Towards a more integrated money market in Europe? A comparison study on bank contagion risk in Europe and in the U.S.A. via extreme dependence of credit default swap spreads.

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May 2009

(Preliminary, comments welcome)

Abstract:

Comparing bank contagion in Europe and in the US could be interesting in a context of banking integration in Europe and huge financial crisis affecting severely banking sector. In order to this, the paper uses bivariate extreme value theory to assess bank contagion through credit default swap spread of 30 biggest banks of the two areas. The analysis is completed by an application of the same framework to stock returns. Results from CDS spreads are quite different from those from stock returns: CDS spreads analysis shows more bank contagion in Europe but stock returns analysis concludes the opposite. Referring to results based on CDS spreads mentioning important cross-border contagion in Europe related to the UK, we think there is a sign of need for a more integrated money market.

Key words: banking, contagion, extreme dependence, extreme value theory, CDS, cross-Atlantic comparison

JEL code: C49, G21, G28

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1. Introduction

The current financial crisis is also a huge crisis in banking sector. Banking system stability is a very important subject to discuss as well as in this crisis context. In Europe, the construction of the single market for financial services in conjunction with the EMU has led to progressing banking integration. It would be interesting to assess banking contagion risk in this context of banking integration.

The theoretical banking literature has focused on contagion among banks via the interbank market. Allen and Gale (2000) show that in a Diamond/Dybvig (1983) liquidity framework an “incomplete” market structure, with only unilateral exposure chains across banks, is the most vulnerable to contagion. In contrast, a “complete” structure, with banks transacting with all other banks, contains less risk of contagion. Hartmann, Straetmans and de Vries (2005) conclude that despite the fact that available balance-sheet data show higher interbank exposure in the euro area, the U.S banking system seems to be more prone to contagion risk. We can think that in a very integrated banking system, interbank liabilities and assets are very diversified across many banks, and shocks would be absorbed more easily.

However, Gropp, Lo Duca and Vesala (2006) show the integrated money market may have resulted in an increase in contagion risk. They find a greater presence of contagion after the euro in euro area, even the contagion to and from the UK. They explain this result by an increased exposure to the common euro area money market. Given this controversy, our study is motivated by an investigation of “more integrated money market, more bank contagion” or “more integrated money market, less bank contagion”. However the question is complex. In an attempt to contribute to the answer, this paper aims to assess the bank contagion in Europe and in the US.

These two areas hold the biggest banks of the world, and in each area a single interbank market[1] exists for banks that trade liquidity. On the one hand, we have European banks of which interbank exposures are higher, and on the other hand US banks that, except the interbank market, can obtain liquidity by another way that is commercial papers. Consequently, comparison of contagion risk in the US and in Europe (Euro area and the UK) could be interesting; unfortunately few studies are made on this point, we can quote Hartmann, Straetmans and de Vries (2005).

Measuring interbank relationships that can be at the origin of bank contagion is a very hard task. Even central banks and supervisory authorities usually do not have continuous information about interbank exposures. A large part of literature uses more indirect market indicators like bank stock prices, Aharony and Swary (1983) and Swary (1986) are the pioneers, Kho, Docking, Hirschey and Jones (1997) show significant contagion effects associated with bank loan-loss reserve announcement on stock prices, Lee and Stulz (2000) study the contagion effects of the LTCM crisis on banking sector via bank stock prices. Some others use banks' distances to default: Gropp and Moerman (2004) measure the banking risk by the first difference of distance to default and abnormal returns. By applying this measure to EU banks, Chan-Lau and Sy (2006) suggest a similar measure called distance to capital that considers capital adequacy threshold and asset volatility. There are also some non market indicators applied to bank contagion studies like bank failures (Grossman (1993) and Hasan and Dwyer (1994)) and survival time (Calomiris and Mason (2000)).

Regarding the methods, in order to measure interbank linkage some papers use (auto)correlation of stock prices and of bank failures or survival time tests controlling for macro variables or event studies. Schoenmaker (1996), De Nicolo and Kwast (2002) and Calomiris and

[1] We note that the UK does not belong to Euro area.

Mason (2000) provide an example. Gropp, Lo Duca and Vesala (2006) use logit models to estimate the number of coexceedances in one country as a function of the number of coexceedances in the other countries, Hartmann, Straetmans and de Vries (2005) use multivariate extreme value theory to analyze cross-Atlantic bank contagion risk. The two last papers focus on extreme distribution to estimate contagion risk. Taking into account the specificity of tail distribution seems necessary to quantify tail dependence as well as the assumption of normality tends to be violated in financial data[1]. In this paper, we adopt also the bivariate extreme value theory for the above reasons to estimate bank contagion.

What is the bank contagion? The paper considers the contagion as the transmission of a shock affecting one bank or a group of banks to other banks or as a common shock affecting all banks simultaneously. In the light of bivariate extreme value theory, we define the contagion as extreme co-movement of two banks, in other words, the extreme dependence of these banks through a given asset or class of assets. Although, there is pure contagion if extreme dependence is greater than normal linkage[2], otherwise we talk about a long term relationship or interdependence.

