Bank Fragility and Contagion: Evidence from the CDS market

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Abstract
This paper provides an evaluation of contagion among banks and banking sectors in different countries and regions during a period of prolonged financial distress. Using banks CDS spreads as an indicator of bank risk, we investigate contagion in banking markets during the period January 2004 to March 2013. Following a Generalised VAR (GVAR) approach, we distinguish between two types of contagion: systematic contagion (linked to global factors), and idiosyncratic contagion (linked to bank specific factors). While the overall contagion was driven by the systematic component during the global financial crisis, with US banks being net transmitters, the idiosyncratic component becomes more relevant during the Eurozone crisis. US banks are not receiving instability from Eurozone banks. Banks in EU peripheral countries are net transmitters of idiosyncratic contagion whereas banks in Euro-Core countries are net transmitters of systematic contagion.

Keywords: CDS spreads, large financial institutions, financial stability, financial crisis
JEL classification: G15, G21, C58

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1. Introduction

The on-going turmoil in the world financial systems, which started with the 2007 US sub-prime crisis and spread to most large financial institutions, has spurred a new debate on bank fragility and contagion. This has been compounded by the recent sovereign crisis in the Eurozone, which started with the Greek announcement of a revised deficit-to-GDP ratio in 2009. Since then, the development of the European sovereign debt crisis has placed an increased emphasis on the link between bank and country risk. This resulted in a new examination of the too-big-to-fail hypothesis, which argues that large banks benefit from implicit bail-out guarantees. As the Eurozone crisis evolved, governments were increasingly seen as unable to bail out their large banks as a countries' public finances would have not be sufficient to cover large banks' potential losses. As a consequence, European Union (EU) financial institutions became too-big-to-save. Since the start of the Eurozone crisis in 2009, Eurozone countries with the weakest public finances (also known as the GIIPS countries, Greece, Ireland, Italy, Portugal and Spain) also fell victims of speculative attacks by financial markets, indicating that their increased vulnerability was linked to a country's credibility rather than to fundamentals.

Whether it was speculative attacks or weak fundamentals, the fear of financial contagion within the Eurozone prompted the ECB to carry out a series of non-conventional measures to ensure the stability of the euro. Because of their central role in the transmission of policy interest rate decisions, the ECB's non-standard response to the crisis has been primarily focused on banks.[3] Despite these measures, in late 2011 the Eurozone crisis intensified and the euro area banking system came increasingly under pressure, as the adverse interaction between sovereigns and banks deepened, mainly via banks' portfolio exposure to weakened foreign sovereign bonds. In this context, the ECB policies were aimed at stopping this downward spiral or contagion.

Although a very intuitive concept, "contagion" is difficult to define. Financial institutions are highly interconnected through a network composed by the interbank market, the payment system, the financial markets and so on. Similarly, economies are interconnected through financial and trade linkages. The increased globalization of trade and markets has strengthened these linkages, which are also described as spillovers of

[3] For a discussion of the ECB's key policy measures, see Cour-Thimann and Winkler (2013).

channels of interdependence. In the first instance, contagion can be defined as the transmission of shocks over and above what is expected by the interdependence described above. Dornbusch, Park and Cleassen (2000), Kaminsky, Reinhart and Vegh (2003), Bae, Karolyi and Stulz (2003) and Longstaff (2010), among others, define contagion as an episode in which there is a significant increase in cross-market linkages when a shock occurs. According to Forbes and Rigobon (2002) when two markets exhibit a high degree of co-movement during stable periods, and these co-movements do not increase significantly after a shock, then it is interdependence rather than contagion. Bekaert et al (2011) define contagion as the co-movement in excess of what can be explained by fundamentals taking into account their evolution over time.

A common approach to measure contagion is the analysis of correlation coefficients across markets or assets returns and an increase in correlation is seen as evidence of contagion. Pericoli and Sbracia (2003) review different definitions and related measures of contagion that are frequently used in the literature, including changes in the probability of currency crises; volatility spillovers (commonly based on the estimation of multivariate GARCH models); Markov-switching models to test for jumps between multiple equilibria; correlation or co-movements in financial markets and changes in the transmission mechanism, that is when a country-specific shock becomes global. All methodologies have limitations and a number of caveats often apply.

In this study, we contribute to the current literature by analysing contagion in banking markets during the period January 2004 to March 2013. This time period allows us to investigate both the period prior to the 2007-2009 financial crisis, the financial crisis period, and the subsequent EU sovereign crisis period, therefore enabling us to observe contagion during a number of "phases" of market instability. We differ from the existing literature in that we focus exclusively on contagion in the banking sector. We therefore attempt to bring together the literature on contagion and the literature on systemic risk. In this paper, we define contagion as the change in the propagation mechanism when a shock occurs and we measure it in terms of return spillovers. In addition, we improve on current studies by distinguishing between two types of contagion, systematic contagion (linked to global factors), and idiosyncratic contagion (linked to bank specific factors). Following recent literature, we use Credit

Default Swaps (CDS) spreads as an indicator of bank risk.[4] A country's systematic risk can be seen as increasing when there is a uniform reaction of the banks' risk profiles, following a common shock (that is a uniform increase in CDS spread across all systemically important banks in a country).

The methodological approach follows a two-stage procedure. In the first stage, we identify common patterns from individual bank CDS returns (estimated following Berndt and Obreja, 2010). To extract the common factors underlying the correlations among the CDS returns series of individual banks, we use principal components analysis (PCA) over the sample period, using 200-day rolling windows. We then decompose the change in CDS returns into a common or systematic component and an idiosyncratic component. In a further step, we build four equally weighted portfolios of CDS returns. We distinguish among banks headquartered in the following geographical areas: US; "Eurozone core" (i.e. Austria, Belgium, France Germany and Netherlands); "Eurozone peripheral" (Greece, Italy, Portugal and Spain) and finally, non-Eurozone (Denmark, Norway, Sweden, Switzerland and UK). The use of portfolios provides an efficient way to summarize all the information included in individual bank CDS returns, with the advantage of smoothing the noise presents in the data, mainly due to transitory shocks in individual companies.

Following a Generalized VAR (GVAR) approach (Diebold and Yilmaz, 2012) we estimate contagion, in terms of return spillovers, between banks CDS returns portfolios. We estimate contagion for both the total and the idiosyncratic CDS returns, and the difference between the two can be interpreted as systematic contagion.

As a way of preview, our main results are as follows. The proportion of variance of banks' CDS returns series explained by common factors changes considerably during the sample period. Up until mid-2007, banks' CDS returns exhibited a limited amount of co-movement, and the contribution of common factors was limited. The picture changed after July 2007, with the results indicating an increasing amount of commonality in banks' CDS returns. These changes in the co-movement dynamics can be interpreted as first evidence of contagion.

This outcome is confirmed by the results of the G-VAR estimations, which evidence systematic contagion across markets during the global financial crisis (2007-

[4] A CDS is essentially an insurance contract against a credit event of a specific reference entity. The CDS spread is the periodic rate that a protection buyer pays on the notional amount to the protection seller for transferring the risk of a credit event for some period. Since late 2008, the CDS market has attracted considerable attention and CDS are considered a good proxy for bank riskiness and default probability.

