SYSTEMIC RISK MEASURES: THE SIMPLER THE BETTER?[*]

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Abstract

We compute six different sets of systemic risk measures for a sample of the 20 biggest European and 13 biggest US banks from January 2004 to November 2009. The six measures are based on i) Principal components of the bank's Credit Default Swaps (CDSs), ii) Interbank interest rate spreads, iii) Structural credit risk models, iv) Collateralized Debt Obligations (CDOs) indexes and their tranches, v) Multivariate densities computed from CDS spreads and vi) Co-Risk measures. We then rank the measures using three different criteria: i) Causality tests, ii) Price discovery tests and iii) their correlation with an index of systemic events. For the European and US markets, the best indicators are the first Principal Component of the single-name CDSs and the LIBOR-OIS or LIBOR-TBILL spreads, respectively, whereas the least reliable indicators are the Co-Risk measures and the systemic spreads extracted from the CDO indexes and their tranches.

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1. Introduction

The financial system plays a fundamental role in the global economy as the middleman between agents who need to borrow and agents who are willing to lend or invest. As a consequence, it is naturally linked to all economic sectors and therefore, if the financial system does not work properly, its problems have a strong impact on the real economy. For instance, in the current crisis, the total cost to G-20 countries of the bail-out of the financial system is around $10.8 trillion as of September 2009.[1] However, the cost of the crisis is not limited to the bail-outs. Substantial costs are also incurred by the negative evolution of the fundamental macro variables such as GDP growth rate, unemployment rates and government deficits, among others. For instance, the annual GDP growth rate[2] decreased from 3.09% in 2007 to -4.09% in 2009 in the European Union. In the US, this rate decreased from 2.14% to -2.45%. With respect to the unemployment rate, it increased from 7.8% in January 2007 to 9.4% in November 2009 in the European Union. In the US, this rate increased from 4.6% to 10% in the same period. Regarding the government deficits[3], they dramatically increased from 0.8% in 2007 to 6.7% in 2009 in the European Union, and in the same period, US government deficits increased from 1.14% to 9.9%.

As many of these problems come from events related with systemic risk propagating from the banking sector to the real economy, it is important to understand the relationship among measures of systemic risk and give an indication of the relative usefulness of the available measures. This papers aims to shed some light on these pressing issues by means of an

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[1] The BBC stated on 10 September 2009 that according to IMF data, G-20 countries have spent $10.8 trillion. However, most of the bail-outs are in the form of guarantees to the financial system and hence, governments hope to recover some of the money. http://news.bbc.co.uk/2/hi/business/8248434.stm. Concretely, the IMF estimated global losses to be around $3.4 trillion by October 2009. http://www.imf.org/external/pubs/ft/gfsr/2009/02/pdf/press.pdf
[2] Annual percentages of constant price GDP are year-on-year changes.
[3] Government deficits are expressed as a proportion of the GDP.

empirical analysis of the most widely used and well-known measures of systemic risk employed by investors and regulators worldwide.

Acharya and Richardson (2009) discuss the factors causing the near collapse of the global financial system (mainly the combination of a credit boom and a housing bubble) and give several proposals for regulatory reform. Regarding systemic risk, they propose a definition of systemic risk which involves its effect on the real economy and a device for reducing it through taxation.[4] Following a similar approach, Brunnermeier (2009) presents a description of the "originate and distribute" model and an event logbook of the crisis for the period 2007-2008. In an environment of mild economic conditions, financial institutions have taken advantage of many financial innovations (e.g., Credit Default Swaps or Collateralized Debt Obligations, among others), some of them very complex and with unexpected downside effects in scenarios of financial distress. Nonetheless, the problem is not only that the financial system is in trouble during the crisis but the whole economy is also affected. This relationship and the search for the best performing systemic risk measure is our basic motivation for addressing the relative performance of the available systemic risk measures. Billio, Gertmansnki, Lo and Pelizzon (2010) use monthly data to study the interconnectedness among the returns of hedge funds, banks, brokers, and insurance companies but they use only two measures: principal components analysis and Granger-causality tests. They find that all four sectors have become highly interrelated over the past decade, possibly increasing the level of systemic risk in the finance and insurance industries, and they suggest that hedge funds can provide early indications of market dislocation.

