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Contagion Between European and US Banks: Evidence from Equity Prices

by Daniel Fricke

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JEL classification: F36, G15, G21

Keywords: Banking, Contagion, Distance-to-default, Multinomial logit.

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Abstract

This paper employs an Extreme Value Theory framework to investigate the existence of contagion between European and US banks. The fact that many regulators have no detailed data sets about interbank cross-exposures raises the necessity of finding market-based indicators in order to analyze the effects of crises and to quantify the risk of contagion. The Distance-to-default (DD) measure is being employed as an indicator of banks' soundness. Focusing on the negative tail of the daily percentage changes of the DD, a country-specific indicator variable labeled "Coexceedances" is built measuring the number of banks simultaneously experiencing a large shock on a given day. Based on a multinomial logit model, for each country the probability of observing several banks in the tail is estimated. Controlling for common factors and including foreign countries' lagged coexceedances allows to interpret significant coefficients of foreign lagged coexceedances as contagion. The main finding is that there is significant bi-lateral contagion between European and US banks. Furthermore the existence of contagion between European banks is verified by the underlying data set.

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1 Introduction

The recent financial crisis has emphasized how closely banks are connected through the interbank markets, thereby revealing the risk of financial contagion. In general, the term financial contagion describes the process of a crisis spreading from one region/institution to another economically linked region/institution.[2] Hence, an idiosyncratic shock causing the failure of one or few institutions can destabilize the entire system.[3] Banking and financial crises are particularly harmful to economic activity due to the special role of banks in the economy: they provide maturity transformation, monitor investment projects and play an important role in the transmission of monetary policy. Hence the costs associated with banking and financial crises tend to be large, highlighting the importance of stable banking systems.[4] The main aim of this paper is to investigate the risk of contagion between the global players of the world's two major financial markets, namely between European and US banks.

Contagion in the interbank markets can proceed through different channels: First, it can be the result of asymmetric information, where difficulties of one bank can be taken as a signal of possible difficulties of other banks. In this case, financial crises take the form of self-fulfilling panics.[5] Second, contagion can stem from real linkages, such as interbank claims or credit lines. Allen and Gale (2000) show in a Diamond-Dybvig-type framework[6] that the existence of contagion crucially depends on the network structure of the interbank market and hence on the pattern of interbank claims. Despite generating systemic risk, in complete interbank markets, i.e. when each bank is connected with all other banks in the system, idiosyncratic shocks are less likely to propagate.[7] Furthermore the authors stress the importance of central banks in providing stability as these can make the interbank market more

[2]This definition is close to what is usually referred to as systemic risk, see de Bandt and Hartmann (2000).

[3]According to this definition the case that all institutions break down from a systematic shock is not being referred to as contagion.

[4]Fiscal costs associated with crisis management, e.g. costs to recapitalize banks and reimburse insured investors, average about 13.3% of annual GDP, and can be as large as 55.1% of annual GDP. Cumulative output losses during crisis periods are large as well, roughly 15-20% on average of annual GDP, see Laeven et al. (2007) and Hoggarth et al. (2002).

[5]See e.g. Dasgupta (2004) and Kodres and Pritsker (2002).

[6]See Diamond and Dybvig (1983).

[7]See Freixas et al. (2000) as well. In the context of increasingly internationally operating banks, e.g. through foreign subsidiaries, real linkages should play an important role.

complete at relatively low costs. Freixas and Parigi (1998) analyze contagion in different interbank payment systems, i.e. net and gross payment systems. The contagious effect of interbank credit lines is being explored by Mueller (2006), finding that the existence of these credit lines may affect the risk of contagion significantly. Third, if banks hold similar asset types, asset sales resulting from a breakdown of one bank (fire sales) can induce price changes that affect the solvency of other banks. Cifuentes et al. (2005) combine the price channel with the channel of interbank claims and find a significant impact of price effects on the risk of contagion.[8] Furthermore, large capital buffers and high liquidity ratios enhance the financial system's stability suggesting that regulators should pay considerable attention to these figures.

During the recent crisis, the difficulties in the US subprime mortgage markets escalated and spilled over to debt markets around the world.[9] As banks became less willing to provide short-term lending, interbank lending rates increased dramatically and thus triggered a liquidity and credit crunch.[10] As a result of increasingly globalizing international financial markets, the crisis had an impact on the soundness of financial institutions around the world. However, the actual type of contagion during the recent crisis came rather surprisingly and existing theoretical models were hardly able to explain the events:[11] The interbank market dried up and central banks stepped in as the major counterpart in the interbank transactions. Hence the channel of real linkages seems to be of minor importance, while the channel of asymmetric information and the price channel are highly relevant.[12] There are at least two additional factors related to the problem of asymmetric information: The first results from the increased usage of securitization products in financial markets, most importantly asset-backed securities like collateralized-debt-obligations (CDOs) and credit-default-swaps (CDSs), antecedently to the crisis. Securitization allowed banks to transform illiquid assets into liquid assets, since loans (and/or the associated credit risks) could be sold in the market. In combination with a loose lending behavior, this situation probably provoked moral hazard motivations in the banking sector. Second, the credit crunch in the interbank market can at least in part be explained by an increased credit (counterparty) and liquidity risk, which induced the world-

[8] In the context of international financial markets, changes in the exchange rate can be seen as an additional price channel.

[9] See, e.g. Reinhart and Rogoff (2008), Laeven, Igan, and Dell'Ariccia (2008) and Swan (2008).

[10] See Taylor and Williams (2008) and Hesse et al. (2008).

[11] See Lux et al. (2009).

[12] See Allen and Babus (2008).

wide increase of risk premia in interbank interest rates.[13]
Empirical studies on contagion risk can be differentiated by the underlying data, which can be either historical or recent data sets. The strand using historical data mostly focuses on survival-time and autocorrelation tests.[14] Survival-time tests try to find factors that explain the survival-time of banks during distress. Autocorrelation tests search for autocorrelation of bank failures controlling for macroeconomic factors, where significantly positive autocorrelation coefficients can be interpreted as contagion. Even though most studies find that this risk is significant, it should be obvious that the approach suffers from the assumption that all relevant macroeconomic factors have been accounted for appropriately. This is problematic as macro-data are mostly available at relatively low frequencies, which holds even more for historical episodes. An advantage of using historical data is that public safety nets such as deposit insurances and the lender of last resort issues can be ignored.[15] However, the results cannot be used to make statements about the risk of contagion in actual banking systems.
Studies based on recent data sets thus try to estimate the likelihood and severity of contagion in real banking systems.[16] Optimally, such studies use actual interbank cross-exposures and stress the system by simulating the effects of a sudden breakdown of one bank at a time. The likelihood of contagion can then be estimated as long as the default probability of the first bank can be quantified. Unfortunately, data sets of detailed interbank cross-exposures are only available for few countries.[17] Mostly, only gross-exposures, i.e. the sum of each bank's interbank assets and liabilities, are collected. With such data it has become standard to use the method of Maximum Entropy, where a uniform distribution of interbank exposures is assumed which reduces the magnitude of the estimated contagion risk.[18] Consequently, most studies find that contagion is hardly significant in practice, even in the presence of large shocks.[19]
Besides the rather implausible assumption of a complete interbank market, two additional reasons make the results of existing studies based on recent data sets not very useful in practice: First, most studies concentrate on the

[13] See for instance Taylor and Williams (2008) for an analysis of the LIBOR spread.
[14] See Hasan and Dwyer (1994) and Calomiris and Mason (2001).
[15] An interesting overview on the changing pattern of the lender of last resort issue is provided in Bordo (1990).
[16] See for instance Furfine (2003), Wells (2004) and Upper and Worms (2004).
[17] Examples for studies using such data sets are Boss et al. (2004), Mueller (2006), Iori et al. (2006) and Nier et al. (2007).
[18] See Mistrulli (2007).
[19] An exception is the study of Upper and Worms (2004), which finds a non-negligible probability of contagion in the German interbank market.

channel of interbank claims ignoring other relevant channels of contagion. Second, they only use national data sets ruling out the possibility of cross-border contagion and neglecting the fact that foreign claims held by the banking system have increased substantially during recent years.[20] Consequently, not just since the recent financial crisis both proceedings can hardly be justified.

The approach taken in this paper is therefore quite different to most of the existing literature. The fact that many regulators have no detailed data sets about interbank cross-exposures raises the necessity of finding market-based indicators in order to analyze the effects of crises and to quantify the risk of contagion. This paper extends and updates the approach of Gropp and Moerman (2004), Gropp et al. (2009) and Duggar and Mitra (2007), all building up on Bae et al. (2003). An extreme value theory framework is employed to analyze contagion risk in the international banking system.[21] The so-called Distance-to-default (DD) measure will be used as an indicator of banks' soundness. In short, the DD gives the number of standard deviations of total assets, that a bank is away from its default point. Focusing on the negative tail of the daily percentage changes of the DD, a country-specific indicator variable labeled "Coexceedances" is built, measuring the number of banks simultaneously experiencing a large shock on a given day. Based on separate multinomial logit models, for each country the probability of observing several banks in the tail is estimated.[22] Controlling for common factors and including foreign countries' lagged coexceedances allows to interpret significant coefficients of foreign lagged coexceedances as contagion. Compared with a large part of existing literature, this approach has the advantage of not being dependent on a set of restrictive assumptions about specific channels of contagion.

While Gropp et al. (2009) find significant cross-border contagion between European banks, this paper accounts for the possibly large impact of US banks on European banks and vice versa by explicitly incorporating major US banks into the sample. Anticipating the main results, there is evidence for significant bi-lateral contagion between European and US banks. Furthermore the existence of contagion between European banks is verified by the underlying data set.

The remainder of this paper is structured as follows: Section 2 introduces the DD model and explains its advantages over competing fragility indicators. Furthermore implementation methods and the model's properties will be dis-

[20] See Degryse et al. (2009).

[21] See also Hartmann et al. (2005).

[22] We are planning to extend our analysis using a panel estimation framework.

cussed. Section 3 introduces the data set and sets up the econometric model. After presenting and interpreting the results, several robustness checks will be carried out. Section 4 concludes and suggests possible avenues of future research.

2 Distance-to-default (DD) Model

In order to investigate the existence of contagion in an econometric model, a variable quantifying a bank's healthiness is needed. Due to the lack of detailed available regulatory data sets there is an increasing trend of regulators (and researchers) relying on some form of market-based measures substituting accounting-based measures. For example, the Basel II Accords[23] explicitly include market discipline as complement to minimum capital requirements and the supervisory review process. This highlights the belief that market forces can reinforce capital regulation and other efforts in order to prevent financial crises.[24]

Market-based measures depend on bank-specific market information such as equity or bond prices. Assuming that the market prices risk adequately, such data may efficiently summarize information beyond and above that contained in other sources.[25] Furthermore, market prices are typically available at higher frequencies than balance-sheet data and regulatory figures.[26]

Market-based data may come from debt or equity markets. Research mostly concentrated on bond (i.e. debt) markets, despite the fact that information from bond markets is known to be biased since debt holders only care about the left tail of the return distribution providing them with minor incentives to supervise banks compared with equity holders. Equity prices and the corresponding returns are also considered to be biased as well due to moral hazard problems caused by the interest of equity holders in upside gains from increased risk-taking. Consequently, the informational amount on banks' default risks contained in simple stock-returns and/or bond yields should be rather low. Nevertheless, without having to rely on the unrealistic assumption of efficient markets, one may at least assume that equity markets process public information and that equity holders should respond rationally to news.[27] Adjusting equity prices for their bias should then allow to extract

[23]See Basel Committee on Banking Supervision (2004).

[24]See Gunther et al. (2001).

[25]See Jobert et al. (2004).

[26]German banks for instance have to report their liquidity ratios each month to the regulator.

[27]See, e.g. Aharony and Swary (1983), Musumeci and Sinkey (1990) and Smirlock and Kaufold (1987).

important information on banks' default risks. The DD model yields such an unbiased equity market-based indicator that displays banks' soundness efficiently and is complete in the sense of processing the relevant information on banks' default risks. In the following, the DD model will be derived and discussed.

2.1 Basic Idea and Derivation

The basic idea of the DD model is to apply the Black-Scholes-Merton[28] model (henceforth BSM model) to the market value of a bank's total assets.[29] In this model equity prices can be interpreted as the value of a call option on the bank's total assets with a strike price equal to the bank's face value of debt.[30] Hence the economic cause of default is the decline in the market value of total assets below the value of its debt obligations at a given horizon.

There are two important model assumptions: First, the market value of total assets (V) follows a geometric Brownian motion, i.e. obeys the following stochastic differential equation

$$dV = \mu_V V dt + \sigma_V V dW, \tag{2.1}$$

where μ_V is the instantaneously expected return (continuously compounded) on V, σ_V is the volatility (standard deviation) of V and dW is a standard Wiener process of the form $\epsilon\sqrt{t}$, where ϵ is the random component of the bank's return on assets which is standard Normal in the BSM model.[31] Hence, the time path of V follows the stochastic process

$$\ln V^T = \ln V + (r - \sigma_V^2/2)T + \sigma_V \sqrt{T}\epsilon, \tag{2.2}$$

where r denotes the risk-free interest rate. Second, the bank has issued one discount bond maturing in T periods and default only occurs at maturity.[32] Under these assumptions, the bank's equity value equals that of an European call option on the underlying value of total assets with a strike price equal to the face value of the bank's debt and a time to maturity of T. Due to limited liability of equity holders and priority of debt over equity, the market value of equity (E) is given by

$$E = \max(0, V - D), \tag{2.3}$$

[28] See Black and Scholes (1973) and Merton (1974).

[29] The analysis of the DD model is of course not limited to banks, but can be employed for any stock-market listed firm.

[30] See Bharath and Shumway (2008).

[31] Time-indices were dropped for convenience.

[32] See Jobert et al. (2004).

where D is the face value of the bank's debt which is assumed to be insured and hence earns the risk-free rate. Given these assumptions and ignoring dividend payments, the value of equity can be written as a European call option

$$E = VN(d_1) - e^{-rT} DN(d_2), \tag{2.4}$$

where $N(\cdot)$ is the cumulative standard Normal distribution, D is the strike price, d_1 is given by

$$d_1 = \frac{ln(V/D) + (r + \sigma_V^2/2)T}{\sigma_V \sqrt{T}} \tag{2.5}$$

and $d_2 = d_1 - \sigma_V \sqrt{T}$.[33] The current distance d from the default point (with $\ln V^T = \ln D$) is

$$d = \ln V^T - \ln D = \ln(V/D) + (r - \sigma_V^2/2)T + \sigma_V \sqrt{T}\epsilon \tag{2.6}$$

and the DD can be calculated as

$$DD = \frac{d}{\sigma_V \sqrt{T}} - \epsilon = \frac{ln(V/D) + (r - \sigma_V^2/2)T}{\sigma_V \sqrt{T}}, \tag{2.7}$$

yielding the number of standard deviations of total assets (σ_V) that the bank is away from its default point. The smaller the DD, the higher the bank's default risk.

There are two unobservable variables in Eq. (2.7), namely V and σ_V. In order to solve for these, another relationship can be derived connecting the volatility of the bank's total assets to the volatility of its (observable) equity value: Given the BSM model assumptions, the value of equity depends on the value of total assets and time. Similar to Eq. (2.1), equity value obeys a stochastic differential equation of the form

$$dE = \mu_E E dt + \sigma_E E dW, \tag{2.8}$$

where μ_E and σ_E are the instantaneously expected return on E and its corresponding volatility, respectively. Using Ito's Lemma the dynamics of equity can be written as

$$dE = \left(\frac{1}{2} \sigma_V^2 V^2 \frac{\partial^2 E}{\partial V^2} + \mu_V V \frac{\partial E}{\partial V} + \frac{\partial E}{\partial t} \right) dt + V \frac{\partial E}{\partial V} \sigma_V dW,^{34} \tag{2.9}$$

[33] Eq. (2.4) is of course the result of the assumptions made. Assuming for instance, that default could occur at any time (not just at T) the value of equity could be modeled as a perpetual barrier option. Assuming that the option could be exercised at any time up to T, the value of equity could be modeled as an American call option.