2009) and subsequent Eurozone crisis (from 2009). Prior to 2007, total return spillovers were low and mostly idiosyncratic in nature. From July 2007 onwards, the total spillover index climbed from 10% to around 60%. While the increase can be attributed to both the idiosyncratic and systematic components, at the height of the financial crisis contagion seem to be overwhelmingly driven by the systematic component. While the idiosyncratic component would quickly return to previous level following a shock; the systematic component would remain high thereby causing the total spillover index to remain high. This seems to indicate that between 2007 and 2009 contagion happened and was mainly due to common components, i.e. to systematic risk. The picture changed during the euro-crisis, as the impact of the idiosyncratic component became more pronounced. Similarly to previous trends, idiosyncratic shocks triggered a sharp temporary increase in the idiosyncratic contagion index, which then translated in the systematic contagion index remaining high for longer periods of time.

In summary, we find evidence of contagion in banking markets, evidenced by an increase in co-movement in CDS returns. Contagion came in different waves, from July 2007 onwards, with the financial and euro-zone crisis being distinct episodes. While during the financial crisis contagion was systematic in nature, during the Eurozone crisis the idiosyncratic part played a more dominant role.

The examination of net directional return spillover measures enables us to identify group of banks in countries that can be seen as net transmitters and receivers of contagion. US banks appear to be net transmitters, particularly during the 2007-2009 period, with all EU countries being net receivers. Unsurprisingly, during the Euro-zone crisis, banks in "Eurozone peripheral" countries were net transmitters in terms of idiosyncratic spillovers (particularly from May 2010 onwards). Eurozone troubles are barely affecting US banks, and only "Eurozone core" and "non-Eurozone" countries' banks appear to be net receivers, with the latter group receiving more contagion than the “Eurozone core”. Interestingly, the role of net transmitters of systematic contagion belongs to banks in "Eurozone core" countries with the "Eurozone peripheral" being net receivers, particularly in the latter stages of the crisis and during the Cyprus episode. This suggests that banks in "Eurozone peripheral" countries are still perceived as extremely fragile as they are seen as transmitter of idiosyncratic contagion and as receivers of systematic contagion. The differences in vulnerability to contagion within the European Union and even within the Eurozone are remarkable, with the Eurozone periphery more exposed to systematic contagion.

The remainder of the paper is organised as follows. Section 2 describes the data and preliminary analysis. Section 3 discussed the methodological approaches. Section 4 presents the results while section 5 concludes.

2. Data and Preliminary Analysis

The data set consists of daily CDS spreads for the largest banks in Europe and US, collected from the Thomson Datastream database and provided by CMA New York.[5] The CDS spread shows the 5-year CDS premium mid expressed in basis points. Following Jorion and Zhang (2007) and Eichengreen et al. (2012), among others, we select 5-year CDS quotes, since these contracts are generally considered the most liquid and constitute the majority of the entire CDS market.

The sample period covers almost a decade, from January 2004 to March 2013.[6] This relatively long time period allows us to investigate both a more stable period (i.e. the pre-crisis period, from January 2004 to June 2007); the global financial crisis period (July 2007 - September 2009) and the on-going European sovereign debt crisis period (October 2009 - March 2013).

Our sample comprises only banks with the largest total assets in each country, as only large banks are actively trading CDS and because we are interested in the role of large financial institutions (LFIs) in the transmission of contagion.[7] Our sample is therefore composed of 55 large banks, headquartered in 15 countries (50 European banks and 5 US banks). More specifically, this results in 122,984 (unbalanced) panel observations for 2,407 days. Table 1 illustrates the sample banks, the available number of observations and the total assets value for each bank.

<Insert Table 1 around here>

As pointed out by Berndt and Obreja (2010), main difficulty in constructing CDS returns is that there is no time series data on actual transaction prices for a specific

[5] Mayordomo, Peña and Swartz (2013) conclude that among the six most widely used CDS data bases CMA is the data source leading the others.
[6] Although data on CDS spreads are available from January 2003, only a very small number of banks (around 18% of the banks in the sample) traded in CDS during 2003, while the majority of banks in our sample started to take part in CDS activities after 2004.
[7] The decision to focus on the banking sector limits the sample size, since only a relatively small number of big banks are involved in CDS activities. Our sample is in line with recent literature, see and Ashraf et.al, 2007; Eichengreen et al, 2012; Chiaramonte and Casu, 2013.

default swap contract. Using daily CDS spreads we first calculate CDS returns, i.e., following the intuitive framework proposed by Berndt and Obreja (2010), using a strategy that replicates the payoff of the contract.[8] CDS returns computed this way capture the change in default risk due to increments in CDS spreads. In addition, CDS returns also incorporate, among other things, the level of CDS spreads in the probability of default. One additional advantage of using CDS returns is that it allows us to obtain stationary returns series.

In a next step, we build four equally weighted portfolios, using average CDS data for each bank headquartered in a country within a specific area. The first portfolio consists of banks headquartered in Greece, Italy, Portugal and Spain. We define this portfolio as Euro-Peripheral, as it includes banks in countries with the more severe debt problems within the Eurozone. The second portfolio consists of banks headquartered in the so-called euro-core countries (Austria, Belgium, France Germany and Netherlands); we label this portfolio as Euro-Core. The third portfolio comprises banks from countries within the European Union but outside the Eurozone (Denmark, Norway, Sweden, Switzerland and the UK); we label this portfolio Non-Euro. Finally, our fourth portfolio consists of US banks.

<Insert Table 2 about here>

Figure 1 illustrates the daily time evolution of CDS spread and return series for the four portfolios; descriptive statistics are reported in Table 2. It can be easily seen that on July 2007 CDS spread started to increase dramatically, both in level and volatility. CDS spreads were relatively stable, at around 16 bps (and this is fairly homogeneous regardless of the country), until July 2007, when they started to grow considerably, mainly for US banks, in response to the sub-prime crisis. In March 2009, CDS spreads peaked at over 216 bps for Euro-Peripheral; 274 bps for Euro-Core; 228 bps for Non-Euro and 338 bps for US banks respectively. Note that all the banks in the sample experienced positive CDS returns (on average) during the pre-crisis period, whereas throughout the global financial crisis returns became negative on average. This may suggests that during periods of instability CDS spreads are not fully explained by banks' credit risk (default component), but are also driven by the overall market

[8] See Appendix A for methodological details.

situation (common global component). For US banks, negative average returns were around 50% lower than CDS returns for European banks. Outside the US, countries whose banks were the most affected by the global financial crisis were Belgium, Greece and Spain. With hindsight, this can be seen as a prelude to the trouble their bank faced in more recent times.

<Insert Figure 1 about here>

In months following the peak of the sub-prime crisis, the level of CDS spreads for US and European banks began to fall, but still remained higher compared to the pre-crisis period. After December 2009, substantial differences can be evidenced between US and EU banks in terms of CDS spreads. In the US, CDS spreads peaked in March 2009, at over 338 bps (increasing by 600% in means). The trend then reverted reaching a minimum in December 2009 and spreads have remained fairly stable since. Indeed, in the period, 2009-2013 US banks CDS spreads stabilised at values below those seen previously but higher than pre-crisis period values. In Europe, however, the recovery phase was short lived and turmoil persisted during the 2009-2013 period. For Eurozone banks, CDS spreads started increasing gradually during the last quarter of 2009 and displayed record peaks in November 2011 and then again in May 2012. It is during this period that the differences between US and EU banks CDS spreads became more evident, thus indicating that, while EU banks were badly affected by the sub-prime crisis, US banks are relatively immune to Eurozone banks' troubles. Indeed, US banks are the only banks with positive average CDS returns during the most recent part of our sample period.