In this paper, we concentrate on what are widely acknowledged to be the most important systemic actors: the biggest banks in the two biggest economic areas (the European Union

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[4] These ideas are extended in other papers: Acharya, Pedersen, Philippon and Richardson (2010a and 2010b).

and the US).[5] We employ daily data and we compare a comprehensive set of measures. Specifically, we compute six different sets of systemic risk measures for a sample of the 20 biggest European and 13 biggest US banks from January 2004 to November 2009.[6] The six measures are based on i) Principal components of the bank's Credit Default Swaps (CDSs), ii) Interbank interest rates, iii) Structural (Merton (1973)) credit risk models, iv) Collateralized Debt Obligations (CDOs) indexes and their tranches v) Multivariate densities computed from CDS spreads and vi) Co-Risk measures. We then compare them using three different criteria: i) Causality tests, ii) Price discovery test, and iii) their correlation with an index of systemic events.

Our main empirical findings are as follows. For the European market, the best indicator is the LIBOR-OIS spread followed by the first Principal Component of the single-name CDSs whereas the least reliable indicator is the Delta Co-Expected Shortfall. For the US market, the best indicator is the first Principal Component of the single-name CDSs followed by the spread LIBOR-TBILL, whereas the least reliable indicator is the systemic spread extracted from the CDO indexes and their tranches.

Therefore, our results imply that the better performing measures of systemic risk are based on simple indicators obtained from credit derivatives and interbank markets. On the other hand, indicators relying on structural models or complex statistical procedures do not perform particularly well in our sample. The implications for investors and regulators are straightforward. Look for simple, robust indicators based directly on liquid market prices and be aware of overcomplicated modelling based on dubious assumptions and of the inferences from the prices of financial products traded in thin markets.

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[5] Billio et al. (2010) find that banks may be more central to systemic risk than non-bank financial institutions that engage in banking functions.

[6] In a recent study, the International Monetary Fund (2009) posits that smaller institutions may also contribute to systemic risk if they are closely interconnected. However, systemic risk should be most readily observed in the largest banks.

This paper is divided into 6 sections. Section 2 reviews the literature. In Section 3, we give a brief description of the dataset employed in our analysis. Section 4 describes the different measures of systemic risk proposed in the extant literature. This section also includes the estimation of these measures using our database. In Section 5, we compare these measures among groups and run a "horse race" among them using three different criteria. Section 6 concludes.

2. Literature Review

There is no general agreement on the definition of systemic risk.[7] De Bandt and Hartmann (2002) survey theoretical and empirical approaches and define systemic risk as a "systemic event that affects a considerable number of financial institutions or markets, thereby severely impairing the general well-functioning of the financial system". A different approach is taken by Kaufman (2000) and Kaufman and Scott (2003), who define systemic risk as "the risk or probability of breakdown in an entire system and it is evidenced by co-movements (correlations) among most or all the parts". They assign the most frequent concepts about systemic risk to three groups: macro shocks, micro level and spillover effects though indirect interconnections. Billio et al. (2010) state that "Systemic risk can be defined as the probability that a series of correlated defaults among financial institutions, occurring over a short time span, will trigger a withdrawal of liquidity and widespread loss of confidence in the financial system as a whole". Recently, the Financial Stability Report of ECB (December 2009) classified theoretical and empirical papers about systemic risk into three categories: contagion, macro shocks and unwinding of imbalances.

Although the definition of systemic risk diverges among papers, the common factor is the generalized distress of financial institutions, which makes it difficult for the financial system

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[7] In the Global Financial Stability Report by the IMF (2009), it is recognized that systemic risk is a term widely used but difficult to define and quantify.

to perform well. On the basis of this characteristic, we define systemic risk as the risk of suffering an adverse effect on the real economy derived from the malfunctioning of the financial sector. Clearly, the worse is the situation in the financial system, the stronger is the systemic risk, although this relationship is not necessarily linear.