Unlike Hartmann, Straetmans and de Vries (2005) who analyze banks' stock returns, we choose credit default swap spreads to measure default risk and we calculate extreme dependence of the first difference of daily CDS spreads via extreme value theory to assess bank contagion in recent years. Since its creation, CDS market has experienced a tremendous growth, and CDS is the most liquid credit derivative instrument traded in the over-the-counter market. A CDS seller provides insurance against default risk of a reference entity (company or sovereign). In return for the insurance against default events, the protection buyer makes periodic payments. The annual payment that is expressed as a percentage of the notional value of a contract is called the CDS

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[1] For more details, see for example (Embrechts, Mc Neil and Straumann 1999)
[2] See the concept of shift-contagion proposed by Forbes and Rigobon (2001), and an application of extreme value theory on contagion identification proposed by XU (2009).

spread. By definition, CDS spread is measured in basis point, an increase of CDS spread means a rise of credit risk. It provides a direct measure of credit risk for the underlying reference if the market is liquid. CDS spreads are considered as determinants of default risk as well as related liquidity risk (Hull, Predescu and White (2004)), banks' CDS spreads also provide many information concerning observed default risk in interbank market including the ones observed by peers. We are not aware of any other study that uses CDS spreads to evaluate bank contagion. For comparison, the same method is taken on stock returns which have been used in previous studies on bank contagion and which incorporate different information. In order to distinguish between extreme dependence obtained from CDS spread and the one obtained from stock price, the first one is called credit contagion and the last one called stock contagion. Finally, to complete analysis, for each class of asset, we estimate extreme dependence with a lag of one day in the expectation of capturing some delay effects.

The remaining sections are organized as follows: Section 2 briefly describes our method based on multivariate extreme value theory to measure bank contagion risk. Section 3 presents the dataset. Section 4 discusses the results, and Section 5 concludes.

2. Extreme dependence measure

If one is interested in studying the extreme dependence between two random variables X and Y, this might involve quantities like the joint probability:

$$\lim_{x,y\to\infty} \Pr(X > x, Y > y) \quad (1)$$

Or the conditional probability:

$$\lim_{x,y\to\infty} \Pr(X > x / Y > y) \quad (2)$$

In financial applications, X and Y stand for asset returns, and in the case of this bank contagion risk study, they refer to the first difference of CDS spreads. For multivariate analysis, it is often useful to remove the influence of marginal distributions by transforming the original marginal distribution to ones with a common marginal distribution[1,2]. Poon, Rockinger and Tawn (2004) suggest transforming the bivariate series (X,Y) to unit Fréchet marginals (S,T) using the transformation:

$$S = \frac{-1}{\log F_x(X)} \quad and \quad T = \frac{-1}{\log F_y(Y)} \tag{3}$$

where F_x and F_y are the respective marginal distribution functions for X and Y. Actually, the marginal distribution functions are unknown; we calculate their empirical counterpart to replace them. Since the marginal distribution functions are identical, one natural measure of extreme dependence is

$$\chi = \lim_{s\to\infty} \Pr(T > s / S > s) \quad \text{and} \tag{4}$$

$$\chi = 2 - \lim_{s\to\infty} \frac{\log \Pr(S < s, T < s)}{\log \Pr(S < s)} \tag{5}$$

$\chi = 0$ means the variables are independent; $\chi = 1$ means they are perfectly dependent. Hartmann, Straetmans and de Vries (2004) use χ to study the probability of a co-crash given that one is observed in a market. Counting $E[k \mid k \geq 1]$ where k counts the number of crashes among the two markets is useful. It is straightforward to show that this expectation is equivalent to $\chi + 1$.

However tail dependence is a very special form of extreme dependence. It means that tail realizations of both variables always occur together. For random variables which are

[1] See Ledford and Tawn (1996) and Embrecht, McNeil and Strautman (1999).
[2] If the transformation is strictly increasing, the dependence structure is always the same (it is one of the properties of copula).

asymptotically independent, χ is unable to provide information on relative strength of dependence (Coles, Heffernan and Tawn (1999)) since by definition $\chi = 0$ for these variables[1]. Coles et al. (1999) define a second dependence measure:

$$\bar{\chi} = \lim_{s \to \infty} \frac{2 \log \Pr(S > s)}{\log \Pr(T > s, S > s)} - 1 \qquad (6)$$

$\bar{\chi} \in [-1,1]$ with $\bar{\chi} > 0$, $\bar{\chi} = 0$ and $\bar{\chi} < 0$ describes respectively that the variables are positively associated, independent and negatively associated. In the case of the bivariate Gaussian distribution, $\bar{\chi} = \rho$. $\bar{\chi}$ seems to be a "kind of correlation coefficient" in extreme.

The pair of these two dependence measures $(\chi, \bar{\chi})$ provides complete information regarding the structure of extreme dependence. For asymptotically dependent variables $\bar{\chi} = 1$, their dependence intensity is measured by χ. For asymptotically independent variables $\chi = 0$ and their extreme linkage is measured by $\bar{\chi}$, $\bar{\chi} < 1$.

In summary, in this study we test firstly for (X, Y) if $\bar{\chi} = 1$. If yes, we say that the variables are dependent in extreme, and there is bank contagion; the intensity of extreme dependence is measured by χ. Then we compare $\bar{\chi}$ to correlation coefficient ρ of normal time (part of the distributions excepting extreme). If $\bar{\chi}$ is significantly greater than ρ, we say there is pure contagion because the extreme dependence is not related to a continuity of interdependence in normal time; it reflects a jump of relationship due to crisis. On the contrary, if $\bar{\chi} < 1$, the variables are not dependent in extreme, and there is no bank contagion.

