "incomplete" market structure with only unilateral exposure among banks may exhibit contagion; and it is consistent with Freixas, Parigi, and Rochet (2000), who show that a tiered structure with money-center banks is also vulnerable. In both papers, contagion transmits via liquidity problems, i.e., banks withdrawing interbank deposits at other institutions (like in the recent case of Bear Stearns).[2]

Alternatively, our evidence may support a notion of contagion due to asset sales by one bank, resulting in declining market valuations and increased counterparty risks. The results may reflect that large banks hold similar assets, such as structured instruments or credit derivatives, which are not typically intermediated by smaller banks. Hence, our evidence is also consistent with a channel of contagion via market valuations and counterparty risks as in Cifuentes,

[1]This distinguishes this paper from Calomiris and Mason (2000), who find evidence of contagion within specific regions of the United States during the Great Depression, or Iyer and Peydró-Alcalde (2005b), who estimate the contagion of the failure of one large regional bank in India. In addition, a number of papers have used actual or estimated interbank links to simulate domino effects in interbank markets (Furfine 2003 for the United States, Sheldon and Maurer 1998 for Switzerland, Upper and Worms 2004 for Germany, and Degryse and Nguyen 2007 for Belgium).

[2]Iyer and Peydró-Alcalde (2005a) model the mechanism of contagion through the money market and show how the reactions of banks initially unaffected by the shock can result in an endogenous reduction in liquidity, which in turn results in further stress on the banking system.

Ferrucci, and Shin (2004).[3] This contagion effect is different from the one captured by our common-shock variables, as it is an endogenous result of the behavior of other banks, i.e., extraordinarily large asset sales. Finally, one could view the results as evidence in favor of a "run" by equity holders, even in the absence of explicit financial links or common exposures. In the presence of asymmetric information, difficulties in one bank may be perceived as a signal of possible difficulties in others, especially if banks' assets are opaque and balance-sheet data and other publicly available information are uninformative (Morgan 2002) or stale (Gropp and Kadareja 2006).[4] 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 that there may be insufficient liquid assets in the banking system.

The paper also suggests a new methodology for the measurement of international bank contagion in the absence of accurate and comparable data on interbank and asset-side exposures of banks. The approach is related to Hartmann, Straetmans, and de Vries (2006), who use multivariate extreme-value theory to estimate contagion in Europe and the United States. They find that contagion may have increased from the mid-1990s onward both in Europe and the United States.[5]

The remainder of the paper is organized as follows. In the next section, we describe the data used in the paper and give some descriptive statistics. Section 3 explains our primary econometric

[3]In Cifuentes, Ferrucci, and Shin (2004), contagion arises through fire sales of illiquid assets as banks are subject to regulatory solvency constraints. If banks use fair-value accounting to value at least some of their illiquid assets at imputed market prices and the demand for illiquid assets is less than perfectly elastic, sales by distressed institutions depress the market prices of such assets. Prices fall, inducing a further round of sales. Ultimately, banks may have difficulties meeting solvency requirements. In their model, relatively small shocks can result in contagious failures in the banking system.

[4]An example of an extreme version of a reaction by equity holders was the "run" on European life insurance companies in the summer of 2002. For recent evidence that banks may not be more opaque than nonfinancial firms, see Flannery, Kwan, and Nimalendran (2004).

[5]Gropp and Moerman (2004) use the distance to default to identify systemically important banks using the same sample as this paper.

approach. Section 4 presents the econometric results. Section 5 discusses the robustness of our findings. Finally, section 6 concludes the paper.

2. Sample, Definition of Variables, and Descriptive Statistics

In our sample selection, we started with all banks in France, Germany, Italy, the Netherlands, Spain, and the United Kingdom that are listed at a stock exchange and whose stock price and total debt are available from Datastream during January 1994 to January 2003 (fifty banks). Almost all large, internationally active European banks are headquartered in these countries (see table 1). We deleted all banks that had trading volume below 1,000 shares in more than 30 percent of the trading days and banks that had less than 100 weeks of stock data available (seven banks). We deleted three additional banks where we had serious concerns about data quality.[6] For those banks where the distance to default could not be calculated for the entire period under review due to missing data (five banks), we imputed a total of 342 missing values, using linear interpolation and random numbers (for details, see the notes to table 2). Doing that ensures that the "coexceedances" (see below) for each country are built using the same banks during the entire period under analysis. This yields a complete data set for forty banks. For each bank, the sample contains 2,263 daily observations, i.e., a total of 94,520 observations.

The banks in the sample are generally quite large relative to the population of banks in the European Union (EU) (table 1). On average, their total assets amount to €178 billion (median: €132 billion). The relatively large average size is an outcome of the requirement that the bank must be traded at a stock exchange. Nevertheless, the size variation is considerable within the sample. For example, the largest bank, Deutsche Bank, is more than 300 times the size of the smallest bank. The degree of coverage in each country depends on the number of banks traded at a stock exchange and on the structure of the banking system, but despite the relatively low number

[6]The banks showed zero equity returns on a high number of trading days.

Table 1. Sample Banks (Sorted by Total Assets in 2000, Millions of Euro)

1	Deutsche Bank AG	DE	927,900
2	Bayerische Hypo- und Vereinsbank	DE	694,300
3	BNP Paribas	FR	693,053
4	ABN AMRO Bank N.V.	NL	543,200
5	Barclays	UK	486,936
6	Societe Generale	FR	455,881
7	Commerzbank	DE	454,500
8	ING Bank NV	NL	406,393
9	Banco Santander Central Hispano	ES	347,288
10	Banca Intesa	IT	331,364
11	Abbey National plc	UK	293,395
12	Banco Bilbao Vizcaya Argentaria	ES	292,557
13	HSBC	UK	288,339
14	Royal Bank of Scotland	UK	206,176
15	Bankgesellschaft Berlin	DE	203,534
16	UniCredito Italiano	IT	202,649
17	Sanpaolo IMI	IT	171,046
18	Standard Chartered	UK	161,934
19	DePfa Group	DE	156,446
20	Banca di Roma	IT	132,729
21	Natexis Banques Populaires	FR	113,131
22	BHF-BANK	DE	53,863
23	Banco Espanol de Credito	ES	44,381
24	Banca Pop Bergamo	IT	37,670
25	IKB Deutsche Industriebank	DE	32,359
26	Banco Popular Espanol	ES	31,288
27	Banca Popolare di Milano	IT	28,282
28	Banca Lombarda	IT	26,816
29	Banca Popolare di Novara	IT	20,959
30	Credito Emiliano	IT	15,148
31	Banca Agricola Mantovana	IT	10,190
32	Banco Pastor	ES	9,404
33	Credito Valtellinese	IT	7,416
34	Banco Guipuzcoano	ES	5,518
35	Kas-Associatie N.V.	NL	5,417
36	Banco Zaragozano	ES	5,175
37	Schroders	UK	4,180
38	Banca Popolare di Intra	IT	3,929
39	Close Brothers	UK	3,241
40	Singer & Friedlander Group	UK	2,792

Table 2. Variable Definitions and Summary Statistics

Variable	Definition	n	Mean	Median	Std. Dev.	Min.	Max.
Bank-Specific Variables							
dd_{it}	Distance to default of bank i in week t (see appendix 1)	94,520	4.13	3.73	1.73	0.55	16.59
$\Delta dd_{it}/\lvert dd_{it-1}\rvert$	Percentage change in the distance to default	94,520	0.00	0	0.01	−0.77	0.69
	(of which missing values replaced)[a]	343	—	—	—	—	—
tail	Takes value 1 if bank i is in 95th percentile negative tail of distribution of $\Delta dd_{it}/dd_{it-1}$	94,520	0.05	0	0.22	0	1
Country-Specific Variables							
Coexceedances DE	No. of banks in 95th percentile negative tail of $\Delta dd_{it}/dd_{it-1}$in DE	2,363	0.34	0	0.75	0	7
Coexceedances ES	No. of banks in 95th percentile negative tail of $\Delta dd_{it}/dd_{it-1}$in ES	2,363	0.34	0	0.71	0	6
Coexceedances FR	No. of banks in 95th percentile negative tail of $\Delta dd_{it}/dd_{it-1}$in FR	2,363	0.16	0	0.48	0	3
Coexceedances IT	No. of banks in 95th percentile negative tail of $\Delta dd_{it}/dd_{it-1}$in IT	2,363	0.56	0	1.12	0	11
Coexceedances NL	No. of banks in 95th percentile negative tail of $\Delta dd_{it}/dd_{it-1}$in NL	2,363	0.16	0	0.47	0	3
Coexceedances UK	No. of banks in 95th percentile negative tail of $\Delta dd_{it}/dd_{it-1}$in UK	2,363	0.48	0	0.90	0	7
Systemic Risk DE	No. of markets in 95th percentile negative tail among US, emerging, Europe, and DE	2,363	0.2014	0	0.6104	0	4
Systemic Risk ES	No. of markets in 95th percentile negative tail among US, emerging, Europe, and ES	2,363	0.2014	0	0.6034	0	4
Systemic Risk FR	No. of markets in 95th percentile negative tail among US, emerging, Europe, and FR	2,363	0.2014	0	0.6146	0	4

(continued)

Table 2. (Continued)

