JOHANN WOLFGANG GOETHE-UNIVERSITÄT
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Cross-Border Bank Contagion in Europe

No. 175
Februar 2007

WORKING PAPER SERIES: FINANCE & ACCOUNTING

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No. 175
Februar 2007

ISSN 1434-3401

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Abstract

This paper analyses cross-border contagion in a sample of European banks from January 1994 to January 2003. We use a multinomial logit model to estimate the number of banks in a given country that experience a large shock on the same day ("coexceedances") as a function of variables measuring common shocks and coexceedances in other countries. Large shocks are measured by the bottom 95th percentile of the distribution of the first difference in the daily distance to default of the bank. We find evidence in favour of significant cross-border contagion. We also find some evidence that since the introduction of the euro cross-border contagion may have increased. The results seem to be very robust to changes in the specification.

JEL codes: G21, F36, G15

Keywords: Banking, Contagion, Distance to default, Multinomial logit model

1. Introduction

Contagion is widely perceived to be an important element of banking crises and systemic risk. Very prominently, for example, the private sector rescue operation of LTCM in 1998, co-ordinated by the Federal Reserve Bank of New York was justified by the risk of contagion. 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, 2003). The aim of this paper is to estimate the extent of cross-border contagion among the banking sectors of the largest EU countries. It is intended to contribute to a better understanding of the degree 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 a 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. In this paper, we use the distance to default (e.g. KMV, 2002), a market based indicator of the soundness of the bank. 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[1]. In order to investigate contagion among banking systems we focus on the behaviour of the tail of the distribution of the change in the distance to default[2]. For each country we construct an indicator variable named "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 (in the bottom 95th percentile of the distribution) percentage changes in the daily distance to default of the bank. We then estimate the probability of several bank simultaneously experiencing a large shock in country j as a function of systemic risk emanating from domestic and international risk factors and from coexceedances in the other large EU countries. Econometrically, our approach builds on a recent papers by Bae et al. (2003) which uses a similar methodology to study contagion among stock market returns in emerging economies.

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1 We give a detailed description of the distance to default in the next section.

2 Our choice of focusing on the tails of the distribution has already been adopted in the literature. Gropp and Moerman (2004) use the co-incidence of extreme shocks in banks' distance to default to examine contagion. They employ 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.

For our sample of (predominately) large banks[3] for January 1994 to January 2003 that are stock market listed, we find evidence of significant cross border contagion. We also find some evidence that cross-border contagion increased in importance after the introduction of the euro. We subject the results to a battery of robustness checks and find them to be quite robust to changes in specification, method of estimation, selection of banks and other considerations.

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.[4] 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.[5]

There may be contagion even in the absence of explicit financial links between banks. In the presence of asymmetric information difficulties in one bank may be perceived as a signal of possible difficulties in others, especially if one thinks that banks’ assets may be opaque and balance sheet data and other publicly available information may be uninformative (Morgan, 2002).[6] 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. Recently, Cifuentes et al. (2004) have proposed that there may be contagion through fire sales of illiquid assets. 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 and so forth.

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3 We use the largest stock listed banks in Germany, France, Italy, The Netherlands, Spain and the United Kingdom.

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

5 Iyer and Peydro-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.

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

In their model, relatively small shocks can result in contagious failures in the banking system.[7]

There is a vast previous empirical literature on within-country 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.[8] 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 using a stock market-based default risk indicator (distance to default). In this way, we hope to uncover information that may still be indicative of the links during times of actual crisis. In this sense, studies examining the reaction of stock prices to news and studies using actual interbank data and simulating the failure of one or more banks are more closely related to our work. 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.[9]

A large number of papers for different countries have used actual or estimated interbank links to simulate contagion. Generally, the evidence of contagion resulting in significant bank failures is mixed. While Furfine (2003) for the US and Sheldon and Maurer (1998) for Switzerland find relatively benign effects, Upper and Worms (2003) estimate a matrix of interbank loans for German banks and find some stronger evidence of contagion risk. Degryse and Nguyen (2004) for Belgium find that the patterns of linkages changed from a structure with complete links among banks to one in which

[7] Other channels of contagion could be the payment system, where difficulties in one bank may lead to credit losses to other banks (in netting systems) or gridlock in the entire system or ownership links among banks.

[8] 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.

[9] For a survey see De Bandt and Hartmann (2001).

there are multiple money centre banks. Overall, the change in structure suggests a decrease in the risk of contagion. While Degryse and Nguyen discuss the possibility of cross-border contagion, generally the simulations studies concentrate on contagion risk within one country, rather than across countries.

Most closely related to the approach in this paper and the only other paper we are aware of that examines cross-border contagion among banking systems, Hartmann et al. (2004b) use multivariate extreme value theory to estimate contagion in Europe and the US. They find that contagion may have increased from the mid-1990s onwards both in Europe and the US. Overall, however, the level of contagion risk in the US remains higher than in the EU. Iyer and Peydro-Alcalde (2005b) estimate in a unique dataset for India the effect of the failure of one large regional bank (due to fraud). They find that banks' exposures with the failed bank in the interbank market as an important determinant of depositor withdrawals of the banks. The evidence is strongly supportive of contagion in interbank markets.

The remainder of the paper is organised as follows. In the next Section, we describe the data used in the paper and give some descriptive statistics. Section III explains our primary econometric approach, the multinomial logit model. Section IV presents our econometric results. Section V discusses a few issues related to the robustness of our findings. Finally, Section VI 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 (50 banks). We limited ourselves to these countries, as almost all largest internationally active European banks are headquartered in these countries (see Table 1). 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). We deleted three additional banks where we had serious concerns about data quality.[10] For those banks where the distant to default was not available for the entire period under review (5 banks), we imputed a total of 342 missing values using linear interpolation and random numbers (for details see the notes to table 2). In this

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

way, we ensure 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 40 banks. For each bank the sample contains 2263 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 EU (Table 1). On average, their total assets amount to EUR 178 billion (median: EUR 132 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 more than 300 times the size of the smallest. 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, but despite the relatively low number of banks the coverage is quite high. The fraction of the total assets of commercial banks covered in our data varies from 36% for France to 68% for Spain.[11]

The distance to default (KMV, 2002), 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. In order to compute the distance to default some assumptions must be made. Intuitively, the value of equity of a company can be seen as a call option, since at the time of the repayment of the debt the value of equity is the maximum between zero and the difference between total assets and total debt. Equity is therefore modelled as a call option on the assets of the company. The level and the volatility of assets are calculated with the Black and 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 either when the values of assets increases or/and when volatility of assets goes down. An increase in the distance to default means that the firm is moving away from the default point and that the bankruptcy event becomes less likely. Being a market based measure of distress, the distance to default has the advantage that it contains expectations of market participants and therefore it is forward looking. Gropp et al. (2004, 2006) 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 default 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

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

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 daily distance to default for each bank in the sample and for each time period, t,. We then defined large shocks as the negative 95th percentile of the common distribution of the percentage change in distance to default ($\Delta dd_{it} / | dd_{it} |$) across all banks.[12] Choosing the bottom 95th 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, which we, following Bae et al. (2003), labelled the coexceedances of banks in a given country.

In order to control for common shocks we rely on the existing literature on financial crises and contagion (Forbes and Rigobon, 2002, and Rigobon, 2003). Our model is basically a factor model in which the occurrence of coexceedances is a function of some domestic and international common factors and coexceedances in other countries. In our model, coexceedances in other countries are the source of potential contagion. We use four variables to control for common shocks. The main selection criterion was that the variables can be measured at a daily frequency. This is essential, as we want to model daily innovations in the distance to default.[13]

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 as follows: Emulating our approach to modelling large shocks in banks, we use indicator variables that we set equal to one if a 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 the Euro Area stock market index, the US and Emerging market stock indices. We use total market indices as provided by Datastream; except for emerging markets the MSCI Emerging Market Index is used. "Systemic risk" is then the sum of indicator variables measuring whether or not the domestic stock market, the US stock market, the European

[12] 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 to be reasonable, however, as redoing the analyisis reported below with bank-specific tail occurrences yields quantitatively very similar results.

[13] As a consequence, many other variables available at lower frequency that might have explanatory power as common shocks do not enter into the model directly. We don't think this is a problem. Since financial variables incorporate news and expectations regarding several factors affecting the business scenario, we believe that any relevant information we might want to include regarding economic growth, monetary policy or other shocks, is discounted in financial prices.

stock market and the index of emerging market stock markets are in the tail on a given day. Hence, it ranges from 0 to 4.[14] This variables measures something that we would label a "global shock", i.e. if many markets experience large shocks simultaneously. This distinguishes it from a domestic shock, which we measure using 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 10 year government bond and the yield of the 1 year note in a given country.[15] 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. Bae et al. (2003) found this variable to be particularly important when explaining emerging market coexceedances and we follow their approach here. Stock market volatility has been estimated using a GARCH(1,1) model of the form

$$\sigma_{tc}^2 = \alpha + \beta_1 \varepsilon_{c,t-1}^2 + \beta_2 \sigma_{c,t-1}^2 \tag{1}$$

using maximum likelihood, where σ_{tc}^2 represents the conditional variance of the stock market index in country c in period t and ε represents the error term. 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, it is possible that there are volatility spill-overs from other parts of the world as well. To control for these, we also control for the stock market volatility from the US in the regressions, estimated also with a GARCH (1,1) ("volatility US"). [16] As US markets open later than European markets, we used data from the previous day to estimate US volatility. Further, we include one lag of the domestic coexceedances, as we suspect that first-differencing and using only the large

[14] 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 US and emerging markets, respectively.

[15] If the yield of the 1 year treasury note was not available, we used the interbank rate for the same maturity. The source of the data are Datastream and the BIS.

[16] "Volatility own" and "volatility US" were rescaled by multiplying the estimated values by 1000.

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). However, this hides substantial variation in the health of banks. Only one bank shows distances to default below one. At the other end of the spectrum, there were a number of banks with a maximal distance to default of above 10. As expected, the mean of the first difference in the distance to default is approximately zero, the largest negative change is 77%, which can truly be considered a sizeable daily shock. The negative 95th percentile is at about -1%.

Tables 3 and 4 present some additional descriptive statistics on the variable of interest, 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 12 banks in the sample, while in France and the Netherlands there are only three. The UK, Spain and Germany are also well represented with 8, 7 and 7 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. This is explored in more detail in Table 4.