[34] Duan (1994) argues that this specification of a stochastic equity volatility causes Eq. (2.11) to be a redundant condition, providing a restriction only because equity volatility is inappropriately treated as a constant. In fact, Eq. (2.11) only holds instantaneously as it was derived via Ito's Lemma.

where $(dV)^2$ is being approximated by $\sigma_V^2 V^2 dt$.[35] Obviously, diffusion terms in Eqs. (2.8) and (2.9) must conincide, hence

$$\sigma_E E = V \frac{\partial E}{\partial V} \sigma_V. \tag{2.10}$$

Since $\frac{\partial E}{\partial V} = N(d_1)$ in the BSM model,[36] the volatility of equity and the volatility of total assets are connected through

$$\sigma_E = \left(\frac{V}{E}\right) N(d_1) \sigma_V.^{37} \tag{2.11}$$

The two nonlinear Eqs. (2.4) and (2.11) allow to derive the unobservable value of total assets, V, and its volatility, σ_V. While the BSM model generally allows to calculate the unobserved value of an option as a function of four observable variables (strike price, time-to-maturity, the underlying asset price and the risk-free interest rate) and one variable that has to be estimated (volatility), the DD model works the other way round. Here the value of the option is observed in terms of the bank's equity (market capitalization) and the unobservable inputs are solved for to calculate the DD in Eq. (2.7).

2.2 Implementation

The critical inputs to the DD model are clearly the market value of equity, the corresponding volatility and the face value of debt. To implement the model, typically the first step is to estimate σ_E using either historical stock returns data or implied volatilities from option prices. The second step is to define the forecast horizon, which is commonly assumed to be one year ($T = 1$) since there is usually a lack of detailed information on the maturity structure of banks' debt. The third step is to collect data on the face value of debt, the risk-free interest rate and the market capitalization. It is common to take the book value of the bank's total debt liabilities as the face value of its debt. The proxy for the risk-free interest rate is either taken from government bond yields or from interbank benchmark rates. The market capitalization is simply the number of outstanding shares multiplied by the stock price. After performing all these steps, the values for each of the variables in Eqs. (2.4) and (2.11) are known, except for V and σ_V.

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[35] See Hull (2000).

[36] In fact, this is the well known delta of a European call option.

[37] Obviously, Eq. (2.11) captures the leverage effect since equity volatility typically exceeds the volatility of total assets. See Jobert et al. (2004).

Solving Eqs. (2.4) and (2.11) for the two unknowns, usually labeled as Ronn-Verma-method[38], has the advantage of being relatively easy to implement. This is the standard approach in the literature (see e.g. Gropp et al. (2009)) and will be used here as well, despite having several drawbacks.[39] For example, since the Ronn-Verma method builds upon equity volatility based on historical returns data, the default probability tends to be overestimated in periods of increasing equity volatility, while the opposite happens when equity volatility decreases.[40] Thus, the computation of the DD is known to be sensitive to shifts in derived asset volatility with very volatile estimates of equity volatility leading to large variations in the DD. Therefore smoothed volatility estimates are usually employed (see Section 3.1).

2.3 Properties

The DD is widely agreed to be a useful measure for assessing banks' default risks.[41] Part of its popularity stems from the successful implementation of the DD model by Moody's KMV.[42] Vulpes et al. (2006) discuss the properties of the DD and show that it is both a complete and unbiased indicator of banks future default probability. Completeness means that it captures all influences affecting the default probability (market value of assets, leverage in terms of total debt and asset volatility), while unbiasedness refers to the alignment to supervisors' interests. Therefore the DD is preferred over biased indicators such as simple stock returns.

Additionally Vulpes et al. (2006) show that the DD is forward-looking and can pre-warn a crisis 12 to 18 months in advance.[43] The authors also show that public safety nets do not affect the predictive power of the DD, because equity holders are not covered even in broad safety nets.[44] The existence of such a safety net could induce moral hazard problems, leading to increased leverage and risk-taking of both banks and equity holders. Contrary to bond market indicators, the DD can capture these effects. Similarly the DD is

[38]See Ronn and Verma (1986).

[39]See Duan (1994), Vassalou and Xing (2004) and Bharath and Shumway (2008) for alternative approaches.

[40]See Gropp et al. (2009) and Moody's KMV (2003).

[41]See e.g. Sy and Chan-Lau (2006). However, the authors also note that the DD is not useful when comparing nonfinancial corporations with banks. The risk from leverage differs significantly between banks and nonfinancial corporations, since the business model of banks rests on leverage. Therefore the DD would assign a higher risk score to banks.

[42]See Moody's KMV (2003).

[43]In Section 3 it will be shown that the DD is indeed a good indicator of distress but at a much shorter time horizon.

[44]See Vulpes et al. (2006)

likely to provide earlier information on a bank's weakening financial condition than bond market indicators. This is a direct consequence of the different payoff structures of equity and (subordinated) debt holders. Debt holders care only about the left tail of the distribution of the returns, while equity holders are interested in the whole distribution of returns.
However, it should be clear that the DD model suffers from several drawbacks. First of all, and this is a natural critique concerning practically all models based on the BSM model, the assumption of a Normal distribution for the underlying asset values might be inappropriate. For example, adjustments in debt liabilities, which are more likely the closer the bank is to its default point, are not captured by the Normal distribution. Furthermore, the assumption that default only occurs at maturity, i.e. in one year, is quite restrictive. An interesting avenue for future research would be to assume that default can occur at any time, with the result that the value of equity can be modeled as a perpetual barrier option. Third, it is assumed that the bank's total equity capital can be used as a buffer. Obviously regulators take action before the bank's total equity capital is exhausted, hence the DD is not the only relevant information regulators should look upon.
To summarize, modeling the value of equity as a European call option in terms of the BSM model is straightforward. While the DD is considered useful on the one hand in terms of incorporating several pleasant properties that make it superior to other measures of fragility, the underlying model assumptions on the other hand are in part quite restrictive and should be kept in mind.

3 Empirical Analysis

This Section builds up the empirical analysis of cross-border contagion between European and US banks. The reference study to this paper (Gropp et al. (2009)) is based on a data set of 40 stock market listed European banks for a sample period from January 1994 to January 2003. The authors find significant cross-border contagion between several European countries. Furthermore banks exhibit a home bias, i.e. they react most heavily on shocks affecting banks in their home country.[45] Despite controlling for spillover effects from US to European stock markets, the analysis neglects the possible impact of US banks on the healthiness of European banks and vice versa. One should expect significant interaction effects, not just since the recent (global) financial crisis originated in the US subprime mortgage markets. The novelty of this paper is therefore the explicit investigation of cross-atlantic contagion

[45] See Kaminsky and Reinhart (2000) for further evidence of the home bias.

by introducing US banks into the sample.
The empirical analysis is structured as follows: after giving an overview of the underlying data and sample, the calculations of the DD and its percentage changes will be explained and summary statistics will be presented. The subsequent analysis focuses on the left tail of the daily percentage changes of the DDs. For each country a variable counting the number of banks in the negative tail on a given day ("Coexceedances") is set up. These country-specific coexceedances will be the dependent variables in the econometric analysis. Owing to the discrete nature of these dependent variables, appropriate econometric approaches will be discussed that allow for the analysis of daily innovations in the country-specific coexceedances. It will be shown that the multinomial logit model fits best for this purpose. After briefly introducing the multinomial logit, estimation results will be presented and interpreted. Eventually, several robustness checks will be carried out.

3.1 Data and Sample

The entire data set was taken from `Datastream` and `Osiris`. It contains the sample banks' daily stock prices (closing prices), market capitalization, yearly (book) values of debt and country-specific market indices and interest rates. Debt values were taken from `Osiris` due to doubts about the quality of the values from `Datastream`. `Osiris` is a subset of `Bankscope`, one of the most commonly used database with respect to banks' balance sheet data.[46]
The main criteria for the choice of the sample banks were the availability and the reliability of the required data. As a first step, all major European and US banks that are listed at a stock exchange and whose stock prices are available at `Datastream` in the period from January 1994 to January 2009 (56 banks in total) were considered. To ensure the highest liquidity, stock prices are always taken from the largest stock exchange where trading volume tends to be highest. The fact that European and US stock markets are open at different time periods, makes timing patterns quite important.[47]
For example, today's European closing prices can affect today's US closing prices. These in turn, however, can only affect tomorrow's closing prices in Europe. Therefore the timing structure will always be explained if there is some potential for confusion.
Unfortunately, the availability of debt values is restricted for a large number of banks which are often only available from January 1998 onwards. The

[46] In order to check for robustness, the calculations were carried out using the debt values from `Datastream` as well (see below).

[47] To be precise, European markets mostly close around 6 a.m. while the New York Stock Exchange closes at 10 a.m. Central European time.

final sample therefore runs from January 1998 to January 2009. This period contains one major crisis period, namely the recent financial crisis from the midst of 2007 onwards. Furthermore the aftermath of the Asian crisis in 1997, the Russian default in 1998, the bursting of the dot.com bubble and the slight worldwide recession following the attacks of 11 September 2001 fall into the sample period.[48] While Russia's default had a severe impact on the stability of the international financial system,[49] only the Asian crisis, being a currency crisis in the first place, and the recent financial crisis can be considered as banking crises.

Due to severe data restrictions, Austrian and Irish banks were deleted from the sample (6 banks). Furthermore, one bank was deleted since its debt data was available for less than half of the sample period (HBOS), leaving a total number of 52 sample banks. There are 2870 daily observations for each bank, except for Washington Mutual (2801 observations) which declared its default on 26 September 2008 (see below). This leaves a total number of 149171 observations for 52 banks located in the following 13 countries: Belgium (3 banks), Denmark (2), Germany (4), Spain (4), France (3), Greece (3), Netherlands (2), Italy (5), Portugal (3), Switzerland (3), the US (9), Sweden (4) and the UK (7). A complete overview over all sample banks and their total assets in 2004 (in bn EUR) is given in Table 5 in Appendix A. Clearly sample banks tend to be large, with a mean of total assets (in 2004) of 329 bn EUR (median: 162 bn EUR) highlighting that the size of the sample banks tends to be biased upwards. Of course this is a natural result, as mostly large banks are listed at a stock exchange so the banks under consideration are likely to be systemic and can be expected to have an impact on the stability of the national and international financial system.[50]

Nevertheless, the large difference between mean and median of total assets suggests that the size of the sample banks is quite heterogenous. The largest value of total assets in 2004 is 1127.01 bn EUR (UBS), whereas the smallest value is 2.88 bn EUR (Marfin Egnatia). The heterogeneity in the size of sample banks is not only apparent between but also within countries. In the Swiss case for example, UBS and Credit Suisse clearly belong to the largest sample banks whereas Zuger Kantonalbank is substantially smaller and in fact the third smallest bank of the entire sample.

For each bank the calculations of the DD involve daily values of the respective market capitalization, the equity volatility, the domestic 1 year interest

[48] A thorough treatise of the Asian and the Russian crisis can be found in Allen and Gale (2007).

[49] See Dungey et al. (2002).

[50] See Gropp and Moerman (2004).

rate and the values of debt.[51] As noted above, daily values of the market capitalization are available for all sample banks over the entire sample period.

Daily values for the 1-year equity volatility are obtained as follows: First, a GARCH(1,1) model[52] of the form

$$\sigma^2_{E,i,t} = \alpha + \beta_1 \pi^2_{E,i,t-1} + \beta_2 \sigma^2_{E,i,t-1} \tag{3.1}$$

is fitted for each bank i using ML estimation, where $\sigma^2_{E,i,t}$ is the conditional variance of bank i's log-returns at date t and $\pi^2_{E,i,t}$ are the squared daily log-returns.[53] Based on the fitted model, daily values of equity variance can be obtained. Multiplying these estimates by the number of trading days (assumed to be 252) and taking the square root yields values for the 1-year equity volatility. As noted in Section , the DD is sensitive to changes in equity volatility. Market participants are unlikely to use very noisy volatility estimates, hence estimates where smoothed using a 5-month moving average filter (backwards) in order to reduce noise.

Concerning the 1-year interest rates, usually 1-year government bond yields are taken as a benchmark. However, these benchmark yields are not available for all countries over the entire sample period leading to the use of 1-year interbank rates instead. The difference between the two is typically small for short maturities, hence the qualitative results should not be affected by preferring one over the other.

The yearly book values of debt consist of deposits, short term funding and other funding (interest and non-interest bearing). Using a cubic spline, daily observations are obtained.[54] Of course this proceeding implicitly assumes that there are no jumps in the value of debt which should not necessarily hold in practice. However, the above-mentioned severe data limitations justify this approach. Finally, it should be noted that the debt values for 2008 were not available for 7 banks. For these banks, debt values were kept constant from December 2007 onwards.[55]

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[51] Recall that $T = 1$.

[52] Parameter estimates are not reported for the sake of brevity.

[53] For those banks with $\beta_1+\beta_2 \geq 1$ a constrained GARCH(1,1) was fitted with $\beta_1+\beta_2 < 1$ in order to obtain a stationary process for the variance.

[54] See Gropp and Moerman (2004) and Gropp et al. (2009).

[55] The banks affected are IKB, Marfin Egnatia, National Bank of Greece, Credito Emiliano, Credito Valtellinese, Kas-Bank and Washington Mutual. Interestingly, this assumption was found to be irrelevant for the final results, as the calculated DDs were found to be identical to those based on the (available) debt values from `Datastream` (see below).

3.2 Summary Statistics

Daily values for all of the variables above allow to solve Eqs. (2.4) and (2.11) numerically for each bank over the entire sample period. For this purpose, an iterative trust-region algorithm is being employed. This algorithm was found to yield robust results with respect to starting values and convergence was typically reached after few iterations. As a further robustness check, the calculations were carried out using debt values from `Datastream` and were essentially found to be identical to the values of the base calculations.

3.2.1 DD and its Percentage Changes

The first row of Table 1 gives an overview of the DDs for the entire sample. A more detailed overview for all banks is given in Table 6 in Appendix A.

Table 1: Summary statistics of DD and $\Delta\%DD$ for the entire sample period.

Variable	Mean	Std. Dev.	Min.	Max.	N
DD	4.1610	1.8166	-0.9273	14.9576	149171
%-change DD	-0.0008	0.031	-6.5823	0.307	149119

The mean DD over all sample banks is 4.16 with a standard deviation (std. dev.) of 1.81.[56] The maximum average values of DD over all sample banks are 7.74 (Zuger Kantonalbank) and 7.60 (Banco Espirito Santo), respectively. The global maximum is 14.96 (Banco Espirito Santo).[57] The minimum average value over all sample banks is 2.70 (Marfin Egnatia Bank). The global minimum is -0.93 (Fortis) and there are four additional banks for which negative values were observed (Washington Mutual, Bank of America, Citigroup and RBS). Observing negative values indicates that these banks defaulted or at least faced severe difficulties during the sample period. In fact, all these banks were hit particularly hard by the recent financial crisis and often had to be rescued on basis of government bail-outs.[58] As an example, Figures

[56]Despite using a different sample (period), the values are close to those reported in Gropp and Moerman (2004) and Gropp et al. (2009).

[57]While Banco Espirito Santo is an internationally operating bank that is listed in the Euronext-100-index, the Zuger Kantonalbank is a predominantly regionally operating Swiss bank of whose stocks the canton Zug holds 50%.

[58]See Demirguc-Kunt and Serven (2009).