Variable	Definition	n	Mean	Median	Std. Dev.	Min.	Max.
Country-Specific Variables							
Systemic Risk IT	No. of markets in 95th percentile negative tail among US, emerging, Europe, and IT	2,363	0.2014	0	0.5935	0	4
Systemic Risk NL	No. of markets in 95th percentile negative tail among US, emerging, Europe, and NL	2,363	0.2014	0	0.6062	0	4
Systemic Risk UK	No. of markets in 95th percentile negative tail among US, emerging, Europe, and UK	2,363	0.2014	0	0.6048	0	4
Yield Curve DE	Change in slope of yield curve in DE	2,363	0.0004	0.0000	0.0385	−0.1900	0.3800
Yield Curve ES	Change in slope of yield curve in ES	2,363	0.0006	−0.0020	0.0682	−0.5400	0.4840
Yield Curve FR	Change in slope of yield curve in FR	2,363	0.0006	−0.0046	0.0645	−0.8000	0.3198
Yield Curve IT	Change in slope of yield curve in IT	2,363	0.0002	−0.0010	0.1511	−2.5580	2.5960
Yield Curve NL	Change in slope of yield curve in NL	2,363	0.0003	0.0000	0.0512	−0.3000	0.3210
Yield Curve UK	Change in slope of yield curve in UK	2,363	0.0013	0.0000	0.0814	−0.8740	0.5460
*Volatility DE**	Change in volatility of stock market in DE	2,362	0.0072	−0.3141	3.0809	−10.5551	47.7505
*Volatility ES**	Change in volatility of stock market in ES	2,362	0.0011	−0.3486	2.4996	−9.2267	32.1450
*Volatility FR**	Change in volatility of stock market in FR	2,362	0.0044	−0.2951	1.9286	−4.8973	47.0638
*Volatility IT**	Change in volatility of stock market in IT	2,362	0.0045	−0.6004	4.1482	−15.1464	63.3724
*Volatility NL**	Change in volatility of stock market in NL	2,362	0.0060	−0.2482	2.8988	−10.9020	32.1924
*Volatility UK**	Change in volatility of stock market in UK	2,362	0.0045	−0.1762	1.5277	−6.5127	21.0707
*Volatility US**	Change in volatility of stock market in US	2,362	0.0054	−0.2353	2.1676	−5.2696	34.7094
Memo Items							
Cutoff point of the 95th percentile of $\Delta dd_{it}/\lvert dd_{it-1}\rvert$		−0.0085					

[a]Number of observations imputed by linear interpolation: Close Brothers (20 observations), ING (1 observation), Natexis (1 observation). Number of observations added with random number generator: BHF (113 observations), BNP (208 observations).
*This variable has been multiplied by 1,000.

of banks, the coverage is quite high. The fraction of the total assets of commercial banks covered in our data varies from 36 percent for France to 68 percent for Spain.[7]

The distance to default is defined as the difference between the current market value of assets of a firm and its estimated default point, divided by the volatility of assets (KMV Corporation 2002). The value of equity is modeled as a call option on the assets of the company. The level and the volatility of assets are calculated with the Black/Scholes model using the observed market value and volatility of equity and the balance-sheet data on debt. A detailed description of the method used to compute the distance to default is in appendix 1. The distance to default increases when the values of assets increase and/or when the volatility of assets declines. An increase in the distance to default means that the firm is moving away from the default point and that bankruptcy becomes less likely. Gropp, Vesala, and Vulpes (2004, 2006) argue that the distance to default may be a particularly suitable and all-encompassing measure of default risk for banks. In particular, its ability to measure default risk correctly is not affected by the potential incentives of the stockholders 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).

In order to obtain our dependent variable, we calculated the distance to default for each bank in the sample and for each day, t. Following the approach of Bae, Karolyi, and Stulz (2003) and Gropp and Moermann (2004), we then arbitrarily defined as large shocks those observations falling in the negative 95th percentile of the common distribution of the percentage change in distance to default ($\Delta dd_{it}/dd_{it-1}$) across all banks.[8] Choosing the bottom 95th percentile is a compromise between the need for "large" shocks in the

[7]The total assets of commercial banks in a country were taken from the OECD's Bank Profitability data.

[8]This definition relies on the assumption that the stochastic process governing the distance to default at different banks is the same. This assumption turns out

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, which we, following Bae, Karolyi, and Stulz (2003), labeled "coexceedances."

Gropp and Moerman (2004) use the coincidence of large shocks to banks' distance to default to examine systemically important banks. They employ Monte Carlo simulations to show that standard distributional assumptions (multivariate normal, Student t) cannot replicate the patterns observed in tails of the data. This implies not only that the distribution of distances to default of individual banks exhibits fat tails, but also that the correlation among banks' distances to default is substantially higher for larger shocks. Bae, Karolyi, and Stulz (2003) do the same for emerging-market stock returns. Both papers suggest that it is necessary to examine the tails of the distribution of returns or the distance to default separately from the overall distribution.

In order to control for common shocks, we rely on the existing literature on financial crises and contagion (Forbes and Rigobon 2002; Rigobon 2003). In total, we use four control variables, which take into account (i) the occurrence of shocks in stock markets, (ii) movements of the yield curve, and the level of volatility in (iii) domestic and (iv) international markets.

The first common factor, which we label "systemic risk," is an indicator measuring the number of stock markets that are experiencing a large shock at time t. We construct this variable similarly to modeling large shocks to banks. We use indicator variables that we set equal to 1 if the stock market of a given country experienced a shock large enough to be in the bottom 95th percentile of the distribution of daily returns. Equivalently, we calculate indicator variables for a euro-area stock market index and the U.S. and emerging-market stock indices. We use total market indices as provided by Datastream and, for emerging markets, the MSCI Emerging

to be reasonable, however, as redoing the analysis reported below with bank-specific tail occurrences yields quantitatively very similar results. A further alternative would have been to estimate 95th percentiles separately for tranquil and volatile periods. The 95th percentile in this paper is higher (lower) for tranquil periods (volatile periods) than it would be using only data from the tranquil period.

Market Index. "Systemic risk" is then the sum of the indicator variables measuring whether or not the domestic stock market, the U.S. stock market, the euro-area market index, and the emerging-market index are in the tail on a given day. Hence, it ranges from 0 to 4.[9] We also include a domestic shock, measured as the domestic conditional stock market volatility (see below). "Systemic risk" should be positively related to the number of coexceedances.

The second factor ("yield curve") is the daily change in absolute value of the slope of the yield curve. The slope is defined as the difference between the yield of the ten-year government bond and the yield of the one-year note in a given country.[10] This variable is a commonly used measure of expectations on economic growth and monetary policy. One view of banks suggests that they transform short-term liabilities (deposits) into long-term assets (loans). A flattening of the yield curve results in an increase of the interest rate banks have to pay on their short-term liabilities without a corresponding increase in the rates they can charge on their loans. We would, thus, expect this variable to be positively related to the number of coexceedances.

The third factor ("volatility own") is the daily change in the volatility of the domestic stock market. In Bae, Karolyi, and Stulz (2003), this variable is particularly important for explaining emerging-market coexceedances. We estimate stock market volatility using a GARCH (1,1) model of the form

$$\sigma^2_{tc} = \alpha + \beta_1 \varepsilon^2_{c,t-1} + \beta_2 \sigma^2_{c,t-1} \tag{1}$$

using maximum likelihood, where σ^2_{tc} represents the conditional variance of the stock market index in country c in period t, and ε represents stock market returns in that market. The estimated parameters are reported in appendix 2. We obtain, depending on the country, values of between 0.06 and 0.11 for β_1 and between 0.89 and 0.93 for β_2. While we are interested in contagion among European banks,

[9] We also experimented with including the indicator variables for each market separately. However, their correlation is generally above 0.5 within the EU and around 0.2 and 0.3 with the U.S. and emerging markets, respectively.

[10] If the yield of the one-year Treasury note was not available, we used the interbank rate for the same maturity. The sources of the data are Datastream and the Bank for International Settlements.

Table 3. Description of the Sample by Countries

	Number of Observations	Number of Banks	Percentage of Total Assets of Commercial Banks	Number of Observations per Bank	Maximum Number of Coexceedances
France	7,089	3	36.0	2,363	3
Germany	16,541	7	46.5	2,363	7
Italy	28,356	12	52.1	2,363	11
The Netherlands	7,089	3	58.9	2,363	3
Spain	16,541	7	68.3	2,363	6
United Kingdom	18,904	8	56.1	2,363	7
Total	94,520	40	—	—	20

it is possible that there are volatility spillovers from other parts of the world as well. In order to control for this, we insert stock market volatility from the United States in the regressions. This has also been estimated with a GARCH (1,1) and is labeled "volatility US."[11] Because U.S. markets open later than European markets, "volatility US" is lagged by one day.

Further, we include one lag of the domestic coexceedances, as we suspect that first-differencing and using only the large negative tail events of the distance to default may not have removed all autocorrelation in the dependent variable.

Table 2 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 4.13). One bank shows distances to default below 1, and there are a number of banks with a distance to default of above 10. The mean of the first percentage change in the distance to default is approximately 0; the largest negative change is 77 percent. The negative 95th percentile is at about -1 percent.

Tables 3 and 4 present some additional descriptive statistics on the number of banks simultaneously in the tail on a given day, i.e., the number of coexceedances. The number of banks per country differs somewhat: In Italy there are twelve banks in the sample, while in France and the Netherlands there are only three. The United Kingdom, Spain, and Germany are also well represented, with eight,

[11] "Volatility own" and "volatility US" were rescaled by multiplying the estimated values by 1,000.

Table 4. Coexceedances by Countries

	France* (FR)	Germany (DE)	Italy (IT)	Netherlands* (NL)	Spain (ES)	United Kingdom (UK)
Coexceedances = 0	2,085	1,822	1,591	2,066	1,795	1,628
Coexceedances = 1	203	385	495	219	407	486
Coexceedances = 2	75	89	152	78	111	161
Coexceedances ≥ 3	—	67	125	—	50	88
Total	2,363	2,363	2,363	2,363	2,363	2,363

*Due to the small number of banks in the sample, for France and the Netherlands the analysis is limited to coexceedances ≥ 2.

seven, and seven banks, respectively. Table 3 also shows that there is at least one day on which all, or almost all banks, experienced a large adverse shock simultaneously.

Table 4 shows that in Spain, for example, there were 50 days with three or more coexceedances, in the United Kingdom there were 88 such days, and in Italy 125 such days, while in the Netherlands and France there were 78 and 75 days with two or more coexceedances, respectively. The number of coexceedances is a function of the number of banks included in the sample and does not necessarily reflect the strength or weakness of the banking sector. Still, comparing countries with an equal number of banks in the sample suggests that Spanish banks tend to experience fewer shocks compared with German banks and that Dutch banks tend to be subject to large shocks about as frequently as French banks. Of the total of forty banks in the sample, a maximum of twenty are simultaneously in the tail (on October 2, 1998), and there are fourteen days with more than fifteen coexceedances (not reported).