Until recently, academic research has mainly focused on measuring idiosyncratic and systematic risk, ignoring, at least in part, the importance of systemic risk. For instance, for the case of the banking industry, the Basel I (1988) and Basel II (2004) Accords design risk management policy on the basis of the banks' portfolios, ignoring interconnection among banks. Therefore, no provision for systemic risk is included in the current regulatory framework.

Interest in systemic risk is relatively new. At the end of the 1990s, concern about the stability of the international financial system increased as a consequence of the crisis in Mexico (1994), Asia (1997), Russia (1998) and Brazil (1999).[8]

Nevertheless, systemic risk measures have attracted more attention in recent years. Going beyond traditional approaches based on pure contagion, new dimensions of systemic risk have been developed. These dimensions are related to interconnections to common factors. Researchers realize that the rise in the complexity and globalization of financial services has contributed to establishing strong interconnections among financial institutions. In this vein, credit derivatives like CDOs and CDSs have played a crucial role, in part because they are new products which are traded in bilateral transactions Over-The-Counter (OTC), and as result, they involve greater counterparty risk and less transparency. As a consequence, the disquiet about systemic risk has been growing as well as the notional value of

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[8] This disquiet was voiced by none other than Alan Greenspan, chairman of the Federal Reserve (1986-2006):
"Second only to its macrostability responsibilities is the central bank's responsibility to use its authority and expertise to forestall financial crises (including systemic disturbances in the banking system) and to manage such crises once they occur."

Testimony of Alan Greenspan, March 19, 1997

outstanding CDSs and CDOs.[9] In fact, the relationship between these credit derivatives and economy-wide risk has already been documented in the literature (see Mayordomo and Peña, 2010).

Regarding the measurement of systemic risk, two complementary approaches, *macro* and *micro*, can be employed. The *macro* or *aggregated* approach focuses on the evolution of macro indicators in order to detect possible bubbles in the economy. Some examples of this approach are Borio and Lowe (2002a, 2002b and 2004) and Borio and Drehmann (2009), who propose to measure the financial unwinding of imbalances by means of price misalignments in some key indicators like inflation-adjusted equity prices or private sector leverage. The *micro* approach focuses on the individual institutions' financial health to determine the level of systemic risk in the economy (i.e., portfolio) by means of analyzing both market and accounting information. In this paper, we focus mainly on the micro level, analyzing the market information provided by individual institutions. The macro level is also studied by means of the interest rates. In any case, we realize that both approaches are complementary to each other.

Although some papers have addressed the problem of systemic risk[10], few of them propose measures that allow surveillance institutions to monitor the aggregate level of the systemic risk and its concentration in key financial intermediaries. These measures could play a relevant role as leading indicators of future impending crises. Lehar (2005) proposes extracting systemic risk measures on the basis of Merton's model (1973). Using Monte Carlo simulations, the author proposes a measure of systemic risk which is based on the probability that banks with total assets of more than a certain percentage ε of all banks'

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[9] To give an example, the outstanding notional amount of CDS was $8.42 trillion at the end of 2004 and $62.2 trillion at the end of 2007. Once the subprime crises broke out, the outstanding notional amount decreased to $38.6 trillion at the end of 2008 (source ISDA).

[10] See Bartram, Brown and Hund (2005), who analyze the global banking system through event study methodology; Brühler and Prokopczuk (2007), who analyze tail dependence of stock returns by means of an Archimedean copula; and Avesani, García and Li (2006), who construct an indicator for sector surveillance using the default probabilities of an nth-to-default CDS basket of large and complex financial institutions.