As we will estimate a multinomial logit model, which implies that we will estimate one coefficient per outcome, we follow Bae et al. (2003) and limit the number of outcomes to 0,1,2, and 3 or more coexceedances, except for France and The Netherlands where we limit the number of outcomes to 2 or more. Table 4 shows, for example, that in Spain, 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 2 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 per se. Still, comparing countries with an equal number of banks in the sample suggests that Spanish banks tend to experience fewer shocks compared to German banks and that Dutch banks tend to be about equally frequently subject to large shocks compared to French banks. Of the total of 40 banks in the sample, a maximum of 20 are simultaneously in the tail (on October 2, 1998) and there are 14 days with more than 15 coexceedances (not reported in Tables).

3. Econometric model

We study whether contagion is one factor associated with negative large 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, the distance to default.

Our 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, multinomial 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) also 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 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. This leaves ordered logit and multinomial logit models as the preferred method. 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 be 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, while the multinomial logit model permits for full flexibility in this regard. The trade-off is that in a multinomial logit model, there are many more parameters to estimate and one may loose degrees of freedom.

Given these considerations, we decided to use a multinomial logit model as our primary specification and use the results from an ordered logit model as a robustness check (see section V). 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, controlling for common shocks:

$$\Pr_c[Y = j] = \frac{e^{\left[\alpha_j' F_c + \beta_j C_{ct-1} + \gamma_j' C_{dt}\right]}}{\sum_k^J e^{\left[\alpha_k' F_c + \beta_k C_{ct-1} + \sum_{d \neq c} \gamma_{dk} C_{dt}\right]}} \qquad (2)$$

,

where j = 1,2,3…J represents the number of banks in the tail simultaneously ("coexceedances") in country c, F_c the common shocks in country c, C_{ct-1} the lagged number of coexceedances in country c, and C_{dt} represents the coexceedances in period t in country d. As common shocks are controlled for, the significant coefficients of C_{dt} would signal cross-border contagion.

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 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

$$\Pr[Y=j]=\frac{e^{\left[\alpha_j' F_c+\beta_j C_{ct-1}+\gamma_j' C_{dt}\right]}}{1+\sum_k^J e^{\left[\alpha_k' F_c+\beta_k C_{ct-1}+\gamma_k' C_{dt}\right]}} \qquad (3)$$

Differentiating with respect to C_{dt} yields

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

which can be computed from the parameter estimates, with the independent variables evaluated at suitable values, along with its standard errors.[17] In all tables we will report the estimated coefficients alongside the marginal probabilities obtained from (5).

4. Estimation results

4.1. Base model

The results for the basic contagion estimation 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. Subsequently, we add the coexceedances from other countries. Recall that the dependent variable is the number of banks whose first-differenced distance to default was in the negative 95th tail in a given week in a given country. In all countries with more than 3 banks (DE, ES, IT, UK), we limited the model to estimating four outcomes, 0, 1, 2 and 3 or more coexceedances, while in FR and NL we estimated three outcomes, 0,1 and 2 or more coexceedances.

[17] The computation of the standard errors is exceedingly time consuming and most studies do not report them. However, both the significance and even the sign could differ between the coefficients and their marginal effects (Greene, 2000).

First consider the base model without contagion variables for the five countries (Table 5, first columns for each country). Recall that in a multinomial logit model we estimate coefficients for each outcome. Following the convention, we take the outcome of coexceedances equal to zero as the base case. 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.[18]

The notion that the number of coexceedances are autocorrelated is supported: The lagged (by one day) number of coexceedances tends to be positive and significant for all countries. Further, global systemic risk (as measured by the number of stock markets in the tail) tends to be positive and significant. A steepening of the yield curve tends to be only weakly associated with a higher number of coexceedances in most countries; the effect is somewhat stronger in DE and FR. As in Bae et al. (2003), increases in conditional volatility are very important in our specification and are always significantly (at the 1 percent level) positively related to a higher number of coexceedances. All these results conform to expectations. We also checked whether conditional volatility in the US stock market matters for coexceedances among European banks, but the coefficients tend to be insignificant, except in case of German and Italian banks and not for UK banks, where we would have expected US volatility to be particularly important.[19]

In order to aide the interpretability of the results, we also report marginal probabilities for each coefficients (reported in the second column). We see, for example, that a one 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 of three or more coexceedances by 0.001 percent. All of these marginal probabilities are significant at the one percent level. Similar magnitudes are found for all six countries.

Now consider the evidence on contagion. We measure contagion by including the one-day lagged coexceedances in the other five countries. If, controlling for common shocks, as we have done, 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. We find that the contagion variables are jointly significant at least

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[18] 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).

[19] Given that there is ample evidence for stock market spill overs from the US to Europe (see Hartmann et al. (2003), these may be captured by our "systemic risk" variable.

at the five 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. It is important to note that adding the one-day lagged coexceedances from other 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.

The patterns of contagion among countries can be more easily examined using Chart 2. In this chart, we represented 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. A few observations can be made. One, we only find one country pair where we have evidence in favour of bi-lateral contagion, namely UK and DE. This means that adverse shocks affecting German banks have an impact upon UK banks and vice versa. Second, aside from being exposed to contagion from the UK, German banks are also exposed to contagion from Spanish and Dutch banks. Second, Spanish banks tend to be particularly important for the banking systems in other countries, which may be somewhat surprising. In addition to German banks, also French, UK and Dutch banks have been exposed to contagion from the Spanish banking system. Third, Spanish banks themselves are exposed to contagion from Italian banks only.

While we find the contagion variables to be econometrically highly significant, their economic magnitude is difficult to interpret. Hence, in order to shed some light on this, we have plotted the probability of one or more banks being in the tail (experiencing a large shock) conditional on the number of banks in other countries being in the tail on the previous day, setting all other control variables to their unconditional mean. Bae et al. (2003) in a similar exercise have labelled these types of curves "coexceedance response curves" and report that these curves have their origin in epidemiology, where they were used to show the spread of infectious disease across regions.

First let us examine the effect of conditional volatility of the stock market ("volatility own") on coexceedances of banks. In Chart 1 we plotted coexceedances in each country as a function of conditional volatility increasing from the lowest 5^{th} percentile (i.e. conditional volatility strongly decreasing) to the highest 5^{th} percentile. Hence, the charts show the effect of the most important common shock on coexceedances. We find that the curves are highly non-linear, supporting our use of a multinomial logit model. In general, if conditional volatility increases strongly (i.e. above the 75^{th} percentile), the probability of more than one coexceedance increases to between 20% (FR) and 50% (IT) from 3% and 20%, respectively. Three or more coexceedances increase from essentially zero at negative changes in volatility to 2% (ES) to 10% (IT). These results give use a benchmark against which we can evaluate the effects of contagion.

Now in comparison consider the effect of contagion. First consider the upper left hand panel of Chart 3, which shows contagion from French banks to German banks. The Chart shows that the probability of 3 or more German banks being in the tail is 1.1 percent if no French banks are in the tail. If three French banks are 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 Chart 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 are 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. In the econometric analysis we found this effect is 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 Chart 3). In this case, the probability of one or more coexceedances in Germany is not a function of coexceedances in Spain, but the probability three or more coexceedances increases from less than one percent to 3.5%. Contagion from Spain tends to affect many banks, rather than just one.

In the case of France (Chart 4), we only found statistically significant contagion from Spain, where the probability of two or more coexceedances increases from 0.2% to 5%. Contagion to Italian banks is also important (Chart 6). For example, in the case of no German coexceedances the probability of three or more coexceedances in Italy is 2.4%; for three or more German coexceedances this probability increases to 5.4%. This change is significant at the one percent level. It is also interesting to note that the probability that only one bank in Italy is in the tail is not affected by German coexceedances. Finally consider the case of contagion to the UK. The case of the UK 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 UK from German and Spanish banks. If there are no coexceedances in Germany the probability of three or more coexceedances in the UK is 1.1%, which increases to 6.7% if there are three or more German coexceedances (the change is significant at the one percent significance level). The contagion effects from Spain to the UK, although also statistically significant is much smaller: the increase is from 1.2% to 3.5%.[20] Given the size and importance of its banking system it may be at first glance surprising that we do not find evidence of stronger contagion from the UK to euro area countries. UK coexceedances are only significantly related to German coexceedances. The relationship between UK banks and the unified euro area money market after 1999 will be explored 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 on 1 January 1999 would give rise to further cross-border contagion risk, since it has led to a single money market for liquid reserves in euro, strengthening the cross-border interbank links among banks. This would be the case, especially, if cross-border transactions are mainly conducted by money centre banks. On the other hand, Allen and Gale (2000) have argued that in a system, in which interbank liabilities and assets are very 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. It is also interesting to see the effect of the introduction of the euro on contagion risk to and from the UK, as the UK has not joined the euro.

In order to analyse this issue we estimate the model separately for the pre- and a post-euro periods. For the pre-euro period we have 1302 daily observations in the sample and for the post euro period we have 1058 observations, i.e. the sample is split about in half. The results are reported in Table 6. Before we discuss the results regarding contagion, there may be a few issues worth noting about the results more generally. One, the fit of the model is better in almost all countries for the post-euro period. The pseudo R^2 is higher by 2 percentage points (UK, IT) to 7 percentage points (FR). Only in Germany and Spain does it remain the same.

This result is consistent with the idea that idiosyncratic factors explain less of the coexceedances after the euro was introduced and may be suggestive of financial integration (see for example Baele et al., 2004). Second, the coefficients on some of the

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

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.

Charts 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. In order to systematise the discussion, let us 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. In the first category, we find that contagion from ES to UK and FR and the bilateral contagion between UK and DE have prevailed. As to the second category, we find that there is no longer contagion from NL to DE, from FR to IT and from ES to DE. In the third case of new contagion patterns, we find that after the euro there is evidence of contagion from FR to UK, UK to ES and bilateral contagion between DE and IT.

In our view, this evidence is consistent not only with somewhat overall higher cross-border contagion risk, but also with the idea that this higher cross-border contagion risk may be related to the integration of the money market in the euro area.

We now turn to the question whether the economic magnitude of contagion has also changed. To examine this, we prepared the conditional probability charts for the two periods separately (see Charts 11-16). We conclude from the charts that, overall, the economic magnitude of contagion before and after the introduction of the euro has remained largely unchanged. Hence, we would conclude that the main change relates to the greater presence of contagion after the euro, rather than, given its presence, that its effect is stronger. One exception to this may be contagion to and from the UK, which we find to possibly have somewhat increased in magnitude, in particular to and from IT, NL and ES. Again, we would interpret this as evidence that UK banks may have increased their exposure to the common euro area money market.