During the most recent part of our sample period, differences also become apparent between EU banks. Specifically, banks from Euro-Peripheral countries exhibit larger increase in CDS spreads. This was driven by increased spreads on bank CDS from Greece (up to a peak of 4,191 bps), Portugal (with a peak of 1,484 bps) and, to a lesser degree, Spain (peak 770 bps), Belgium (peak 709 bps) and Italy (peak 695 bps). These exceptionally high values are linked to national debt crisis. In contrast, CDS spreads for German and UK banks barely rose during the same time period. In addition, banks from countries outside the Eurozone showed, on average, lower levels and volatility compared to the CDS spread curve for their Eurozone counterparts.

3. Empirical methodology

Using CDS spreads as an indicator of bank fragility, we analyse the contagion effect among banks over time. We define contagion as the change in the propagation mechanism when a shock occurs and we measure it in terms of return spillovers. In addition, we distinguish between two types of contagion, systematic contagion, linked to global factors, and idiosyncratic contagion, due to bank specific factors.

The methodology follows a two-stage empirical procedure.

3.1. First stage: Identification of common patterns

The first step of the analysis consist of the identification of common factors in bank CDS spreads. Principal component analysis (PCA) allows us to extract the common factors that can satisfactorily explain the correlations over time among the returns series in order to determine idiosyncratic bank CDS returns.

Let Y be the $T \times k$ CDS returns data matrix, where T is the sample size and k is the number of banks considered in the analysis. We project the data matrix on a d-dimensional plane of the form

$$Y = PC \cdot W' + \upsilon \qquad (1)$$

where the columns of the $k \times d$ matrix W are d eigenvectors corresponding to the largest d eigenvalues of the correlation matrix YY'/T, the columns of the $T \times d$ matrix PC are the first d principal components, while the resulting residuals are gathered in the columns of the $T \times k$ matrix υ.

Throughout this analysis, bank CDS returns series are decomposed in two non-observable components, the common and the residual component, that is, the idiosyncratic bank CDS return. Using these residuals we construct the same four portfolios sorted by geographical zones as in the previous section. This way, we have the idiosyncratic CDS returns of the four portfolios in addition to their total CDS returns. This enables us to study contagion, in the next step, in terms of return spillovers, both for the total and the idiosyncratic CDS returns portfolios. The difference between the two components can be interpreted as systematic contagion.

If the CDS returns for individual banks are not correlated, then we can assume that the risk of failure of a bank is related to bank-specific factors. On the other hand, if there is an increasing amount of co-movement, then we can assume that all banks are exposed to a common (systematic) risk.

In addition to that, PCA provides us with a measure of the percentage of variance explained by each principal component, which is computed as the ratio between the d eigenvalues divided by the sum of all eigenvalues. Moreover, if we observe a significant increase in cross-market co-movements around the sample period this can be considered as an indicator that contagion has occurred.[9]

3.2. Second stage: Return spillover estimation

The return spillover effects are obtained following the Generalized Vector Autoregressive framework (GVAR) methodology developed by Diebold and Yilmaz (2009, 2012), which is a VAR-based spillover index particularly suited for the investigation of systems of highly interdependent variables. Spillovers are measured from a particular variance decomposition associated with an *N*-variable vector autoregression framework, which allow us to parse the forecast error variances of each variable into parts which are attributable to the various system shocks. The major advantage of this approach is that it eliminates the possible dependence of the results on ordering in contrast to the traditional Cholesky factorization.[10] In addition to that, it includes directional contagion indicator from/to a particular series, not only the total spillovers.

More specifically, this approach consists of two steps. First, we consider a covariance stationary N-variable VAR(p)

$$x_t = \sum_{i=1}^{p} \phi_i \, x_{t-i} + \varepsilon_t \qquad (2)$$

[9] See Gentile and Giordano (2012) and Andernmatten and Brill (2011), among others.
[10] This problem is circumvented by exploiting the generalized VAR framework of Koop, Pesaran and Potter (1996) and Pesaran and Shin (1998), among others.

where $\varepsilon \sim (0, \Sigma)$ is a vector of independently and identically distributed disturbances and x_t denotes a *N*-variable vector of CDS returns. In particular, since the analysis is performed twice, x_t will be first, the total and second, the idiosyncratic CDS returns of the four portfolios previously built. To ease the analysis the model is written as the moving average representation $x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$, where the $N \times N$ coefficient matrices are estimated by $A_i = \phi_1 A_{i-1} + \phi_2 A_{i-2} + \dots + \phi_p A_{i-p}$, with A_0 being the identity matrix and $A_i = 0$ for $i < 0$.

Next, we calculate the variance decompositions. The variance shares defined as the fractions of the *H*-step-ahead error variances in forecasting x_i that are due to shocks to x_j, for $H = 1,2, \dots$, are given by

$$\theta_{j \to i}^{G}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)}, \text{ for } i, j = 1,2, \dots, N \tag{3}$$

where σ_{jj} is the standard deviation of the error term for the j^{th} equation, i.e. the squared root of the diagonal elements of the variance-covariance matrix Σ and e_i is the vector with one as the i^{th} element and zeros otherwise. As the shocks to each variable are not orthogonalized, the row sum of the variance decomposition is not equal to 1. Thus, each entry of the variance decomposition matrix can be normalized by the row sum as

$$\tilde{\theta}_{j \to i}^{G}(H) = \frac{\theta_{j \to i}^{G}(H)}{\sum_{j=1}^{N} \theta_{j \to i}^{G}(H)} \times 100, \text{ for } i, j = 1,2, \dots, N \tag{4}$$

where the multiplication by 100 is just to have it in percentage terms. Note that, by construction $\sum_{j=1}^{N} \tilde{\theta}_{j \to i}^{G}(H) = 100$ and $\sum_{i,j=1}^{N} \tilde{\theta}_{j \to i}^{G}(H) = N \times 100$.

Note that return spillovers show the degree of variation in CDS returns of portfolio *i* which is not due to the historical information of the CDS returns of portfolios *i* and *j* but to shocks (innovations) in CDS returns of portfolio *j*. This indicator takes higher values as the intensity of the contagion effect, caused by the specific shocks of *i*'s CDS returns, increases. In the extreme case in which there are no spillovers from one series to the other, the indicator is equal to zero.

Using the above normalized variance contributions we can then construct some different spillover measures. The *total return spillover* index, which measures the contribution of spillovers of return shocks across all N series to the total forecast error variance is given by:

$$TS^{G}(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{j \to i}^{G}(H)}{N} \tag{5}$$

It indicates on average the percentage of the forecast error variance in all the series that comes from spillovers (from contagion due to shocks).

The *net directional return spillover* indices measure the spillover transmitted by portfolio *i* to all others

$$NDS_{i \to all}^{G}(H) = \sum_{\substack{j=1 \\ i \neq j}}^{N} \tilde{\theta}_{i \to j}^{G}(H) - \sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{j \to i}^{G}(H), \text{ for } i = 1,2,\dots,N \tag{6}$$

It is simply the difference between the gross return shocks transmitted by *i* to all other portfolios and those received by *i* from all other portfolios. Positive (negative) values of the NDS index indicate that portfolio *i* is a transmitter (receiver) of return spillover effects, in net terms.