3. Econometric Model

The dependent variable is the number of coexceedances of banks on a given day, which is a count variable. There are many methods to estimate a model with count data as the dependent variable, including tobit models, Poisson models, negative binomial models, and multinomial and ordered logit models. A tobit model relies on the assumption that the dependent variable is truncated normal, an assumption that Gropp and Moerman (2004) show to be 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 also rejected in our sample. The negative binomial model avoids this restrictive assumption of mean/variance equality. Nevertheless, it does rely on the assumption that the dependent variable was drawn from a mixture of Poisson random variables. Given the evidence and arguments in Bae, Karolyi, and Stulz (2003) and Gropp and Moerman (2004), we do not think that the estimation of this model would be advisable. This leaves ordered logit and multinomial logit models as potential estimation methods. The main difference between the two is that the ordered logit model restricts the marginal effects at each outcome to be the same. On the other hand, in a multinomial logit model, there are many more parameters to estimate.

Given the relatively large sample size, we decided to use a multinomial logit model as our primary specification. We present results from an ordered logit model as a robustness check (see section 5). Hence, we estimate the number of coexceedances in one country (the number of banks simultaneously in the tail) as a function of the number of coexceedances in the other countries lagged by one day, controlling for common shocks:

$$\Pr_c[Y=j] = \frac{e^{\left[\alpha'_j F_c + \beta_j C_{ct-1} + \sum_{d \neq c} \gamma_{dj} C_{dt-1}\right]}}{\sum_k^J e^{\left[\alpha'_k F_c + \beta_k C_{ct-1} + \sum_{d \neq c} \gamma_{dk} C_{dt-1}\right]}}, \tag{2}$$

where $j = 1, 2, 3 \ldots J$ represents the number of banks in the tail simultaneously ("coexceedances") in country c, F_c represents the common shocks in country c, C_{ct-1} represents the lagged number of coexceedances in country c, and C_{dt-1} represents the coexceedances in period $t-1$ in country d. Insofar as common shocks are controlled for, the significant coefficients of C_{dt-1} would signal cross-border contagion. Given that we estimate a multinomial logit model, which implies that we will estimate one coefficient per outcome, we follow Bae, Karolyi, and Stulz (2003) and limit the number of outcomes to zero, one, two, and three or more coexceedances, except for France and the Netherlands, where we limit the number of outcomes to two or more.

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 are estimated relative to this base. Still, the coefficients from this model are difficult to interpret and, therefore, it is useful to also report the marginal effect of the regressors. The marginal effects are obtained from the probability for each outcome j:

$$\Pr[Y = j] = \frac{e^{\left[\alpha_j' F_c + \beta_j C_{ct-1} + \sum\limits_{d \neq c} \gamma_{dj} C_{dt-1}\right]}}{1 + \sum\limits_{k}^{J} e^{\left[\alpha_k' F_c + \beta_k C_{ct-1} + \sum\limits_{d \neq c} \gamma_{dk} C_{dt-1}\right]}}. \qquad (3)$$

Differentiating with respect to C_{dt-1} yields

$$\frac{\partial \Pr_c[Y = j]}{\partial C_{dt-1}} = \Pr[Y = j] * \left[\gamma_j - \sum_{k=1}^{J} P_k \gamma_k\right], \qquad (4)$$

which can be computed from the parameter estimates, with the independent variables evaluated at suitable values, along with its standard errors. In all tables we will report the estimated coefficients alongside the marginal probabilities obtained from (4).

4. Estimation Results

4.1 Base Model

The baseline results are given in table 5. For each country, we first report the results for a specification in which the controls for systemic risk and common factors are the only explanatory variables (model 1 in table 5). We then add the lagged coexceedances from other countries (model 2 in table 5). Recall that the dependent variable is the number of banks whose daily percentage change in distance to default was in the negative 95th tail in a given country.

First consider the base model without contagion variables for the five countries (table 5, model 1). Overall, we are able to explain between 9 percent (IT) and 17 percent (NL) of the variation in the dependent variable using variables measuring common shocks only.[12]

[12]As a comparison, in the context of emerging markets, Bae, Karolyi, and Stulz (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).

Table 5. Multinomial Logit Model: Contagion in Daily Coexceedances of the Percentage Change in Distance to Default, Large EU Countries, January 1994–January 2003

	France				Germany				Italy			
	Model 1		Model 2		Model 1		Model 2		Model 1		Model 2	
	Coeff.	**ΔProb.**	**Coeff.**	**ΔProb.**	**Coeff.**	**ΔProb.**	**Coeff.**	**ΔProb.**	**Coeff.**	**ΔProb.**	**Coeff.**	**ΔProb.**
Coexceedances=1												
Constant	−2.47***		−2.57***		−1.78***		−1.92***		−1.35***		−1.41***	
Coex. Lagged	0.40**	0.030**	0.28*	0.021*	0.61***	0.078***	0.51***	0.065***	0.36***	0.045***	0.31***	0.039***
Systemic Risk	0.24**	0.018**	0.21*	0.016*	0.15	0.020	0.11	0.014	0.24***	0.034**	0.22**	0.031**
Yield Curve	0.40	0.032	0.36	0.028	1.97	0.241	1.96	0.241	−0.01	−0.010	−0.19	−0.012
Volatility Own	0.29***	0.022***	0.29***	0.022***	0.15***	0.018***	0.16***	0.020***	0.10***	0.013***	0.10***	0.013***
Volatility US	−0.01	−0.001	−0.02	−0.002	0.02	0.002	0.01	0.000	0.02	0.002	0.01	0.001
Contagion DE			0.03	0.002							−0.01	−0.007
Contagion FR							0.07	0.009			0.05	0.010
Contagion IT			−0.09	−0.007			0.11	0.016*				
Contagion NL			−0.08	−0.006			0.40***	0.053***			0.12	0.017
Contagion ES			0.29***	0.022***			−0.10	−0.017			0.01	0.001
Contagion UK			0.15	0.011			0.16**	0.020*			0.14**	0.023*
Coexceedances=2												
Constant	−4.35***		−4.62***		−3.59***		−3.87***		−2.81***		−2.94***	
Coex. Lagged	0.90***	0.012***	0.68***	0.009**	0.95***	0.024***	0.77***	0.018***	0.70***	0.034***	0.62***	0.030***
Systemic Risk	0.39**	0.005**	0.35**	0.004**	0.09	0.002	0.01	−0.000	0.36***	0.017***	0.31***	0.015**
Yield Curve	−0.27	−0.004	−0.31	−0.0044	6.39***	0.178***	6.44***	0.168***	0.55	0.032	0.57	0.032
Volatility Own	0.64***	0.009***	0.65***	0.008***	0.30***	0.008***	0.31***	0.008***	0.15***	0.007***	0.15***	0.007***
Volatility US	0.08*	0.001*	0.07	0.001	0.05	0.001	0.02	0.001	−0.00	−0.000	−0.01	−0.001
Contagion DE			0.28	0.004							0.23*	0.012*
Contagion FR							0.09	0.002			−0.08	−0.005
Contagion IT			−0.07	−0.001			−0.14	−0.004				
Contagion NL			−0.25	−0.003			0.48**	0.011**			0.11	0.005
Contagion ES			0.54***	0.007**			0.29*	0.008*			0.09	0.005
Contagion UK			0.09	0.001			0.37***	0.009***			0.12	0.005

(continued)

Table 5. (Continued)

	France				Germany				Italy			
	Model 1		Model 2		Model 1		Model 2		Model 1		Model 2	
	Coeff.	**ΔProb.**	**Coeff.**	**ΔProb.**	**Coeff.**	**ΔProb.**	**Coeff.**	**ΔProb.**	**Coeff.**	**ΔProb.**	**Coeff.**	**ΔProb.**
Coexceedances=3												
Constant					−4.61***		−5.01***		−3.91***		−3.99***	
Coex. Lagged					1.28***	0.015***	1.07***	0.011***	1.15***	0.026***	1.11***	0.025***
Systemic Risk					0.39***	0.005**	0.22	0.002	0.39***	0.008**	0.37***	0.007**
Yield Curve					0.12	−0.005	0.54	0.000	0.09	0.001	0.15	0.003
Volatility Own					0.39***	0.005***	0.41***	0.004***	0.29***	0.007***	0.30***	0.007***
Volatility US					0.12**	0.002**	0.09*	0.001*	0.09***	0.002**	0.08**	0.002**
Contagion DE											0.30**	0.007**
Contagion FR							0.32	0.004			0.09	0.002
Contagion IT							0.26	0.003				
Contagion NL							0.10	0.000			0.20	0.004
Contagion ES							0.42**	0.005**			−0.00	−0.000
Contagion UK							0.20	0.002			−0.12	−0.004
Pseudo-R^2	0.14		0.15		0.10		0.12		0.09		0.10	
Log-Likelihood	−878		−867		−1,523		−1,493		−1,982		−1,972	
N	2,361		2,361		2,361		2,361		2,361		2,361	
ΣContagion DE			1.36								4.21**	
ΣContagion FR							1.07				0.03	
ΣContagion IT			0.66				0.81					
ΣContagion NL			0.56				5.30**				1.34	
ΣContagion ES			11.08***				4.08**				0.14	
ΣContagion UK			0.92				9.01***				0.33	
ΣContagion			4.69**				25.91***				6.47**	

(continued)

Table 5. (Continued)