1 and 2 show the development of the DD and the market capitalization for Washington Mutual and Fortis over the sample period. Both Figures indicate that the overall development of the DD and that of the market capitalization tend to be closely connected. However, the DD is obviously less volatile which goes along with expectations since the overall condition of a bank should not change as strongly as equity prices in the short-run. The negative values of the DD for Washington Mutual in the midst of September 2008 are an early indicator for the collapse of the entire bank, which declared its default on 26 September 2008.[59] By contrast, the negative values of DD for Fortis were

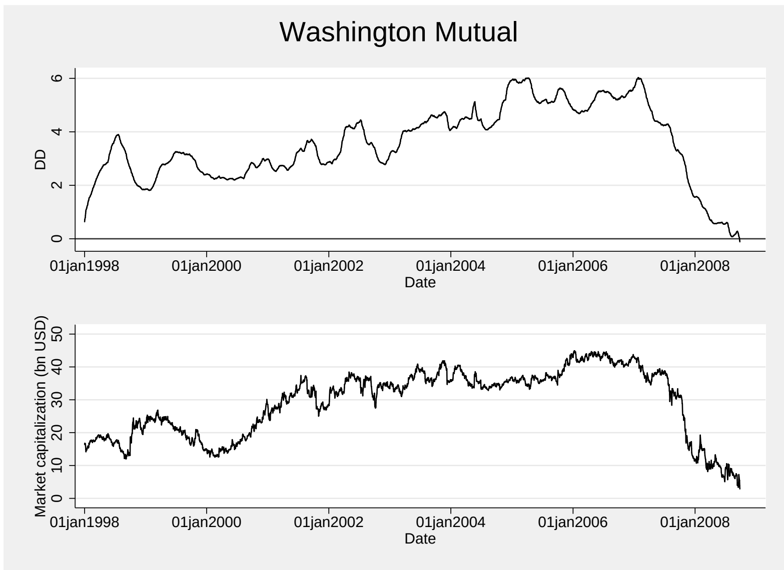

Figure 1: DD and market capitalization of Washington Mutual.

observed at the end of October 2008, although the bank already faced severe problems in September 2008, the time when the bail-out plans of Belgium, Luxembourg and the Netherlands for the troubled bank were published as well. Therefore, these negative values appear rather late. Nevertheless, from the reported values the DD seems to perform astonishingly well as a fragility indicator. There are several other banks with values below one and in fact for the majority of banks minimum DD values were observed during the recent crisis period. These results further stress the severe impact of the subprime crisis on banks' healthiness.

As this paper aims at investigating cross-border contagion, Table 7 in Appendix A provides a country-specific overview of the DDs. The reported values are of course to be interpreted with care, since all banks of one coun-

[59]Washington Mutual was then taken over by JPMorgan Chase.

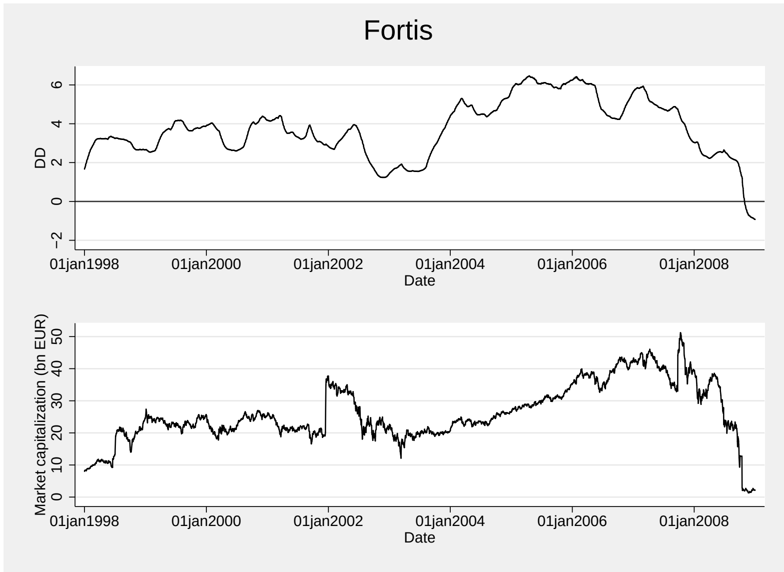

Figure 2: DD and market capitalization of Fortis.

try are being treated equally, irrespective of their relative sizes. Owing to the large average values of Banco Espirito Santo, Portuguese banks have both the highest average DD (5.53) and the highest std. dev. (2.78). A similar argument holds for Swiss banks, which have the second highest average DD (5.01) and a similar std. dev. (2.32) as Portuguese banks. Greek banks have both the lowest mean (3.07) and lowest std. dev. (0.81) and therefore appear to be the most homogenous group of sample banks. Another interesting aspect is the similarity of the average DDs (around 3.80) and the std. devs. (around 1.40) of Belgian, German, French, Dutch, Italian, and UK banks. These results stand in line with the perception of a relatively high integration of the European financial market and suggest that European banks are exposed to similar risks. By contrast, both the average DD (4.38) and the std. dev. (1.93) of US banks are substantially higher. The same is true for Spanish banks (mean 4.76, std. dev. 1.89).

Average values of variables with level changes are obviously not very informative. Therefore the main focus of this paper is on the negative tail of the daily percentage changes of the DD rather than on absolute values. The existence of several negative values of the DD rules out the computation of log-differences, hence daily percentage changes of the DD are being calculated as

$$\frac{DD_t - DD_{t-1}}{|DD_t|} = \Delta\% DD.$$

The second row of Table 1 gives an overview of $\Delta\% DD$ for the entire sample, whereas Tables 8 and 9 in Appendix A provide detailed bank-specific and country-specific overviews. The mean percentage change over the entire sample is slightly negative with -0.0008 (std. dev. 0.031)[60] and the global maximum/minimum are 0.31 (Marfin Egnatia Bank) and -6.58 (Washington Mutual), respectively. Such a huge negative change indicates an extremely quick step towards (in this case even below) the default point. While the mean percentage changes are approximately zero for all sample banks, std. devs. vary substantially: the largest values are 0.1286 (Washington Mutual) and 0.1238 (RBS), two of the banks for which negative DD values were observed. To be precise, volatility increases for banks with absolute DDs close to or below zero. These banks in turn influence country-specific average volatilities. Consequently, std. dev. of $\Delta\% DD$ is highest for Belgian, US and UK banks, whereas std. dev. is lowest for French and Italian banks (both 0.0052).

As argued before, the minimum values of the DDs were observed in 2008 for most banks and the development of the DDs in Figures 1 and 2 suggests a strong downward pressure from the midst of 2007 onwards. Thus it can be presumed that both absolute values and percentage changes of the DD are significantly lower for 2008 compared to the entire sample period, whereas the std. dev. of percentage changes should be significantly higher. Evidence in favor of these presumptions can be found in Table 10 in Appendix A. This Table is structured similarly to Table 1 and shows that the mean of DD for 2008 is 2.62 across all banks (whole sample period: 4.16). The average percentage change is lower with -0.009 and the std. dev. is indeed higher with 0.101 compared with the std. dev. of the entire sample period (which was 0.031).

In the following, the direction of contagion between European and US banks is investigated by focusing on the negative tail observations of the DDs. This approach allows to distinguish common shocks from contagion.

3.2.2 Exceedances and Coexceedances

The negative tail comprises those observations falling in the lower 5% percentile of the distribution of $\Delta\% DD$. These observations are labeled as "exceedances" and can be interpreted as a large step towards the default point.[61]

[60] These values are again close to those reported in Gropp and Moerman (2004) and Gropp et al. (2009).

[61] Choosing the lower 5% percentile is a compromise between the need for large shocks (in the sense of EVT) and maintaining an adequate sample size. See Bae et al. (2003) and Gropp et al. (2009).

For each country a variable "Coexceedances" is then set up containing the number of simultaneous exceedances on a given day in that specific country. The 5% percentile of $\Delta\%DD$ is taken with respect to the common distribution across all sample banks (joint tails), where it is implicitly assumed that the stochastic process governing the DD at different banks is the same (see below). Using joint tails obviously has the advantage of defining a large shock relative to the overall performance of all other banks. Based on this definition, a tail event is an observation equal to or lower than -0.01 or -1.0%.[62] Table 2 gives a country-specific summary of the coexceedances, while Table 11 in Appendix A provides a bank-specific overview of the respective exceedances.

Table 2: Summary statistics: Coexceedances by country (joint tails)

Variable	Mean	Std. Dev.	Min.	Max.
Coexceedances: Belgium	0.1799	0.5795	0	3
Coexceedances: Denmark	0.0784	0.3187	0	2
Coexceedances: Germany	0.2621	0.7122	0	4
Coexceedances: Spain	0.2224	0.667	0	4
Coexceedances: France	0.1541	0.5347	0	3
Coexceedances: Greece	0.1192	0.4344	0	3
Coexceedances: Netherlands	0.1331	0.3886	0	2
Coexceedances: Italy	0.1875	0.6504	0	5
Coexceedances: Portugal	0.1157	0.3897	0	3
Coexceedances: Switzerland	0.1666	0.5189	0	3
Coexceedances: US	0.4723	1.4542	0	9
Coexceedances: Sweden	0.1631	0.6226	0	4
Coexceedances: UK	0.3444	1.0282	0	7
Sum of Coexceedances	2.5988	6.4411	0	51
N		2869		

Interestingly, the country-wise maximum number of coexceedances coincides with the number of sample banks for all countries. Hence there was at least one day where all sample banks of each country were simultaneously in the tail. The last row of Table 2 provides summary statistics for the sum of coexceedances across all countries and Figure 3 displays their development over

[62]This value is again close to the one reported in Gropp et al. (2009).

the sample period. The first peak at the beginning of 1998 can be interpreted

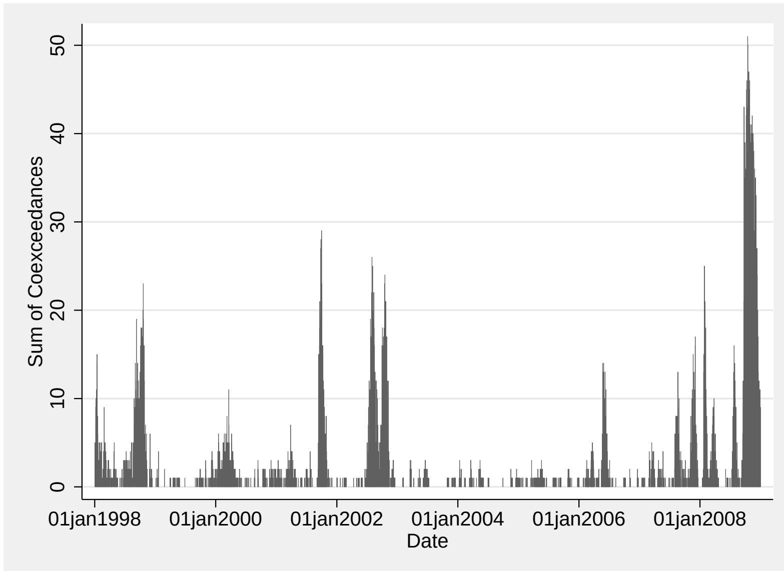

Figure 3: Coexceedances over the entire sample (joint tails).

as the aftermath of the Asian crisis of 1997, while the peak in the midst of 1998 is the effect of the Russian crisis, which had a severe impact on the stability of the international financial system. After a relatively calm period, several peaks appear at the end of 2001 which are probably the effects of the attacks of 11 September and the following worldwide recession (maximum peak: 29 coexceedances). In the following, there are several large peaks in 2002 which were followed by another relatively calm period. From the midst of 2007 onwards there is an upward shift in the level and the volatility of coexceedances. Finally, the impact of the recent crisis period is quite astonishing: before 2008 there were only few days with more than 20 banks simultaneously in the tail. From then on the values skyrocketed with a maximum of 51 banks simultaneously in the tail on 15 October 2008.[63] These large values near the end of the sample period are probably an effect of the default of Lehman Brothers in September 2008 that shook the entire financial system and had an impact on a large number of financial institutions.[64] To summarize, all these observations show that the development of the number of coexceedances displays crisis periods well and stand go along with the

[63]Recall that Washington Mutual dropped out of the sample before this date, hence all 51 remaining sample banks were simultaneously in the tail on this day.

[64]The main effect of Lehman's default was a sudden increase in the fear of counterparty defaults among financial institutions, see e.g. Jorion and Zhang (2008).

perception of a deteriorating healthiness of European and US banks during the recent crisis. Unfortunately, the sample period ends relatively early since the crisis still endures at the time of writing. In the future, it would be interesting to carry out the analysis again for the entire crisis period.
As was noted above, the tail was defined by assuming a joint stochastic process governing the changes in the DD. This proceeding has the danger of distributing probability mass unequally between countries. In order to check if this happens, tails were also calculated under the assumption of a country-wise joint stochastic process of the DD (country-specific tails) and with regard to the 5% percentile of the distribution of $\Delta\%DD$ for each bank (bank-specific tails) yielding essentially the same results as in the base calculations (Tables 12 and 13 in the Appendix). Hence each definition of the tail should yield the same qualitative results (see Section 3.4.2). As an additional

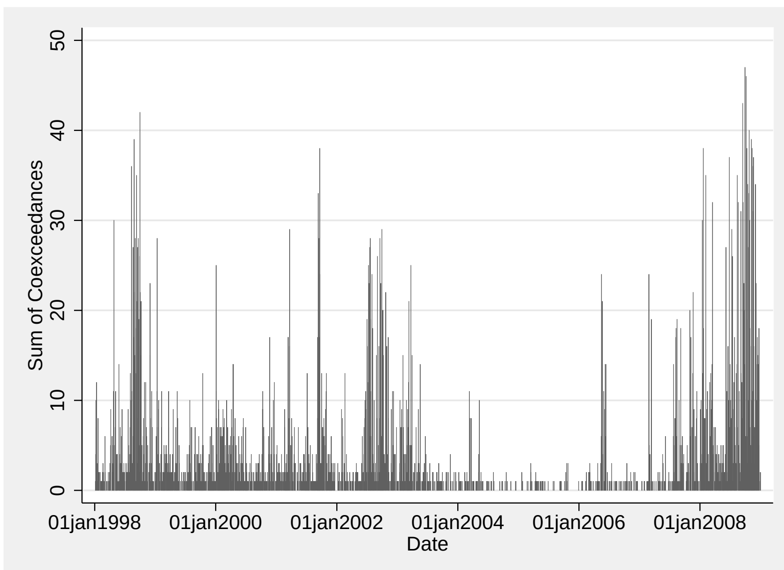

Figure 4: Coexceedances over the entire sample (simple stock returns).

check, the tails were calculated with respect to the joint distribution of simple stock (log-)returns across all banks (see Figure 4). The development of the sum of coexceedances defined this way is highly volatile over time and obviously quite different from the base calculations. Hence the arguments from Section 2 on the informational content of simple equity returns are supported by the underlying data set and the (more time-consuming) calculations of the DDs are justified.

3.3 Econometric Model

In this Section, daily innovations in the country-specific coexceedances are estimated as a function of lagged foreign coexceedances and a number of common shocks. Controlling for common shocks leaves other countries lagged coexceedances as the potential source of cross-border contagion.

Modeling daily innovations in the negative tail of the DD requires the selection of an appropriate econometric model.[65] The dependent variables, i.e. the country-specific coexceedances, are obviously discrete in nature and a variety of econometric approaches allow to analyze models with discrete and limited dependent variables, e.g. tobit models, Poisson models, negative binomial models, ordered logit and multinomial (i.e. unordered) logit models. Tobit models rely on the assumption of a truncated Normally distributed dependent variable, while Poisson models assume that the mean and the variance of the dependent variable are the same. Both assumptions are clearly implausible for the underlying data (cf. Table 3). Negative binomial models are a generalization of Poisson models and relax the assumption of the identity of (conditional) mean and variance but the dependent variable is assumed to be drawn from a mixture of Poisson random variables. Again this assumption is quite restrictive. Furthermore the negative binomial model is usually employed in cross-sectional rather than time-series analysis and will thus not be employed in this paper.[66]

The main difference between the ordered and the multinomial logit model is that the ordered logit restricts the marginal effects to be the same for each outcome. This means that in the ordered logit the effect of coexceedances in another country going from 0 to 1 is the same as going from 1 to 2 banks. By contrast, the multinomial logit permits full parameter flexibility, obviously leaving more parameters to be estimated and thereby decreasing the degrees of freedom. Due to the relatively large sample size, the benefits of the multinomial logit model make it the preferred specification. As a robustness check, the ordered logit will be employed in Section 3.4.2.

Consequently, the number of coexceedances in each country will be estimated as a function of lagged coexceedances of other countries and a number of common shocks. For each country the basic structure of the multinomial logit model is

$$P(Y_{c,t} = j) = \frac{\exp[\beta'_{c,j}\mathbf{x}_{c,t}]}{\sum_{k=0}^{J}\exp[\beta'_{c,k}\mathbf{x}_{c,t}]} \text{ for } j = 0, 1, \ldots, J, \tag{3.2}$$

[65] See Greene (2002), Chapter 21, for a good overview of relevant models.