Finally, the *net pairwise return spillover* indices between series *i* and *j* are defined as

$$NPS_{i \to j}^{G}(H) = \tilde{\theta}_{i \to j}^{G}(H) - \tilde{\theta}_{j \to i}^{G}(H), \text{ for } i,j = 1,2,\dots,N \tag{7}$$

It is simply the difference between the gross return shocks transmitted from *i* to *j* and those transmitted from *j* to *i*. Hence, it is positive (negative) when the impact of *i*'s shocks is higher (lower) than vice versa, indicating that portfolio *i* is net transmitter (receiver) of return spillovers to (from) portfolio *j*.

4. Empirical results

4.1 Common factors in bank CDS returns

The first step to understand contagion is to explore the pair-wise correlations between the returns of CDS spreads for banks in the sample. A preliminary correlation analysis indicates that the pair-wise correlations between the bank CDS returns is high, not only among banks for the same country, but also among different countries.[11] Given this result, it is necessary to explore bank CDS returns co-movements over time in more detail. To do so, we perform a PCA with a rolling sample framework using 200-day rolling windows.

<Insert Figure 2 about here>

Figure 2 plots the time evolution of the proportion of variance explained by the first four principal components[12] of bank CDS returns series[13]. The analysis shows that the contribution of the common factors to the total variation in CDS returns change largely through the sample. Before mid-2007, the proportion of variability due to common factors was around 10% and 40% (with an increasing trend). On average, in tranquil periods, bank CDS returns exhibited a limited amount of co-movement. The first four factors explained on average the 33% of the total variance of the returns, thus suggesting that during stable periods bank credit risk may be mainly linked to bank fundamentals and not be driven by global macroeconomic factors.

The picture changed after the onset of the sub-prime crisis on July 2007. The co-movements in CDS returns increased significantly, fluctuating between 40% and 70%. After July 2007, the contribution of the first four components doubled and the percentage of total variance explained by the four components became, on average the 44%, 50%, 56% and 60% respectively. These results indicate that common factors play an important role in bank CDS market during periods of financial distress. It is possible to identify significant events in financial markets' recent years and observe the corresponding increase in co-movement in CDS returns.

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[11] Not shown, available upon request.

[12] The fifth principal component individually explains less than 4 percent of the variance. Thus, the rolling PCA is based on the first four principal components.

[13] In order to check the potential presence of serial correlation in bank CDS returns correlation matrix we have filtered for autocorrelation and the results are the same and available upon request.

In the period between January 2007 and March 2008, the portion of variance explained by the first four components jumped from 30% to 63% (increasing by 110%). During this period we observe three main peaks. On August 2007 the co-movement increased quickly up to 58%; in January 2008 co-movement increased to 62%, and in March 2008 (at the time of the Bear Stearns troubles) co-movements in CDS returns rose to 64%. Following the Bearn Stearns rescue, the percentage of variance explained by common components remained high, at 50-60%. Following the Lehman Brothers failure, the increase of co-movements became even more evident. Further increases in co-movement were related to episodes of the Eurozone sovereign debt crisis. For example, in May 2010, at the time of the Greek bailout, we observe the highest share of explained variance accounted by principal components: it reached 73%, and remained very high until February 2011.

In summary, the results of the PCA indicate that there is a significant amount of commonality in CDS returns across all the 55 banks. These results are consistent with the idea that during periods of international financial crises, correlations between assets and markets are higher and this is often a key element in the underestimation of risk in stress periods. Changes in the co-movements dynamics among financial institutions' CDS returns that are in excess of analyst expectations can be seen as signals of contagion.

4.2: Return spillovers

Once we have established high co-movements in bank CDS returns, the next step is then to evaluate if contagion occurred. We measure the spillover effects using the variance decomposition approach of Diebold and Yilmaz (2012). We produce spillover measures using a 200-day rolling samples and assess the variation over time via the corresponding time series of spillover indices. The model is estimated twice, for total and idiosyncratic CDS returns of the four portfolios built previously (US; Euro-Peripheral; Euro-Core and Non-Euro). Idiosyncratic returns are obtained from bank residuals, which are calculated once the PCA's common component is extracted from total returns.

At each window, the lag p of the GVAR model is determined using the likelihood ratio test, which confirms that p varies over time.[14] To choose the forecast horizon of ten days ($H = 10$) we compute at each window the *total return spillover* index for H varying from 1 to 16. The results show that the index is sensitive to the choice of the forecast horizon for low values of H, but in general it is stabilized for $H = 10$. This is the forecasting horizon commonly used in similar studies (see for example Diebold and Yilmaz, 2012).

<Insert Figure 3 here>

Figures 3 to 5 present the evolution over time of the different return spillover measures corresponding to the total contagion, obtained using total CDS returns, (in blue in the Figures) and to the idiosyncratic contagion, computed using idiosyncratic returns (in grey in the Figures), due to bank specific factors. The difference between the two types of contagion will be systematic contagion, linked to global or common factors.

The time dependent *total return spillover* index illustrated in Figure 3 reveals high levels of contagion across markets, especially after the onset of the global financial crisis on July 2007. Previous to the credit crunch, the *total return spillover* index was in general quite low (around 15%) and it was mostly idiosyncratic in nature, probably reflecting the stable financial environment of that period. In July 2007 with the onset of the sub-prime crisis total contagion started to increase: it climbed from 10 to 60% in the following months and it remained around 50% the rest of the sample period, indicating a high level of interconnectedness across bank CDS international markets.

Idiosyncratic contagion also increased (to 25%) in July 2007, but the peak only lasted a few days and then it decreased to previous levels. As the sub-prime crisis started to have its full effects all around the world financial markets, thereby becoming a global financial crisis, we find strong evidence of systematic contagion across banking markets. For instance, only 14% of the total 64% of the spillover effects observed in March 2008 after the Bearn Stearns' bailout can be attributed to the idiosyncratic component, the remaining 50% is thus imputable to the systematic component.

[14] The Akaike information criterion does lead in some cases to higher values, but this criterion tends to overestimate the number of lags.

During the European sovereign debt crisis (2009-2013) idiosyncratic contagion became more pronounced, increasing from 15% to 25% on average, although the systematic component remained high (25%) and equally important. At the height of the Greek crisis, the idiosyncratic spillover index increased to 35%, but the systematic component still played an important role (27% of the total 62%). Despite the fact that the increase in the overall spillover index was driven by a spike in the idiosyncratic component, the impact on the systematic component had a longer lasting effect as it took a longer time for the index to return to previous levels.

A similar pattern can be observed in the second half of 2011. During this period, the increasing concerns about the worsening of public finances in several Eurozone countries together with the perspective of a restructuring of Greek sovereign debt heightened financial market tensions in the Eurozone. This lead to an increase in idiosyncratic component of 40% (the biggest increase over the whole sample period), whereas the systematic component remained at around 13%.

The policy measures conducted by ECB in December 2011 and February 2012 appeared to have had a positive impact on the situation of banks and it encouraged a more benign financial market sentiment in the first half of 2012.[15] The total return spillover index, our chosen measure of contagion, remained high fluctuating at around 50%. Interestingly, however, the idiosyncratic component declined significantly after December 2011, while the systematic component remained high.