5. Robustness

As we are estimating a large number of coefficients, we were concerned that some of our results may be spurious. Hence, we subjected the results to five robustness checks: (i) we excluded from the sample well-identified systemic crisis periods; (ii) we re-estimated the model using ordered logit, rather than multinomial logit models; (iii) we added foreign country conditional volatilities to the specification; (iv) we re-estimated the model for the largest and smallest banks in the sample separately and (v) we relax the assumption of a common stochastic process driving the returns across banks.[21] Rather than report a full set of results for each specification, we summarised the robustness checks in simple matrix tables reported in Appendix III.

As a first robustness check, we re-estimated the base model with contagion effects (Table 5) excluding the following periods: the week of September 11 (US terror attacks), the July and October of 1997 (Asia and Hong Kong crisis) and the first two weeks of October 1998 (Russia's default). The results are reported in the second panel in Appendix III. During these 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 control variables to properly account for either event, given that they are clearly identified as common shocks, rather than contagion. Comparing the results to the first panel of Appendix III, which summarises the base specification in Table 5, however, reveals that the results are unaffected by the exclusion of these episodes of systemic financial stress. Indeed, the only difference is that we find additional contagion risk, namely from ES to IT and from UK to ES.

As we discussed in section II, there are a number of alternatives for the estimation of count data. While we would consider Poisson models and tobit models inappropriate for reasons specified above, an ordered logit model seems to represent a useful robustness check. As discussed above the main difference is that the ordered logit model relies on the assumption of constant marginal effects across the different outcomes, while the multinomial logit model permits full flexibility in this regard. The advantage of the ordered logit model is that we gain degrees of freedom, as we have to estimate each covariate only once and not once for each outcome in the dependent variable. When performing this estimation, the results of which are reported in the third panel of Appendix III, we found almost identical patterns of contagion compared to the base line. The only difference is that we are no longer able to detect any contagion from ES to DE.

Next, it is possible that our results are at least in part driven by volatility spill-overs from other countries rather than contagion. In order to examine this, we re-estimated the base model and included also the conditional volatility variables of the

[21] We also estimated the model with domestic stock market tail events as a separate explanatory variable (rather than subsumed in "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.

other countries in cases where we found significant contagion. For example, we detect contagion from the UK to Germany. It is possible that the coexceedances in the UK only proxy for large changes in conditional volatility in the UK, which in turn have an effect on coexceedances in Germany. The results of this exercise are reported in panel 4 of Appendix III 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 or whether the presence of relatively small banks has introduced some error or noise into the estimation. In general, large banks can be expected to be more important in cross-border contagion simply because they are large, but also because interbank money market links tend to be primarily through these banks. There is evidence that in the euro area at least, tiered structures have emerged in which smaller banks conduct their international business through a few large banks. This has resulted in a tiered interbank market structure with respect international operations (see e.g. Degryse and Nguyen, 2004).

To test whether large banks play a disproportionate role in our results we split the sample in small and large banks and re-estimated the basic model. An such sample split is somewhat arbitrary. In this paper we use all banks larger than EUR 170 billion (the median). The results (reported in panel 5 of Appendix III) 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 III, panel 6). These results are consistent with a tiered interbank structure, in which only large banks operate across borders in the interbank market and act as money centres for smaller domestic banks.

Finally, we also re-defined our threshold for exceedances. In the base specifications, we used the five percent tail of the joint distribution of all banks in the sample. This means that each individual banks 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 distance to default of individual banks is the same. This, given the definition of the distance to default (see Appendix I) seems reasonable; however, to check the robustness of the results with respect to this assumption we re-estimated the models taking bank-specific cut off points at the five 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 analyse cross-border contagion in the EU banking sector using a multinomial logit approach, focussing 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 large 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, we control for tail events in domestic stock markets, changes in the yield curve and changes in conditional volatility in the home and the US stock market.

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. Moreover the patterns of contagion were robust across a wide variety of specifications. This suggests an important pan-European dimension in the monitoring of systemic risk; a conclusion which is even strengthened by the fact that we also find the relevance of cross-border contagion after the introduction of the euro to have increased. While in this paper we do not take a position on the channel of contagion (i.e. payment systems, money markets, ownership links, pure contagion), the results suggest that the integrated money market 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, combined with our finding that there is virtually no contagion among small banks, 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.

Overall we would argue that our results should be viewed as a lower bound to the true existing contagion risk in the euro area. One, 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 very quickly, 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.

Finally, there may be a puzzle related to the fact that bank by bank interbank exposures are not available to the market as a whole (as they are not available to the authors). The way we interpret our results implicitly relies on the assumption that markets have this data or if they do not, at least use estimates. Alternatively, our results could be driven by market participants that do have the data, which are the banks themselves. From our perspective this would be a very interesting avenue for further research.

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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 I)	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) 1/	343	/	/	/	/	/
tail	takes value 1 if bank *i* is in the 95th percentile negative tail of the distribution of $\Delta dd_{it}/dd_{it-1}$	94,520	0.05	0	0.22	0	1
Country specific variables							
Coexceedances DE	Number of banks in the 95th percentile negative tail of $\Delta dd_{it}/dd_{it-1}$ in DE	2363	0.34	0	0.75	0	7
Coexceedances ES	Number of banks in the 95th percentile negative tail of $\Delta dd_{it}/dd_{it-1}$ in ES	2363	0.34	0	0.71	0	6
Coexceedances FR	Number of banks in the 95th percentile negative tail of $\Delta dd_{it}/dd_{it-1}$ in FR	2363	0.16	0	0.48	0	3
Coexceedances IT	Number of banks in the 95th percentile negative tail of $\Delta dd_{it}/dd_{it-1}$ in IT	2363	0.56	0	1.12	0	11
Coexceedances NL	Number of banks in the 95th percentile negative tail of $\Delta dd_{it}/dd_{it-1}$ in NL	2363	0.16	0	0.47	0	3
Coexceedances UK	Number of banks in the 95th percentile negative tail of $\Delta dd_{it}/dd_{it-1}$ in UK	2363	0.48	0	0.90	0	7
Systemic risk DE	Number of markets in the 95th percentile negative tail among US, Emerging, Europe and DE	2363	0.2014	0	0.6104	0	4
Systemic risk ES	Number of markets in the 95th percentile negative tail among US, Emerging, Europe and ES	2363	0.2014	0	0.6034	0	4
Systemic risk FR	Number of markets in the 95th percentile negative tail among US, Emerging, Europe and FR	2363	0.2014	0	0.6146	0	4
Systemic risk IT	Number of markets in the 95th percentile negative tail among US, Emerging, Europe and IT	2363	0.2014	0	0.5935	0	4
Systemic risk NL	Number of markets in the 95th percentile negative tail among US, Emerging, Europe and NL	2363	0.2014	0	0.6062	0	4
Systemic risk UK	Number of markets in the 95th percentile negative tail among US, Emerging, Europe and UK	2363	0.2014	0	0.6048	0	4
Yield curve DE	Change in the slope of the yield curve in DE	2363	0.0004	0.0000	0.0385	-0.1900	0.3800
Yield curve ES	Change in the slope of the yield curve in ES	2363	0.0006	-0.0020	0.0682	-0.5400	0.4840
Yield curve FR	Change in the slope of the yield curve in FR	2363	0.0006	-0.0046	0.0645	-0.8000	0.3198
*Yield curve IT**	Change in the slope of the yield curve in IT	2363	0.0002	-0.0010	0.1511	-2.5580	2.5960
Yield curve NL	Change in the slope of the yield curve in NL	2363	0.0003	0.0000	0.0512	-0.3000	0.3210
Yield curve UK	Change in the slope of the yield curve in UK	2363	0.0013	0.0000	0.0814	-0.8740	0.5460
*Volatility DE**	Change in the volatility of the stock market in DE	2362	0.0072	-0.3141	3.0809	-10.5551	47.7505
*Volatility ES**	Change in the volatility of the stock market in ES	2362	0.0011	-0.3486	2.4996	-9.2267	32.1450
*Volatility FR**	Change in the volatility of the stock market in FR	2362	0.0044	-0.2951	1.9286	-4.8973	47.0638
*Volatility IT**	Change in the volatility of the stock market in IT	2362	0.0045	-0.6004	4.1482	-15.1464	63.3724
*Volatility NL**	Change in the volatility of the stock market in NL	2362	0.0060	-0.2482	2.8988	-10.9020	32.1924
*Volatility UK**	Change in the volatility of the stock market in UK	2362	0.0045	-0.1762	1.5277	-6.5127	21.0707
*Volatility US**	Change in the volatility of the stock market in US	2362	0.0054	-0.2353	2.1676	-5.2696	34.7094
	Memo items						
Cut off point of the 95th percentile of $\Delta dd_{it}/\lvert dd_{it-1}\rvert$		-0.0085					

1/ 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 1000.

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	2363	3
Germany	16,541	7	46.5	2363	7
	28,356	12	52.1	2363	11
The Netherlands	7,089	3	58.9	2363	3
Spain	16,541	7	68.3	2363	6
UK	18,904	8	56.1	2363	7
Total	94,520	40	/	/	20

Table 4. Coexceedances by countries

	France* (FR)	Germany (DE)	Italy (IT)	The Netherlands* (NL)	Spain (ES)	United Kingdom (UK)
Coexceedances = 0	2085	1822	1591	2066	1795	1628
Coexceedances = 1	203	385	495	219	407	486
Coexceedances = 2	75	89	152	78	111	161
Coexceedances ≥ 3	-	67	125	-	50	88
Total	2363	2363	2363	2363	2363	2363

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

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Table 5. Multinomial logit model: Contagion in daily coexceedances of the first differenced distance to default, large EU countries, January 1993-January 2003

*Dependent variable: number of domestic banks simultaneously in the tai ("coexceedances"). Base case: Zero coexceedances. *, ** indicate statistical significance at the 5% and 1% levels, respectively. All models estimated with 2362 daily observations. Robust standard errors are used.*

	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***	
Coexceedances 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***	
Coexceedances 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

Table 5 (continued). Multinomial logit model: Contagion in daily coexceedances of the first differenced distance to default, large EU countries, January 1993-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=3												
Constant					-4.61***		-5.01***		-3.91***		-3.99***	
Coexceedances 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 R2	0.14		0.15		0.10		0.12		0.09		0.10	
Log-likelihood	-878		-867		-1523		-1493		-1982		-1972	
N	2361		2361		2361		2361		2361		2361	
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**	

Table 5 (continued). Multinomial logit model: Contagion in daily coexceedances of the first differenced distance to default, large EU countries, January 1993-January 2003

	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***	
Coexceedances 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***	
Coexceedances 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**				

Table 5 (continued). Multinomial logit model: Contagion in daily coexceedances of the first differenced distance to default, large EU countries, January 1993-January 2003

	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***	
Coexceedances 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 R2	0.17		0.18		0.12		0.13		0.12		0.13	
Log-likelihood	-881		-866		-1531		-1516		-1848		-1821	
N	2361		2361		2361		2361		2361		2361	
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***	

Table 6. Multinomial logit model: Contagion in daily coexceedances of the first differenced distance to default, large EU countries, January 1993-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***	
Coexceedances 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***	
Coexceedances 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*

Table 6 (continued). Multinomial logit model: Contagion in daily coexceedances of the first differenced distance to default, large EU countries, January 1993-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=3												
Constant					-4.78***		-5.69***		-3.68***		-4.58***	
Coexceedances 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 R2	0.14		0.21		0.15		0.14		0.10		0.12	
Log-likelihood	-506		-332		-808		-639		-1168		-766	
N	1302		1058		1302		1058		1302		1058	
ΣContagion DE	0.76		0.17						0.01		9.40***	
ΣContagion FR					0.47		0.14		3.77*		4.47** 1/	
ΣContagion IT	0.66		0.44		2.10		3.97**					
ΣContagion NL	2.73* 1/		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*	

1/ The sum of the coefficients is significantly negative. Not represented as an arrow in Charts 9 and 10.