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[1] For exemple all normal variables for which the correlation coefficient $\rho \neq 1$ are asymptotically independent, and $\chi = 0$ (Sibuya (1960)).

To estimate $(\chi, \bar{\chi})$, we define a new variable $Z = \min(S,T)$. Based on the assumption of independent observations on Z, as suggested by Poon, Rockinger and Tawn (2004) the estimators for $\bar{\chi}$ and its variance are as follows:

$$\hat{\bar{\chi}} = \frac{2}{n_u}\left(\sum_{j=1}^{n_u}\log(\frac{z_{(j)}}{u})\right) - 1 \tag{7}$$

$$Var(\hat{\bar{\chi}}) = (\hat{\bar{\chi}}+1)^2 / n_u \tag{8}$$

with asymptotic normality of $\hat{\bar{\chi}}$ ensured by results in Smith (1987). $z_{(1)},...,z_{(n_u)}$ are the n_u observations of the variable Z that exceed u. Notice that all the description of methodology is made on the analysis of largest realizations of (X,Y) in CDS spreads data, and stock returns study concentrates on the smallest realizations[1]. Given the asymptotic normality of $\hat{\bar{\chi}}$, two comparison tests can be carried out: we compare $\hat{\bar{\chi}}$ to 1 in order to determine the extreme dependence of the pair of variables; we can also compare $\hat{\bar{\chi}}$ to ρ calculated over the normal period and conclude if there is pure contagion[2].

Under the constraint $\hat{\bar{\chi}} = 1$, our estimator of χ is:

$$\hat{\chi} = \frac{un_u}{n} \tag{9}$$

The estimators critically depend on the choice of the threshold u or, equivantly, of the number n_u. Basically, the choice involves a trade-off between the bias of the estimator, which gets large when n_u increase as we head towards the center of the distribution, and its variance, which is large when a limited number of observations is chosen. Some authors use ad-hoc values

[1] It is easy to reformulate the problem this way since $\min(z_{(1)},...,z_{(n_u)}) = -\max(-z_{(1)},...,-z_{(n_u)})$.

[2] For each test, a confidence interval of the 95% level is established.

like 5% of the observations (Chan-Lau, Mathieson and Yao (2004)), or advocate the use of heuristic Hill plot method (Hartmann, Straetmans and de Vries (2005; 2004)). More efficient methodologies exist but most of them necessitate a very large number of observations (Danielsson and de Vries (1997)) or need to postulate assumptions on the underlying distribution (Longin and Solnik (2001)). In this paper, we use the threshold selection technique which is developed by Huisman et al. (2001) as it is data-driven and particularly adapted to small sample (in the time series dimension) like ours. It is based on a weighted least-square model of the bias of the estimator[1].

3. Data

Regarding the sample selection, we started with the 30 biggest banks in each area by market capitalization of current year (Bankscope). We check then availability and regularity of CDS spread data of these banks. Finally our dataset is composed by 23 EU banks and 7 US banks[2] which are reported in Table 1.

For these selected banks, we collected daily senior five-year CDS spreads (five-year contracts are the most liquid and constitute over 85% of the entire CDS market). And extreme dependence analysis is carried out from daily first difference of middle spread of these CDS[3].

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[1] In practice, we impose the constraint that tail represents from 1% to 10% of the observations. In average, 5% of distribution is considered as tail. Estimation without constraint leads on average to select 6% of observations of the sample.

[2] We have to take into account the specificity of US banking market where there are few very large international banks and all other small banks. Note that after the last selected bank American Express which has a market capitalization of USD 11 841 million, the capitalization of all other smaller banks is less than USD 4 600 million.

[3] CDS is a class of financial products which is criticized by liquidity lack. However, we believe that CDS of selected banks (large banks) are liquid enough. Daily difference between bid and ask price of these CDS in on average 4 or 5 basis point, except American Express, Natixis, Banco Popular Espanol and Dexia which average daily bid-ask are respectively 6, 8.6, 7.5 and 8.2 bp.

The sample covers the period from January 1, 2004 to May 8, 2009. It includes particularly the current crisis since the summer 2007 subprime crisis. The data of CDS is provided by CMA, a credit information specialist. For the data of daily stock price, we take the stock price of the bank on the market of its home country, so in local money; all the data is provided by Datastream. And then we calculate stock returns as daily variation in percentage of stock prices in order to analyze extreme linkages and risk of contagion.

Extreme value methods, and notably the extreme dependence estimator here adopted, are based on the assumption that the variables are independent. Financial returns are known to exhibit time-series dependence, mostly in terms of heteroskedasticity. Moreover, it has been repeatedly shown that changes in volatility across time might lead to spurious evidence of contagion effects or extreme dependence linkages[1]. In order to remove these effects, we apply GARCH(n,m)[2] filters on raw data before applying extreme dependence estimators. Models are estimated over the full period, assuming a t-Student conditional distribution in order to take into account the skewness and kurtosis of the innovations.

In Table 2 and Table 3, we report descriptive statistics on first difference of CDS spreads and stock returns, respectively. In both cases, we distinguish between raw data and filtered data for GARCH dynamics.

Daily variation of CDS spread is in average positive during the period. For all series the normality is rejected at the 1% level with a very huge excess kurtosis. These distributions could be characterized by a peak near the average and a presence of fat tail. GARCH-filter reduced

[1] See among others, Forbes and Rigobon (2002) or Poon et al. (2004).