[66] See Bae et al. (2003).

where $J+1$ is the number of possible outcomes of the dependent variable, $Y_{c,t}=j$ is the number of coexceedances in country c on day t and $\beta_{c,j}$ contains the parameters on the explanatory variables $\mathbf{x}_{c,t}$. In order to remove the indeterminacy of the model[67], $Y_{c,t}=0$ will be defined as the base category and all coefficients are estimated relative to this base. Hence $\beta_{c,0}=0$ and the probabilities are

$$P(Y_{c,t}=j|\mathbf{x}_{c,t})=P_{c,j}=\frac{\exp[\beta'_{c,j}\mathbf{x}_{c,t}]}{1+\sum_{k=1}^{J}\exp[\beta'_{c,k}\mathbf{x}_{c,t}]} \text{ for } j=1,\ldots,J. \tag{3.3}$$

The model will be estimated separately for each country using ML. The log-likelihood function can be derived by defining an indicator $I_{c,t,j}=1$ if outcome j was observed on day t in country c and $I_{c,t,i}=0$, where $i\neq j$, for those outcomes not observed. Doing this for all observations allows to write the log-likelihood as

$$ln(L)=\sum_{t=1}^{T}\sum_{j=0}^{J}I_{c,t,j}lnP(Y_{c,t}=j). \tag{3.4}$$

The interpretation of parameter estimates is difficult in the multinomial logit model since, different from linear probability models, coefficients and marginal effects are not identical.[68] Hence the usual focus is on the signs of the estimated coefficients that measure the direction of the impact of the explanatory variables (positive or negative influence), not on their absolute values. Marginal effects can be derived by differentiating Eq. (3.3):

$$\delta_{c,j}=\frac{\partial P_{c,j}}{\partial \mathbf{x}_{c,t}}=P_{c,j}[\beta_{c,j}-\sum_{k=0}^{J}P_{c,k}\beta_{c,k}]=P_{c,j}[\beta_{c,j}-\bar{\beta}_c].^{69} \tag{3.5}$$

Eq. (3.5) shows that $\beta_{c,j}$ is not only associated with the jth outcome, but also depends on every subvector of β_c that enters through $P_{c,j}$ and the weighted average appearing in $\delta_{c,j}$.[70] It should be noted that $\beta_{c,j}$ does not necessarily have the same sign as $\delta_{c,j}$ at all levels of $\mathbf{x}_{c,t}$ though this is usually the case. In order to aide the interpretability of the results, marginal effects (evaluated at the mean of the explanatory variables) are always presented along with the

[67] The indeterminacy problem results from the fact that the probabilities must sum to one, so only J parameter vectors are needed to determine the J+1 probabilities, see Greene (2002).

[68] This holds for nonlinear models in general.

[69] It should be clear from Eq. (3.5) why marginal effects are also often labeled as marginal probabilities. Both terms are used interchangeably in the following.

[70] See Maddala (1983).

estimated coefficients. The matrix of second partial derivatives delivers the information matrix and asymptotic covariance matrix of the ML estimator for tests of significance of the estimated coefficients. In the following, robust standard errors are used. Goodness-of-fit is measured using the pseudo-R^2 of McFadden (1974) which compares the log-likelihood of a restricted model with just the intercept ($ln(L_R)$) to that of an unrestricted model with all parameters ($ln(L_U)$)

$$\text{pseudo-}R^2 = 1 - \frac{ln(L_U)}{ln(L_R)}. \tag{3.6}$$

Since the log-likelihood is the sum of log-probabilities, it follows that $ln(L_R) \leq ln(L_U) \leq 0$ and it can be shown that the pseudo-R^2 takes on values between zero and one.[71]

As the multinomial logit model estimates one coefficient per outcome, this paper follows Duggar and Mitra (2007) by limiting the number of outcomes to 0, 1 and 2 or more coexceedances for all countries with more than two sample banks. This proceeding can be justified by the need of a model that is parsimonious but also captures the range of possible outcomes. Table 17 in Appendix A shows the country-specific dependent variables. For example, it can be seen that there are 368 days with 2 or more US banks simultaneously in the tail and 2317 days without an exceedance of a Spanish bank. Owing to the definition of the dependent variables, it should be noted that the number of observations for the possible outcomes is clearly unbalanced since the majority of observations is zero for all countries.

An important question is of course how to appropriately control for relevant domestic and international common factors so that significantly positive coefficients on lagged foreign coexceedances can be interpreted as contagion. To anticipate several arguments below, the relevance of common factors (in terms of parameter significance of the explanatory variables) was found to differ between the 13 sample countries.

The main selection criterion for the relevant explanatory variables is their daily availability over the entire sample period. This implies that several variables will be missed, e.g. GDP forecasts and monetary policy actions. Nevertheless, the forward-looking nature of financial markets should capture all relevant information in market prices.[72] The data availability of the explanatory variables over the entire sample period poses an additional prob-

[71] The zero bound follows from the case that all estimated coefficients are equal to zero. Then it follows that $ln(L_R) = ln(L_U)$ such that Eq. (3.6) is zero. The upper bound of one is relevant if the unrestricted model would be able to generate (estimated) probabilities corresponding exactly to the observed values, all probabilities in the likelihood would be equal to one and $ln(L_R)$ would be equal to zero.

[72] See Bae et al. (2003).

lem for several variables which have been published on a frequent basis only significantly after 1998, e.g. the LIBOR-Overnight-index-swap spread (OIS) and CDS spreads.[73] Especially in the light of the recent financial crisis, these variables should carry information on market and (funding) liquidity risks. In the following, five common factors will be included for each country.[74]

The first common factor ("Systemic risk") measures the number of equity markets experiencing a large shock on a given day and is based on the domestic, the US, the Euro Area and the emerging market stock indices.[75] For each stock market index an indicator variable is set equal to one if the corresponding log-return is in the lower 5% percentile of the stock market's return distribution. The variable "Systemic risk" is the sum of these indicator variables with values ranging between 0 and 4, where large values indicate periods of global distress. For the US, the domestic market index coincides with the US market index, hence "Systemic risk: US" is restricted to a maximum of 3.

Systemic shocks can be either global or domestic depending on how broad the banking system is defined. While the variable "Systemic risk" is able to identify global shocks (partly taking account of the domestic stock market), the second factor captures changes in domestic risk. The variable "Volatility" contains the daily differences in the variance of the domestic stock market (multiplied by 100 and in absolute values). Similar measures have been found to be particularly important when explaining emerging market coexceedances.[76] Stock market variance was again estimated using a GARCH(1,1) model (see Eq. (3.1) in Section 3.1) and an overview of the estimated coefficients is given in Table 14 in Appendix A. In order to control for global volatility spillovers, lagged "Volatility: US" is inserted for Europe while "Volatility: Europe" is inserted for the US.

The fourth common factor ("Term structure") is an approximation of the change of the slope of the yield curve, where the slope of the yield curve is defined as the difference between the yields of a 10-year government bond and the 3-month interbank rate.[77] This variable is supposed to capture expectations on economic growth and monetary policy. The basic idea is that banks transform liquid deposits into illiquid loans (maturity transformation), hence a flattening of the yield curve suggests that the interest paid by banks

[73] See Hesse et al. (2008) for an analysis of LIBOR-OIS spreads and CDS spreads during the recent crisis period.

[74] See Gropp et al. (2009).

[75] For the emerging market the MSCI Emerging Market Index is used.

[76] See Bae et al. (2003).

[77] Values for the 3-month interbank rate were not available for Greece and the 1-month interbank rate is used instead.

rises by more than the interest received. It should be noted that this variable can also be seen as a proxy for funding risks in the interbank markets. Since a flatter yield curve is usually associated with a decline in real activity, the variable "Term structure" should be negatively related to the number of coexceedances.[78]

The last factor takes owes to the fact that the underlying data set is in the respective domestic currencies. Contrary to the majority of empirical studies on cross-border contagion risk (including Gropp et al. (2009)), this paper explicitly accounts for possible remaining spillover effects from foreign exchange markets using a factor "Exchange rate". Unfortunately, the number of parameters increases rapidly for each additional regressor in the multinomial logit model hence the most promising variable capturing exchange rate effects is based on the according effective (i.e. trade-weighted) exchange rates. Being multilateral indices that display how the value of the domestic currency changed relative to the value of other currencies, effective exchange rates have the advantage of allowing for a parsimonious model since only one additional regressor for each outcome enters the model.[79] In order to control for volatility spillovers from foreign exchange markets, the factor "Exchange rate" is set up similarly to the "Volatility" factor and contains daily differences of the estimated variance of the foreign exchange market. Parameter estimates can be found in Table 15 in Appendix A. It should be noted that effective exchange rates are less volatile than bi-lateral exchange rates and stock-market indices. Estimates were therefore rescaled by a factor of 1000 (rather than 100 as for "Volatility"). Setting up this factor stands in line with the results of Bae et al. (2003), who find that a depreciation makes extreme stock returns (positive and negative) more likely. In principle, despite the obvious effect on equity volatility, the final effect on the number of coexceedances can hence have either sign. Volatility spillovers from foreign exchange markets should be most relevant for countries with a large number of banks actively operating on international capital markets.

Furthermore, one lag of domestic coexceedances is additionally included as a regressor for each country, in order to remove any possible remaining autocorrelation in the dependent variable. Summary statistics for the explanatory variables are given in Table 16 in Appendix A. Further checks on the explanatory variables are reported below.

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[78] See Moneta (2005). It should be noted that Gropp et al. (2009) found a similar variable hardly ever significant in their estimations.

[79] Effective exchange rates are published by a number of institutions. This paper employs those published by the Bank of England (Source: `Datastream`).

3.4 Estimation Results

3.4.1 Results and Interpretation

In the following, the estimation results of the multinomial logit model(s) will be presented. The corresponding Tables 18 - 30 in Appendix A show parameter estimates (marginal effects in parentheses), the corresponding significance levels, the log-likelihood and the pseudo-R^2. The upper (lower) parts of the Tables show the estimation results for the first (second) outcome. Similar to Gropp et al. (2009), two models are estimated for each country: The first specification (Model 1, left columns) only controls for common factors as described above, whereas the second specification (Model 2, right columns) adds lagged foreign coexceedances as potential source of contagion. For each country, the dependent variable comprises the number of banks simultaneously falling into the bottom 5 % percentile of the joint distribution of $\Delta\%DD$.

In the first specification, the pseudo-R^2 varies between 0.382 (Greece) and 0.657 (France) indicating significant variation in the explanatory potential of the common factors between countries.[80] For the majority of countries the pseudo-R^2 lies around 0.50, which is astonishingly high compared with the values reported in Gropp et al. (2009).[81] Concerning the results, Model 1 shows that coexceedances are indeed autocorrelated since lagged values are always highly (positively) significant at the 1 percent level and marginal effects are always positive as well. Similarly, "Volatility" and "Systemic risk" both are mostly positively and highly significantly related to the number of coexceedances. Therefore an increase in conditional volatility and a large number of stock markets under stress are important factors in explaining the occurrence of a higher number of coexceedances. These findings stand in line with the results of Gropp et al. (2009), where similar factors were always highly significant at the one percent level. Nevertheless, there are examples where none or only one of the two factors appears to be important, e.g. Denmark and Portugal. Similar to Gropp et al. (2009), the factor "Term structure" is found to be insignificant in almost all estimations and hence tends to be only weakly associated with a higher number of coexceedances for the underlying sample period (exception: Netherlands). Nevertheless, parameter estimates and marginal effects mostly have the expected negative sign. Evidence for the existence of stock market spillovers from the US to Europe (see e.g. Hartmann, Straetmans, and de Vries (2004)) is verified by the underlying data set since volatility spillovers from the US to Europe

[80] See Greene (2002) for comparisons of pseudo-R^2's of different models.

[81] These authors report a maximum pseudo-R^2 of 0.17 for Model 1.

are informative for a number of European countries, e.g. Switzerland and Spain. Contrary to the results in Gropp et al. (2009), spillovers from the US to the UK are significant as well while European volatility is insignificant (and tends to be negative) for the US. In this case, possible spillover effects may be captured by the "Systemic risk" factor. The factor "Exchange rate" is insignificant for the majority of countries and the signs of the estimated parameters (and marginal effects) can even differ between outcomes. As a surprise, the sole exceptions are Italy and Sweden for which this factor is significantly positively related to a higher number of coexceedances.

While the focus is on the sign and significance of the estimated parameters, the reported marginal effects allow for an economic interpretation. In Spain for example, an increase in "Volatility US" raises the probability of observing 2 exceedances by 0.22 percent. An increase in "Systemic risk" raises the probability of the occurrence of 1 exceedance by 1.37 percent for Switzerland. It should be noted that marginal effects are often relatively small in absolute terms, in particular for the second outcome of the dependent variable.

Summarizing the main results of the first specification, one can argue that the importance of the common factors is similar to the findings in Gropp et al. (2009) that were obtained based on a sample containing only French, German, Italian, Dutch, Spanish and UK banks during a different sample period (January 1994 to January 2003). Hence, controlling for common factors remains highly relevant when a number of countries are added to the sample and, even more important, when the recent financial crisis is taken into the sample period.

Model 2 considers the existence of contagion between European and US banks by including one day lagged foreign coexceedances.[82] After controlling for common shocks, each of those positive parameters on the contagion variables being (jointly) significantly different from zero can be interpreted as contagion from that country. Including the contagion variables results in an increase of pseudo-R^2 of several percentage points for all countries (maximum increase: UK and France with 4 percentage points). Most importantly, adding lagged coexceedances does in general not affect the sign or significance of the Model 1 explanatory variables for the majority of countries. Furthermore the absolute values of parameter estimates and the corresponding marginal effects are similar to those of the first specification. Consequently, the information content increases in Model 2. Nevertheless, there are countries for which the foregoing arguments hold only weakly, e.g. Denmark and Sweden. For these countries, the results appear to be not very robust. Fi-

[82]Owing to the timing structure of markets, European coexceedances inserted for the US are of the same trading day.

nally, it can be seen that marginal effects tend to be relatively small, so that the economic impact is often minor. However, it should be noted that this paper only aims at investigating the existence of contagion rather than the relative strength of these relationships.[83]

Table 3: Wald tests (Multinomial logit): significance of Contagion variables at 10 (*), 5 (**) and 1 (***) percent level, respectively. Parentheses indicate at least one significantly negative parameter.

to/from	BE	DK	DE	ES	FR	GR	NL	IT	PO	CH	US	SW	UK
BE	X						**		**		*		
DK		X		(*)						**			
DE	*		X					***	**		**	(**)	
ES	*	(***)	**	X		(*)		**	***		(**)		
FR	**			***	X			***	***		**		
GR	**	*		(*)		X				*			
NL	***						X		*	*			
IT		***	***					X					
PO	*								X				
CH		***	**						**	X	***		
US			*							***	X		
SW					*							X	
UK	**								**	**	***		X

Significance was tested using separate Wald tests for the (joint) significance of each country-specific contagion variable. As there are two outcomes, i.e. two parameters jointly to be tested, the resulting test statistic is distributed as $\chi^2(2)$. If the test statistic is larger than the corresponding critical value, the hypothesis of zero coefficients for the contagion variable for both outcomes can be rejected.
The basic finding is that there is evidence for cross-atlantic contagion between European and US banks. Furthermore, cross-border contagion is important between European banks as well. The final results can be depicted most easily in Table 3, where the joint significance of the contagion variables is displayed by significance stars. Those stars in parentheses indicate that at

[83] In Duggar and Mitra (2007) try to gauge the relative effect of one variable to another by comparing the relative size of the estimated coefficients. Since coefficients have no economic interpretation per se, the relative magnitude of two coefficients should not have one either.

least one parameter is significantly negative, hence those relationships tend to be significant but do not obey the definition of contagion used in this paper (cf. Section 1).[84] Table 3 shows for example, that there is evidence of contagion from Italy to Spain at the one percent level. Surprisingly there is no evidence of any contagion from UK banks for the underlying sample period and the influence of French banks seems to be weak as well. Furthermore, contagion from Greece and Sweden is irrelevant for most countries as well. The non-existence of contagion between Swedish and Danish banks may stem from the fact that these countries could share common factors. Belgian, Portuguese and US banks seem to be most contagious, which stands in line with the recent crisis period (see above). In particular, US banks influence Belgian, German, French, Swiss and UK banks. US banks themselves are influenced only by German and Swiss banks. Consequently, US banks tend to have a larger impact on European banks than the other way round.