Table 6 (continued). Multinomial logit model: Contagion in daily coexceedances of the first differenced distance to default, large EU countries, January 1993-January 2003, pre and post euro

	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***	
Coexceedances 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***	
Coexceedances 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**				

Table 6 (continued). Multinomial logit model: Contagion in daily coexceedances of the first differenced distance to default, large EU countries, January 1993-January 2003, pre and post euro

	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***	
Coexceedances 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 R2	0.18		0.23		0.15		0.15		0.14		0.16	
Log-likelihood	-509		-334		-837		-632		-991		-780	
N	1302		1058		1302		1058		1302		1058	
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**	

Chart 1. Response curves to volatility shocks.

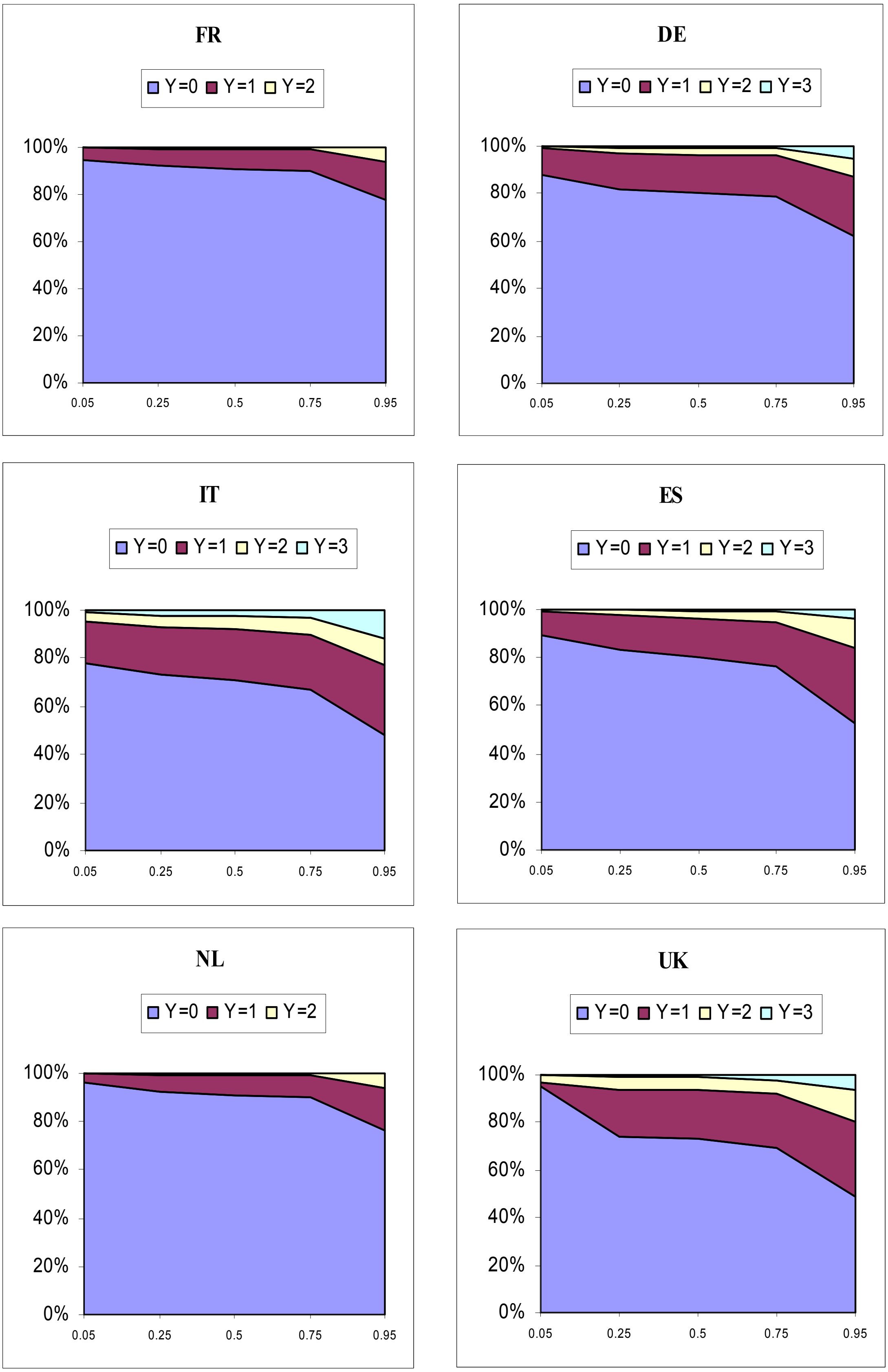


Chart 2. Contagion directions (dotted line indicate significance of contagion parameters at 10% level)

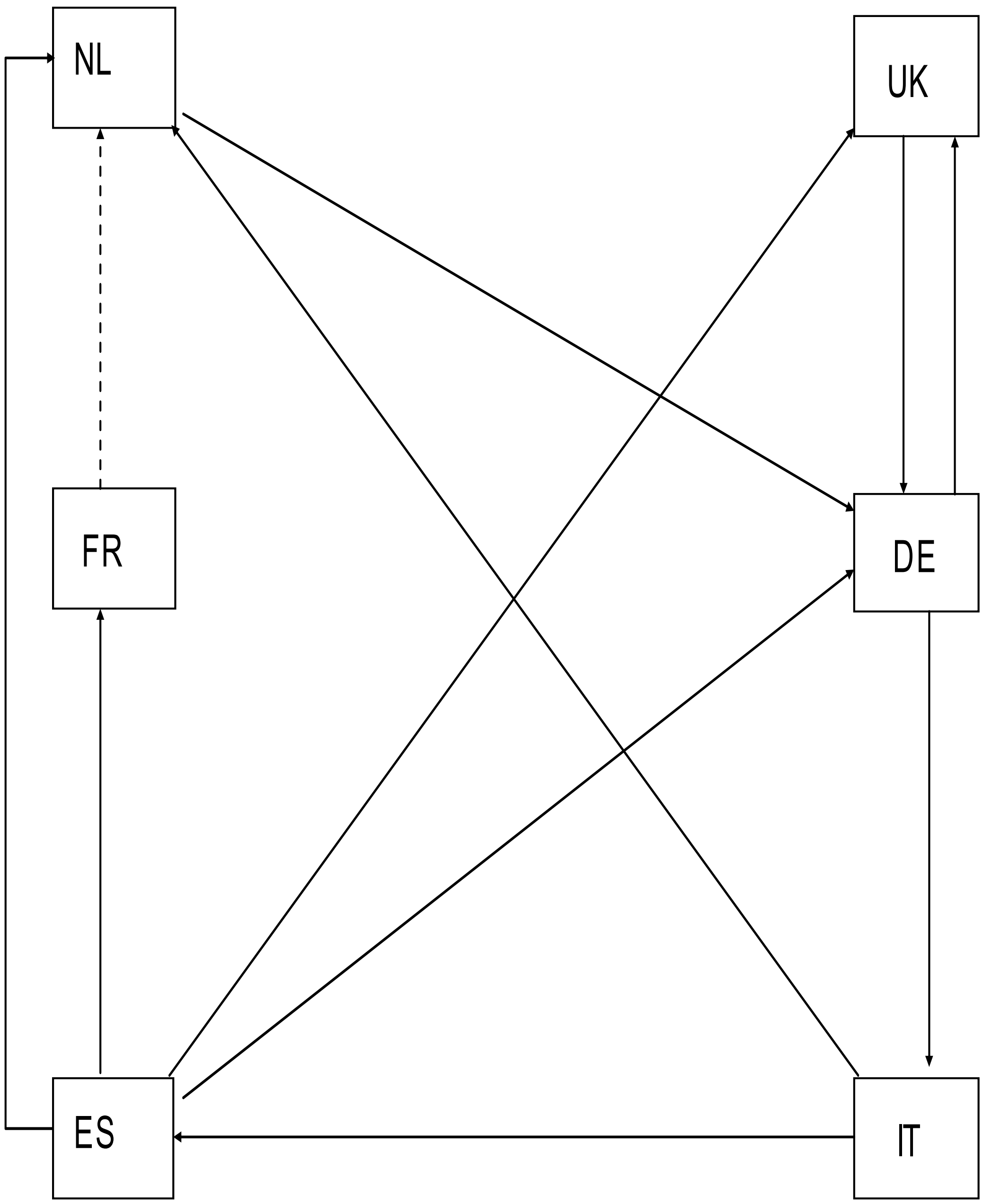
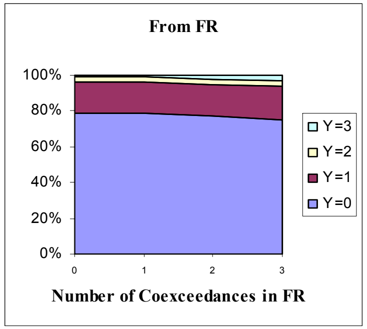
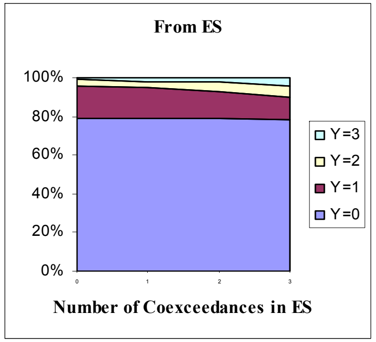
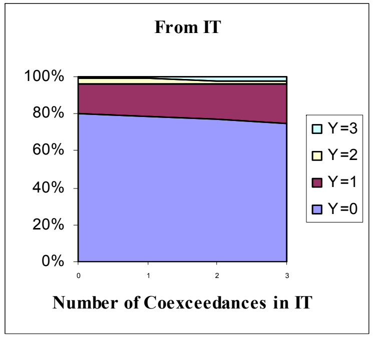
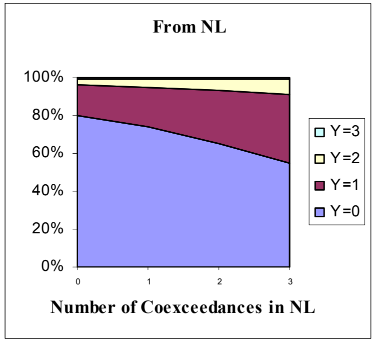