A further significant increase in the idiosyncratic spillover effects occurred in the period September-December 2012 (over 30%), this time accompanied by a decrease in the systematic component, as the total spillover index did not change. One possible explanation is that market worried about the fate of Spanish banks, as Spain's cost of borrowing shot up. Uncertainty on how to respond to Spanish problems unsettled the markets; however, similarly to previous idiosyncratic shocks, it triggered temporary increases in such type of contagion index, while systematic contagion remained high for a longer period of time.

The next step of the analysis is to account to directional information. To this end, we compute the *net directional return spillover* index, which is presented in Figure 4. The *net directional return spillover* index will enable us to identify the net transmitters

[15] ECB decided to conduct refinancing operations that significantly extended the horizon at which credit institutions could obtain liquidity from the Eurosystem.

and receivers of contagion. In addition we compute the *net pairwise return spillovers* effects between two markets (as shown in Figure 5).

<Insert Figure 4 here>

<Insert Figure 5 here>

Looking at Figure 4 and Figure 5, we can see that the idiosyncratic component of contagion observed during the first part of the sample period (until July 2007) appears to have been present in all portfolios, which indicates that all banks in all countries were both the giving and receiving ends of the net transmissions, with similar magnitudes. Nevertheless, the most interesting part of the *net directional return spillover* index plot concerns the recent financial crises.

Banks in the US were the only ones that remained positive, in net systematic terms, throughout the several stages of the crises, especially during the global financial crisis (2007-2009). In July 2007 the net return spillovers from US banks were as high as 140% (of which 130% systematic and 10% idiosyncratic). Systematic contagion was mostly transmitted to banks located in Euro-Peripheral countries (76%) and to banks in Non-Euro countries (57%). After this extraordinary impact, systematic contagion declined significantly. Surprisingly, the impact of the sub-prime crisis from US banks was limited for Euro-Core banks (7%), which were not affected by the global financial crisis until the end of January 2008. The Bear Stearns and Lehman Brothers episodes impacted systematically (both around 30%) in all other zones. In summary, US banks were a natural net systematic return spillover transmitter during the global financial crisis, while banks in the three other markets were net systematic return spillover receivers. By contrast, we find limited amount of idiosyncratic contagion. There were some isolated significant events linked to specific domestic episodes in some countries, but in general net spillover measures were low. Banks in Euro-Peripheral countries became net transmitters during the first days of the global financial crisis started in July 2007. The index was over 30% and it was transmitted to all other markets, with a bigger impact on banks Non-Euro countries (around 20%).

During European sovereign debt crisis, banks in the Euro-Peripheral countries were the natural net idiosyncratic transmitter (to all other countries), mostly since May 2010 following the Greek's bailout and with a bigger impact during the second half of 2011. However, the impact of the Greek bailout seems to be stronger for banks in Non-

Euro countries while banks in Euro-Core countries were less affected. Banks in the US barely felt it.

However, looking at the whole picture, banks in Euro-Peripheral countries did not have a net systematic transmitter role during the European debt sovereign crisis. It was banks in Euro-Core countries that were the unique net systematic transmitter. Its spillovers mostly affected banks in Euro-Peripheral countries, with even a bigger impact than the idiosyncratic spillover they received in the opposite direction, especially after 2012.

Finally, note that banks Euro-Peripheral countries have started to receive both types of contagion from Non-Euro and Euro-Core zones after 2013. The Cyprus debt crisis on March 19, 2013 caused a significant increase in both spillover total indices. Following the Cyprus crisis, the index decreased again, signaling that the immediate risk of the Eurozone breakup seemed to have been averted and confidence was slowly recovering. However, the situation still remains fragile and systemic contagion still remains at much higher levels compared to pre-2007.

5. Conclusion

This paper provides an evaluation of contagion among banks and banking sectors in different countries and regions during a period of prolonged financial distress. Increased integration in global financial markets strengthened the linkages between banks in different countries. This increased interdependence ultimately resulted in the sub-prime crisis - a problem in a sector of the US financial market - becoming a global financial crisis. Despite a growing literature, the transmission mechanisms of contagion are still not fully understood. Banks are likely to remain vulnerable to episodes of instability and continued stress in the markets.

In this paper, to evaluate contagion during the period January 2004 to March 2013, we use banks CDS spreads as an indicator of bank risk. In a first step, we build series of CDS returns. We then use principal component analysis (PCA) to extract the common factors underlying the daily variation in the CDS returns of individual banks. Throughout the analysis, bank CDS returns series are decomposed in the common and the residual component. This way, for each bank, we have the total CDS return and the idiosyncratic bank CDS return. We then build four equally weighted portfolios, on the basis of geographical areas: US; "Eurozone core"; "Eurozone peripheral"; and Non-

Eurozone. We construct the portfolios using both the total CDS returns and the residuals. We estimate contagion, in terms of return spillovers, between banks CDS returns portfolios, both for the total and the idiosyncratic CDS returns by employing a Generalized VAR (GVAR) approach. We interpret the difference between the total and the idiosyncratic component as systematic contagion.

We find evidence of contagion in banking markets, evidenced by an increase in co-movement in CDS returns. Contagion came in different waves, from July 2007 onwards, with the financial and Eurozone crises being distinct episodes. Indeed, while during the financial crisis contagion was systematic in nature, during the Eurozone crisis the idiosyncratic part played a more dominant role. The examination of net directional return spillover measures enabled us to identify group of banks in countries that can be seen as net transmitters and receivers of contagion. US banks appear to be net transmitters, particularly during the 2007-2009 period. During the Eurozone crisis, banks in "Eurozone peripheral" countries were net transmitters in terms of idiosyncratic spillovers although Eurozone troubles are barely affecting US banks. Differences in vulnerability to contagion within the European Union and even within the Eurozone are remarkable, with the Eurozone periphery more exposed to systematic contagion.

The results of our analysis have a number of implications for regulators and policymakers as they provide an insight into bank specific and country/region specific vulnerabilities and how these vulnerabilities are transmitted. Finally, our results also have implications for the portfolio diversification strategies.

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Appendix A. Estimation of banks' CDS returns

Following Berndt and Obreja (2010) daily CDS return is given by

$$r_{CDS,t} = -\Delta CDS_t(T) \times A_t(T) = -\Delta CDS_t(T)\,\frac{1}{4}\sum_{j=1}^{4T} \delta\left(t, \frac{j}{4}\right) q\left(t, \frac{j}{4}\right) \qquad \text{(A.1)}$$

where $\Delta CDS_t(T)$ is the daily change in the CDS spreads with T maturity and $A_t(T)$ is the value of a defaultable quarterly annuity over the next T years. We denote the risk-free discount factor for day *t* and *s* years out as $\delta(t, s)$ and it is fitted from Datastream Euro and US zero curves. Assuming a constant risk-neutral default intensity λ for each bank, the risk-neutral survival probability of the bank over the next *s* years can be written as $q(t, s) = e^{-\lambda(t-s)}$. As a consequence, λ can be computed directly from observed CDS spreads by $\lambda = 4log\left(1 + \frac{CDS}{4L}\right)$, which can be used to calculate the annuity and hence the CDS return. L denotes the risk-neutral expected fraction of notional lost in the event of default. It is fixed at 60%.

Table 1
List of European and US Banks

Banks are assigned to countries based on the Datastream classification. Obs. refers to the available number of observations (CDS spread) for each bank in the sample. Total assets (December 2012 data) are expressed in thousand euros. For non euro countries Datastream average exchange rate in December 2012 is used.