	The Netherlands				Spain				United Kingdom			
	Model 1		Model 2		Model 1		Model 2		Model 1		Model 2	
	Coeff.	ΔProb.	Coeff.	ΔProb.	Coeff.	ΔProb.	Coeff.	ΔProb.	Coeff.	ΔProb.	Coeff.	ΔProb.
Coexceedances=1												
Constant	−2.54***		−2.72***		−1.72***		−1.82***		−1.48***		−1.60***	
Coex. Lagged	0.77***	0.060***	0.55***	0.043***	0.59***	0.079***	0.54***	0.073***	0.42***	0.057***	0.33***	0.044***
Systemic Risk	0.49***	0.039***	0.43***	0.034***	0.23**	0.029**	0.21**	0.027**	0.61***	0.092***	0.58***	0.089***
Yield Curve	0.78	0.064	0.65	0.053	0.11	0.007	0.03	−0.002	−0.35	−0.052	−0.42	−0.062
Volatility Own	0.25***	0.019***	0.26***	0.020***	0.27***	0.035***	0.27***	0.036***	0.29***	0.041***	0.33***	0.046***
Volatility US	0.02	0.001	0.00	0.0002	0.04	0.005	0.03	0.005	0.02	0.003	0.00	0.001
Contagion DE			0.14	0.011			0.07	0.010			0.12	0.017
Contagion FR			0.28*	0.022*			0.02	0.000			0.02	0.007
Contagion IT			0.24***	0.019***			0.21***	0.030***			0.07	0.012
Contagion NL							−0.07	−0.011			0.14	0.022
Contagion ES			−0.01	−0.001							0.24***	0.035**
Contagion UK			0.00	0.000			0.01	−0.001				
Coexceedances=2												
Constant	−4.39***		−4.76***		−3.51***		−3.71***		−3.00***		−3.16***	
Coex. Lagged	1.16***	0.016***	0.65***	0.008**	0.91***	0.030***	0.73***	0.021***	0.87***	0.043***	0.76***	0.037***
Systemic Risk	0.38*	0.005	0.25	0.003	0.55***	0.020***	0.48***	0.015***	0.70***	0.030***	0.68***	0.029***
Yield Curve	−0.76	−0.012	−1.44	−0.020	0.76	0.024	0.46	0.015	−0.71	−0.036	−0.89	−0.044
Volatility Own	0.47***	0.006***	0.48***	0.006***	0.46***	0.014***	0.47***	0.014***	0.54***	0.0326**	0.56***	0.026***
Volatility US	0.08**	0.001**	0.05	0.001	−0.03	−0.001	−0.06	−0.002	−0.01	−0.001	−0.03	−0.002
Contagion DE			0.08	0.001			0.08	0.002			0.15	0.006
Contagion FR			0.23	0.003			0.30	0.010			−0.22	−0.012
Contagion IT			0.30**	0.004**			0.10	0.002			0.00	−0.001
Contagion NL							0.04	0.002			0.25	0.012
Contagion ES			0.47***	0.006***							0.43***	0.020***
Contagion UK			0.07	0.001			0.28**	0.010**				

(continued)

Table 5. (Continued)

	The Netherlands				Spain				United Kingdom			
	Model 1		Model 2		Model 1		Model 2		Model 1		Model 2	
	Coeff.	ΔProb.	Coeff.	ΔProb.	Coeff.	ΔProb.	Coeff.	ΔProb.	Coeff.	ΔProb.	Coeff.	ΔProb.
Coexceedances=3												
Constant					−5.04***		−5.37***		−4.50***		−4.92***	
Coex. Lagged					1.11***	0.008***	0.82***	0.006***	1.01***	0.015***	0.94***	0.011***
Systemic Risk					0.78***	0.006***	0.68***	0.005***	1.01***	0.013***	0.95***	0.011***
Yield Curve					2.55	0.021	2.12	0.017	0.43	0.009	0.24	0.005
Volatility Own					0.56***	0.004***	0.57***	0.004***	0.82***	0.011***	0.88***	0.010***
Volatility US					0.07*	0.001	0.04	0.000	0.07	0.001	0.05	0.001
Contagion DE							0.30*	0.002*			0.65***	0.008***
Contagion FR							0.27	0.002			−0.52*	−0.007*
Contagion IT							0.32*	0.002			0.24	0.003
Contagion NL							0.03	0.000			−0.26	−0.004
Contagion ES											0.47***	0.005**
Contagion UK							0.20	0.001				
Pseudo-R^2	0.17		0.18		0.12		0.13		0.12		0.13	
Log-Likelihood	−881		−866		−1,531		−1,516		−1,848		−1,821	
N	2,361		2,361		2,361		2,361		2,361		2,361	
ΣContagion DE			0.97				2.19				13.35***	
ΣContagion FR			2.84*				1.91				2.21	
ΣContagion IT			10.38***				5.77**				1.82	
ΣContagion NL							0.00				0.10	
ΣContagion ES			4.47**								17.31***	
ΣContagion UK			0.12				2.65					
ΣContagion			18.44***				13.40***				9.61***	

Notes: Dependent variable: Number of domestic banks simultaneously in the tail ("coexceedances"). Contagion effects are captured by the coefficient of lagged coexceedances in country i (labeled Contagion i). Base case: Zero coexceedances. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are used. Tests reporting the joint significance of the coefficients capturing contagion from each country and from all countries are reported below and labeled with Σ. Example: The row ΣContagion DE reports the statistic for the test of the joint significance of the coefficients capturing contagion from Germany.

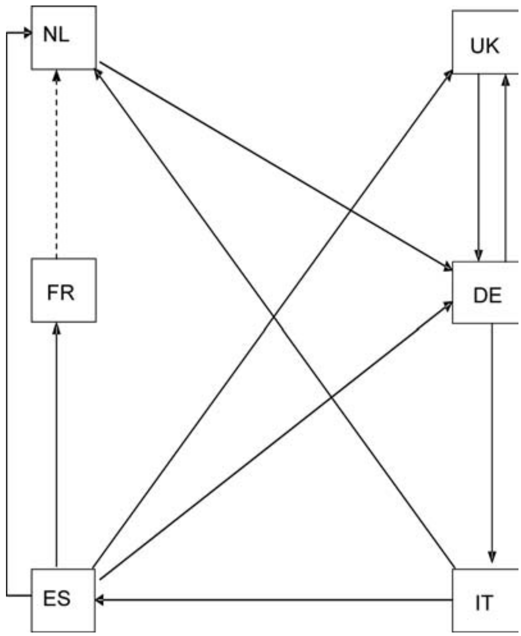
The notion that the number of coexceedances is autocorrelated is supported: The lagged (by one day) number of coexceedances is positive and significant for all countries. Further, the effect of global systemic risk (as measured by the number of stock markets in the tail) is positive and significant. A steepening of the yield curve tends to be only weakly associated with a higher number of coexceedances in most countries, maybe with the exception of Germany and France. As in Bae, Karolyi, and Stulz (2003), increases in conditional volatility are very important in our specification and are always significant at the 1 percent level. All these results conform to expectations. We also checked whether conditional volatility in the U.S. stock market matters for coexceedances among European banks, but the coefficients tend to be insignificant, except in the case of German and Italian banks.

In order to aid the interpretability of the results, we also report marginal probabilities for each coefficient (reported in the second column). We see, for example, that a 1 percent increase in the conditional volatility of the stock market in Germany increases the probability of one exceedance by 0.02 percent, the probability of two coexceedances by 0.01 percent, and the probability of three or more coexceedances by 0.005 percent. All of these marginal probabilities are significant at the 1 percent level. Similar magnitudes are found for all six countries.

Now consider the evidence on contagion (table 5, model 2). We measure contagion by including the one-day lagged coexceedances in the other five countries. If, after controlling for common shocks, any of these variables turn out to be positive and significant, we interpret this as contagion from that country. We also report significance tests for the sum of the contagion variables from each country, as well as the sum of all contagion variables.[13] We find that the contagion variables are jointly significant at least at the 5 percent level for explaining the number of coexceedances in all six countries. This is also reflected in an increase in pseudo-R^2 of generally about 1 to 2 percentage points. The one-day lagged coexceedances from other

[13]The tests are reported in the last rows of table 5 and are denoted with Σ. Example: The row ΣContagion DE reports the statistic for the test of the joint significance of the coefficients capturing contagion from Germany (i.e., the coefficients of the lagged coexceedances from Germany).

Figure 1. Contagion Directions

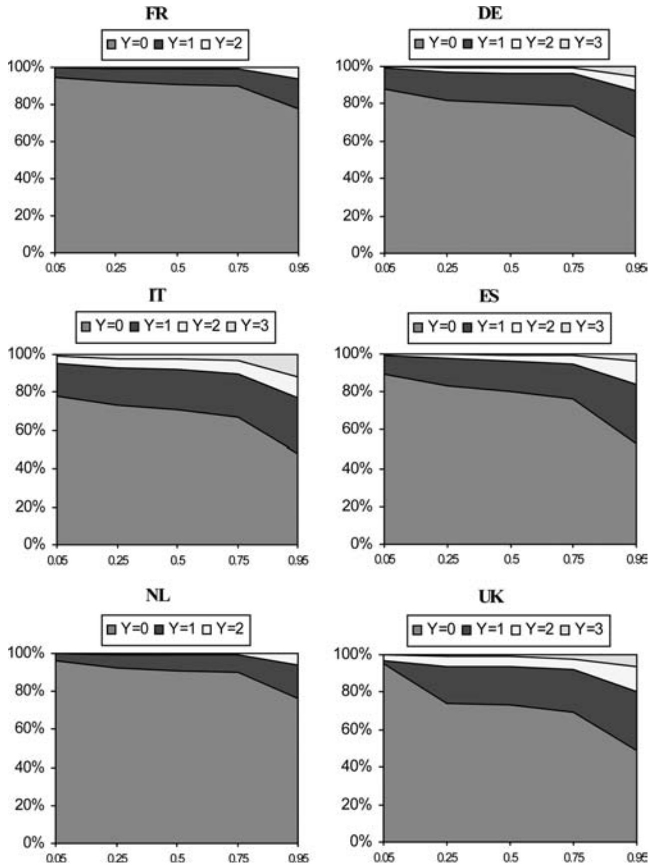


Note: Solid lines indicate significance of contagion parameters at least at the 5 percent level, and dotted line at the 10 percent level.

countries does not result in large changes in the level or significance of the controls, suggesting that adding foreign coexceedances adds information to the specification.