Chart 3. contagion to Germany









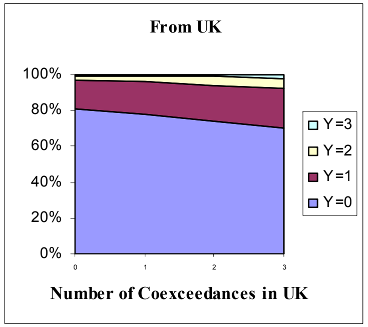
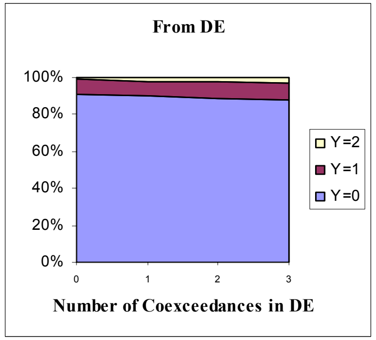
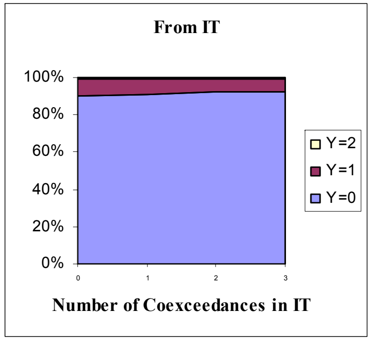
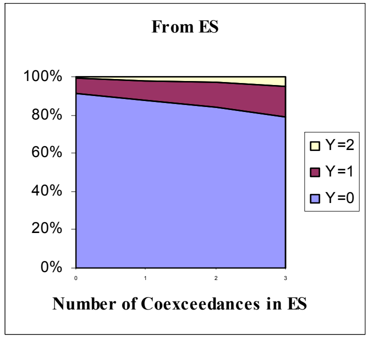
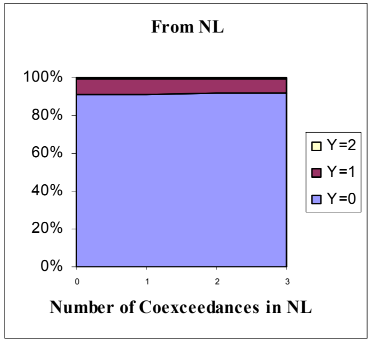


Chart 4. contagion to France









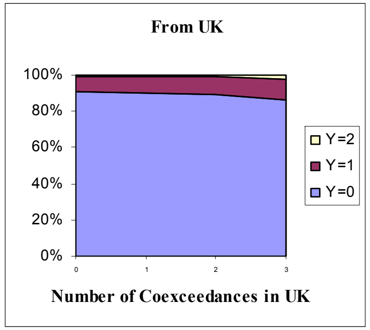
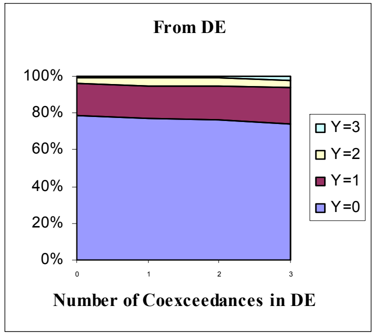
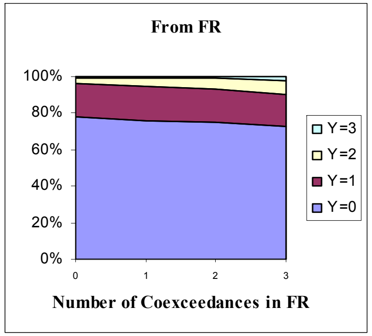
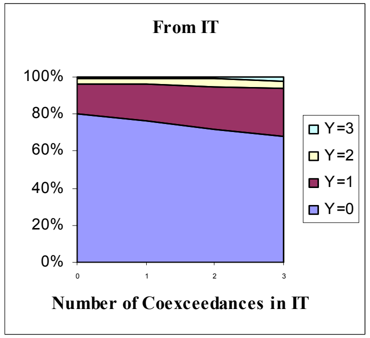
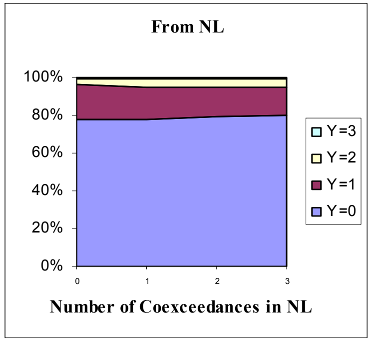


Chart 5. contagion to Spain









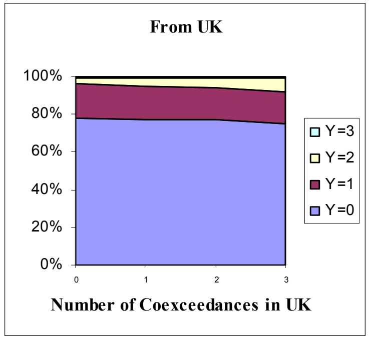


Chart 6. Contagion to Italy

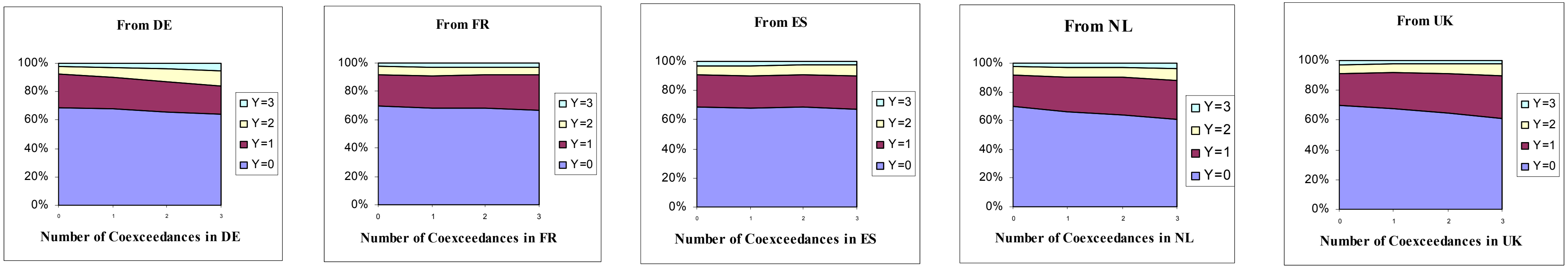


Chart 7. Contagion to the Netherlands

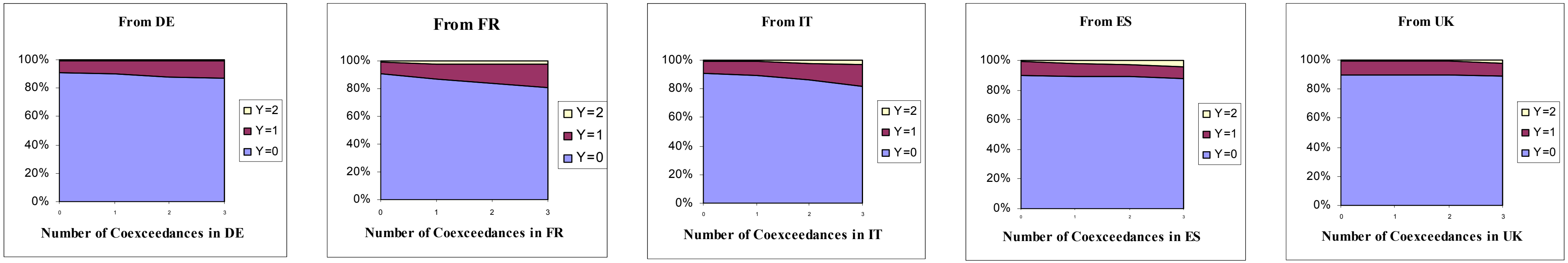


Chart 8. Contagion to the United Kingdom

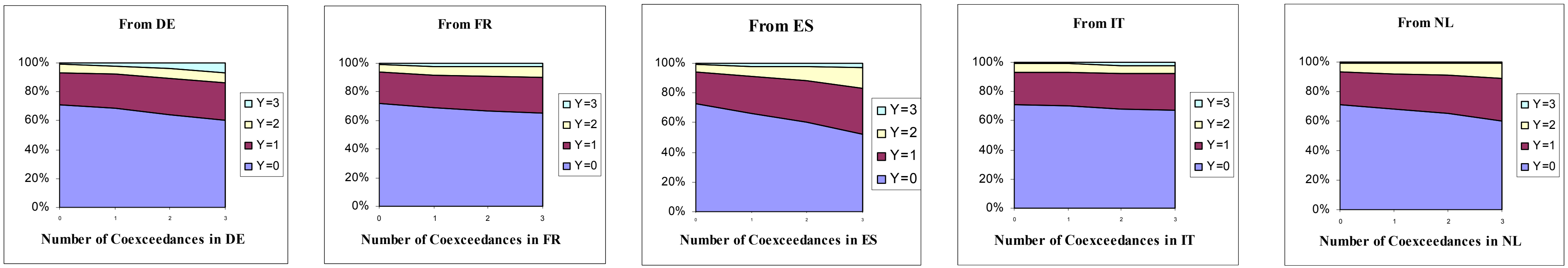


Chart 9. Contagion directions – pre euro (dotted line indicate significance of contagion parameters at 10% level)