Country	Bank Name	Obs.	Total Assets
Euro-Peripheral (20)			
Greece (4)	National Bank of Greece	915	104,798
	Alpha Bank	2407	58,357
	EFG Eurobank Ergasias	1935	67,653
	Piraeus Bank	927	70,406
Italy (7)	Unicredito Italiano	2407	926,827
	Intesa San paolo	2407	673,475
	Banca Monte Paschi Siena	2407	197,081
	Unione di Banche Italiane (Ubi Banca)	2364	132,433
	Banco Popolare	2402	131,921
	Banco Popolare Milano	2407	52,475
	Banca Italease	1516	10,531
Portugal (3)	Banco Espirito Santo	2407	83,690
	Banco Comercial Português	2407	89,744
	Banco Português de Investimento	2407	44,564
Spain (6)	Banco Santander	2407	1,269,628
	Banco Bilbao Vizcaya Argentaria	2407	637,785
	Banco Popular Español	2407	157,618
	Banco de Sabadell	1496	161,547
	Bankinter	2004	58,165
	Banco Pastor	2263	31,135
Euro-Core (16)			
Austria (2)	Erste Group Bank	2407	213,824
	Raiffeisen Zentralbank	2407	145,955
Belgium (2)	KBC Bank	2405	224,824
	Dexia	2407	357,210
France (5)	BNP Paribas	2407	1,907,290
	Société Générale	2407	1,250,696
	Crédit Agricole	2406	1,842,361
	Natixis	2407	528,370
	BPCE SA	1904	1,147,521
Germany (4)	Deutsche Bank	2407	2,012,329
	Commerzbank	2407	635,878
	Deutsche Postbank	2380	193,822
	HSH Nordbank	2407	130,606
Netherlands (3)	ING Bank NV	2407	836,068
	Rabobank	2407	752,410
	ABN AMRO Bank	2407	394,404

Table 1 ***(continued)***
List of European and US Banks

Non-Euro (14)			
Denmark (1)	Danske Bank	2394	466,708
Norway (1)	DNB NOR ASA	1274	273,743
Sweden (4)	Nordea Bank	2407	677,309
	Svenska Handelsbanken	2407	276,972
	Skandinaviska Enskilda Banken	2407	285,047
	Swedbank	2294	214,572
Switzerland (1)	Credit Suisse Group	2407	752,006
UK (7)	HSBC Holdings PLC	2407	3,318,590
	Lloyds Banking Group	2407	1,139,523
	Standard Chartered	2050	784,517
	Alliance and Leicester PLC	2090	92,739
	Barclays	2407	1,837,366
	Royal Bank of Scotland Group	2407	1,617,422
	HBOS	2407	717,455
US (5)	Bank of America corporation	2407	1,673,231
	JP Morgan Chase & Co.	2407	1,786,754
	US Bancorp	1314	268,001
	Wells Fargo & Co.	2406	1,077,720
	Citigroup Inc	2407	1,412,247

Table 2
Descriptive statistics of European and US bank CDS spread and return series

This table contains descriptive statistics (minimum, maximum and mean) for the daily 5-year CDS spreads (Panel A) and returns (Panel B). The banks of the sample are summarized in equally weighted portfolios sorted by geographic zone using average CDS data of each zone's countries. CDS spreads are reported in basis points and CDS returns in percentage form. Results are shown for the complete period, from January 2004 to March 2013, and for three sub-periods: January 2004 to June 2007 (Pre-Crisis), July 2007 to September 2009 (Global Financial Crisis) and October 2009 to March 2013 (European Sovereign Debt Crisis). The lack of statistics for Norway in the first sub-period is due to the lack of data for the Norwegian bank until May 2008.

Panel A

	CDS spreads											
	Jan2004-Mar2013			Pre-Crisis Jan2004-Jun2007			Global Financial Crisis Jul2007-Sep2009			European Sovereign Debt Crisis Oct2009-Mar2013		
	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean
Euro-Peripheral	12.91	1,625.26	277.91	12.91	31.02	19.46	19.58	216.25	100.70	113.47	1,625.26	652.67
Greece	15.00	4,190.93	491.38	15.00	41.00	25.66	21.59	172.55	34.61	147.00	4,190.93	1,255.79
Italy	9.07	694.93	157.47	9.07	36.87	20.60	21.83	379.23	144.21	67.72	694.93	303.69
Portugal	10.50	1,483.58	273.57	10.50	31.39	16.75	17.63	171.09	86.56	79.30	1,483.58	653.04
Spain	10.38	769.58	189.22	10.38	23.19	14.81	17.08	309.62	137.43	121.75	769.58	398.16
Euro-Core	10.13	384.93	110.31	10.13	35.10	15.68	24.37	274.42	119.84	98.31	384.93	199.27
Austria	3.83	510.25	123.24	3.83	117.83	26.05	74.15	510.25	170.10	123.05	364.59	190.60
Belgium	5.50	709.49	175.81	5.50	13.40	9.75	10.60	395.70	172.89	136.14	709.49	344.68
France	5.18	356.17	89.69	5.18	58.23	14.96	9.92	156.01	78.85	60.32	356.17	171.87
Germany	10.22	276.11	87.01	10.22	37.10	19.09	16.25	182.29	99.02	88.95	276.11	147.53
Netherlands	3.83	254.40	75.77	3.83	14.53	8.54	6.83	172.73	78.35	64.07	254.40	141.68
Non-Euro	7.50	245.60	75.42	7.50	18.70	12.80	11.19	227.82	91.65	63.79	245.60	127.86
Denmark	1.00	344.80	83.59	1.00	21.00	8.80	4.10	225.00	81.76	60.56	344.80	158.91
Norway	37.50	212.00	100.46	-	-	-	37.50	188.11	103.21	49.54	212.00	99.35
Sweden	9.63	242.38	68.69	9.63	25.43	15.93	13.17	242.38	88.46	67.00	216.96	108.92
Switzerland	9.20	262.88	74.68	9.20	25.50	16.25	17.50	262.88	99.82	52.80	213.45	117.14
UK	4.37	285.29	88.50	4.37	20.40	10.11	9.97	230.15	107.52	77.90	285.29	154.98
US	8.13	337.73	86.39	8.13	30.93	17.67	14.53	337.73	123.78	74.15	262.02	131.25

Table 2
Descriptive statistics of European and US bank CDS spread and return series *(continued)*