The countries most affected by contagion are Spain and France. The result for Spain stands in contrast to the findings in Gropp et al. (2009), where Spanish banks were those least exposed to contagion. Hence the patterns seem to change if additional countries and, somewhat more importantly, the recent financial crisis are incorporated into the sample (period). Interestingly, there is evidence for bi-lateral contagion between a number of country-pairs, most importantly Belgium-Netherlands, Germany-Italy, Germany-US and Switzerland-US. Accordingly, for example, adverse shocks affecting German banks can influence US banks, which in turn may have further knock-on effects on Swiss banks.

All in all the results are consistent with the findings in Gropp et al. (2009) of a greater presence of cross-border contagion after the introduction of the Euro. Furthermore they stand in line not only with a high cross-border contagion risk between European banks, but also with the idea that this risk may be related to the integration of international money markets. Thus, tendencies of more and more globalizing international financial markets seem to intensify the existence of cross-border contagion between European and US banks as well. In a sense, the results verify the theoretical findings of Allen and Gale (2000) on the severity of contagion in different interbank networks. Even though the authors concentrated on the channel of interbank claims neglecting other relevant channels of contagion, the results of this paper suggest that the international interbank market might be considered incomplete in the sense that not each bank is connected with all other banks in the system. While a complete interbank market would yield the most stable financial system, real interbank markets are obviously incomplete due

[84] In this case the coexceedances of different countries tend to be negatively correlated.

to the large costs a complete system would induce.[85] Thus central banks, in particular the European Central Bank (ECB) and the Federal Reserve Bank (Fed), should work together more closely in order to contain systemic financial crises.[86] It should be noted that significant contagion between a number of Euro-area countries indicates that the ECB has not been very successful in completing the Euro-area interbank market. This may stem from the fact that especially during the recent crisis period a number of other relevant factors were present that amplified contagious effects and were hardly predictable or even influenceable by the ECB, e.g. the widespread usage of structured products.

3.4.2 Robustness Checks

This Subsection discusses several robustness checks. For example, a variety of alternative definitions for the common factors was employed, e.g. the "Systemic risk" factor was set up using different market indices and "Term structure" was set up using differences between 10 year and 1 year/1 month interbank lending rates, respectively. Furthermore country-specific and bank-specific tail definitions (cf. Section 3.2) for the number of coexceedances were used. All these alternatives yielded similar results as the base specification. Additionally to these data robustness checks, a different econometric model was employed as well, namely the ordered logit model.
Since the multinomial logit fails to account for the ordinal nature of the dependent variables, efficiency may be lost compared to an ordered logit model, which is explicitly designed to capture the ordering information. The ordered logit requires the odds, i.e. the ratio of probabilities, of adjacent categories, defined by different cutoff points along the ordinal scale, to have the same ratio for all combinations of the independent variables. To be precise, the ordered logit requires the marginal effect to be the same for each outcome, leaving only one set of coefficients to be estimated. Obviously, such a constraint will generate less efficient estimates if the odds are not proportional. Estimation results (not reported for the sake of brevity) suggest similar values of the pseudo-R^2 and the estimated coefficients. Furthermore the significance of the common factors compared to the multinomial logit remains unaffected. Results on the existence of contagion are summarized in Table 4.

[85] For the structure of real interbank networks see Boss et al. (2004), Upper and Worms (2004) and Mueller (2006).

[86] Cui and Belke (2009) provide evidence for a leader-follower relationship between the Fed and the ECB.

Table 4: Wald tests (Ordered logit): significance of Contagion variables at 10 (*), 5 (**) and 1 (***) percent level, respectively. Parentheses indicate at least one significantly negative parameter.

to/from	BE	DK	DE	ES	FR	GR	NL	IT	PO	CH	US	SW	UK
BE	X						***		***		**		
DK		X								**			
DE			X						**		**		
ES	***			X		(**)		***	***			(*)	
FR	*				X				***		**		
GR				(***)		X							
NL	*						X			***		(*)	
IT	**	**	*					X					
PO								*	X			(*)	
CH			*				*	*	**	X	*		
US			**			(**)		(*)		***	X	(**)	
SW	**			(**)	***		*			*		X	
UK	**								*	**	***		X

The results are similar to the basic results in Table 3. While the absolute significance level may change, the majority of new relationships is significantly negative and therefore not referred to as contagion. These relationships present in the multinomial logit but absent from the ordered logit were mostly significant at the 10 percent level before. Most importantly, evidence for contagion between European and US banks remains unaffected, while the patterns between European banks can change. For example, Danish banks are much less contagious in the ordered logit, while contagion from Spain vanishes. Results on contagion to Sweden change as well, but as already mentioned above even the results in the multinomial logit seemed to be not very robust for Sweden and Denmark. Somewhat surprisingly, the non-existence of contagion from UK banks remains unaffected. Therefore the interpretational remarks given for the multinomial logit hold for the ordered logit as well.

4 Conclusion

This paper explored the existence of contagion between European and US banks. Based on the negative tail of the daily percentage changes of the DD, separate multinomial logit models were estimated for 13 different countries and a number of significant contagion relationships were found. Most importantly, there is evidence for contagion from the US to a number of European countries whereas only German and Swiss banks seem to directly influence US banks. Furthermore there is significant contagion between a number of European countries. These results were found to be quite robust with respect to a number of different specifications for most countries.

The findings have several important implications for both regulators and policy makers: First, while the existence of contagion between European and US banks comes as no surprise, it suggests that regulators and central banks throughout the world should work together more closely in order to overcome and contain financial crises. Central bank actions during the recent crisis indicate that some forms of these international cooperations in part actually do already exist.[87] This is less true for fiscal policy and regulatory actions which often differ substantially between countries, e.g. government bail-out plans during the recent crisis.[88] The results of this paper suggest that failures of systemic financial institutions are harmful to foreign countries as well, giving too-big-to-fail considerations an international dimension that requires more intensive cooperations between policy makers.

Second, significant contagion between a number of Euro-area countries indicates that the ECB was not very successful in completing and stabilizing the Euro-area interbank market. However, especially during the recent crisis a number of other relevant factors, not influenceable by the ECB, intensified the problems in the interbank markets. In the future, new international (binding) regulatory standards need to be established. One of the key lessons of this paper is that past financial regulation seems to have overemphasized measures to preserve the soundness of individual institutions, whereas the interconnectedness of banks and its implications for systemic stability were underemphasized. Future surveillance of banking stability should therefore take place across borders. A possible framework would be to mandate central banks explicitly to oversee systemic stability. This would include gathering and analyzing information on asset positions and risk exposures in a standardized form. Standardizing the regulatory analysis is crucial for permitting comparisons between foreign institutions when information between central banks is exchanged.

Another interesting approach would be to focus on the absolute values of the DDs. From the empirical results of this paper it can be presumed that a stable long-run relationship between the DDs of different banks exists. Several (unreported) tests show that the DDs of all sample banks contain a unit

[87] See Eisenschmidt et al. (2009) and Coenen et al. (2008).

[88] See e.g. Borio (2008).

root, so it would be interesting to use the methods of cointegration analysis by building a vector error-correction model. Another alternative would be to investigate contagion in terms of Granger-causality in a vector autoregression (VAR).

A Appendix

This Appendix contains all Tables that were mentioned in the text.

Table 5: Sample banks and total assets in bn EUR (2004). The values for Danish, Swedish, Swiss, UK and US banks were converted using the respective exchange rates. Source: `Osiris`.)

	Name	Country	Total assets
1	Fortis	BE	614.09
2	Dexia	BE	404.64
3	KBC Bank	BE	285.16
4	Danske Bank	DK	275.60
5	Sydbank	DK	10.55
6	Deutsche Bank	DE	840.07
7	Commerzbank	DE	424.88
8	Landesbank Berlin	DE	130.30
9	IKB	DE	39.50
10	Banco Santander	ES	664.49
11	BBVA	ES	329.44
12	Banco Espanol de Credito	ES	69.58
13	Banco Popular Espanol	ES	63.58
14	BNP Paribas	FR	1002.50
15	Societe Generale	FR	678.82
16	Natixis Banques Popolaires	FR	139.32
17	National Bank of Greece	GR	54.49
18	Alpha Bank	GR	33.24
19	Marfin Egnatia Bank	GR	2.88
20	ING	NL	876.39
21	Kas-Bank	NL	6.04
22	Intesa Sanpaolo	IT	272.28
23	UniCredito Italiano	IT	260.91
24	Banca Popolare Di Milano	IT	37.82
25	Credito Emiliano	IT	19.58
26	Credito Valtellines	IT	11.60
27	Banco Comercial de Portuges	PO	71.32
28	Banco Espirito Santo	PO	43.05
29	Banco Portuges de Investimento	PO	25.76
30	UBS	CH	1127.01

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... table 5 continued

	Name	Country	Total assets
31	Credit Suisse	CH	706.83
32	Zuger Kantonalbank	CH	5.75
33	Citigroup	US	1089.57
34	JPMorgan Chase	US	849.61
35	Bank of America	US	815.25
36	Wells Fargo	US	314.11
37	Washington Mutual	US	226.06
38	US Bancorp	US	143.24
39	SunTrust Bank	US	116.64
40	PNC Financial Services	US	58.53
41	Comerica Bank	US	38.00
42	Nordea	SW	280.07
43	SEB	SW	178.31
44	Svenska Handelsbanken	SW	146.15
45	Swedbank	SW	113.32
46	RBS	UK	987.65
47	HSBC Holding	UK	939.71
48	Barclays	UK	763.12
49	Lloyds	UK	415.25
50	Standard Chartered	UK	108.01
51	Close Brothers	UK	5.85
52	Schroders	UK	3.87

Table 6: Summary statistics of DD per bank

Variable	Mean	Std. Dev.	Min.	Max.	N
Dexia	4.049	1.44	0.314	6.981	2870
Fortis	3.747	1.471	-0.927	6.465	2870
KBC Bank	3.847	1.133	0.436	6.075	2870
Danske Bank	4.228	1.289	1.33	7.25	2870
Sydbank	5.812	1.945	1.231	11.134	2870
Landesbank Berlin	3.297	1.27	0.834	6.547	2870
Commerzbank	3.107	0.822	0.73	4.903	2870
Deutsche Bank	3.453	1.06	0.789	5.932	2870
IKB	5.109	1.895	0.44	8.961	2870
BBVA	4.18	1.477	1.345	7.025	2870

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… table 6 continued

Variable	Mean	Std. Dev.	Min.	Max.	N
Banco Espanol de Credito	5.894	2.218	2.074	11.741	2870
Banco Popular Espanol	5.009	1.684	1.407	8.568	2870
Banco Santander	3.987	1.453	1.301	6.825	2870
BNP Paribas	3.59	1.202	1.124	6.213	2870
Natixis Banques Popolaires	4.393	1.613	0.457	7.75	2870
Societe Generale	3.363	1.211	0.855	5.707	2870
Marfin Egnatia Bank	2.696	0.899	0.932	6.144	2870
National Bank of Greece	3.194	0.727	1.071	4.48	2870
Alpha Bank	3.335	0.649	1.447	4.629	2870
ING	3.674	1.395	0.193	6.539	2870
Kas-Bank	4.101	1.147	1.391	6.438	2870
Intesa Sanpaolo	3.448	1.188	1.13	5.778	2870
Credito Emiliano	3.359	0.827	1.724	5.091	2870
Credito Valtellines	5.214	1.096	2.737	7.205	2870
Banca Popolare di Milano	3.143	0.58	1.743	4.195	2870
UniCredito Italiano	4.231	1.721	0.919	8.111	2870
Banco Comercial Portuges	4.668	1.642	2.175	9.519	2870
Banco Espirito Santo	7.603	3.506	2.152	14.958	2870
Banco Portuges de Investimento	4.338	1.329	1.69	8.481	2870
Credit Suisse	3.361	1.141	0.641	5.573	2870
UBS	3.941	1.385	0.514	6.825	2870
Zuger Kantonalbank	7.738	1.306	5.364	10.355	2870
Bank of America	4.486	2.131	-0.043	8.586	2870
Citigroup	4.106	1.91	-0.154	7.725	2870
Comerica Bank	4.166	1.414	0.411	7.208	2870
JPMorgan Chase	3.815	1.734	0.54	7.135	2870
PNC Financial Services	4.519	1.628	0.969	7.708	2870
SunTrust Bank	4.638	1.693	0.233	8.447	2870
US Bancorp	4.850	2.286	1.277	10.477	2870
Washington Mutual	3.562	1.397	-0.113	6.03	2801
Wells Fargo Bank	5.331	2.323	0.665	10.265	2870
Nordea	4.313	1.423	1.607	7.28	2870
SEB	3.305	0.978	0.639	5.579	2870
Svenska Handelsbanken	4.104	1.049	1.574	6.402	2870
Swedbank	3.797	1.126	0.726	6.259	2870
Barclays	3.434	1.234	0.499	5.67	2870
Close Brothers	3.667	1.072	1.555	5.847	2870
HSBC Holding	4.965	2.097	1.864	9.716	2870

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... table 6 continued

Variable	Mean	Std. Dev.	Min.	Max.	N
Lloyds	3.884	1.583	0.484	7.071	2870
RBS	3.602	1.556	-0.007	6.416	2870
Schroders	3.398	1.392	0.953	6.468	2870
Standard Chartered	3.31	1.21	0.617	5.95	2870

Table 7: Summary statistics of DD per country

Variable	Mean	Std. Dev.	Min.	Max.	N
Belgium	3.881	1.362	-0.927	6.981	8610
Denmark	5.020	1.83	1.231	11.134	5740
Germany	3.742	1.546	0.44	8.961	11480
Spain	4.767	1.892	1.301	11.741	11480
France	3.782	1.426	0.457	7.75	8610
Greece	3.075	0.813	0.932	6.144	8610
Netherlands	3.887	1.295	0.193	6.539	5740
Italy	3.879	1.378	0.919	8.111	14350
Portugal	5.536	2.782	1.69	14.958	8610
Switzerland	5.013	2.326	0.514	10.355	8610
United States	4.388	1.933	-0.154	10.477	25761
Sweden	3.88	1.217	0.639	7.28	11480
United Kingdom	3.751	1.574	-0.007	9.716	20090

Table 8: Summary statistics of $\Delta\%DD$ per bank

Variable	Mean	Std. Dev.	Min.	Max.	N
Dexia	-0.0008	0.0066	-0.0495	0.0212	2869
Fortis	-0.0038	0.0779	-3.6098	0.0292	2869
KBC Bank	-0.0007	0.0064	-0.0365	0.0255	2869
Danske Bank	-0.0004	0.0049	-0.0311	0.0267	2869
Sydbank	-0.0005	0.0054	-0.027	0.0227	2869
Landesbank Berlin	-0.0003	0.0078	-0.0488	0.0529	2869
Commerzbank	-0.0005	0.0057	-0.0326	0.0207	2869
Deutsche Bank	-0.0005	0.0054	-0.0307	0.0217	2869