[2] (n,m) are chosen in the interest of efficiency and parcimony. For most data, GARCH(1,1) is applied and for the others (n,m) are greater to improve data independency. See table 2 for more details.

considerably autocorrelation and ARCH effect of the data[1]. About stock returns, the average is positive for ones and negative for the others. All returns exhibit high volatility (annualized volatility vary from 25% to 72%) and rejection of normality. After being GARCH-filtered, there is almost no autocorrelation and ARCH effect.

4. Empirical results

In this section, extreme dependence results are reported. We start by presenting analyses of bank contagion from CDS spreads, and then we compare them with the ones from stock returns.

a. CDS spread – credit risk contagion

Having totally 30 banks, we estimate extreme dependence for 435 pairs[2] of banks. Among these pairs, 61 pairs of CDS spreads are dependent in extreme, i.e. 14% of total pairs. We can also say that 14% of linkage of banks during market shock is contagion. And among these contagion cases, 89% of them are characterized by pure contagion because there are 54 pairs whose linkage intensifies significantly in extreme.

Table 4 presents extreme dependence results per area or couple of areas. In the US, 14% of pairs of banks are dependent in extreme but in EU, this part is 21%. The figures show there are more credit contagion cases in Europe than in the US. However, for dependent pairs, in the US, their intensity of dependence seems higher than the European one (the US average of dependence intensity measure χ is higher)[3]. We note that there are few cross-Atlantic credit contagion cases (only 5% of cross-Atlantic pairs of banks).

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[1] We should be content with the result despite there are always 4 autocorrelated series because of lack of adapted GARCH model.

[2] 30*29/2=435

[3] A rigorous statistical test is necessary to confirm it.

In Europe, credit contagion is essentially explained by cross-border contagion that represents about 80% (43/53) of total contagion cases. But it seems that domestic extreme dependence is more important than cross-border extreme dependence when we compare average χ values in the UK, France, Italy and Spain to cross-border ones.

Although, the table shows that the UK plays an important role in credit contagion in Europe as the country is involved in 23 credit contagion pairs out of 53 total cases or 43 cross-border cases since there are 5 British banks out of 23 European banks.

Finally, all the US contagion pairs are related to the pure contagion but in Europe, about 11% (1-47/53) of credit contagion reflects a long term relationship (or interdependence) existing between banks; it is particularly true for the relationship between UK banks and other ones (4 cases of interdependence out of 6 in total).

To have a comprehensive idea on cross-border credit contagion, Table 5 lists number of times banks of a considered country are involved in a credit contagion[1]. The UK, France, Spain and Italy are the countries whose banks are more involved in the contagion, but we do not believe that this is mainly explained by the greater number of these banks in the sample. However, Portugal and Belgium, despite the fact that each country has only one bank in the sample, the number of times banks are involved in the contagion is very important[2]. We note also that Denmark and Sweden seem to be isolated from credit contagion as their banks have never been in an extreme dependence pair.

The same framework between a series of first difference of CDS spread and a series with a one-day-lag can help us to detect existence of some delayed effect of contagion. In technical terms, we look for extreme dependence between a series and another series or itself delayed by

[1] For an extreme dependence pair constituting of two banks of the same country, the calculated number is increased by two.
[2] Note there are BCP (Banco Comercial Portugues) and DEXIA.

one day. For instance, a pair of banks (A, B) matches the series of A to the one-day-later series of B. If their extreme dependence is confirmed, we could interpret it as contagion from A to B. There are consequently 870 possible pairs (30*29). Only 20 contagion cases are identified (it represents only 2% of total pairs), and all these cases are related to pure contagion. Table 6 summarizes some results which include these interesting ones: There are few domestic contagion cases in the US and Europe, few cross-border contagions in Europe; however cross-Atlantic contagion is more significant than in the previous analysis; there are as many contagion cases from the US to Europe as from Europe to the US; and DEXIA is the only bank whose credit extreme movement is dependent with itself with one-day-lag, we say loosely that confidence deterioration calls confidence deterioration, DEXIA is really severely affected by the crisis to be the only one.

b. Stock returns – stock contagion

Some studies employ stock returns to assess bank contagion. After doing our analysis focused on credit risk contagion, we attempt to estimate bank contagion via stock returns in order to complete the previous results. The framework is exactly the same. First, extreme dependence estimation concludes 43 stock contagion cases out of 435 pairs, i.e. 10% of total pairs. Among these contagion cases, only 12 are related to pure contagion (28%). Compared to credit contagion where 89% are pure contagion, stock contagion reflects much more a long term relationship between stock prices. There are many more co-movements in stock prices whatever the market conditions than in CDS spreads which tend to jump together only in poor market conditions.

Table 7 reports extreme dependence results of banks' stock returns. Among US banks' pairs, 33% are dependent in extreme. This part is only 13% in Europe. There are thus more stock contagions in the US. Although, their extreme dependence degree seems higher than European banks' one because the average of χ for US banks is higher[1]. More stock contagion in the US is the most different result than for credit contagion. There are always few cross-Atlantic pairs of contagion. And regarding to domestic contagion in Europe, it represents 16% (5/32) of all stock contagion cases. It is interesting to mention that all pairs of domestic contagion whatever the country (the UK, Spain and the US) are referred to long term relationship (interdependence). As in analysis of credit contagion, stock contagion in Europe is essentially explained by cross-border contagion. Finally, unlike credit contagion, the UK's role played in cross-border contagion is reduced since there 8 cross-border contagion cases involving the UK for a total of 32 contagion cases or 27 cross-border contagion cases in Europe[2]. This role may be fairly shared with Spain, Germany and France or Sweden like shows Table 8. The table indicates also no country is immune from stock contagion despite only one contagion case for Denmark and the Netherlands.