assets go bankrupt within a short period of time. Additionally, the author proposes a similar measure of systemic risk as the probability that more than a certain fraction of all banks go bankrupt at the same time. Allenspach and Monnin (2007) improve Lehar's measure by estimating, through a structural model, the banks' asset-to-debt ratio. As an alternative to structural models, other authors employ CDSs to measure systemic risk. Bhansali, Gingrich and Longstaff (2008) extract the idiosyncratic, systematic and systemic risks from U.S (CDX) and European (iTraxx) prices of indexed credit derivatives by means of a linearized three-jump model. Huang, Zhou and Zhou (2009) propose creating a synthetic CDO whose underlying portfolio consists of debt instruments issued by banks to measure the systemic risk of the banking system through the spread of the tranche that captures losses higher than 15%. Segoviano and Goodhart (2009) propose a set of banking stability measures[11] based on distress dependence, which is estimated by the Banking System Multivariate Density (BSMD). Their procedure for estimating the multidensity function (CIMDO-copula) is able to capture both linear and non-linear distress dependences and allows changes throughout the economic cycle.[12] Finally, Adrian and Brunnermeier (2008) propose a set of "co-risk management" measures based on traditional management tools. They estimate the institution i's Co-Value-at-Risk ($CoVaR_i$) as the whole system (i.e., portfolio)'s Value-at-Risk (VaR_s) conditioned on institution i being in distress (i.e., being at its unconditional VaR_i level). On the basis of $CoVaR$, they calculate the marginal contribution of institution i to the overall systemic risk as the difference between $CoVaR$ and the unconditional whole system's VaR, which we denoted as $\Delta CoVaR_i$.

In this article, we shed light on the relative quality of the aforementioned measures, comparing them by using three different criteria in the context of the current financial crisis.

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[11] The authors propose three different categories of measures: (a) common distress in the banks of the system; (b) distress between specific banks; (c) distress in the system associated with a specific bank.

[12] By means of CIMDO-copula, the authors overcome the drawbacks of the characterization of distress dependence of financial returns with correlations, which has been one of the most popular approaches for measuring systemic risk.

3. Dataset

Our analysis of systemic risk is based on two portfolios which contain the largest western Europe (including non-Eurozone) and United States (US) banks. Regarding the former portfolio, we select the largest western European banks according to the "The Banker" ranking for which we have information about CDS spreads, liabilities and equity prices. With respect to the US bank portfolio, we select the largest US banks according to the FED ranking[13] for which we have information about CDS spreads, liabilities and equity prices. Our final sample is composed of 20 European banks and 13 US banks and is summarized in Table 1, which also contains the average portfolio weights on the basis of their market capitalization during the sample period.

The main inputs of the measures are single-name CDS spreads, liabilities and equity prices. The CDS spreads and equity prices are reported on a daily basis (end of day) while the liabilities are reported on annual terms. These variables are obtained either from Reuters or DataStream depending on the data availability in both data sources. Additionally, other variables are required. For instance, the 3-month and 10-year LIBOR, swap rates and treasury yields are needed. We employ interest rates from the two economic areas: US and the Eurozone.[14, 15] These variables are obtained from Reuters. Moreover, CDO index spreads are also employed: the US CDO index Investment Grade (IG) spreads (CDX IG 5y) and the European one (iTraxx IG 5y) as well as their tranches. The CDX index has six tranches with attach and detach points at 0%, 3%, 7%, 10%, 15%, 30% and 100% while the

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[13] In both cases, we require the bank to have been included in the top 25 and 40 of the list of western Europe and US banks, respectively, at least once between 2004 and 2009. Banks that have been taken over or gone bankrupt are employed until the moment when such events happened.

[14] Reuters uses French government bonds as the benchmark for the Eurozone up to 05/08/2010. After that date, German government bonds are the benchmark.

[15] Our western European portfolio is composed of Eurozone and non-Eurozone banks (i.e., Denmark, Sweden, Switzerland and the UK). Regarding the second group, we also analyzed the UK's Libor spreads because of the global importance of that financial system. However, analysis of UK spreads does not add additional information to Eurozone spreads.

iTraxx has also six tranches with attach and detach points at 0%, 3%, 6%, 9%, 12%, 22% and 100%. Those index spreads for the different tranches are gathered from Markit.