Figure 1 summarizes the patterns of contagion. In the figure, we represent the joint significance of the lagged coexceedance variable in country A in the specification for country B as an arrow from country A to country B. First, we see that the United Kingdom (UK) and Germany (DE) is the only country pair where we have evidence in favor of bilateral contagion. Adverse shocks affecting German banks have an impact upon UK banks and vice versa. Second, Spanish banks tend to be particularly important for the banking systems in other countries. In addition to German banks, French, UK, and Dutch banks have also been exposed to contagion from the Spanish banking system. Third, Spanish banks themselves are exposed to contagion from Italian banks only.

Figure 2. Response Curves to Volatility Shocks



In order to assess the economic magnitude of the effects, we use "coexceedance response curves" (Bae, Karolyi, and Stulz 2003). First let us examine the effect of conditional volatility of the stock market ("volatility own") on coexceedances of banks. In figure 2 we plotted coexceedances in each country as a function of conditional volatility increasing from the lowest 5th percentile (i.e., conditional volatility strongly decreasing) to the highest 5th percentile. We find that the curves are highly nonlinear, supporting our use of a multinomial logit model. If conditional volatility increases strongly (i.e., above the 75th percentile), the probability of more than one coexceedance increases to between 20 percent (FR) and 50 percent (IT) from 3 percent and 20 percent, respectively. Three or more coexceedances increase from about zero at negative changes in volatility to 2 percent (ES) to 10 percent (IT).

In comparison, consider the effect of contagion, shown in figures 3–8. The upper left-hand panel of figure 3 shows contagion from French banks to German banks. The probability of three or more German banks being in the tail is 1.1 percent if no French banks were in the tail the day before. If three French banks were in the tail, this probability increases to 2.8 percent. In the econometric analysis, we found this effect to be insignificant. Now consider the case of contagion from the Netherlands to Germany (depicted in the fourth panel from the left in figure 3). The probability that three or more German banks are in the tail remains unchanged at just above 1 percent no matter how many Dutch banks were in the tail, but the probability that at least one German bank is in the tail increases from 20 percent in the case of no Dutch banks in the tail to 42 percent in the case of three Dutch banks in the tail the day before. In the econometric analysis, we found this effect to be significant at the 5 percent level. Contagion from Dutch banks to the German banking system is significantly stronger than contagion from French banks, but it tends to affect only one or two banks, rather than a large number of banks. The opposite is true for contagion from Spain to Germany (panel 2 in figure 3). In this case, the probability of one or more coexceedances in Germany is not a function of lagged coexceedances in Spain, but the probability of three or more coexceedances increases from less than 1 percent to 3.5 percent. Contagion from Spain tends to affect many banks, rather than just one.

Finally, consider the case of contagion to the United Kingdom (figure 8). The case of the United Kingdom is particularly interesting, because it is the only country in the sample that did not introduce the euro in 1999. We find that there is significant contagion to the United Kingdom from German and Spanish banks. If there are no lagged coexceedances in Germany, the probability of three or more coexceedances in the United Kingdom is 1.1 percent, which increases to 6.7 percent if there are three or more German coexceedances the day before (the change is significant at the 1 percent significance level). The contagion effects from Spain to the United Kingdom, although also statistically significant, are much smaller:

Figure 3. Contagion to Germany

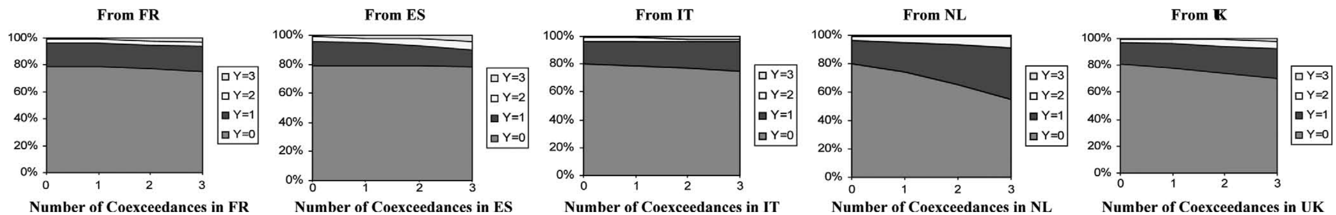


Figure 4. Contagion to France

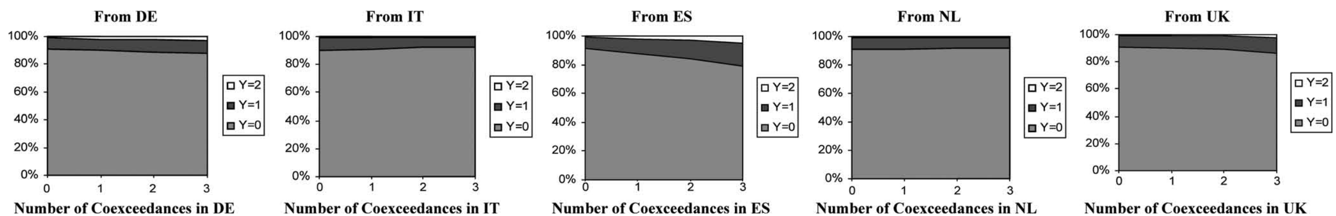


Figure 5. Contagion to Spain

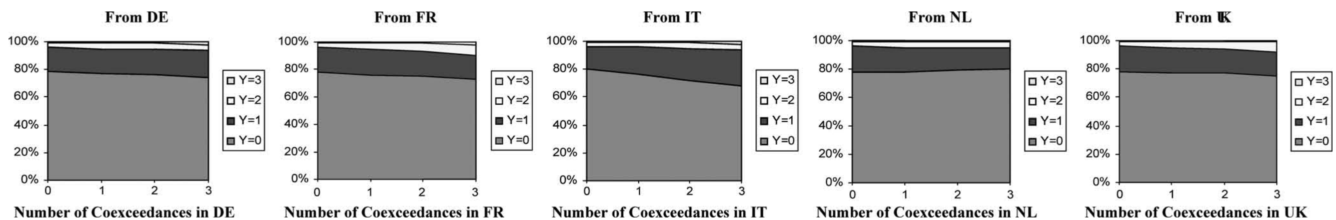


Figure 6. Contagion to Italy

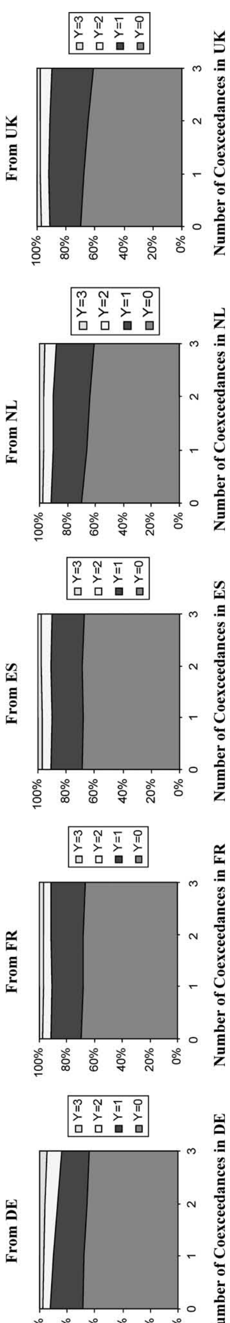


Figure 7. Contagion to the Netherlands

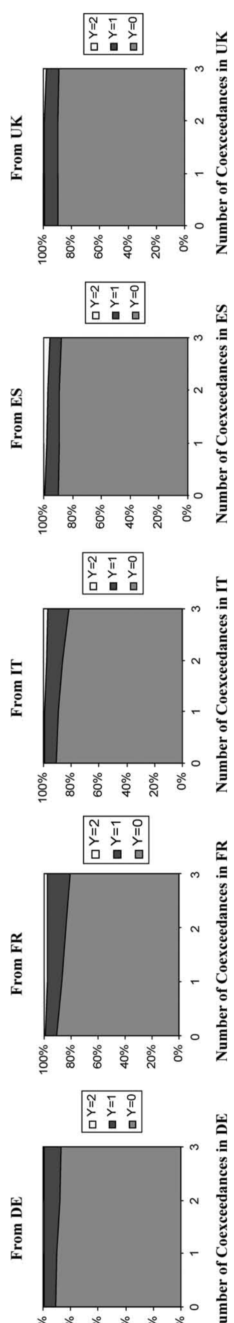
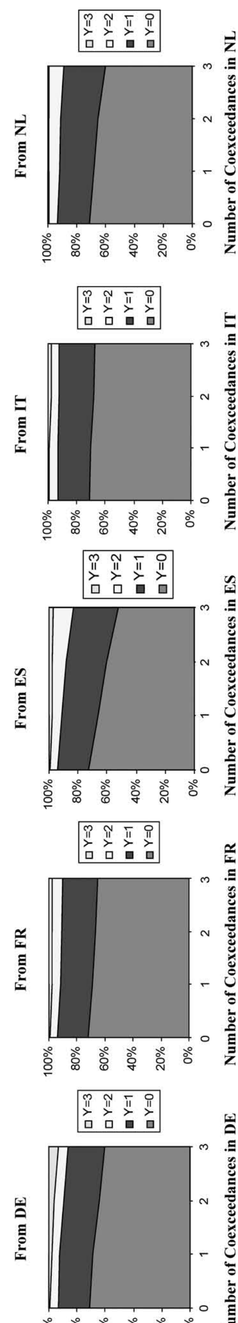


Figure 8. Contagion to the United Kingdom



the increase is from 1.2 percent to 3.5 percent.[14] We explore the relationship between UK banks and the euro area before and after 1999 in more detail in the next section.

4.2 Extension: Effect of the Introduction of the Euro

The effect of the introduction of the common currency on cross-border contagion risk among EU countries is ambiguous ex ante. One could argue that the common currency may result in an increase of cross-border contagion risk, since it led to a single money market for liquid reserves in euro, strengthening the cross-border interbank links among banks. On the other hand, Allen and Gale (2000) argue that when interbank liabilities and assets are well diversified across many banks, cross-border contagion risk should decrease. Hence, the integration of the money market in the wake of the introduction of the common currency may have resulted in a reduction in contagion risk.