Secondly, a same extreme dependence evaluation with one-day-lag is achieved for 870 pairs of stock returns. There is only a pair knowing contagion, i.e. from a British bank to a French bank. We can say that there is no contagion with one day delayed, this is another difference compared to credit contagion.

5. Conclusion

The paper uses bivariate extreme value theory to estimate extreme dependence through CDS spread variation and stock returns to assess bank contagion. Actually, results in credit contagion and in stock contagion are quite different. These differences are not surprising since CDS spread

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[1] Result has to be confirmed by a rigorous statistical test.
[2] Note that there 5 British banks out of 23 European banks in the sample.

and stock price incorporate different information about the considered entities[1]. Stock price reflects market's expectation on future earnings or losses. But CDS spread of a bank is related to credit risk of the bank (liquidity or solvency), which constitutes the major channel of transmission of bank contagion. As a consequence, we think that the use of CDS spread could help to a better understanding of bank contagion[2].

More precisely, on the one hand, our results obtained from stock prices are consistent with Hartmann, Straetmans and de Vries (2005) which also use stock prices: the US banking system seems to be more prone to contagion risk. On the other hand, our results obtained from CDS spread data show there is more contagion in Europe, and contagion in Europe is rather explained by cross-border contagion involving in many cases the UK. We think this is a signal of need for a more integrated interbank market or money market in Europe since the UK does not belong to Euro area. We also think that less credit contagion in the US[3] could be explained by their unique interbank market and by additional way to finance liquidity, which is commercial paper.

[1] There are of course differences regarding the functioning of stock market and CDS market.
[2] For example, credit contagion is massively related to pure contagion but only a small part of stock contagion is pure contagion. This reflects the specificity of credit contagion which could be informational and where confidence plays a very important role.
[3] Despite of a possible higher degree of extreme dependence which is not confirmed in the paper.

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Table 1: List of banks in the sample

	market capitalization mil USD	country code	bank code
Royal Bank of Scotland Group Plc (The)	117 349	UK (United Kingdom)	ROYAL
HSBC Holdings Plc	101 635	UK	HSBC
UniCredit SpA	91 954	IT (Italy)	UNI
Banco Santander SA	84 967	ES (Spain)	STDR
Barclays Plc	68 923	UK	BARC
Crédit Agricole S.A.	68 415	FR (France)	CA
BNP Paribas	66 424	FR	BNP
Deutsche Bank AG	56 626	DE (Germany)	DBK
Société Générale	48 691	FR	SG
ING Groep NV	38 621	NL (Netherlands)	ING
Banco Bilbao Vizcaya Argentaria SA	37 129	ES	BBVA
Natixis	26 873	FR	NAT
Nordea Bank AB (publ)	24 776	SD (Sweden)	NORDEA
Standard Chartered Plc	21 395	UK	STAN
Danske Bank A/S	18 590	DK (Denmark)	DANSKE
Lloyds Banking Group Plc	14 139	UK	LLOY
Banca Monte dei Paschi di Siena SpA	13 748	IT	BMPS
Svenska Handelsbanken	11 593	SD	SVK
Mediobanca SpA	10 820	IT	MB
Banco Popular Espanol SA	10 436	ES	POP
Banco Comercial Português, SA	8 696	PO (Portugal)	BCP
Dexia	7 819	BE (Belgium)	DEXIA
Deutsche Postbank AG	7 818	DE	DPW
Bank of America Corporation	177 052	US	BAC
JP Morgan Chase & Co.	166 884	US	JPM
Citigroup Inc	150 774	US	CITI
Wells Fargo & Company	99 084	US	WFC
Goldman Sachs Group, Inc	66 012	US	GS
Morgan Stanley	50 831	US	MS
American Express Company	11 841	US	AXP