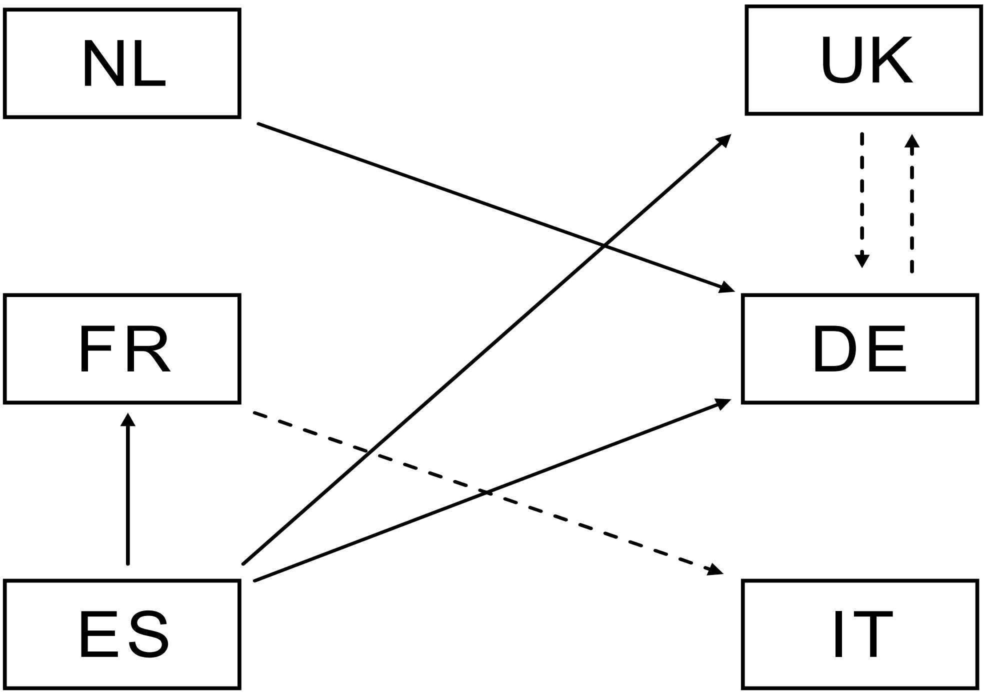


Chart 10. Contagion directions - post euro (dotted line indicate significance of contagion parameters at 10% level)

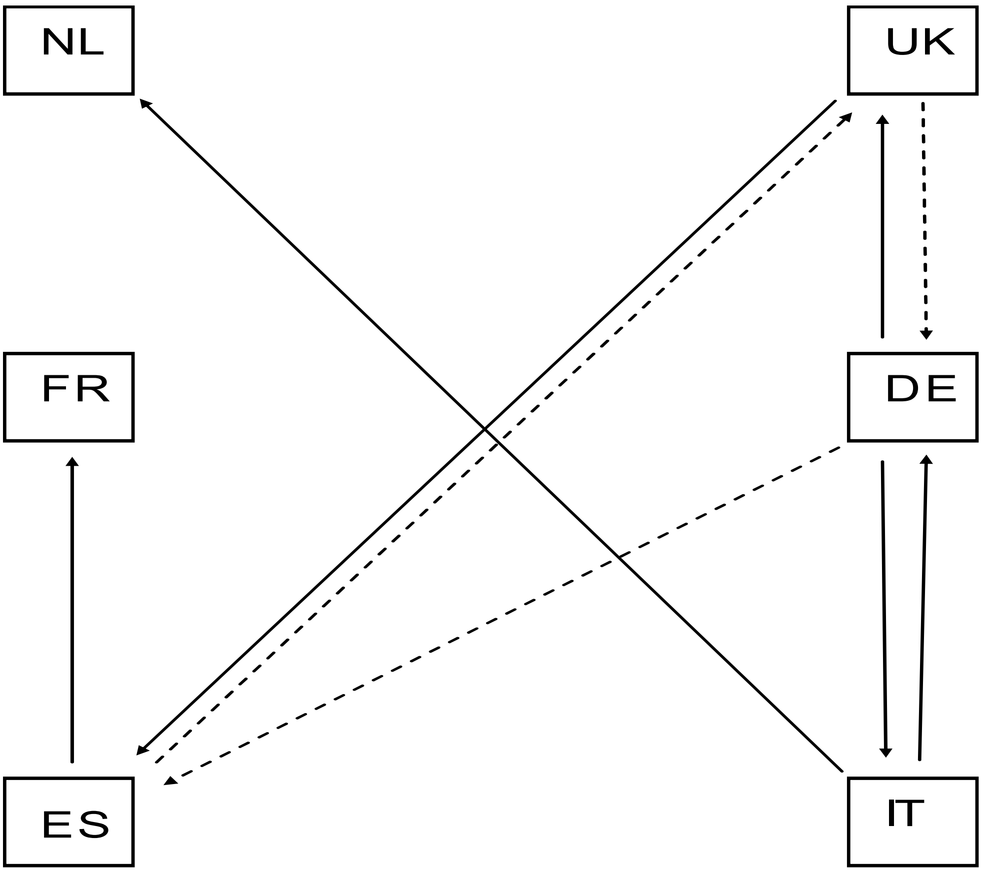


Chart 11. Response curves pre and post euro for Germany.

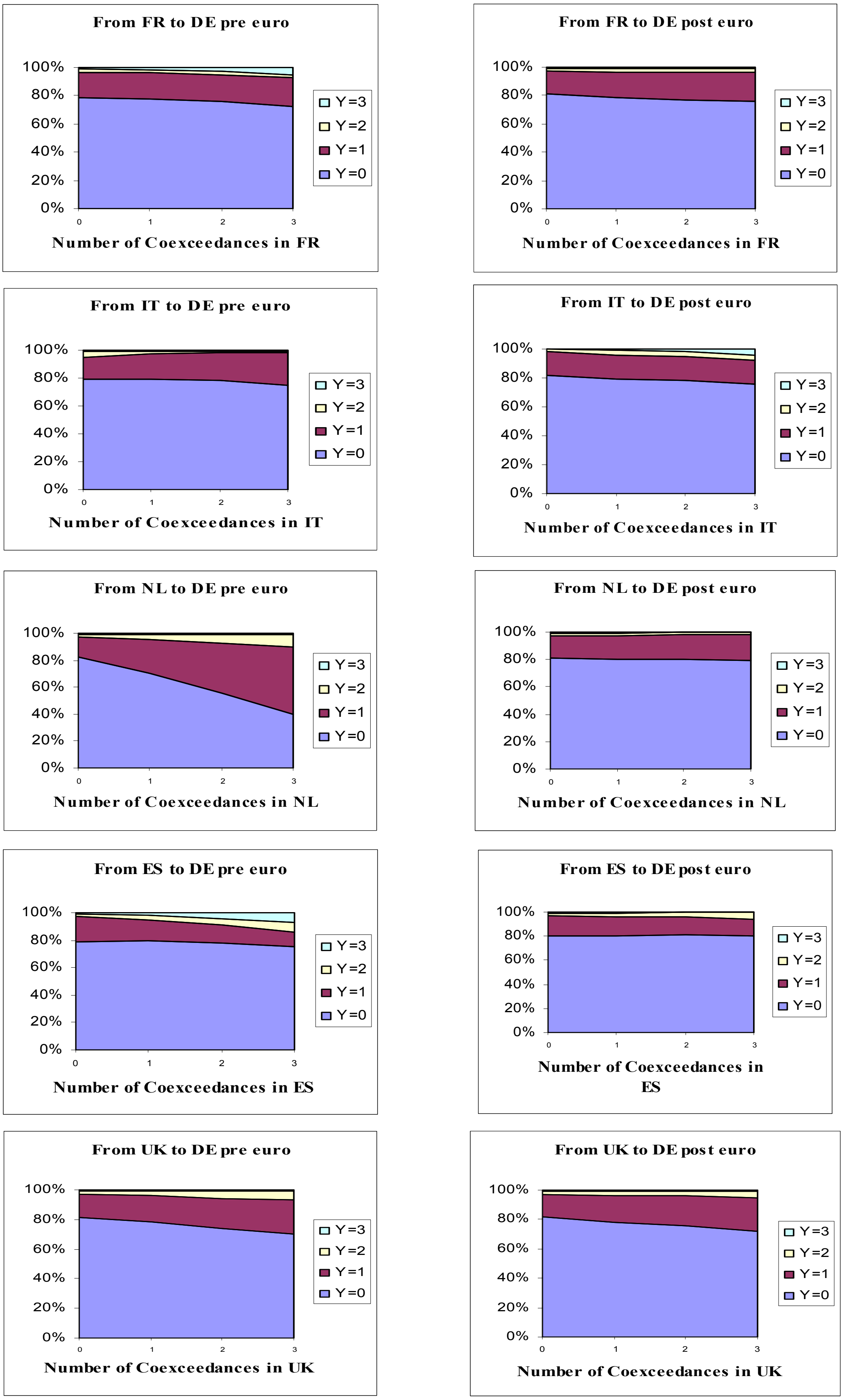
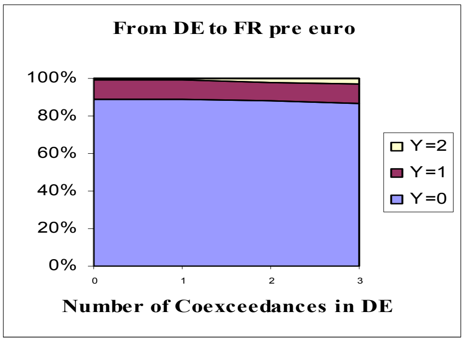
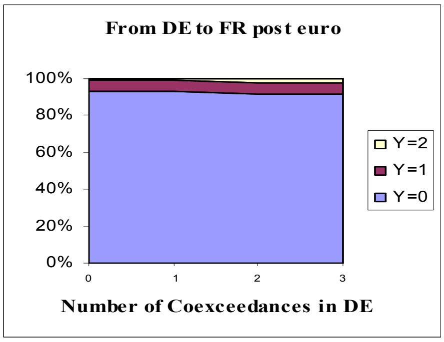
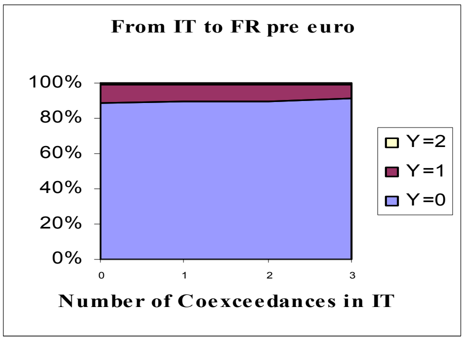
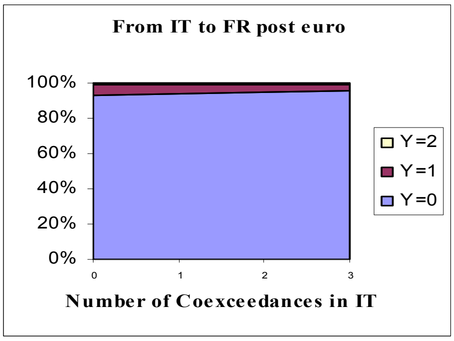


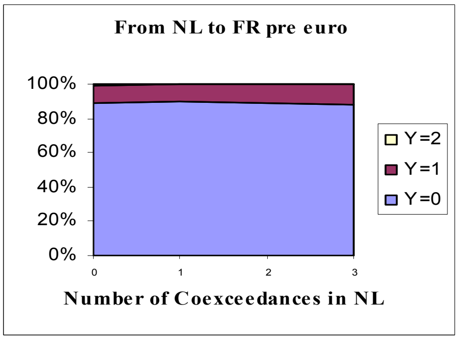
Chart 12. Response curves pre and post euro for France.