The sample spans from January 1, 2004 to November 4, 2009. This sample period allows us to study the behavior of the systemic risk measures in both pre-crisis and crisis periods because August 2007 is commonly considered the starting point of the sub-prime crisis. However, the sample period used for the CDO indexes is slightly shorter. Concretely, CDX IG 5y spans from March 2006 to November 2009 while iTraxx IG 5y spans from March 2005 to November 2009 due to the lack of data at the beginning of the sample period. During certain periods of the crisis, the on-the-roll (i.e., the one that corresponds to the current index's series and version) market is dried out and no spreads are available. In these cases, we replace them with the closest available out-the-roll series spreads.

4. Measures

In this section, we briefly summarize the systemic risk measures which are proposed in the literature and based on market information and report our estimation for these measures using our dataset. We classify those measures into six different groups: (i) based on a Principal Component Analysis (PCA) of CDS spreads; (ii) based on interbank interest rates; (iii) based on structural models; (iv) based on the Collateralized Debt Obligations (CDO) indexes and their tranches; (v) based on multivariate densities which are recovered through CDS spreads; (vi) based on "co-risk management" measures such as Delta *CoVaR*.[16]

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[16] "Co-risk management" measures refer to the conditional, co-movement or even contagion measures which are estimated on the basis of traditional risk management tools like Value-at-Risk and Expected Shortfall.

a. PCA of CDS

CDSs are credit derivatives that provide insurance against the risk of default of a certain company ("name"), and hence, their spreads measure the risk that is faced by bondholders of the reference entity.

The first measure that we implement consists of performing a Principal Component Analysis (PCA) on a pool of the CDS spreads. Longstaff and Rajan (2007) analyze the CDS spreads of the components of the CDX index. They find that there is a dominant factor that mainly drives the spreads across all industries, which is consistent with the existence of an economy-wide or systemic risk component.

In our sample, we find that 93% and 90% of the bank's CDSs variance is explained by the first Principal Component Factor (PCF) in European and US banks, respectively, in agreement with Longstaff and Rajan (2008).

Figure 1 shows the evolution of both principal components during the whole sample period. From January 2004 to July 2007, both components remain almost flat. When the crisis starts in August 2007, and until March 2009, both variables follow an upward trend in which three peaks are clearly noticeable: March 2008, September 2008 and March 2009.[17] Both factors are largely similar but in the period from September 2008 to December 2008, which corresponds to a period of high stress in the US markets after the bankruptcy of the Lehman Brothers, the US factor is higher. After March 2009, both variables decrease noticeably and at the end of the sample period, the levels of these variables return to a level similar to the one at the beginning of 2008, but still clearly above their pre-crisis levels.

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[17] The first two peaks coincide with the Bear Stearns and Lehman Brothers episodes. Regarding the last one, there is not a clear reason as in the previous cases, although we guess that it is due to huge losses of the insurance giant AIG which were publically reported on March 2, 2009, and were the largest quarterly loss in US corporate history.

The first principal components are highly correlated with all banks' CDS. In the European (US) case, the highest correlation is 0.98 (0.98) with respect to BBVA (State Street Corp) and the lowest is 0.84 (0.85) with respect to Fortis (Capital One FC).

b. Libor Spreads

The second group of systemic risk measures involves the use of the LIBOR[18] as the reference interest rate relative to either the Overnight Interest Swap (OIS) or Treasury bills (TBill)[19], usually known in the literature as LIBOR spreads.[20] The first measure is defined as the difference between the 3-month LIBOR rate and the 3-month Overnight Interest Swap (OIS). The second measure is defined as the difference between the 3-month LIBOR rate and 3-month Treasury bills. These measures are employed by Brunnermeier (2009) to describe the event logbook of the current crisis and by the Global Financial Stability Report by the IMF (2009), among others.