In order to address this issue, we estimate the model separately for the pre- and post-euro periods. The results are reported in table 6. Before we discuss the results regarding contagion, note that the fit of the model is better in most countries for the post-euro period. This result is consistent with the idea that idiosyncratic factors explain less of the coexceedances after the euro was introduced and may reflect increasing financial integration (see, e.g., Baele et al. 2004). In addition, the coefficients on some of the control variables change substantially, both in terms of economic magnitude and in terms of econometric significance, although conditional volatility remains the most important variable explaining coexceedances.

Figures 9 and 10 represent graphically the estimated patterns of cross-border contagion for the two periods. Overall, the introduction of the euro appears to have increased cross-border contagion. We distinguish three cases: (i) contagion between two countries exists before and after the introduction of the euro, (ii) contagion exists only before the introduction of the euro, and (iii) contagion exists only after the introduction of the euro. While

[14] It is in line with our priors that we find that German and Spanish banks have contagious effects on the United Kingdom. German banks have large interbank exposures to the United Kingdom, and Spanish banks have quite close ties with UK banks, as evidenced by the recent merger between Banco Santander and Abbey National.

Table 6. Multinomial Logit Model: Contagion in Daily Coexceedances of the Percentage Change in Distance to Default, Large EU Countries, January 1994–January 2003, Pre- and Post-Euro

	France				Germany				Italy			
	Pre-Euro		Post-Euro		Pre-Euro		Post-Euro		Pre-Euro		Post-Euro	
	Coeff.	ΔProb.	Coeff.	ΔProb.	Coeff.	ΔProb.	Coeff.	ΔProb.	Coeff.	ΔProb.	Coeff.	ΔProb.
Coexceedances=1												
Constant	−2.36***		−3.01***		−1.96***		−1.88***		−1.15***		−1.77***	
Coex. Lagged	0.40*	0.034*	0.28	0.015	0.38***	0.050***	0.74***	0.096***	0.31***	0.040***	0.22*	0.0232
Systemic Risk	0.07	0.005	0.45***	0.024***	0.41**	0.056**	−0.08	−0.012	0.35**	0.053*	0.22*	0.030*
Yield Curve	−0.08	−0.006	3.78	0.205	4.36**	0.575**	−2.07	−0.286	−0.10	−0.024	0.30	0.033
Volatility Own	0.54***	0.046***	0.18**	0.009**	0.26***	0.032***	0.13***	0.017***	0.11***	0.015***	0.10***	0.013***
Volatility US	−0.16	−0.014	0.01	0.001	0.01	0.001	−0.00	−0.000	−0.02	−0.005	0.01	0.001
Contagion DE	−0.00	−0.001	−0.01	−0.001					−0.23**	−0.046**	0.32**	0.045**
Contagion FR					0.10	0.013	0.08	0.010	0.20	0.028	−0.20	−0.021
Contagion IT	−0.07	−0.006	−0.25	−0.014	0.14*	0.023*	0.02	0.001				
Contagion NL	0.07	0.007	−0.92**	−0.050**	0.64***	0.086***	0.05	0.008	0.19	0.032	0.03	−0.001
Contagion ES	0.25*	0.021*	0.41**	0.022**	−0.15	−0.025	−0.04	−0.007	−0.11	−0.018	0.22	0.030
Contagion UK	0.04	0.003	0.37**	0.020**	0.17	0.021	0.18	0.023	0.09	0.021	0.20*	0.027
Coexceedances = 2												
Constant	−4.56***		−4.76***		−3.66***		−4.23***		−2.58***		−3.51***	
Coex. Lagged	0.82**	0.009**	0.46	0.005	0.43**	0.009**	1.24***	0.026***	0.53***	0.028***	0.71***	0.027***
Systemic Risk	0.46**	0.005*	0.31	0.003	0.34	0.007	−0.09	−0.002	0.48**	0.025**	0.26*	0.009
Yield Curve	−1.07	−0.012	2.50	0.028	8.68***	0.209***	−1.52	−0.028	0.2	0.017	1.45	0.058
Volatility Own	0.91***	0.010***	0.59***	0.007***	0.59***	0.014***	0.25***	0.005***	0.15***	0.008***	0.16***	0.006***
Volatility US	0.02	0.000	0.10*	0.001*	0.05	0.001	−0.04	−0.001	−0.03	−0.002	−0.01	−0.001
Contagion DE	0.31	0.004	0.22	0.003					0.17	0.016	0.37*	0.012
Contagion FR					−0.10	−0.003	0.11	0.002	0.33	0.018	−0.96**	−0.038**
Contagion IT	−0.15	−0.002	0.04	0.001	−0.55***	−0.015***	0.22	0.005				
Contagion NL	−1.02**	−0.012**	0.38	0.005	0.68***	0.015**	0.00	−0.000	0.08	0.001	0.38	0.016
Contagion ES	0.48*	0.005*	0.72**	0.008**	0.38*	0.010**	0.38	0.009	−0.16	−0.009	0.42**	0.016**
Contagion UK	0.12	0.001	−0.20	−0.003	0.39**	0.009**	0.28	0.006	−0.06	−0.005	0.33*	0.012*

(continued)

Table 6. (Continued)

	France				Germany				Italy			
	Pre-Euro		Post-Euro		Pre-Euro		Post-Euro		Pre-Euro		Post-Euro	
	Coeff.	ΔProb.	Coeff.	ΔProb.	Coeff.	ΔProb.	Coeff.	ΔProb.	Coeff.	ΔProb.	Coeff.	ΔProb.
Coexceedances=3												
Constant					−4.78***		−5.69***		−3.68***		−4.58***	
Coex. Lagged					0.89***	0.010***	1.40***	0.008***	1.00***	0.028***	1.26***	0.019***
Systemic Risk					0.24	0.002	0.35*	0.002	0.56***	0.014**	0.32	0.004
Yield Curve					−1.45	−0.031	5.04	0.037	0.04	0.002	0.55	0.007
Volatility Own					0.73***	0.009***	0.34***	0.002***	0.32***	0.009***	0.29***	0.004***
Volatility US					−0.09	−0.001	0.15**	0.001**	0.12***	0.004***	0.03	0.000
Contagion DE									0.08	0.004	0.62**	0.001**
Contagion FR					0.50	0.006	0.08	0.000	0.32	0.008	−0.36	−0.005
Contagion IT					−0.06	−0.001	0.68**	0.005*				
Contagion NL					0.20	0.001	−0.21	−0.002	0.31	0.008	0.16	0.002
Contagion ES					0.67***	0.009***	−0.12	−0.001	0.03	0.002	−0.12	−0.003
Contagion UK					0.06	0.000	0.34	0.002	−0.21	−0.007	0.11	0.001
Pseudo-R^2	0.14		0.21		0.15		0.14		0.10		0.12	
Log-Likelihood	−506		−332		−808		−639		−1,168		−766	
N	1,302		1,058		1,302		1,058		1,302		1,058	
ΣContagion DE	0.76		0.17						0.01		9.40***	
ΣContagion FR					0.47		0.14		3.77*		4.47**[a]	
ΣContagion IT	0.66		0.44		2.10		3.97**					
ΣContagion NL	2.73*[a]		0.53		6.94***		0.04		1.67		0.62	
ΣContagion ES	4.98**		8.27***		5.80**		0.17		0.60		0.98	
ΣContagion UK	0.23		0.20		3.28*		3.75*		0.27		2.42	
ΣContagion	0.00		1.28		8.33***		5.98**		2.83*		3.29*	

[a]The sum of the coefficients is significantly negative. Not represented as an arrow in figures 9 and 10.

(continued)

Table 6. (Continued)