Table 2: Descriptive statistics on first difference of CDS spreads

	raw											filtered				
	N	Mean	SD	Min	Max	Q(99%)	SK	KU	JB	Q(5)	Q²(5)	SK	KU	JB	Q(5)	Q²(5)
ROYAL	1396	0.1	6.16	-96.3	74.6	15.36	-3.2	86.18	434397	64.01	232.12	0.69	8.89	4706	8.95	2.56
HSBC	1396	0.05	3.45	-29.5	31.7	11.37	-0.04	20.09	23487	33.55	450.01	36	1325.48	102000000	0.01	0
UNI	1396	0.06	4.72	-40.5	50.8	15.61	0.03	25.71	38446	6.57	360.11	1.34	13.51	11031	4.88	1.52
STDR	1396	0.05	4.01	-33	29.8	12.32	-0.39	15.92	14781	79.51	720.41	0.8	8.18	4046	2.34	2.7
BARC	1396	0.1	5.54	-66.2	45.5	14.01	-1.79	36.44	77982	147.57	506.84	1.43	20.48	24867	0.95	0.54
CA	1395	0.06	3.49	-30.8	34	9.8	-0.22	26.53	40922	30.41	486.05	1.72	16.22	15977	9	1.56
BNP	1396	0.04	3.16	-26.3	25.3	10.07	-0.09	18.59	20108	16.18	505.68	-10.29	217.41	2774034	3.17	0.09
DBK	1396	0.06	4.53	-51.8	42	12.71	-0.51	29.27	49905	57.8	341.6	1.92	21.55	27861	3.46	1.42
SG	1396	0.06	3.49	-28.5	33.3	10.82	0.27	19.98	23236	38.64	738.07	0.94	6.99	3046	11.53	2.55
ING	1396	0.05	4.18	-29.4	40	11.73	0.13	24.99	36319	39.81	807.18	18.62	546.81	17472254	1.61	0.02
BBVA	1396	0.05	3.93	-32.3	28.5	11.32	-0.13	17.35	17518	66.79	519.32	1.62	13.63	11421	8.95	20.48
NAT	1396	0.16	7.36	-71.4	79.55	25	0.33	39.86	92448	46.4	186.43	-5.77	138.6	1125090	46.53	41.33
NORDEA	1396	0.05	3.48	-31.1	42.4	9.12	1.52	41.25	99527	45.75	111.07	18.5	391.46	8993127	0.05	0.04
STAN	1039	0.14	5.76	-44.1	37.5	18.18	-1.16	16.4	11884	31.39	392.95	0.17	6.54	1855	9.82	2.36
DANSKE	1383	0.08	4.08	-49.9	95.3	9.42	7.23	244.88	3467461	3.45	0.02	16.87	559.73	18119260	0.01	0.02
LLOY	1396	0.1	4.35	-40.8	41.7	13.02	-0.96	33.91	67120	81.54	582.22	0.49	3.11	618	18.83	2.32
BMPS	1396	0.04	3.76	-28.1	26	12.91	-0.24	13.3	10299	49.82	628.7	2.73	33.89	68555	4.98	0.57
SVK	1396	0.06	2.55	-27.1	35.7	7.81	1.74	69.01	277727	23.19	76.48	14.48	264.79	4126918	0.04	0.1
MB	1396	0.05	3.54	-34.2	40.89	10.7	1.24	46.55	126412	15.52	37.65	6.15	339.55	6715186	0	0.06
POP	1396	0.14	6.1	-73.4	115.22	17.52	3.41	131.34	1006039	15.32	5.18	5.21	203.69	2419577	5.64	0.7
BCP	1396	0.05	3.51	-40	22.6	10.8	-1.41	21.95	28487	56.88	438.44	1.63	27.07	43255	6.9	0.72
DEXIA	1396	0.23	8.25	-125	93.3	22.65	-1.11	74.24	320877	6.16	196.77	-5.62	172.05	1729112	7.3	34.61
DPW	1369	0.01	2.21	-14.8	15.7	7.33	0.39	6.98	2811	25.03	455.34	0.1	7.78	3453	8.5	6.38
BAC	1396	0.12	6.58	-49.48	55.64	21.32	-0.53	25.83	38888	110.83	409.01	0.47	6.02	2156	6.55	7.14
JPM	1396	0.07	5.16	-51.7	48.5	16.13	-0.79	33.02	63555	89.55	314.55	0.87	9.95	5938	12.7	4.14
CITI	1396	0.23	14.13	-242.9	132.5	42.57	-2.83	89.92	472212	44.83	108.66	3.36	57.35	193930	26.08	77.14
WFC	1395	0.08	6.05	-53.4	45.87	20.7	-1.06	28.79	48456	112.23	336.6	0.75	7.17	3119	8.58	2.62
GS	1396	0.1	13.53	-185	176.7	34.11	-1.26	89.55	466830	137.85	967.4	-3.55	78.18	358463	11.08	4.06
MS	1396	0.15	28.24	-655.5	270	36.22	-7.77	243.85	3472787	187.25	104.43	1.65	94.61	521330	86.79	330.63
AXP	1396	0.19	11.71	73.3	240.5	31.58	6.51	140.69	1161139	48.46	52.18	1.03	9.07	5029	4.06	3.32

Notes. Acronyms for various banks are given in the first column (see Table 1 for correspondence). Filtered first difference of CDS spreads are obtained through GARCH(n,m) filters applied on raw data. For NAT, STAN, SVK and BAC, GARCH(2,1) is used; for HSBC, STDR, BARC, DBK, SG, BBVA, NORDEA, DANSKE, POP and WFC, GARCH(1,2) is used; for DEXIA, GARCH(2,3) is used; for GS, GARCH(3,2) is used and finally for the others GARCH(1,1) is sufficient. GARCH models are estimated assuming a t-Student conditional distribution. N is the number of observations. M is the mean, Std the standard deviation, Min the minimum weekly return, Max the maximum weekly return. Q (99%) is the empirical quantile at the 99% risk level, SK is the skewness, KU the excess kurtosis. JB the Jarque-Bera normality-test statistics. Under the null of normality, it is asymptotically distributed according to a χ^2 distribution with two degrees of freedom with critical value equal to 9.21 at the 99% level. Q(5) is the Ljung-Box statistic with five lags applied to first difference of CDS spreads. Under the null of no autocorrelation for orders 1 to 5, it is asymptotically distributed according to a χ^2 distribution with five degrees of freedom with critical value equal to 15.09 at the 99% level. $Q^2(5)$ is the equivalent statistics but applied to squared data.