These two proxies of systemic risk are similar, but important conceptual differences appear between them. The LIBOR represents the unsecured interest rate at which banks lend money to other banks which satisfy certain creditworthiness criteria. Typically, the banks' credit rating must be at least AA. LIBOR is not totally free of credit risk because it reflects liquidity risk and the bank's default risk over the following months. On the other hand, OIS is equivalent to the average of the overnight interest rates expected until maturity. It is almost riskless and hence it is not subject to pressures associated with those risks. Therefore, LIBOR minus OIS, or LIBOR-OIS (LO henceforth), reflects liquidity and default risk over the following months. In tranquil periods, this measure should be very low because AA

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[18] We use the LIBOR for the main currencies under study (i.e., USD LIBOR and EURIBOR, obtained from Reuters).

[19] In Section 3, we work with Eurozone Treasury bills. We repeated the analysis of this section, using German Treasury bills as a benchmark, and results did not change significantly.

[20] These measures do not directly refer to the individual financial institution's financial health, but give information about the overall situation of the banking industry.

credit rating institutions should not have either significant liquidity risk or default risk. However, in periods of turmoil, this spread should widen so as to capture these risks.

LIBOR minus Treasury bill or LIBOR-TBILL (LT henceforth) is the second systemic risk measure considered in this section. Treasury bill rates are the rates that an investor earns on Treasury bills. In times of crisis, most lenders only accept Treasuries as collateral, pushing down Treasury rates. Hence, LT captures not only liquidity and default risk but also the additional fact that, during periods of turmoil, investors lend against Treasury bills (the best form of collateral), measuring the "flight to quality" effect. In tranquil periods, LT should be very low, while in periods of turmoil, this spread should be larger. Additionally, we computed what we name the "Natives Are Restless Factor" (NARF)[21], namely, the difference between the LT and LO spreads (or, equivalently, the OIS-TBILL difference). In normal times, the NARF should be close to zero. However, when investors feel growing disquiet because of an unexpected increase in market uncertainty, they are more willing to pay an extra amount to buy the supposedly safer government securities (lowering their yields) and then the NARF increases.

Figure 2 depicts the evolution of the Libor spreads and the dashed area shows the size of the NARF. Panel A refers to the Eurozone (EU) and Panel B refers to the United States (US). The difference between the pre-crisis and crisis periods is clearly seen. The first period is characterized by low and almost constant spreads. These spreads are lower than 10 basis points (b.p.) with the exception of the US LT, which remains around the 30 b.p. line. Note that this Libor spread starts an upward movement by May 2007, while other spreads remain unchanged up to August 2007. The reason could be associated with the role that Treasury bills play as collateral.[22]

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[21] This phrase was famously used in "The Island of Lost Souls", a 1933 film based on the H.G. Wells novel "The Island of Doctor Moreau".

[22] In May 2007, UBS shut down its internal hedge fund Dillion Read after suffering some large subprime related losses. See Appendix A1 for other events on these days.

Since the subprime crisis started on August 2007, two phases of the crisis can be distinguished. The first phase spans from August 2007 to August 2008. It is characterized by a general increment in both the mean level of the spreads around 55 b.p. and high volatility. Like before, the US LT reacts earlier and in a more volatile way in comparison with the other spreads. The second phase of the crisis starts by a generalized jump after the Lehman Brothers bankruptcy.[23] The US LT hits up to 458 b.p. followed by the US LO by 363 b.p. (see Table 2, which contains their descriptive statistics). Regarding the NARF, we observe some differences between the Eurozone and the US. The former is almost zero up to the Lehman episode. In the latter, a there is a perceptible level of disquiet that grew substantially from July 2007 to the Lehman episode. After that episode, all spreads followed a downward trend, ending the sample period at pre-crisis levels. This behavior may be related to the announcement of generalized bail-out plans and the very lax stance of the monetary policy.

The main advantage of these measures is that they are easy and quick to compute and could provide some intuition about the evolution of the systemic risk among banks. However, it is important to keep in mind that short term rates are policy targets in the current framework of the monetary policy applied in both Europe and the US and therefore may be subject to external pressures.[24]

c. Structural Models

The third group of measures is based on the framework of Merton's model (1973). The basic reference is Lehar (2005) although other authors like Allenspach et al. (2007), Chan-Lau and Kong (2004) or Gray, Merton, and Bodie (2008) use similar approaches.