Panel B

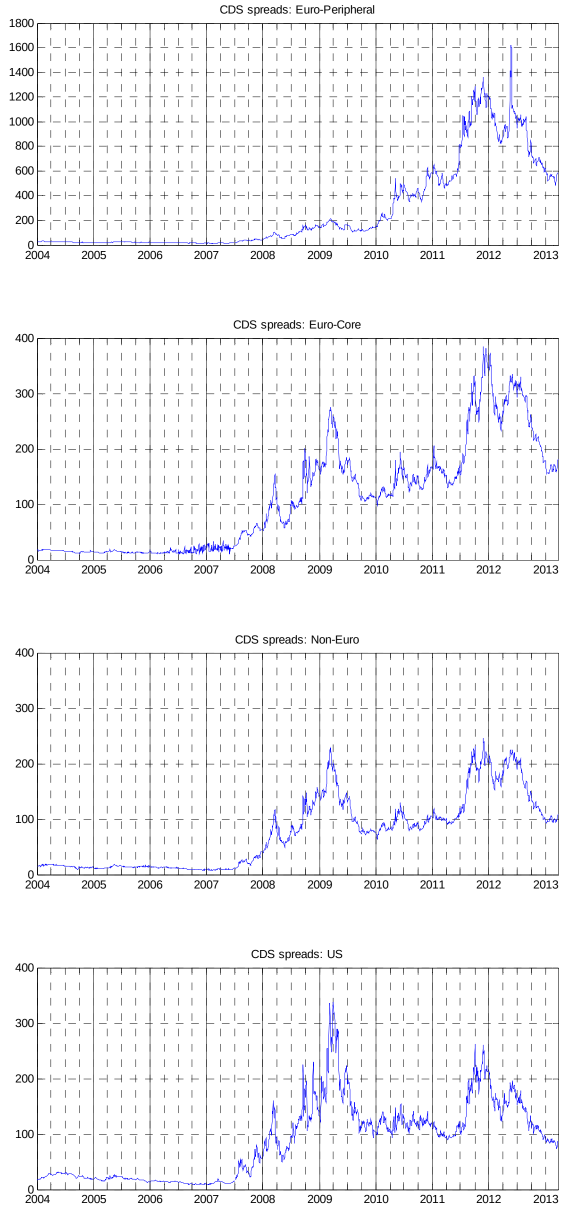
	CDS returns											
	Jan2004-Mar2013			Pre-Crisis Jan2004-Jun2007			Global Financial Crisis Jul2007-Sep2009			European Sovereign Debt Crisis Oct2009-Mar2013		
	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean
Euro-Peripheral	-529.32	1,113.66	-0.38	-20.17	24.82	0.04	-119.99	49.87	-0.56	-529.32	1,113.66	-0.69
Greece	-1,679.64	4,246.79	0.12	-46.03	66.70	0.06	-429.05	38.91	-0.75	-1,679.64	4,246.79	0.75
Italy	-207.26	290.88	-0.58	-28.04	18.66	0.06	-145.56	168.71	-0.23	-207.26	290.88	-1.46
Portugal	-312.20	527.90	-0.52	-26.66	26.85	0.03	-143.22	97.19	-0.56	-312.20	527.90	-1.05
Spain	-199.67	305.07	-0.54	-35.43	34.18	0.02	-147.80	134.64	-0.69	-199.67	305.07	-1.01
Euro-Core	-136.94	162.02	-0.22	-71.55	49.50	0.04	-136.94	105.44	-0.53	-120.39	162.02	-0.29
Austria	-345.24	289.12	-0.14	-345.24	224.47	-0.07	-246.66	289.12	-0.31	-150.47	210.10	-0.11
Belgium	-366.81	246.17	-0.40	-11.74	11.46	0.00	-366.81	246.17	-0.95	-220.90	204.95	-0.44
France	-179.67	222.69	-0.22	-179.67	153.02	0.10	-114.20	80.18	-0.40	-159.43	222.69	-0.44
Germany	-168.58	116.51	-0.12	-77.69	94.34	0.12	-111.95	107.78	-0.59	-168.58	116.51	-0.05
Netherlands	-146.38	115.22	-0.24	-9.33	9.49	0.02	-146.38	115.22	-0.40	-71.83	113.77	-0.40
Non-Euro	-96.17	102.68	-0.15	-16.88	14.75	0.02	-96.17	83.68	-0.41	-81.73	102.68	-0.15
Denmark	-392.76	209.57	-0.21	-64.29	36.70	0.01	-392.76	209.57	-0.43	-167.62	150.21	-0.27
Norway	-202.99	157.05	-0.10	-	-	-	-202.99	157.05	-0.01	-126.47	112.43	-0.13
Sweden	-188.22	100.05	-0.12	-24.14	21.53	0.04	-188.22	69.78	-0.46	-73.63	100.05	-0.06
Switzerland	-167.31	195.38	-0.13	-24.68	21.98	-0.01	-167.31	195.38	-0.35	-142.30	186.97	-0.10
UK	-191.07	227.54	-0.16	-43.43	45.80	0.03	-191.07	227.54	-0.45	-103.86	182.30	-0.17
US	-178.96	230.81	-0.13	-19.23	14.69	0.02	-178.96	230.81	-0.85	-168.85	118.20	0.20

Figure 1

Time evolution of CDS spread and returns series

Panel A: Daily time series of CDS spreads (in basis points); Panel B: and CDS returns (in percentage). Panel A and Panel B report the CDS spreads and returns for the four equally weighted portfolios, sorted by the geographical area where banks are headquartered. The sample period is January 2004 to March 2013.

Panel A



Panel B

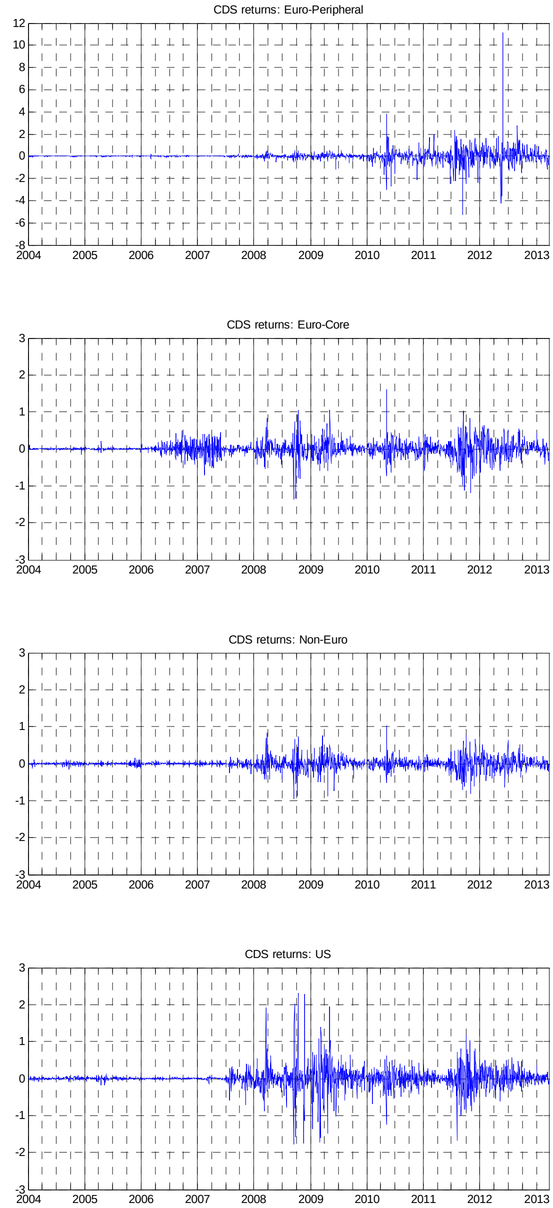


Figure 2
Principal Component Analysis

This figure reports the time evolution of the proportion of variance explained by the first four principal components of banks CDS returns series. The sample period is January 2004 to March 2013, but the figure starts on October 2004 since a 200-day rolling window is used to get the evolution over time.

Figure 3
Total return spillover index

This figure reports the time evolution of the *total return spillover* index for total contagion in blue, computed using total CDS returns, and idiosyncratic contagion in grey, computed using idiosyncratic returns. It measures on average the percentage of the forecast error variance in all the series that comes from contagion due to shocks. Returns of the four equally weighted portfolios sorted by geographical area where banks are headquartered are used. The sample period is January 2004 to March 2013, but the index starts on October 2004 since a 200-day rolling window is used to get the evolution over time.