Table 3: Descriptive statistics on stock returns

	raw											filtered				
	N	Mean	SD	Min	Max	Q(1%)	SK	KU	JB	Q(5)	$Q^2(5)$	SK	KU	JB	Q(5)	$Q^2(5)$
ROYAL	1396	-0.06	4.10	-66.57	35.67	-11.49	-2.59	67,00	259594	36.19	66.19	-0.25	6,00	2307	4.92	4.62
HSBC	1396	0,00	1.91	-18.79	15.52	-6.34	0.17	19,00	21226	12.87	237.26	0,00	3,00	381	2.13	3.64
UNI	1396	-0.02	2.55	-13.11	19.18	-8.41	0.56	12,00	8371	58.23	606.51	-0.1	2,00	275	2.95	0.98
STDR	1396	0.01	2.03	-11.95	14.33	-6.88	0.46	11,00	6638	17.07	391.9	-0.16	1,00	113	5.09	3.43
BARC	1396	0.03	3.91	-24.85	73.24	-10.9	4.93	95,00	529456	12.04	31.86	0.09	2,00	281	7.83	4.35
CA	1396	0.01	2.68	-13.33	26.38	-8.32	0.88	12,00	8494	12.44	228.69	0.12	3,00	574	3.08	0.69
BNP	1396	0.03	2.51	-17.24	20.83	-7.79	0.95	14,00	12349	21.21	226.59	0.05	2,00	160	5.4	7.4
DBK	1396	0,00	2.66	-16.54	24.97	-8.34	1.16	17,00	16831	25.04	317.67	0.11	3,00	544	7.32	2.5
SG	1396	0,00	2.62	-15.54	19.93	-8.32	0.14	9,00	4437	19.04	488.99	0.01	2,00	178	6,00	4.18
ING	1396	0,00	3.37	-27.47	29.21	-11.32	1.14	21,00	26173	6.54	735.28	0,00	1,00	106	7.8	11.7
BBVA	1396	0,00	1.93	-12.79	13.94	-6.29	0.38	9,00	5158	24.4	494.52	-0.05	1,00	73	9.18	6.34
NAT	1396	-0.03	3.14	-16.25	25.45	-10.87	0.69	12,00	8075	7.39	197.77	1.69	16,00	14683	5.45	1.12
NORDEA	1396	0.06	2.29	-11.32	16.1	-6.16	1.02	8,00	4397	20.62	376.54	0.35	2,00	272	11.28	4.72
STAN	1396	0.07	2.83	-15.78	30,00	-8.26	1.19	17,00	16555	14.69	330.72	0.38	2,00	245	5.94	3.14
DANSKE	1396	-0.01	2.09	-15.79	15,00	-6.7	0.15	10,00	5357	42.04	777.64	-0.44	3,00	750	5.89	3.19
LLOY	1396	-0.03	3.83	-33.92	50.77	-12.2	1.03	43,00	105527	33.01	211.25	-0.01	3,00	551	1.89	2.63
BMPS	1396	-0.01	1.77	-11.14	13.19	-4.87	0.08	6,00	2157	4.65	87.98	-0.45	8,00	4033	5.59	0.77
SVK	1396	0.02	2.11	-10.18	14.21	-6.63	0.59	8,00	3812	30.31	398.27	0.08	2,00	308	8.92	1.03
MB	1396	0.01	1.57	-9.55	8.06	-4.41	0.19	4,00	1117	7.87	212.63	0.16	2,00	320	7.12	2.28
POP	1396	-0.01	1.89	-9.58	16,00	-5.98	0.77	10,00	5858	16.55	227.25	0.07	2,00	331	11.57	3.38
BCP	1396	-0.03	1.87	-12.25	11.83	-5.14	0.34	5,00	1653	20.72	130.02	1.31	13,00	10779	8.24	0.45
DEXIA	1396	-0.03	3.23	-29.67	33.68	-10.91	0.7	26,00	40318	28.55	408.5	0.03	2,00	193	3.36	4.78
DPW	1273	0.01	2.74	-23.78	15.22	-8.67	-1.13	14,00	10975	7.98	231.69	-0.1	3,00	467	9.54	1.18
BAC	1396	0.01	4.19	-28.97	35.33	-13.88	1.1	20,00	23980	28.15	354.87	-0.05	2,00	236	1.82	7.11
JPM	1396	0.05	3.18	-20.73	25.09	-9.76	1.2	16,00	14504	28.12	380.22	0.23	2,00	213	2.44	7.19
CITI	1396	-0.08	4.54	-38.99	57.85	-15.45	1.72	36,00	74674	25.46	288.46	-0.06	3,00	396	2.17	1.56
WFC	1396	0.06	3.59	-23.82	32.76	-10.9	2.01	23,00	30636	32.65	170.64	0.81	8,00	4198	14.41	1.05
GS	1396	0.07	2.90	-18.98	26.39	-7.91	1.22	17,00	17459	14.15	224.2	0.22	3,00	425	3.88	7.07
MS	1396	0.05	4.44	-25.89	86.91	-13.05	5.57	113,00	744540	64.52	61.33	0.16	3,00	411	8.14	12.49
AXP	1396	0.01	2.83	-17.6	20.64	-9.09	0.71	12,00	8270	26.81	348.66	0.42	3,00	478	15.98	4.21