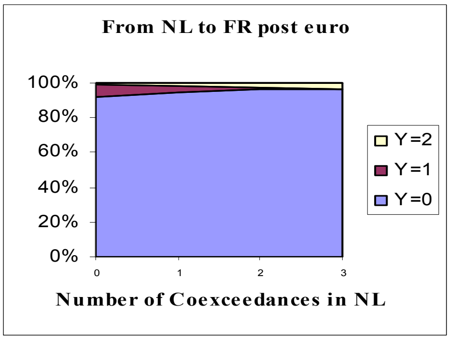


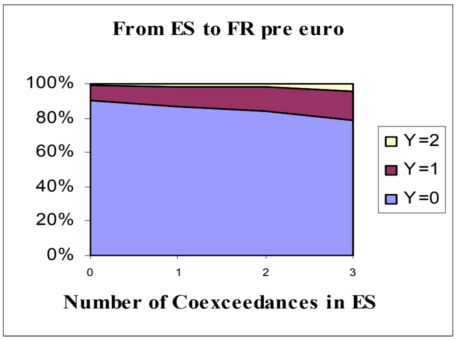


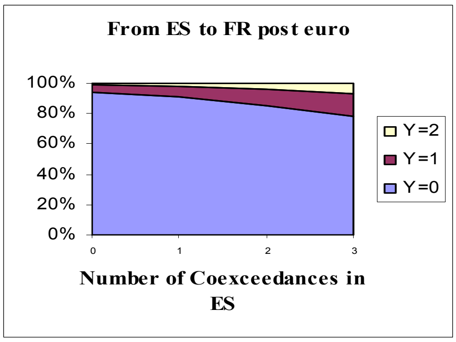


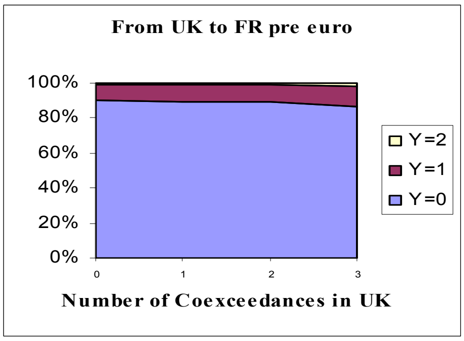












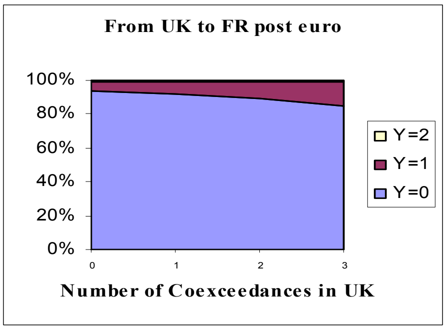


Chart 13. Response curves pre and post euro for Italy.

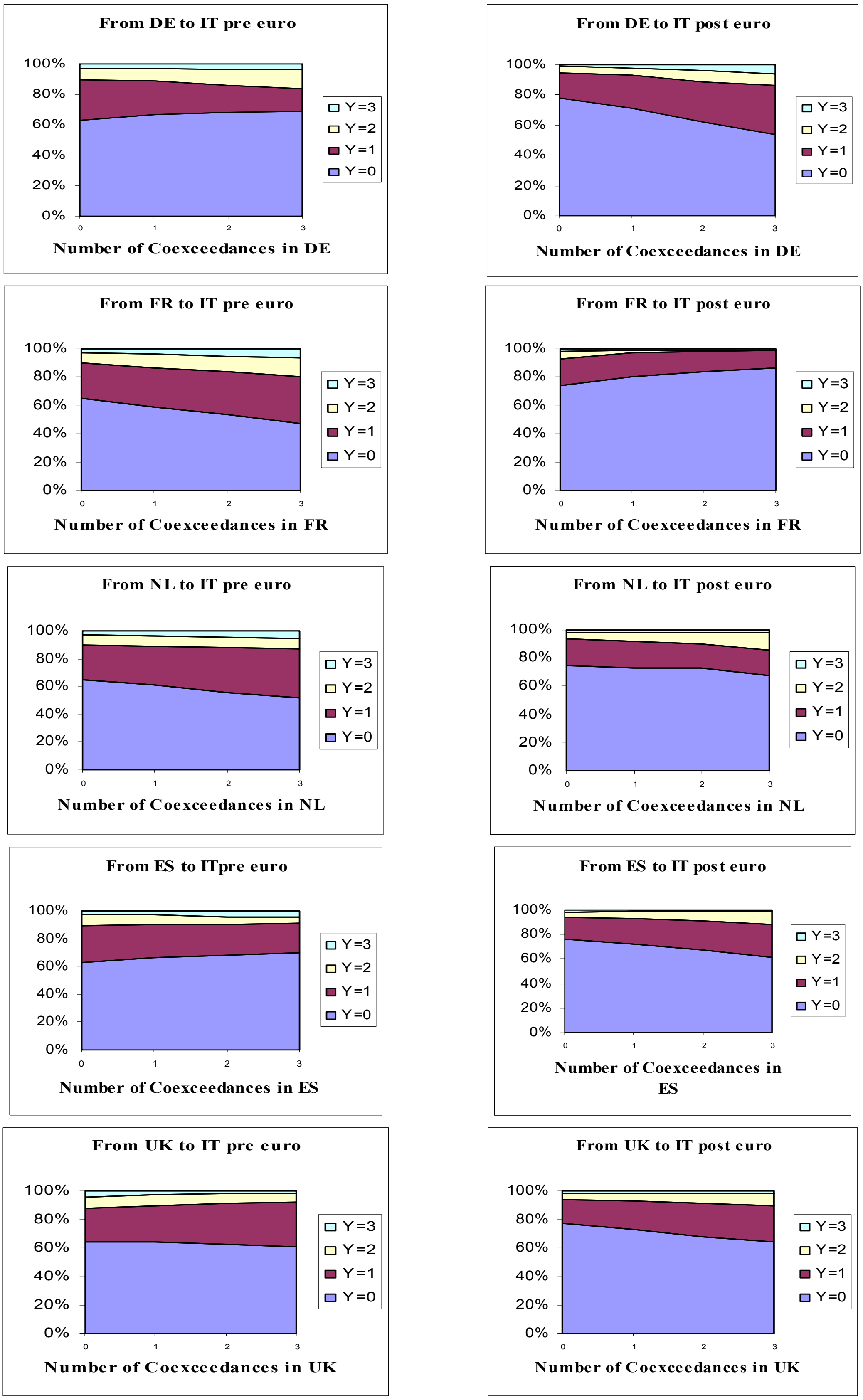


Chart 14. Response curves pre and post euro for the Netherlands.

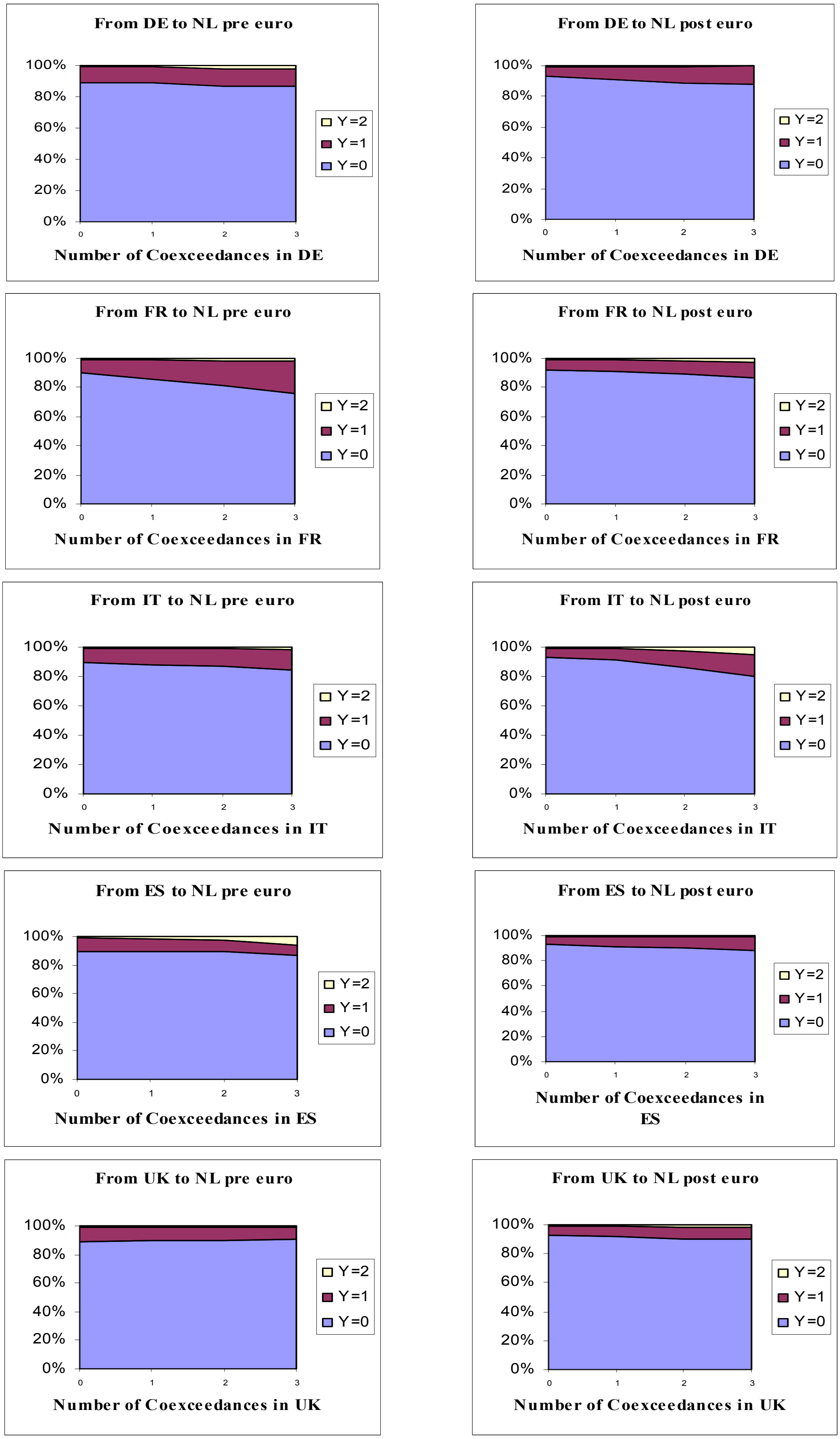


Chart 15. Response curves pre and post euro for Spain.