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... table 8 continued

Variable	Mean	Std. Dev.	Min.	Max.	N
IKB	-0.0006	0.0083	-0.0597	0.0363	2869
BBVA	-0.0003	0.0059	-0.0276	0.0205	2869
Banco Espanol de Credito	-0.0003	0.007	-0.0635	0.0326	2869
Banco Popular Espanol	-0.0004	0.0052	-0.0663	0.0183	2869
Banco Santander	-0.0003	0.0061	-0.0268	0.0314	2869
BNP Paribas	-0.0003	0.0051	-0.085	0.0603	2869
Natixis Banques Popolaires	-0.0006	0.0053	-0.0266	0.0207	2869
Societe Generale	-0.0004	0.0052	-0.045	0.0206	2869
Marfin Egnatia Bank	-0.0001	0.0083	-0.0994	0.307	2869
National Bank of Greece	-0.0003	0.0048	-0.0386	0.0198	2869
Alpha Bank	-0.0003	0.0042	-0.0277	0.0187	2869
ING	-0.0009	0.0087	-0.059	0.0255	2869
Kas-Bank	-0.0003	0.0065	-0.0538	0.0339	2869
Intesa Sanpaolo	-0.0003	0.0054	-0.0645	0.0306	2869
Credito Emiliano	-0.0001	0.0045	-0.0413	0.0179	2869
Credito Valtellines	-0.0001	0.0048	-0.0475	0.0254	2869
Banca Popolare di Milano	-0.0002	0.0052	-0.065	0.0484	2869
UniCredito Italiano	-0.0003	0.0061	-0.0332	0.0205	2869
Banco Comercial Portuges	-0.0002	0.006	-0.056	0.0574	2869
Banco Espirito Santo	-0.0003	0.0045	-0.0186	0.0208	2869
Banco Portuges de Investimento	-0.0002	0.0062	-0.0755	0.0546	2869
Credit Suisse	-0.0005	0.0068	-0.0407	0.0308	2869
UBS	-0.0006	0.006	-0.0321	0.0414	2869
Zuger Kantonalbank	-0.0001	0.0036	-0.025	0.0165	2869
Bank of America	-0.0046	0.0825	-3.8261	0.0385	2869
Citigroup	-0.004	0.0642	-2.561	0.0566	2869
Comerica Bank	-0.0007	0.006	-0.0373	0.0268	2869
JPMorgan Chase	-0.0006	0.0053	-0.0354	0.0289	2869
PNC Financial Services	-0.0005	0.0048	-0.0234	0.0172	2869
SunTrust Bank	-0.0009	0.0063	-0.0711	0.0374	2869
US Bancorp	-0.0003	0.0054	-0.0271	0.0577	2869
Washington Mutual	-0.004	0.1286	-6.5823	0.1144	2800
Wells Fargo Bank	-0.0006	0.0053	-0.0337	0.0663	2869
Nordea	-0.0002	0.0071	-0.0254	0.1884	2869
SEB	-0.0005	0.0051	-0.0295	0.0178	2869
Svenska Handelsbanken	-0.0003	0.0038	-0.0146	0.0177	2869
Swedbank	-0.0005	0.0047	-0.0357	0.0183	2869
Barclays	-0.0006	0.0055	-0.0293	0.0232	2869

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... table 8 continued

Variable	Mean	Std. Dev.	Min.	Max.	N
Close Brothers	-0.0003	0.0058	-0.0277	0.0215	2869
HSBC Holding	-0.0002	0.0046	-0.03	0.0411	2869
Lloyds	-0.0006	0.0054	-0.026	0.0165	2869
RBS	-0.0052	0.1238	-6.4	0.0465	2869
Schroders	-0.0004	0.0064	-0.0433	0.0325	2869
Standard Chartered	-0.0005	0.005	-0.0356	0.0179	2869

Table 9: Summary statistics of $\Delta\%DD$ per country

Variable	Mean	Std. Dev.	Min.	Max.	N
Belgium	-0.0018	0.0453	-3.6098	0.0292	8607
Denmark	-0.0004	0.0052	-0.0311	0.0267	5738
Germany	-0.0005	0.0069	-0.0597	0.0529	11476
Spain	-0.0003	0.0061	-0.0663	0.0326	11476
France	-0.0005	0.0052	-0.085	0.0603	8607
Greece	-0.0002	0.006	-0.0994	0.307	8607
Netherlands	-0.0006	0.0077	-0.059	0.0339	5738
Italy	-0.0002	0.0052	-0.065	0.0484	14345
Portugal	-0.0002	0.0056	-0.0755	0.0574	8607
Switzerland	-0.0004	0.0056	-0.0407	0.0414	8607
United States	-0.0018	0.0551	-6.5823	0.1144	25752
Sweden	-0.0004	0.0053	-0.0357	0.1884	11476
United Kingdom	-0.0011	0.0471	-6.4	0.0465	20083

Table 10: Summary statistics of DD and $\Delta\%DD$ for 2008.

Variable	Mean	Std. Dev.	Min.	Max.
DD	2.6234	1.384	-0.9273	9.8809
%-change DD	-0.009	0.1011	-6.5823	0.1061
N		13607		

Table 11: Summary statistics: Exceedances

Variable	Mean	Std. Dev.	Min.	Max.
Dexia	0.0568	0.2315	0	1
Fortis	0.068	0.2517	0	1
KBC Bank	0.0551	0.2282	0	1
Danske Bank	0.0314	0.1743	0	1
Sydbank	0.0471	0.2118	0	1
Landesbank Berlin	0.084	0.2774	0	1
Commerzbank	0.0568	0.2315	0	1
Deutsche Bank	0.0443	0.2057	0	1
IKB	0.077	0.2667	0	1
BBVA	0.0638	0.2444	0	1
Banco Espanol de Credito	0.0498	0.2177	0	1
Banco Popular Espanol	0.0397	0.1954	0	1
Banco Santander	0.069	0.2535	0	1
BNP Paribas	0.0519	0.2219	0	1
Natixis Banques Popolaires	0.0495	0.2169	0	1
Societe Generale	0.0526	0.2233	0	1
Marfin Egnatia Bank	0.06	0.2374	0	1
National Bank of Greece	0.0359	0.1861	0	1
Alpha Bank	0.0234	0.151	0	1
ING	0.0847	0.2785	0	1
Kas-Bank	0.0484	0.2148	0	1
Intesa Sanpaolo	0.0467	0.211	0	1
Credito Emiliano	0.0227	0.1488	0	1
Credito Valtellines	0.031	0.1734	0	1
Banca Popolare di Milano	0.0296	0.1696	0	1
UniCredito Italiano	0.0575	0.2329	0	1
Banco Comercial Portuges	0.0432	0.2034	0	1
Banco Espirito Santo	0.023	0.1499	0	1
Banco Portuges de Investimento	0.0495	0.2169	0	1
Credit Suisse	0.0857	0.28	0	1
UBS	0.0652	0.2469	0	1
Zuger Kantonalbank	0.0157	0.1243	0	1
Bank of America	0.0565	0.2309	0	1
Citigroup	0.0544	0.2268	0	1
Comerica Bank	0.0572	0.2322	0	1
JPMorgan Chase	0.0467	0.211	0	1
PNC Financial Services	0.0432	0.2034	0	1

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... table 11 continued

Variable	Mean	Std. Dev.	Min.	Max.
SunTrust Bank	0.0484	0.2148	0	1
US Bancorp	0.0484	0.2148	0	1
Washington Mutual	0.0746	0.2628	0	1
Wells Fargo Bank	0.0429	0.2026	0	1
Nordea	0.0606	0.2387	0	1
SEB	0.046	0.2095	0	1
Svenska Handelsbanken	0.0227	0.1488	0	1
Swedbank	0.0338	0.1808	0	1
Barclays	0.0558	0.2295	0	1
Close Brothers	0.0638	0.2444	0	1
HSBC Holding	0.0241	0.1532	0	1
Lloyds	0.0488	0.2155	0	1
RBS	0.0579	0.2335	0	1
Schroders	0.0606	0.2387	0	1
Standard Chartered	0.0335	0.1799	0	1
N		2869		

Table 12: Summary statistics: Coexceedances by country (country-specific tails)

Variable	Mean	Std. Dev.	Min.	Max.
Coexceedances: Belgium	0.1502	0.5367	0	3
Coexceedances: Denmark	0.1	0.3544	0	2
Coexceedances: Germany	0.2001	0.6412	0	4
Coexceedances: Spain	0.2001	0.6319	0	4
Coexceedances: France	0.1502	0.5289	0	3
Coexceedances: Greece	0.1502	0.4827	0	3
Coexceedances: Netherlands	0.1	0.3414	0	2
Coexceedances: Italy	0.2503	0.7498	0	5
Coexceedances: Portugal	0.1502	0.4482	0	3
Coexceedances: Switzerland	0.1502	0.4920	0	3
Coexceedances: US	0.4489	1.4184	0	9
Coexceedances: Sweden	0.2001	0.6782	0	4
Coexceedances: UK	0.3503	1.0378	0	7
Sum of Coexceedances	2.6009	6.4651	0	51
N		2869		

Table 13: Summary statistics: Coexceedances by country (bank-specific tails)

Variable	Mean	Std. Dev.	Min.	Max.
Coexceedances: Belgium	0.1506	0.5389	0	3
Coexceedances: Denmark	0.1004	0.3578	0	2
Coexceedances: Germany	0.2008	0.6344	0	4
Coexceedances: Spain	0.2008	0.6278	0	4
Coexceedances: France	0.1506	0.5291	0	3
Coexceedances: Greece	0.1506	0.4993	0	3
Coexceedances: Netherlands	0.1004	0.3428	0	2
Coexceedances: Italy	0.251	0.7747	0	5
Coexceedances: Portugal	0.1506	0.4485	0	3
Coexceedances: Switzerland	0.1506	0.4965	0	3
Coexceedances: US	0.4503	1.437	0	9
Coexceedances: Sweden	0.2008	0.6938	0	4
Coexceedances: UK	0.3513	1.051	0	7
Sum of Coexceedances	2.6086	6.4986	0	51
N		2869		

Table 14: Estimation results: parameters of GARCH(1,1) for local market indices

Parameter	Coefficient	(Std. Err.)
Belgium: β_1	0.140	(0.010)
Belgium: β_2	0.847	(0.010)
Belgium: α	0.000	(0.000)
Denmark: β_1	0.111	(0.009)
Denmark: β_2	0.861	(0.012)
Denmark: α	0.000	(0.000)
Germany: β_1	0.096	(0.008)
Germany: β_2	0.896	(0.009)
Germany: α	0.000	(0.000)
Spain: β_1	0.094	(0.006)
Spain: β_2	0.899	(0.007)

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... table 14 continued

Parameter	**Coefficient**	(Std. Err.)
Spain: α	0.000	(0.000)
France: β_1	0.092	(0.008)
France: β_2	0.901	(0.008)
France: α	0.000	(0.000)
Greece: β_1	0.109	(0.008)
Greece: β_2	0.886	(0.007)
Greece: α	0.000	(0.000)
Netherlands: β_1	0.112	(0.008)
Netherlands: β_2	0.882	(0.009)
Netherlands: α	0.000	(0.000)
Italy: β_1	0.112	(0.008)
Italy: β_2	0.881	(0.008)
Italy: α	0.000	(0.000)
Portugal: β_1	0.123	(0.009)
Portugal: β_2	0.870	(0.009)
Portugal: α	0.000	(0.000)
Switzerland: β_1	0.114	(0.010)
Switzerland: β_2	0.874	(0.010)
Switzerland: α	0.000	(0.000)
US: β_1	0.073	(0.007)
US: β_2	0.921	(0.007)
US: α	0.000	(0.000)
Sweden: β_1	0.096	(0.008)
Sweden: β_2	0.897	(0.009)
Sweden: α	0.000	(0.000)
UK: β_1	0.109	(0.010)
UK: β_2	0.883	(0.010)
UK: α	0.000	(0.000)
Europe: β_1	0.105	(0.009)
Europe: β_2	0.886	(0.010)
Europe: α	0.000	(0.000)
Japan: β_1	0.086	(0.008)
Japan: β_2	0.902	(0.009)
Japan: α	0.000	(0.000)
Emerging M.: β_1	0.111	(0.009)
Emerging M.: β_2	0.866	(0.010)
Emerging M.: α	0.000	(0.000)

Table 15: Estimation results: parameters of GARCH(1,1) for effective exchange rates

Parameter	**Coefficient**	(Std. Err.)
Denmark: β_1	0.067	(0.005)
Denmark: β_2	0.923	(0.005)
Denmark: α	0.000	(0.000)
Euro-area: β_1	0.038	(0.004)
Euro-area: β_2	0.952	(0.004)
Euro-area: α	0.000	(0.000)
Switzerland: β_1	0.070	(0.006)
Switzerland: β_2	0.908	(0.009)
Switzerland: α	0.000	(0.000)
US: β_1	0.035	(0.004)
US: β_2	0.958	(0.006)
US: α	0.000	(0.000)
Sweden: β_1	0.067	(0.007)
Sweden: β_2	0.916	(0.009)
Sweden: α	0.000	(0.000)
UK: β_1	0.035	(0.004)
UK: β_2	0.960	(0.004)
UK: α	0.000	(0.000)

Table 16: Summary statistics of the common factors: Systemic risk, Volatility (multiplied by 100), Term structure and Exchange rate (multiplied by 1000).

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Systemic risk: Belgium	0.2008	0.6372	0	4
Systemic risk: Denmark	0.2008	0.6289	0	4
Systemic risk: Germany	0.2008	0.6339	0	4
Systemic risk: Spain	0.2008	0.641	0	4
Systemic risk: France	0.2008	0.648	0	4
Systemic risk: Greece	0.2008	0.5947	0	4
Systemic risk: Netherlands	0.2008	0.641	0	4

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... table 16 continued

Variable	Mean	Std. Dev.	Min.	Max.
Systemic risk: Italy	0.2008	0.6399	0	4
Systemic risk: Portugal	0.2008	0.6205	0	4
Systemic risk: Switzerland	0.2008	0.6388	0	4
Systemic risk: US	0.1506	0.4815	0	3
Systemic risk: Sweden	0.2008	0.635	0	4
Systemic risk: UK	0.2008	0.6496	0	4
Volatility: Belgium	0.6067	1.4592	0.0002	29.3509
Volatility: Denmark	0.3928	0.9591	0.0001	32.2708
Volatility: Germany	0.6663	1.3511	0.0003	24.5788
Volatility: Europe	0.466	1.0135	0	18.393
Volatility: Spain	0.5454	1.1442	0.0008	19.5505
Volatility: France	0.4999	1.0898	0	20.0112
Volatility: Greece	0.8497	1.6501	0	24.1551
Volatility: Netherlands	0.7260	1.6376	0.0001	23.2209
Volatility: Italy	0.5191	1.1589	0	25.4873
Volatility: Japan	0.5586	1.2889	0.0002	33.6249
Volatility: Portugal	0.4731	1.269	0.0003	31.9253
Volatility: Switzerland	0.5102	1.1542	0.0001	27.8399
Volatility: US	0.3272	0.8444	0	19.056
Volatility: Sweden	0.5629	1.108	0.0003	20.4933
Volatility: UK	0.4064	0.9625	0	18.797
Term structure: Belgium	0	0.0485	-0.4123	0.5831
Term structure: Denmark	-0.0011	0.0659	-0.9830	1.357
Term structure: Germany	-0.0006	0.0447	-0.3423	0.3658
Term structure: Spain	0	0.0689	-0.6424	0.6704
Term structure: France	-0.0001	0.0603	-0.9365	0.9202
Term structure: Greece	0.0033	0.1534	-4.5200	1.9193
Term structure: Netherlands	-0.0004	0.0491	-0.4818	0.3665
Term structure: Italy	0.0007	0.0433	-0.3568	0.384
Term structure: Portugal	0.0001	0.0522	-0.4512	0.5511
Term structure: Switzerland	0	0.0515	-0.5335	0.8486
Term structure: US	0.0006	0.0746	-0.4861	0.7167
Term structure: Sweden	-0.0004	0.051	-0.266	1.027
Term structure: UK	0.001	0.061	-0.3499	0.8177
Exchange rate: Denmark	0.0463	0.2635	0	9.0356
Exchange rate: Euro-area	0.0933	0.1606	0.0001	2.5463
Exchange rate: Switzerland	0.1505	0.3423	0	7.4218
Exchange rate: US	0.1844	0.3399	0.0001	8.1113

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... table 16 continued

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Exchange rate: Sweden	0.2576	0.5448	0.0002	11.3352
Exchange rate: UK	0.1435	0.2932	0.0001	6.3757
N		2869		

Table 17: Country-specific coexceedances

Coexceedances	BE	DK	DE	ES	FR
0	2598	2642	2507	2317	2627
1	176	196	269	415	167
≥ 2	94	30	92	136	74
Coexceedances	GR	NL	IT	PO	CH
0	2655	2559	2543	2608	2487
1	173	272	227	237	273
≥ 2	40	37	98	23	108
Coexceedances	US	SW	UK		
0	1895	2535	2242		
1	605	253	429		
≥ 2	368	80	197		

Table 18: Multinomial Logit: Belgium

	(Model 1) Coexceedances: BE	(Model 2) Coexceedances: BE
1		
Lagged Coexceedances	3.272*** (0.142)	2.757*** (0.109)
Systemic risk: Belgium	0.437*** (0.019)	0.339*** (0.013)
Volatility: Belgium	0.441*** (0.019)	0.370** (0.015)
Volatility: US	0.441*** (0.019)	0.381** (0.015)
Term structure: Belgium	4.253** (0.184)	2.404 (0.095)
Exchange rate: Euro-area	-0.301 (-0.013)	-0.184 (-0.007)
Contagion: DK		0.294 (0.011)
Contagion: DE		0.229 (0.009)
Contagion: ES		-0.427* (-0.0167)
Contagion: FR		-0.00109 (-7E-5)
Contagion: GR		-0.164 (-0.006)
Contagion: NL		0.779** (0.031)
Contagion: IT		-0.0595 (-0.002)
Contagion: PO		0.614*** (0.024)
Contagion: CH		0.166 (0.006)
Contagion: US		0.384** (0.015)
Contagion: SW		-0.148 (-0.006)
Contagion: UK		0.344* (0.014)
Constant	-4.021***	-4.294***
2		
Lagged Coexceedances	5.320*** (0.009)	4.329*** (0.008)
Systemic risk: Belgium	0.578*** (0.001)	0.446** (0.0008)
Volatility: Belgium	0.592*** (0.001)	0.507** (0.0009)
Volatility: US	0.740*** (0.001)	0.471** (0.0008)
Term structure: Belgium	3.579 (0.006)	0.723 (0.001)
Exchange rate: Euro-area	0.0662 (0.0001)	0.0263 (6E-5)
Contagion: DK		0.896 (0.0016)
Contagion: DE		0.301 (0.0005)
Contagion: ES		-0.332 (-0.0006)
Contagion: FR		0.415 (0.0008)
Contagion: GR		-0.168 (-0.0003)
Contagion: NL		0.850** (0.0015)
Contagion: IT		0.143 (0.0002)
Contagion: PO		0.839** (0.0015)
Contagion: CH		-0.0955 (-0.0002)
Contagion: US		0.525* (0.0001)
Contagion: SW		0.238 (0.0004)
Contagion: UK		0.000785 (-2E-5)
Constant	-7.846***	-7.936***
pseudo-R^2	0.539	0.567
ln(L)	-557.0	-522.1

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (robust std. err.). Marginal effects in parentheses.