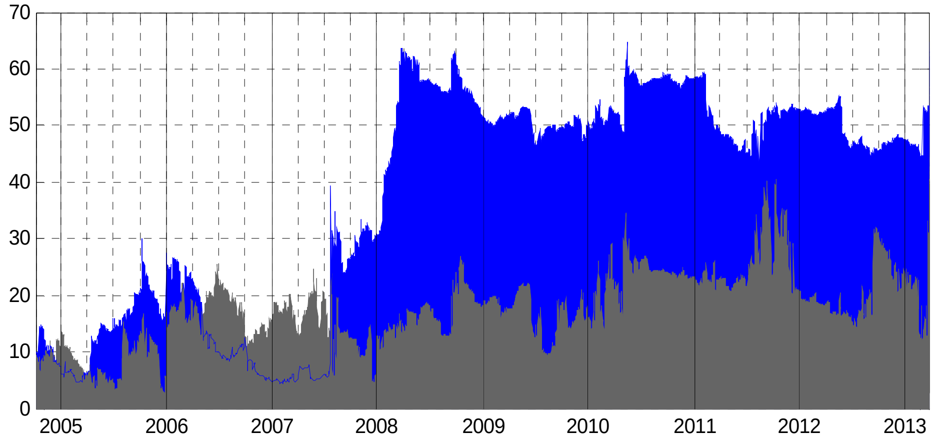
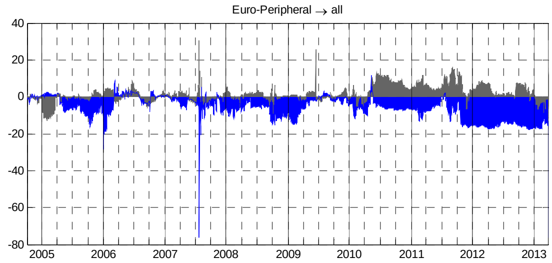


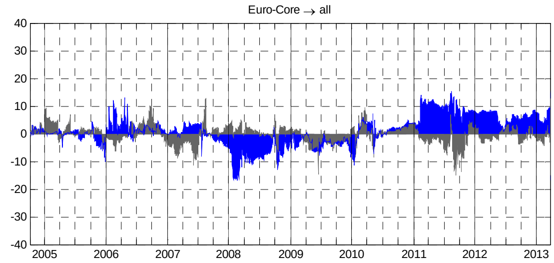
Figure 4
Net directional return spillover indices

This figure reports the time evolution of the *net directional return spillover* indices for total contagion in blue, computed using total CDS returns, and idiosyncratic contagion in grey, computed using idiosyncratic returns. They measure the spillover due to shocks (in percentage terms) transmitted by each portfolio to all others. Positive (negative) values indicate that the corresponding portfolio is in net terms a transmitter (receiver) of return spillover effects to all others. Returns of the four equally weighted portfolios sorted by geographical area where banks are headquartered are used. The sample period is January 2004 to March 2013, but the indices start on October 2004 since a 200-day rolling window is used to get the evolution over time.

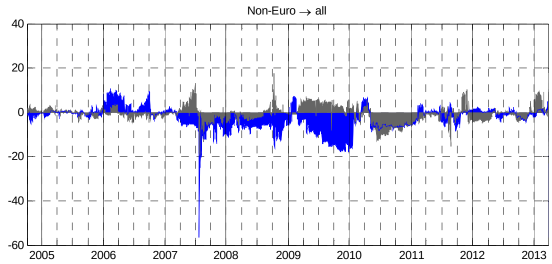
Panel A



Panel B



Panel C



Panel D

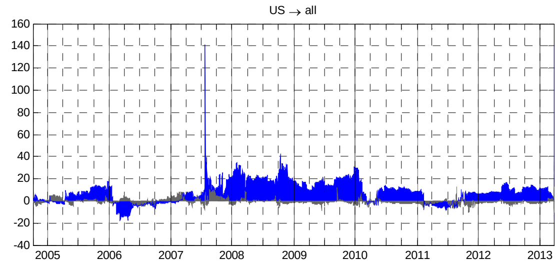
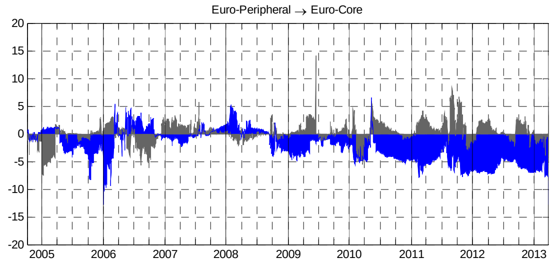


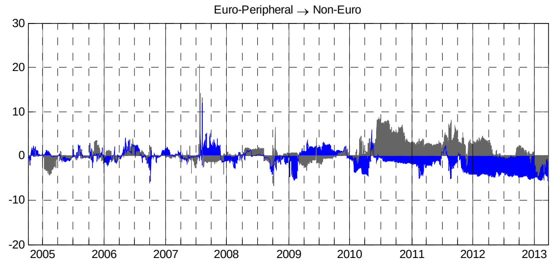
Figure 5
Net pairwise return spillover indices

This figure reports the time evolution of the *net pairwise return spillover* indices for total contagion in blue, computed using total CDS returns, and idiosyncratic contagion in grey, computed using idiosyncratic returns. They measure the spillover due to shocks (in percentage terms) transmitted between each pair of portfolios. Positive (negative) values indicate that the first portfolio is in net terms a transmitter (receiver) of return spillover effects to the second portfolio. Returns of the four equally weighted portfolios sorted by geographical area where banks are headquartered are used. The sample period is January 2004 to March 2013, but the indices start on October 2004 since a 200-day rolling window is used to get the evolution over time.

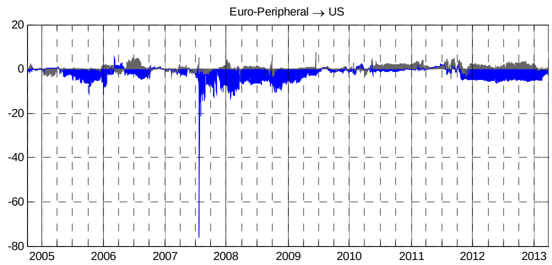
Panel A



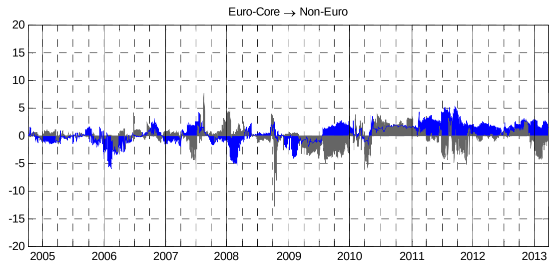
Panel B



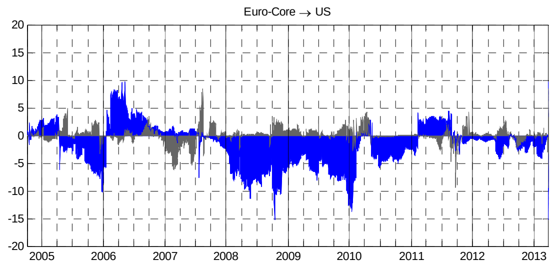
Panel C



Panel D



Panel E



Panel F