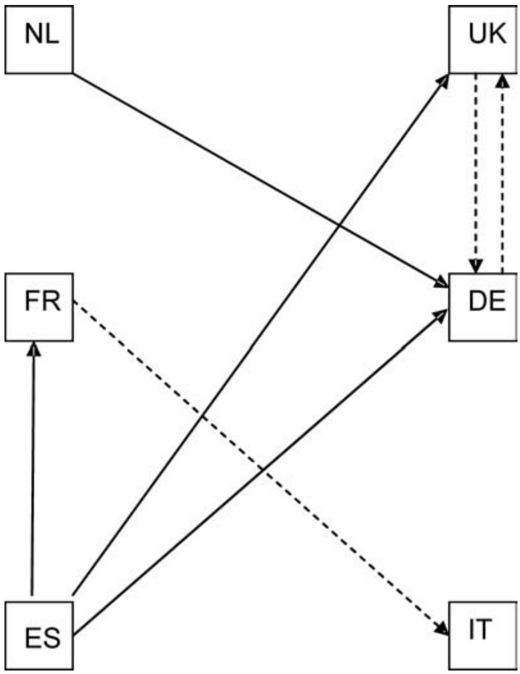
	The Netherlands				Spain				United Kingdom			
	Pre-Euro		Post-Euro		Pre-Euro		Post-Euro		Pre-Euro		Post-Euro	
	Coeff.	**ΔProb.**	**Coeff.**	**ΔProb.**	**Coeff.**	**ΔProb.**	**Coeff.**	**ΔProb.**	**Coeff.**	**ΔProb.**	**Coeff.**	**ΔProb.**
Coexceedances=1												
Constant	−2.40***		−3.16***		−1.58***		−2.10***		−1.51***		−1.79***	
Coex. Lagged	0.56***	0.050***	0.52*	0.033*	0.46***	0.064***	0.66***	0.087***	0.39***	0.058***	0.32**	0.039*
Systemic Risk	0.51***	0.050***	0.46***	0.029***	−0.14	−0.025	0.34***	0.044***	0.63***	0.100***	0.64***	0.094***
Yield Curve	−0.67	−0.060	2.14	0.135	−0.47	−0.080	1.09	0.162	−1.21	−0.212	1.04	0.176
Volatility Own	0.28***	0.024***	0.25***	0.015***	0.42***	0.059***	0.21***	0.026***	0.84***	0.134***	0.20***	0.026***
Volatility US	−0.01	−0.001	0.00	0.000	0.02	0.007	0.02	0.002	−0.02	−0.004	−0.00	0.000
Contagion DE	0.05	0.004	0.24	0.016	0.02	0.002	0.17	0.022	0.16	0.027	0.10	0.009
Contagion FR	0.33*	0.030*	0.15	0.009	0.05	0.005	−0.17	−0.024	0.22	0.046*	−0.31	−0.044
Contagion IT	0.15	0.014	0.34**	0.021**	0.20**	0.030**	0.21*	0.028*	0.05	0.010	0.08	0.012
Contagion NL					−0.23	−0.035	0.11	0.015	0.07	0.011	0.30	0.044
Contagion ES	−0.14	−0.013	0.19	0.012					0.14	0.017	0.42***	0.062***
Contagion UK	−0.11	−0.010	0.10	0.006	−0.20	−0.030*	0.20*	0.026				
Coexceedances = 2												
Constant	−4.69***		−5.04***		−3.51***		−4.26***		−3.00***		−3.37***	
Coex. Lagged	0.62*	0.007	0.48	0.005	0.67***	0.019***	0.93***	0.020***	0.71***	0.034***	0.89***	0.044***
Systemic Risk	0.44*	0.005	0.16	0.001	0.32	0.011	0.65***	0.014***	0.84***	0.038***	0.66***	0.027***
Yield Curve	−0.14	−0.001	0.42	0.003	1.07	0.038	−2.24	−0.06	−0.05	0.016	−1.47	−0.095
Volatility Own	0.66***	0.008***	0.42***	0.004***	0.69***	0.020***	0.40***	0.009***	1.06***	0.047***	0.43***	0.020***
Volatility US	0.03	0.000	−0.06	0.001	−0.65***	−0.022***	−0.00	−0.000	−0.07	−0.003	−0.04	−0.002
Contagion DE	0.21	0.003	−0.24	−0.003	0.08	0.003	0.13	0.002	0.00	−0.002	0.36*	0.018*
Contagion FR	0.18	0.002	0.38	0.004	0.30	0.009	0.15	0.004	−0.24	−0.016	−0.41	−0.018
Contagion IT	0.08	0.001	0.63**	0.006**	0.07	0.001	0.02	−0.000	−0.05	−0.004	0.00	−0.001
Contagion NL					−0.06	−0.001	0.21	0.005	0.21	0.011	0.35	0.015
Contagion ES	0.56***	0.008***	0.12	0.001					0.44***	0.022**	0.43**	0.019*
Contagion UK	−0.04	−0.000	0.32	0.003	0.05	0.003	0.49***	0.011**				

(continued)

Table 6. (Continued)

	The Netherlands				Spain				United Kingdom			
	Pre-Euro		Post-Euro		Pre-Euro		Post-Euro		Pre-Euro		Post-Euro	
	Coeff.	ΔProb.	Coeff.	ΔProb.	Coeff.	ΔProb.	Coeff.	ΔProb.	Coeff.	ΔProb.	Coeff.	ΔProb.
Coexceedances=3												
Constant					−5.12***		−5.78***		−5.38***		−5.02***	
Coex. Lagged					0.66**	0.004*	1.02***	0.006**	1.18***	0.009***	1.01***	0.012***
Systemic Risk					0.86***	0.007***	0.50**	0.003*	1.06***	0.007***	1.03***	0.011***
Yield Curve					1.95	0.016	−1.12	−0.008	−2.87	−0.022	4.10**	0.053*
Volatility Own					0.88***	0.006***	0.43***	0.002***	1.87***	0.014***	0.63***	0.007***
Volatility US					0.09	0.001	0.01	0.000	0.05	0.001	0.05	0.001
Contagion DE					0.17	0.001	0.57**	0.003*	0.48**	0.004**	1.01***	0.013***
Contagion FR					0.24	0.002	0.01	0.000	−0.82*	−0.007*	−0.59	−0.007
Contagion IT					0.21	0.001	0.28	0.002	0.25	0.002	0.08	0.001
Contagion NL					0.13	0.001	−0.07	−0.001	−0.43	−0.004	−0.10	−0.002
Contagion ES									0.68***	0.005**	0.07	−0.001
Contagion UK					−0.08	−0.000	0.51	0.003				
Pseudo-R^2	0.18		0.23		0.15		0.15		0.14		0.16	
Log-Likelihood	−509		−334		−837		−632		−991		−780	
N	1,302		1,058		1,302		1,058		1,302		1,058	
ΣContagion DE	0.84		0.00		0.49		2.98*		3.24*		11.98***	
ΣContagion FR	1.84		1.20		1.12		0.00		1.50		3.02*	
ΣContagion IT	1.32		8.41***		1.94		1.52		0.69		0.14	
ΣContagion NL					0.08		0.13		0.06		0.65	
ΣContagion ES	2.41		0.55						13.49***		3.40*	
ΣContagion UK	0.28		1.51		0.30		7.04***					
ΣContagion	4.06**		12.47***		1.27		9.11***		1.54		4.12**	

Figure 9. Contagion Directions—Pre-Euro



Note: Solid lines indicate significance of contagion parameters at least at the 5 percent level, and dotted lines at the 10 percent level.

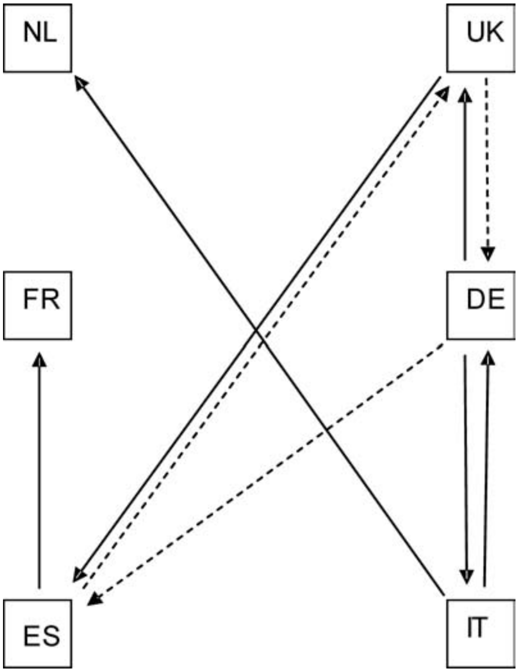
we do not want to discuss these patterns in detail, it clearly emerges that the number of links increases in the post-euro period.

We now turn to the question of whether the economic magnitude of contagion has also changed. To examine this, we prepared the conditional probability charts for the two periods separately (not shown; available from the authors upon request). Overall, the economic magnitude of contagion before and after the introduction of the euro has remained unchanged. Hence, the main effect of the introduction of the euro is the more widespread presence of contagion, rather than a stronger effect due to its presence.

5. Robustness

Because we are estimating a large number of coefficients, we were concerned that some of our results may be spurious. Hence, we

Figure 10. Contagion Directions—Post-Euro



Note: Solid lines indicate significance of contagion parameters at least at the 5 percent level, and dotted lines at the 10 percent level.

subjected the results to five robustness checks: (i) we excluded from the sample well-identified systemic crisis periods; (ii) we reestimated the model using ordered logit, rather than multinomial logit, models; (iii) we added foreign-country conditional volatilities to the specification; (iv) we reestimated the model for the largest and smallest banks in the sample separately; and (v) we relaxed the assumption of a common stochastic process driving the change in distance to default across banks.[15] Rather than report a full set of results for

[15]We also estimated the model with domestic stock market tail events as a separate explanatory variable (rather than incorporated in the variable "systemic risk"). The contagion patterns obtained are broadly unchanged, and the domestic stock market variable is generally insignificant, suggesting that domestic systemic risk is picked up by the conditional volatility variable. The results are available from the authors upon request.

each specification, we summarized the robustness checks in simple matrix tables reported in appendix 3.

As a first robustness check, we reestimated the base model with contagion effects (table 5), excluding the following periods clearly associated with common shocks affecting all banks, rather than contagion: the week of September 11, 2001 (U.S. terror attacks), the second half of October 1997 (Hong Kong crisis), and the first two weeks of October 1998 (Russia's default). The results are reported in table 9 in appendix 3. Comparing the results with table 8 in appendix 3, which summarizes the base specification in table 5, however, reveals that the results tend to strengthen rather than weaken when these crisis periods are excluded.

As we discussed in section 2, an ordered logit model represents a valid alternative to the multinomial logit model used in the baseline specification. The results for an estimation of the baseline model using ordered logit are reported in table 10 in appendix 3 and reveal almost identical patterns of contagion compared with the base line. Our results do not seem to be driven by the estimation method.

Next, it is possible that our results are at least in part driven by volatility spillovers from other countries rather than contagion. Hence, we reestimated the base model and included also the conditional volatility variables of the other countries in cases where we found significant contagion. For example, we detect contagion from the United Kingdom to Germany. It is possible that the coexceedances in the United Kingdom only proxy for large changes in conditional volatility in the United Kingdom, which in turn have an effect on coexceedances in Germany. The results of this exercise are reported in table 11 in appendix 3 and are identical to our baseline results.

As documented earlier, our sample of banks is very heterogeneous in size. This permits a check of whether our results are primarily driven by large banks. In general, large banks can be expected to be more important in cross-border contagion simply because they are large, but also because cross-border interbank money-market links tend to be primarily through these banks (Degryse and Nguyen 2007; Freixas and Holthausen 2005).

Hence, we split the sample into small and large banks and reestimated the basic model. Such a sample split is somewhat arbitrary. In this paper, we use all banks larger than €170 billion (the median). The results (reported in table 12 in appendix 3) suggest that the patterns when estimating the model with large banks are again very similar to those reported earlier, while we find very little contagion from small banks to small banks across borders (appendix 3, table 13). These results are consistent with the tiered interbank structure obtained in a model of the cross-border interbank market in Freixas and Holthausen (2005), in which only large banks operate across borders in the interbank market and act as money centers for smaller domestic banks. However, the evidence is also consistent with large banks sharing common exposures to some sophisticated markets, such as credit derivatives, in which small banks do not participate.