Table 19: Multinomial Logit: Denmark

	(Model 1) Coexceedances: DK	(Model 2) Coexceedances: DK
1		
Lagged Coexceedances	4.364*** (0.107)	4.200*** (0.099)
Systemic risk: Denmark	0.359** (0.087)	0.287 (0.006)
Volatility: Denmark	0.515*** (0.012)	0.394* (0.009)
Volatility: US	0.135 (0.003)	0.0529 (0.001)
Term structure: Denmark	-1.098 (-0.268)	-1.207 (-0.285)
Exchange rate: Denmark	0.0203 (0.0005)	-0.0508 (-0.0012)
Contagion: BE		-0.172 (-0.004)
Contagion: DE		-0.0263 (-0.0006)
Contagion: ES		-0.308 (-0.0072)
Contagion: FR		0.284 (0.0067)
Contagion: GR		-0.0473 (-0.0011)
Contagion: NL		0.0274 (0.0006)
Contagion: IT		0.406* (0.0096)
Contagion: PO		0.128 (0.003)
Contagion: CH		0.629** (0.0149)
Contagion: US		0.00498 (0.0001)
Contagion: SW		-0.152 (-0.003)
Contagion: UK		-0.0539 (-0.001)
Constant	-4.325***	-4.348***
2		
Lagged Coexceedances	7.469*** (0.00029)	7.029*** (9.45E-6)
Systemic risk: Denmark	0.486 (1.91E-5)	0.228 (3.01E-7)
Volatility: Denmark	1.376*** (5.46E-5)	1.081*** (1.46E-6)
Volatility: US	0.181 (7.13E-6)	-0.0827 (1.15E-7)
Term structure: Denmark	-0.237 (8.38E-7)	-0.618 (8.03E-7)
Exchange rate: Denmark	-4.961 (0.0002)	-4.494 (6.13E-6)
Contagion: BE		1.800 (2.46E-6)
Contagion: DE		0.530 (7.23E-7)
Contagion: ES		-1.571*** (-2.13E-6)
Contagion: FR		-1.407 (-1.93E-6)
Contagion: GR		1.347* (1.84E-6)
Contagion: NL		2.384 (3.25E-6)
Contagion: IT		-0.342 (-4.79E-7)
Contagion: PO		-0.421 (-5.79E-7)
Contagion: CH		-0.967 (-1.34E-6)
Contagion: US		1.803 (2.46E-6)
Contagion: SW		0.657 (9.01E-7)
Contagion: UK		0.447 (6.12E-7)
Constant	-11.15***	-15.02**
pseudo-R^2	0.535	0.559
ln(L)	-362.4	-343.7

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (robust std. err.). Marginal effects in parentheses.

Table 20: Multinomial Logit: Germany

	(Model 1) Coexceedances: DE	(Model 2) Coexceedances: DE
1		
Lagged Coexceedances	4.537*** (0.345)	4.510*** (0.329)
Systemic risk: Germany	0.296** (0.0225)	0.275** (0.0200)
Volatility: Germany	0.189** (0.144)	0.202** (0.0147)
Volatility: US	0.286** (0.217)	0.181 (0.0132)
Term structure: Germany	-2.676 (-0.203)	-2.264 (-0.165)
Exchange rate: Euro-area	0.174 (0.0132)	0.103 (0.0075)
Contagion: BE		0.137 (0.010)
Contagion: DK		-0.649 (-0.0474)
Contagion: ES		-0.0267 (-0.0019)
Contagion: FR		0.0379 (0.0028)
Contagion: GR		0.00213 (0.0001)
Contagion: NL		-0.225 (-0.0164)
Contagion: IT		-0.00641 (-0.0005)
Contagion: PO		0.520** (0.0380)
Contagion: CH		-0.259 (-0.0189)
Contagion: US		0.572*** (0.0418)
Contagion: SW		0.101 (0.0074)
Contagion: UK		-0.0878 (-0.0064)
Constant	-3.680***	-3.776***
2		
Lagged Coexceedances	8.334*** (0.002)	7.696*** (0.002)
Systemic risk: Germany	0.564*** (0.0001)	0.535** (0.0001)
Volatility: Germany	0.498*** (0.0001)	0.491*** (0.0001)
Volatility: US	0.525*** (0.0001)	0.291 (0.0001)
Term structure: Germany	0.377 (0.0002)	0.146 (0.0001)
Exchange rate: Euro-area	-0.515 (-0.0001)	-1.381 (-0.0004)
Contagion: BE		0.844* (0.00025)
Contagion: DK		-0.905 (-0.00025)
Contagion: ES		-0.285 (-8.5E-5)
Contagion: FR		0.680 (0.0002)
Contagion: GR		0.137 (4.11E-5)
Contagion: NL		-0.745 (-0.0002)
Contagion: IT		1.075*** (0.0003)
Contagion: PO		0.951** (0.0003)
Contagion: CH		0.0383 (1.76E-5)
Contagion: US		0.440 (0.0001)
Contagion: SW		-0.932* (-0.0003)
Contagion: UK		-0.140 (-3.98E-5)
Constant	-10.53***	-10.34***
pseudo-R^2	0.600	0.616
ln(L)	-634.7	-609.5

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (robust std. err.). Marginal effects in parentheses.

Table 21: Multinomial Logit: Spain

	(Model 1) Coexceedances: ES	(Model 2) Coexceedances: ES
1		
Lagged Coexceedances	2.814*** (0.140)	2.705*** (0.114)
Systemic risk: Spain	0.558*** (0.0277)	0.578*** (0.0243)
Volatility: Spain	0.608*** (0.0302)	0.634*** (0.0267)
Volatility: US	0.249** (0.0124)	0.303** (0.0128)
Term structure: Spain	-2.553 (-0.128)	-2.084 (-0.0885)
Exchange rate: Euro-area	0.476 (0.0237)	0.622 (0.0263)
Contagion: BE		0.524 (0.0221)
Contagion: DK		-1.174** (-0.05)
Contagion: DE		0.476** (0.0202)
Contagion: FR		0.157 (0.0068)
Contagion: GR		-0.667* (-0.0281)
Contagion: NL		-0.456 (-0.0195)
Contagion: IT		0.530*** (0.0225)
Contagion: PO		0.856*** (0.0362)
Contagion: CH		-0.120 (-0.0052)
Contagion: US		-0.492** (-0.021)
Contagion: SW		-0.165 (-0.0069)
Contagion: UK		0.152 (0.0063)
Constant	-3.978***	-4.220***
2		
Lagged Coexceedances	4.093*** (0.0242)	3.242*** (0.0172)
Systemic risk: Spain	1.034*** (0.0062)	1.051*** (0.0056)
Volatility: Spain	0.956*** (0.0057)	0.853*** (0.0045)
Volatility: US	0.369*** (0.0022)	0.294** (0.0015)
Term structure: Spain	-1.612 (-0.010)	-0.691 (-0.0033)
Exchange rate: Euro-area	0.613 (0.0036)	0.439 (0.0023)
Contagion: BE		0.835** (0.0045)
Contagion: DK		-0.0572 (-2.57E-5)
Contagion: DE		0.0424 (0.0001)
Contagion: FR		-0.300 (-0.0017)
Contagion: GR		-1.102** (-0.0059)
Contagion: NL		0.252 (0.0015)
Contagion: IT		0.304 (0.0015)
Contagion: PO		1.005*** (0.0053)
Contagion: CH		0.432 (0.0024)
Contagion: US		0.0689 (0.0005)
Contagion: SW		-0.630 (-0.0034)
Contagion: UK		0.591** (0.0032)
Constant	-6.706***	-6.884***
pseudo-R^2	0.505	0.546
ln(L)	-668.3	-613.7

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (robust std. err.). Marginal effects in parentheses.

Table 22: Multinomial Logit: France

	(Model 1) Coexceedances: FR	(Model 2) Coexceedances: FR
1		
Lagged Coexceedances	4.988*** (0.132)	4.435*** (0.0957)
Systemic risk: France	0.476*** (0.0126)	0.407** (0.0088)
Volatility: France	0.379** (0.010)	0.253** (0.0054)
Volatility: US	0.303** (0.008)	0.235 (0.0051)
Term structure: France	-0.327 (-0.0086)	-0.256 (-0.0055)
Exchange rate: Euro-area	0.160 (0.0042)	0.179 (0.0039)
Contagion: BE		0.771** (0.0166)
Contagion: DK		0.158 (0.0034)
Contagion: DE		0.219 (0.0047)
Contagion: ES		-0.412 (-0.0089)
Contagion: GR		-0.803 (-0.0173)
Contagion: NL		-0.428 (-0.0092)
Contagion: IT		-0.541 (-0.0117)
Contagion: PO		0.804*** (0.0173)
Contagion: CH		0.491 (0.0106)
Contagion: US		0.465** (0.010)
Contagion: SW		-0.0405 (-0.0008)
Contagion: UK		0.196 (0.0042)
Constant	-4.650***	-4.894***
2		
Lagged Coexceedances	7.281*** (0.0032)	5.585*** (0.0021)
Systemic risk: France	0.890*** (0.0004)	0.783*** (0.0003)
Volatility: France	0.762*** (0.0003)	0.661*** (0.0002)
Volatility: US	0.877*** (0.0004)	0.646** (0.0002)
Term structure: France	-2.968 (-0.0013)	-5.064 (-0.0019)
Exchange rate: Euro-area	-0.498 (-0.0002)	-1.178 (-0.0004)
Contagion: BE		0.554 (0.0002)
Contagion: DK		0.483 (0.0002)
Contagion: DE		0.394 (0.0001)
Contagion: ES		1.103* (0.0004)
Contagion: GR		-0.601 (-0.0002)
Contagion: NL		-0.982 (-0.0004)
Contagion: IT		0.536 (0.0002)
Contagion: PO		0.813** (0.0003)
Contagion: CH		-0.0127 (-8.8E-5)
Contagion: US		0.996*** (0.0004)
Contagion: SW		0.531 (0.0002)
Contagion: UK		-0.307 (-0.0001)
Constant	-9.462***	-9.854***
pseudo-R^2	0.657	0.697
ln(L)	-371.0	-327.9

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (robust std. err.). Marginal effects in parentheses.

Table 23: Multinomial Logit: Greece

	(Model 1) Coexceedances: GR	(Model 2) Coexceedances: GR
1		
Lagged Coexceedances	2.707*** (0.111)	2.582*** (0.100)
Systemic risk: Greece	0.796*** (0.0326)	0.860*** (0.334)
Volatility: Greece	0.181*** (0.0074)	0.196*** (0.0076)
Volatility: US	0.124 (0.0051)	-0.0684 (-0.0026)
Term structure: Greece	0.158 (0.0064)	0.0947 (0.0036)
Exchange rate: Euro-area	-0.637 (-0.0262)	-0.754 (-0.029)
Contagion: BE		0.507** (0.0197)
Contagion: DK		0.575* (0.0223)
Contagion: DE		0.00727 (0.0003)
Contagion: ES		-0.705** (-0.0274)
Contagion: FR		0.148 (0.0057)
Contagion: NL		-0.309 (-0.0120)
Contagion: IT		0.219 (0.0085)
Contagion: PO		-0.0948 (-0.0037)
Contagion: CH		0.451* (0.0176)
Contagion: US		0.192 (0.0074)
Contagion: SW		0.202 (0.0079)
Contagion: UK		-0.212 (-0.0082)
Constant	-3.693***	-3.780***
2		
Lagged Coexceedances	4.002*** (0.0079)	3.467*** (0.0067)
Systemic risk: Greece	1.246*** (0.0024)	1.308*** (0.0025)
Volatility: Greece	0.348*** (0.0007)	0.382*** (0.0007)
Volatility: US	0.143 (0.0003)	-0.115 (-0.0002)
Term structure: Greece	1.327 (0.0027)	1.026 (0.0020)
Exchange rate: Euro-area	0.610 (0.0013)	0.476 (0.0010)
Contagion: BE		0.690* (0.0013)
Contagion: DK		0.985** (0.0019)
Contagion: DE		0.0273 (5.37E-5)
Contagion: ES		-0.166 (-0.0003)
Contagion: FR		1.035* (0.0020)
Contagion: NL		-0.642 (-0.0013)
Contagion: IT		0.387 (0.0008)
Contagion: PO		0.615 (0.0012)
Contagion: CH		-0.225 (-0.0005)
Contagion: US		0.317 (0.0006)
Contagion: SW		-0.0901 (-0.0002)
Contagion: UK		-0.785 (-0.0015)
Constant	-7.240***	-7.343***
pseudo-R^2	0.382	0.410
ln(L)	-612.7	-584.9

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (robust std. err.). Marginal effects in parentheses.

Table 24: Multinomial Logit: Netherlands

	(Model 1) Coexceedances: NL	(Model 2) Coexceedances: NL
1		
Lagged Coexceedances	4.811*** (0.161)	4.312*** (0.142)
Systemic risk: Netherlands	0.730*** (0.0244)	0.657*** (0.0217)
Volatility: Netherlands	0.433*** (0.0145)	0.367*** (0.0121)
Volatility: US	0.302** (0.0101)	-0.0641 (-0.0021)
Term structure: Netherlands	-5.344*** (-0.178)	-6.011*** (-0.199)
Exchange rate: Euro-area	0.508 (0.0169)	0.444 (0.0147)
Contagion: BE		0.787*** (0.0260)
Contagion: DK		-0.0849 (-0.0028)
Contagion: DE		-0.265 (-0.0088)
Contagion: ES		0.260 (0.0086)
Contagion: FR		0.395 (0.0131)
Contagion: GR		0.410 (0.0135)
Contagion: IT		0.461** (0.0152)
Contagion: PO		-0.0331 (-0.0011)
Contagion: CH		0.397 (0.0131)
Contagion: US		0.169 (0.0056)
Contagion: SW		-0.452 (-0.149)
Contagion: UK		-0.115 (-0.0038)
Constant	-4.578***	-4.629***
2		
Lagged Coexceedances	8.463*** (0.0005)	7.547*** (0.0003)
Systemic risk: Netherlands	0.797*** (4.42E-5)	0.597** (2.11E-5)
Volatility: Netherlands	0.535*** (2.97E-5)	0.491*** (1.76E-5)
Volatility: US	0.401** (2.24E-5)	0.0791 (2.98E-6)
Term structure: Netherlands	-4.049 (-0.0002)	-6.854** (-0.0002)
Exchange rate: Euro-area	1.076 (6.05E-5)	1.713** (6.23E-5)
Contagion: BE		-0.436 (-1.7E-5)
Contagion: DK		-0.0435 (-1.49E-6)
Contagion: DE		0.247 (9.38e-6)
Contagion: ES		0.410 (1.47E-5)
Contagion: FR		0.0560 (1.56E-6)
Contagion: GR		0.120 (3.88E-6)
Contagion: IT		0.679 (2.43E-5)
Contagion: PO		0.841** (3.09E-5)
Contagion: CH		1.309** (4.75E-5)
Contagion: US		0.182 (6.47E-6)
Contagion: SW		-0.197 (-6.66E-6)
Contagion: UK		-0.214 (-7.69E-6)
Constant	-11.64***	-12.31***
pseudo-R^2	0.638	0.664
ln(L)	-423.1	-393.0

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (robust std. err.). Marginal effects in parentheses.