Notes. Acronyms for various banks are given in the first column (see Table 1 for correspondence). Returns are multiplied by 100. Filtered stock returns are obtained through GARCH(1,1) filters applied on raw data except MB which needs a GARCH(2,1). GARCH models are estimated assuming a t-Student conditional distribution. N is the number of observations. M is the mean, Std the standard deviation, Min the minimum weekly return, Max the maximum weekly return. Q (1%) is the empirical quantile at the 1% risk level, it is also called VaR at the 1% risk level, SK is the skewness, KU the excess kurtosis. JB the Jarque-Bera normality-test statistics. Under the null of normality, it is asymptotically distributed according to a χ^2 distribution with two degrees of freedom with critical value equal to 9.21 at the 99% level. Q(5) is the Ljung-Box statistic with five lags applied to returns. Under the null of no autocorrelation for orders 1 to 5, it is asymptotically distributed according to a χ^2 distribution with five degrees of freedom with critical value equal to 15.09 at the 99% level. $Q^2(5)$ is the equivalent statistics but applied to squared returns.

Table 4: Credit risk contagion in the US and in EU

	dependent pairs	total pairs	%	pure contagion	M($\overline{\chi}$)	M(χ)
US-US	3	21	14%	3	0.82	0.42
EU-EU	53	253	21%	47	0.78	0.34
US-EU	5	161	3%	4	0.78	0.23
UK-UK	5	10	50%	5	0.78	0.37
FR-FR	3	6	50%	1	0.71	0.36
IT-IT	1	3	33%	1	0.79	0.39
ES-ES	1	3	33%	1	0.76	0.47
EU(i)-EU(j) $i \neq j$	43	231	19%	39	0.79	0.33
UK-EU/UK	23	90	26%	19	0.76	0.31

Note: in the first column, the pair of areas means a pair of banks from those areas. For example, FR-FR means the linkage between a French bank and another French bank; EU(i)-EU(j) $i \neq j$ means the relationship between an European bank of country i and an European bank of another country j; UK-EU/UK means pairs composed of a British bank and an European bank that is not British. The column "dependent pairs" reports the numbers of dependent pairs for considered areas; "total pairs" reports the total number of pairs for considered areas; "%" calculates the percentage of dependent pairs in total pairs; "pure contagion" accounts the number of identified pure contagion of considered areas; the last two columns compute averages of $\overline{\chi}$ and χ for considered dependent pairs.

Table 5: European countries and their involvement in European credit contagion

country	number of considered banks	number of extreme dependence
UK	5	32
France	4	23
Spain	3	17
Italy	3	13
Germany	2	2
Sweden	2	0
Portugal	1	9
Belgium	1	2
Denmark	1	0
Netherlands	1	8

Table 6: Credit risk contagion in the US and in EU (with one-day-lag)

	dependent pairs	total pairs	%	pure contagion	M($\bar{\chi}$)	M(χ)
US-US	1	49	2	1	0.88	0.36
EU-EU	7	529	1	7	0.75	0.25
UK-UK	1	25	4	1	0.6	0.2
BE-BE*	1	1	100	1	0.73	0.27
US-EU	6	161	4	6	0.81	0.3
EU-US	6	161	4	6	0.78	0.27
EU(i)-EU(j) $i \neq j$	5	529	1	5	0.78	0.26
UK-EU/UK	1	90	1	1	0.74	0.24

Note: in the first column, the pair of areas means a pair of banks from those areas. For example, US-US means the linkage between a US bank and another US bank or itself; EU(i)-EU(j) $i \neq j$ means the relationship between an European bank of country i and an European bank of another country j; UK-EU/UK means pairs composed of a British bank and an European bank that is not British. The column "dependent pairs" reports the numbers of dependent pairs for considered areas; "total pairs" reports the total number of pairs for considered areas; "%" calculates the percentage of dependent pairs in total pairs; "pure contagion" accounts the number of identified pure contagion of considered areas; the last two columns compute averages of $\bar{\chi}$ and χ for considered dependent pairs. For all pairs, we use one-day-later data for bank of the second area. BE-BE is the only pair which consists of the same bank, ie DEXIA.

Table 7: Stock contagion in the US and in EU

	dependent pairs	total pairs	%	pure contagion	M($\bar{\chi}$)	M(χ)
US-US	7	21	33	0	0.7	0.42
EU-EU	32	253	13	11	0.65	0.34
US-EU	4	161	2	1	0.57	0.25
UK-UK	2	10	20	0	0.72	0.36
ES-ES	3	3	100	0	0.73	0.55
EU(i)-EU(j) $i \neq j$	27	231	12	11	0.59	0.32
UK-EU/UK	8	90	9	4	0.67	0.33

Note: in the first column, the pair of areas means a pair of banks from those areas. For example, US-US means the linkage between a US bank and another US bank; EU(i)-EU(j) $i \neq j$ means the relationship between an European bank of country i and an European bank of another country j; UK-EU/UK means pairs composed of a British bank and an European bank that is not British. The column "dependent pairs" reports the numbers of dependent pairs for considered areas; "total pairs" reports the total number of pairs for considered areas; "%" calculates the percentage of dependent pairs in total pairs; "pure contagion" accounts the number of identified pure contagion of considered areas; the last two columns compute averages of $\bar{\chi}$ and χ for considered dependent pairs.

Table 8: European countries and their involvement in European stock contagion

country	number of considered banks	number of extreme dependence
UK	5	12
France	4	7
Spain	3	15
Italy	3	6
Germany	2	11
Sweden	2	6
Portugal	1	3
Belgium	1	2
Denmark	1	1
Netherlands	1	1