Finally, we also redefined our threshold for coexceedances. In the base specifications, we used the 5 percent tail of the joint distribution of the percentage change in distance to default of all banks in the sample. This implies that each individual bank may be more or less frequently in the tail, depending upon the frequency with which it was hit by a large adverse shock. More fundamentally, the approach implicitly relies on the idea that the stochastic process governing the percentage change in distance to default of individual banks is the same. In order to check the robustness of the results with respect to this assumption, we reestimated the models taking bank-specific cutoff points at the 5 percent negative tail. The results are essentially identical to the base line, which supports the assumption that the stochastic process governing the distance to default of individual banks is similar and more generally enhances the confidence in the robustness of the results.

6. Conclusions

In this paper, we analyze cross-border contagion in the EU banking sector using a multinomial logit approach, focusing on the tail observations in banks' distance to default. We identify contagion by showing that the incidence of tail events in one country is significantly influenced by lagged coexceedances in other countries, controlling for common shocks.

The evidence is consistent with cross-border contagion among large European banks. There is no evidence of cross-border contagion for small banks. The patterns of contagion are robust across a wide variety of specifications. This suggests an important pan-European dimension in the monitoring of systemic risk. This conclusion is strengthened by the increase in cross-border contagion after the introduction of the euro.

While in this paper we do not take a position on the precise transmission channel of contagion, the results suggest that the integrated money market in the euro area may have resulted in an increase in contagion risk. We would take this as evidence that the interbank market is not fully integrated in the sense of Allen and Gale's (2000) complete set of linkages among banks. Instead, the results indicate 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. However, we cannot reject two alternative explanations for the contagion patterns. It is possible that large banks are more likely than smaller banks to be subject to contagion via depressed market valuations of structured instruments and credit derivatives (Cifuentes, Ferrucci, and Shin 2004). In addition, runs by equity holders, in which equity holders are unable to assess the exposures and quality of individual banks, would be consistent with the evidence. We can, however, reject domino effects of defaults as the source for the observed contagion in our results, as contagion occurs even in the absence of any bank in the sample defaulting on its obligations.

The results should be viewed as a lower bound to the true contagion risk in the euro area. First, we estimate the model for a relatively calm period without major financial disruptions in any of the banking systems or in any of the major banks. If contagion risk increases during crises, this is not reflected in our estimates. Second, we use lagged coexceedances (by one day) as our measure of contagion. If financial markets are semi-efficient and incorporate information efficiently, we will miss those cases of contagion taking place within one day. Third, in some countries in the sample (e.g., Spain) banks play a dominant role in the available stock market indices, suggesting that our common-shock variables, such as conditional volatility, may in fact pick up effects that are related to contagion.

Appendix 1. Calculation of Distances to Default

The distance to 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:

$$\ln V^T = \ln V + \left(r - \frac{\sigma^2}{2}\right) T + \sigma\sqrt{T}\varepsilon, \tag{5}$$

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

$$\begin{aligned} &d = \ln V^d - \ln D = \ln V + \left(r - \frac{\sigma^2}{2}\right) T + \sigma\sqrt{T}\varepsilon - \ln D \Leftrightarrow \\ &\frac{d}{\sigma\sqrt{T}} = \frac{\ln\left(\frac{V}{D}\right) + \left(r - \frac{\sigma^2}{2}\right) T}{\sigma\sqrt{T}} + \varepsilon. \end{aligned} \tag{6}$$

That is, the distance to default,

$$dd \equiv \frac{d}{\sigma\sqrt{T}} - \varepsilon = \frac{\ln\left(\frac{V}{D}\right) + \left(r - \frac{\sigma^2}{2}\right) T}{\sigma\sqrt{T}}, \tag{7}$$

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.

$$\begin{aligned} V_E &= VN(d1) - De^{-rT}N(d2) \\ \sigma_E &= \left(\frac{V}{V_E}\right) N(d1)\sigma, \\ d1 &\equiv \frac{\ln\left(\frac{V}{D}\right) + \left(r + \frac{\sigma^2}{2}\right) T}{\sigma\sqrt{T}} \\ d2 &\equiv d1 - \sigma\sqrt{T} \end{aligned} \tag{8}$$

The system of equations was solved by using the generalized reduced gradient method to yield the values for V and σ, which in turn entered into the calculation of the distance to default.[16] 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 (7), yielding the change in the number of standard deviations away from the default point, which is denoted as Δdd.

As underlying data, we used daily values for the equity market capitalization, 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 six-month moving average (backwards) to reduce noise. The presumption is that the market participants do not use the very volatile short-term estimates but, instead, use more smoothed volatility measures. With this approach, equity volatility is accurately estimated for a specific time interval, as long as leverage does not change substantially over that period (see, e.g., Bongini, Laeven, and Majnoni 2002). The total debt liabilities, D, are obtained from published accounts and are interpolated (using a cubic spline) to yield daily observations. This suggests that our variation in the dependent variable arises from either changes in the value of the bank or in changes in volatility. The time to the maturing of the debt, T, was

[16]See Bharath and Shumway (2008), Delianedis and Geske (2003), Eom, Helwege, and Huang (2004), KMV Corporation (2002), and Vassalou and Xing (2004), for a similar derivation and more ample discussions. Duan (1994, 2000) proposes an alternative way to calculate the distance to default, which is based on maximum likelihood estimation of the parameters. We feel that our choice of the "traditional" approach is justified by the fact that the distance to default does not enter directly in our model. Instead, we use it to build a count variable that takes value 1 if the change in distance to default falls in the bottom 95th percentile and 0 elsewhere. In our opinion, this transformation smoothes differences between different computation methods of distance to default. In order to make this point clear, it must be kept in mind that one of the main differences between the traditional method and Duan's approach is that in the former, stock volatility is estimated using historical data. Duan (1994, 2000), hence, corrects the fact that in periods of increasing prices, the traditional approach tends to overestimate the default probability, while the opposite happens in periods of decreasing prices. As we do not consider the level of the distance to default but, rather, the change, the distortion is essentially spread out through the sample. It is also important to stress that in our study we use data at relatively high frequency and therefore any movements in the distance to default will largely be driven by changes in equity prices under either approach.

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. Results from a GARCH (1,1) Model

Table 7. Estimated Coefficients of the Garch (1,1) Model for Daily Stock Market Returns in the Analyzed Countries

	Coefficient	**Std. Error**	**Z-Stat**	**Probability**
FR				
Constant	0.00	0.00	3.03	0.00
ε^2_{t-1}	0.06	0.01	9.60	0.00
σ^2_{t-1}	0.93	0.01	125.21	0.00
DE				
Constant	0.00	0.00	5.64	0.00
ε^2_{t-1}	0.10	0.01	10.47	0.00
σ^2_{t-1}	0.89	0.01	97.08	0.00
IT				
Constant	0.00	0.00	5.00	0.00
ε^2_{t-1}	0.11	0.01	9.84	0.00
σ^2_{t-1}	0.86	0.01	58.21	0.00
NL				
Constant	0.00	0.00	3.68	0.00
ε^2_{t-1}	0.09	0.01	10.11	0.00
σ^2_{t-1}	0.91	0.01	102.81	0.00
ES				
Constant	0.00	0.00	5.67	0.00
ε^2_{t-1}	0.08	0.01	10.08	0.00
σ^2_{t-1}	0.91	0.01	108.16	0.00
UK				
Constant	0.00	0.00	3.61	0.00
ε^2_{t-1}	0.08	0.01	9.17	0.00
σ^2_{t-1}	0.91	0.01	99.71	0.00
US				
Constant	0.00	0.00	4.61	0.00
ε^2_{t-1}	0.07	0.01	11.80	0.00
σ^2_{t-1}	0.92	0.01	144.88	0.00

Note: Equation and variable definitions are given in the text.

Appendix 3. Robustness Checks

The following tables indicate where contagion is present and its direction. Countries receiving contagion are reported in rows; countries transmitting contagion are in columns. The symbols *, **, and *** indicate contagion significance at the 10 percent, 5 percent, and 1 percent levels, respectively. Example: Row 1 of table 8 indicates that contagion goes from the Netherlands (5 percent significance), Spain (5 percent significance), and the United Kingdom (1 percent significance) to Germany.

Table 8. Results of the Basic Contagion Model (See Table 5)

To↓ From→	DE	FR	IT	NL	ES	UK
DE	X			**	**	***
FR		X			***	
IT	**		X			
NL		*	***	X	**	
ES			**		X	
UK	***				***	X

Table 9. Results after Excluding Major Crises from the Sample (Asia, Second Half of October 1997; Russia, First Half of October 1998; and September 11, 2001)

To↓ From→	DE	FR	IT	NL	ES	UK
DE	X				***	**
FR		X			***	
IT	*		X		***	
NL		*	***	X	**	
ES			**		X	*
UK	***				***	X

Table 10. Results Using an Ordered Logit Model

To↓ From→	DE	FR	IT	NL	ES	UK
DE	X			***		***
FR		X			***	
IT	*		X			
NL		**	***	X		
ES			***		X	
UK	***				***	X

Table 11. Adding the Volatilities of the Countries with Significant Contagion Coefficients

To↓ From→	DE	FR	IT	NL	ES	UK
DE	X			**	**	***
FR		X			***	
IT	**		X			
NL		*	***	X	*	
ES			**		X	
UK	***				***	X

Table 12. Results Using Large Banks Only

To↓ From→	DE	FR	IT	NL	ES	UK
DE	X			***		***
FR		X			***	
IT	**		X			
NL		**		X	***	
ES			**		X	*
UK	***		***			X

Table 13. Results Using Small Banks Only

To↓ From→	DE	FR	IT	NL	ES	UK
DE	X					
FR		X				
IT			X	**		
NL				X		
ES			**		X	
UK				*	***	X

Note: We find a negative impact from French and Dutch banks on German banks and from French banks on UK banks.

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