Table 25: Multinomial Logit: Italy

	(Model 1) Coexceedances: IT	(Model 2) Coexceedances: IT
1		
Lagged Coexceedances	3.180*** (0.124)	3.100*** (0.114)
Systemic risk: Italy	0.220* (0.0086)	0.182 (0.0067)
Volatility: Italy	0.488*** (0.0190)	0.436*** (0.0160)
Volatility: US	0.0404 (0.0016)	0.0507 (0.0019)
Term structure: Italy	-1.437 (-0.0560)	-1.826 (-0.0671)
Exchange rate: Euro-area	1.441*** (0.0562)	1.533*** (0.0563)
Contagion: BE		0.583** (0.0215)
Contagion: DK		0.152 (0.0055)
Contagion: DE		0.157 (0.0057)
Contagion: ES		0.265 (0.0098)
Contagion: FR		0.275 (0.0101)
Contagion: GR		-0.478 (-0.0176)
Contagion: NL		0.211 (0.0078)
Contagion: PO		0.314 (0.0116)
Contagion: CH		-0.473 (-0.0174)
Contagion: US		-0.151 (-0.0056)
Contagion: SW		-0.423 (-0.0156)
Contagion: UK		0.0726 (0.0027)
Constant	-4.085***	-4.198***
2		
Lagged Coexceedances	5.212*** (0.0092)	4.922*** (0.0096)
Systemic risk: Italy	0.426*** (0.0008)	0.425*** (0.0008)
Volatility: Italy	0.862*** (0.0015)	0.814*** (0.0016)
Volatility: US	0.278 (0.0005)	0.299 (0.0006)
Term structure: Italy	-3.614 (-0.0064)	-3.914 (-0.0077)
Exchange rate: Euro-area	2.778*** (0.0049)	3.085*** (0.0061)
Contagion: BE		0.585 (0.0011)
Contagion: DK		1.302*** (0.0026)
Contagion: DE		0.900*** (0.0018)
Contagion: ES		0.154 (0.0003)
Contagion: FR		0.0710 (0.0001)
Contagion: GR		-0.573 (-0.0011)
Contagion: NL		-0.192 (-0.0004)
Contagion: PO		0.380 (0.0007)
Contagion: CH		-0.758* (-0.0015)
Contagion: US		-0.326 (-0.0006)
Contagion: SW		-0.335 (-0.0006)
Contagion: UK		0.0639 (0.0001)
Constant	-7.951***	-7.964***
pseudo-R^2	0.542	0.559
ln(L)	-526.6	-506.3

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (robust std. err.). Marginal effects in parentheses.

Table 26: Multinomial Logit: Portugal

	(Model 1) Coexceedances: PO	(Model 2) Coexceedances: PO
1		
Lagged Coexceedances	4.004*** (0.158)	3.921*** (0.151)
Systemic risk: Portugal	0.375*** (0.0148)	0.350*** (0.0135)
Volatility: Portugal	0.449*** (0.0178)	0.420*** (0.0162)
Volatility: US	-0.337* (-0.0133)	-0.340 (-0.0131)
Term structure: Portugal	-0.0429 (-0.0016)	-0.266 (-0.0102)
Exchange rate: Euro-area	-0.348 (-0.0137)	-0.339 (-0.0130)
Contagion: BE		-0.191 (-0.0074)
Contagion: DK		-0.110 (-0.0042)
Contagion: DE		0.0557 (0.0022)
Contagion: ES		0.0952 (0.0037)
Contagion: FR		0.246 (0.0095)
Contagion: GR		-0.227 (-0.0088)
Contagion: NL		0.358 (0.0138)
Contagion: IT		0.377* (0.0145)
Contagion: CH		-0.0544 (-0.0021)
Contagion: US		-0.0767 (-0.0030)
Contagion: SW		-0.521 (-0.0201)
Contagion: UK		0.120 (0.0046)
Constant	-3.738***	-3.777***
2		
Lagged Coexceedances	6.789*** (0.0021)	6.512*** (0.0021)
Systemic risk: Portugal	0.0799 (2.08E-5)	-0.00818 (7.34E-6)
Volatility: Portugal	0.722*** (0.0002)	0.690*** (0.0002)
Volatility: US	-0.259 (-7.9E-5)	-0.243 (-7.57E-5)
Term structure: Portugal	-6.347** (-0.0021)	-6.140* (-0.0020)
Exchange rate: Euro-area	-5.124** (-0.0017)	-4.597** (-0.0015)
Contagion: BE		0.630 (0.0002)
Contagion: DK		-0.355 (-0.0001)
Contagion: DE		-0.511 (-0.0002)
Contagion: ES		0.314 (0.0001)
Contagion: FR		0.543 (0.0002)
Contagion: GR		0.00273 (3.91E-6)
Contagion: NL		-0.380 (-0.0001)
Contagion: IT		0.581 (0.0002)
Contagion: CH		0.0918 (3.1E-5)
Contagion: US		0.265 (8.84E-5)
Contagion: SW		-0.633 (-0.0002)
Contagion: UK		-0.430 (-0.0001)
Constant	-8.550***	-8.553***
pseudo-R^2	0.469	0.479
ln(L)	-545.2	-535.4

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (robust std. err.). Marginal effects in parentheses.

Table 27: Multinomial Logit: Switzerland

	(Model 1) Coexceedances: CH	(Model 2) Coexceedances: CH
1		
Lagged Coexceedances	4.074*** (0.142)	3.594*** (0.123)
Systemic risk: Switzerland	0.392** (0.0137)	0.312** (0.0107)
Volatility: Switzerland	0.552*** (0.0193)	0.510*** (0.0175)
Volatility: US	0.455*** (0.0159)	0.414** (0.0142)
Term structure: Switzerland	-3.516* (-0.123)	-3.144 (-0.108)
Exchange rate: Switzerland	0.0502 (0.0018)	0.0180 (0.0006)
Contagion: BE		0.193 (0.0066)
Contagion: DK		0.265 (0.0091)
Contagion: DE		0.682*** (0.0234)
Contagion: ES		0.319 (0.0110)
Contagion: FR		0.282 (0.0097)
Contagion: GR		-0.158 (-0.0054)
Contagion: NL		0.393 (0.0135)
Contagion: IT		-0.402 (-0.0138)
Contagion: PO		0.178 (0.0061)
Contagion: US		-0.0670 (-0.0023)
Contagion: SW		-0.0805 (-0.0027)
Contagion: UK		-0.0534 (-0.0018)
Constant	-4.452***	-4.589***
2		
Lagged Coexceedances	6.958*** (0.0026)	5.828*** (0.0015)
Systemic risk: Switzerland	0.808*** (0.0003)	0.829*** (0.0002)
Volatility: Switzerland	0.864*** (0.0003)	0.858*** (0.0002)
Volatility: US	0.903*** (0.0003)	0.722*** (0.0002)
Term structure: Switzerland	-4.149* (-0.0015)	-3.237 (-0.0008)
Exchange rate: Switzerland	0.0437 (1.58E-5)	-0.126 (-3.33E-5)
Contagion: BE		0.171 (4.32E-5)
Contagion: DK		1.643*** (0.0004)
Contagion: DE		0.445 (0.0001)
Contagion: ES		0.192 (4.77E-5)
Contagion: FR		0.139 (3.4E-5)
Contagion: GR		-0.532 (-0.0001)
Contagion: NL		0.900* (0.0002)
Contagion: IT		-0.578 (-0.0001)
Contagion: PO		1.173** (0.0003)
Contagion: US		0.835** (0.0002)
Contagion: SW		-0.441 (-0.0001)
Contagion: UK		0.278 (7.37E-5)
Constant	-9.869***	-10.59***
pseudo-R^2	0.643	0.667
ln(L)	-425.0	-397.2

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (robust std. err.). Marginal effects in parentheses.

Table 28: Multinomial Logit: US

	(Model 1) Coexceedances: US		(Model 2) Coexceedances: US	
1				
Lagged Coexceedances	2.935***	(0.200)	2.854***	(0.192)
Systemic risk: US	0.383**	(0.0254)	0.361**	(0.0237)
Volatility: US	0.638**	(0.043)	0.543**	(0.0362)
Volatility: Europe	-0.0343	(-0.0027)	-0.140	(-0.0096)
Term structure: US	1.568	(0.109)	1.425	(0.0972)
Exchange rate: US	0.177	(0.0012)	0.132	(0.0089)
Contagion: BE			0.469	(0.0315)
Contagion: DK			-0.524	(-0.0355)
Contagion: DE			0.484**	(0.0328)
Contagion: ES			-0.192	(-0.0129)
Contagion: FR			-0.176	(-0.0125)
Contagion: GR			0.0562	(0.0041)
Contagion: NL			-0.175	(-0.0114)
Contagion: IT			-0.0202	(-0.0015)
Contagion: PO			-0.324	(-0.0224)
Contagion: CH			0.639**	(0.0427)
Contagion: SW			-0.0663	(-0.0044)
Contagion: UK			-0.00221	(-0.0004)
Constant	-3.508***		-3.526***	
2				
Lagged Coexceedances	4.057***	(0.060)	3.774***	(0.0536)
Systemic risk: US	1.037***	(0.0157)	0.951***	(0.0139)
Volatility: US	1.214***	(0.0182)	0.983***	(0.0142)
Volatility: Europe	0.272*	(0.0043)	-0.0139	(-5.04E-5)
Term structure: US	0.434	(0.0049)	0.701	(0.0089)
Exchange rate: US	0.237	(0.0035)	0.112	(0.0015)
Contagion: BE			0.609*	(0.0086)
Contagion: DK			-0.496	(-0.0068)
Contagion: DE			0.445	(0.0062)
Contagion: ES			-0.245	(-0.0035)
Contagion: FR			0.291	(0.0046)
Contagion: GR			-0.201	(-0.0031)
Contagion: NL			-0.560	(-0.0082)
Contagion: IT			0.0674	(0.0010)
Contagion: PO			0.0471	(0.0011)
Contagion: CH			1.088***	(0.0157)
Contagion: SW			-0.150	(-0.0022)
Contagion: UK			0.199	(0.0030)
Constant	-5.787***		-5.778***	
pseudo-R^2	0.497		0.515	
ln(L)	-805.3		-777.7	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (robust std. err.). Marginal effects in parentheses.

Table 29: Multinomial Logit: Sweden

	(Model 1) Coexceedances: SW	(Model 2) Coexceedances: SW
1		
Lagged Coexceedances	1.597*** (0.0597)	1.180*** (0.0408)
Systemic risk: Sweden	0.720*** (0.0270)	0.642*** (0.0222)
Volatility: Sweden	0.247* (0.0092)	0.144 (0.0050)
Volatility: US	0.356** (0.0133)	0.296* (0.0102)
Term structure: Sweden	-2.498* (-0.0937)	-3.370** (-0.117)
Exchange rate: Sweden	0.282** (0.0105)	0.121 (0.0042)
Contagion: BE		-0.0280 (-0.0010)
Contagion: DK		0.297 (0.0102)
Contagion: DE		0.389* (0.0135)
Contagion: ES		0.144 (0.0051)
Contagion: FR		0.284 (0.0099)
Contagion: GR		-0.202 (-0.0071)
Contagion: NL		0.456 (0.0159)
Contagion: IT		0.227 (0.0080)
Contagion: PO		0.176 (0.0062)
Contagion: CH		-0.223 (-0.0078)
Contagion: US		0.220 (0.0076)
Contagion: UK		0.0123 (0.0005)
Constant	-3.871***	-4.052***
2		
Lagged Coexceedances	3.248*** (0.0117)	2.525*** (0.0085)
Systemic risk: Sweden	0.911*** (0.0032)	0.865*** (0.0029)
Volatility: Sweden	0.419*** (0.0015)	0.287** (0.0010)
Volatility: US	0.759*** (0.0027)	0.534*** (0.0018)
Term structure: Sweden	-2.525 (-0.0090)	-4.707*** (-0.0157)
Exchange rate: Sweden	0.469*** (0.0017)	0.339* (0.0011)
Contagion: BE		0.555* (0.0019)
Contagion: DK		1.021* (0.0035)
Contagion: DE		0.110 (0.0003)
Contagion: ES		-0.396 (-0.0014)
Contagion: FR		0.858** (0.0030)
Contagion: GR		0.440 (0.0015)
Contagion: NL		0.178 (0.0006)
Contagion: IT		0.0232 (5.11E-5)
Contagion: PO		-0.421 (-0.0015)
Contagion: CH		0.433 (0.0015)
Contagion: US		0.374 (0.0013)
Contagion: UK		-0.579 (-0.0020)
Constant	-6.758***	-6.840***
pseudo-R^2	0.426	0.463
ln(L)	-579.4	-541.8

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (robust std. err.). Marginal effects in parentheses.

Table 30: Multinomial Logit: UK

	(Model 1) Coexceedances: UK	(Model 2) Coexceedances: UK
1		
Lagged Coexceedances	1.304*** (0.0965)	1.070*** (0.0800)
Systemic risk: UK	0.709*** (0.0529)	0.696*** (0.0520)
Volatility: UK	0.382** (0.0284)	0.293* (0.0221)
Volatility: US	0.791*** (0.0595)	0.659*** (0.499)
Term structure: UK	-1.906 (-0.144)	-1.662 (-0.125)
Exchange rate: UK	-0.627 (-0.0493)	-0.418 (-0.0327)
Contagion: BE		-0.109 (-0.0088)
Contagion: DK		0.642** (0.0485)
Contagion: DE		0.185 (0.0142)
Contagion: ES		0.209 (0.0159)
Contagion: FR		0.225 (0.0168)
Contagion: GR		-0.311 (-0.0237)
Contagion: NL		0.0525 (0.0038)
Contagion: IT		0.271 (0.0205)
Contagion: PO		0.520*** (0.0394)
Contagion: CH		-0.439* (-0.0340)
Contagion: US		0.345*** (0.0255)
Contagion: SW		0.295 (0.0222)
Constant	-3.144***	-3.311***
2		
Lagged Coexceedances	2.711*** (0.0403)	1.806*** (0.0227)
Systemic risk: UK	1.168*** (0.0172)	1.162*** (0.0146)
Volatility: UK	0.697*** (0.103)	0.340* (0.0042)
Volatility: US	0.881*** (0.0126)	0.640*** (0.0077)
Term structure: UK	-1.607 (-0.0224)	-1.986 (-0.0244)
Exchange rate: UK	0.850 (0.0140)	0.587 (0.0082)
Contagion: BE		0.475* (0.0064)
Contagion: DK		0.672 (0.0082)
Contagion: DE		-0.0213 (-0.0005)
Contagion: ES		0.118 (0.0013)
Contagion: FR		0.373 (0.0047)
Contagion: GR		-0.189 (-0.0022)
Contagion: NL		0.209 (0.0027)
Contagion: IT		0.259 (0.0031)
Contagion: PO		0.392 (0.0046)
Contagion: CH		0.230 (0.0035)
Contagion: US		0.892*** (0.0114)
Contagion: SW		0.386 (0.0048)
Constant	-5.607***	-5.889***
pseudo-R^2	0.385	0.426
ln(L)	-957.4	-892.5

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (robust std. err.). Marginal effects in parentheses.

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