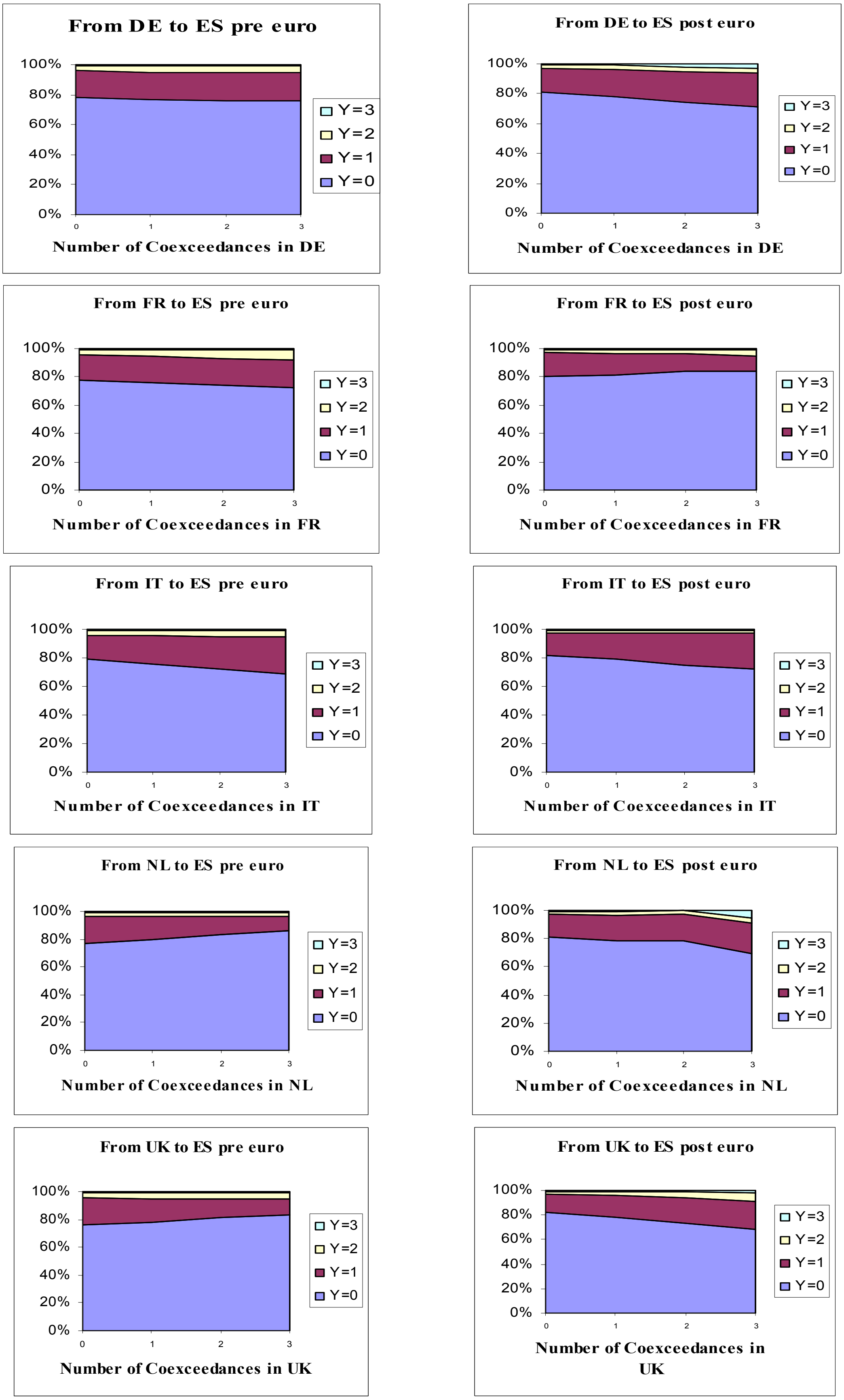
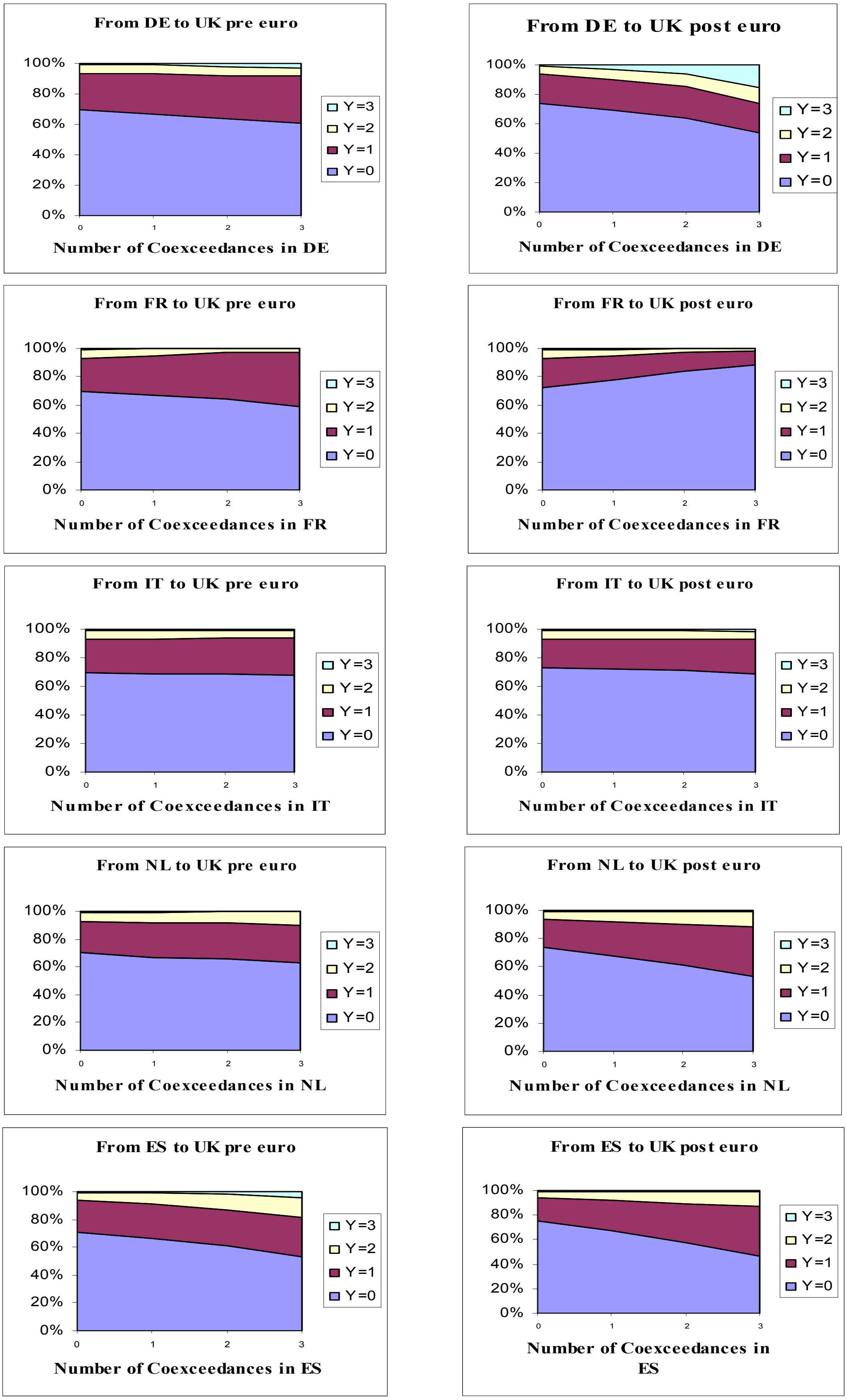


Chart 16. Response curves pre and post euro for UK.



Appendix I. 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:

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

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:

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

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

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:

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

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.. [1] The results were found robust with respect to the choice of starting values. The measure of bank risk used in this paper is then

---

[1] See KMV Corporation (2002), Vassalou and Xing (2004), Eom et al. (2004), Delianedis and Geske (2003), Bharath and Shumway (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 computations 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 the Duan's approach is that in the former stock volatility is estimated using historical data. Duan (1994, 2000), hence, corrects that in periods of increasing prices, the traditional approach tends to overestimate the default probability, while the opposite happens in period of decreasing prices. As we do not consider the level of the distance to default but 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.

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 daily values for the equity market capitalisation, V_E from Datastream. The equity volatility, σ_E, was estimated as the standard deviation of the daily absolute equity returns and, as proposed in Marcus and Shaked (1984), we took the 6-month moving average (backwards) to reduce noise. The presumption is that the market participants do not use the very volatile short-term estimates, but more smoothed volatility measures. This is not an efficient procedure as it imposes the volatility to be constant. However, equity volatility is accurately estimated for a specific time interval, as long as leverage does not change substantially over that period (see for example Bongini et. al., 2001). 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 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 II. Results from a GARCH (1,1) model

Estimated coefficients of the Garch (1,1) model for the daily stock market returns in the analysed countries. Equation and variable definitions given in text.

	coef	*std err*	*z-stat*	*prob*
FR				
Const	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				
Const	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				
Const	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				
Const	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				
Const	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				
Const	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				
Const	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

Appendix III. Robustness checks

Panel 1: 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

Panel 2: Results after excluding major crises from the sample (Asia, July 1997, Russia, 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

Panel 3: 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

Panel 4: 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

Panel 5: 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

Panel 6: 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 of From French and Dutch banks on German banks and from French banks on UK banks.

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