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[23] The Lehman Brother bankruptcy sparked off a wave of bankruptcies and bail-outs in the US and Europe. See Appendix A1 for other events during that period.

[24] For example, the Federal Reserve introduced the Term Auction Facility (TAF) on 12 December 2007 with the key role of reducing LIBOR-OIS spreads (Cui and Maharaj, 2008).

Lehar (2005) and Elsinger, Lehar and Summer (2006) propose a systemic risk measure based on the probability of default of a given proportion of the banks in a given financial system. The probability of default is linked to the relationship between the banks' asset value and their liabilities. In summary, the procedure to estimate this variable consists of recovering the bank's asset values and correlations through Merton's model and an Exponential Weighted Moving Average (EWMA) model, respectively. Then a simulation is carried out to infer future bank values and compare them with their liabilities according to different criteria in order to construct the systemic risk index: SIV and SIN, which refer to a Systemic risk Index based on the Value of assets and Number of defaulted banks, respectively.

Under Merton's framework, the bank's asset value (V) follows a Geometric Brownian motion with drift μ_t and volatility σ_t:

$$dV_t = \mu_t V_t dt + \sigma_t V_t dz \qquad (1)$$

The equity E_t can be seen as a call option on the bank's assets with a strike price equal to the face value of the bank's debt B_t which matures at T. Equity (E_t) is given by

$$E_t = V_t N(d_t) - B_t N(d_t - \sigma_t \sqrt{T}) \qquad (2)$$

where $d_t = \dfrac{\ln(V_t / B_t) + (\sigma_t^2 / 2)T}{\sigma_t \sqrt{T}}$. This model presents two unknowns (V_t and σ_t) and only one equation; therefore, an additional one is needed. In order to solve this problem, we follow Duan's methodology (Duan, 1994, 2000).[25] In both studies, he proposes the following likelihood function:

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[25] In the literature, two alternatives have been proposed. Ronn and Verma (1986) use a framework based on the relationship between equity and asset volatility while Duan (1994, 2000) employs a maximum likelihood framework. Lehar (2005, 2006) follows Duan's methodology because it is consistent with Merton's model while the other one is not.

$$L(E_t, \mu_t, \sigma_t) = -\frac{m-1}{2}\ln(2\pi) - \frac{m-1}{2}\ln{\sigma_t}^2 - \sum_{t=2}^{m}\ln\hat{V}_t(\sigma_t) - \sum_{t=2}^{m}\ln N_t(\hat{d}_t)$$

$$-\frac{1}{2{\sigma_t}^2}\sum_{t=2}^{m}\left[\ln\left(\frac{\hat{V}_t(\sigma_t)}{\hat{V}_{t-1}(\sigma_t)}\right) - \mu_t\right]^2$$

(3)

where $\hat{V}_t(\sigma_t)$ is the solution on V_t of Equation (2) while $\hat{d}_t$ corresponds to d_t in Equation

(3). For each week in the sample period[26], parameters μ_t and σ_t are estimated, assuming that

the maturity of the debt is one year (time until the next audit of the bank). To estimate each

pair of parameters, we apply a rolling window with a length equal to 104 observations (i.e.,

$m = 104$ represents two years of observations). For a given week, parameters μ_t and σ_t are

estimated on the basis of the last 104 observations of market capitalizations (E_t) and total

liabilities (B_t).[27, 28] Then we obtain $\hat{V}_t(\sigma)$ from Equation (2), using the estimated parameters

such that at the end we have a time series of the banks' asset values.

Subsequently, we estimate the covariance between banks' asset values to construct the

variance-covariance matrix. For this purpose, we employ the Exponential Weighted Moving

Average (EWMA) model:

$$\sigma_{ij,t} = \lambda\sigma_{ij,t-1} + (1-\lambda)\log\left(\frac{V_{i,t}}{V_{i,t-1}}\right)\log\left(\frac{V_{j,t}}{V_{j,t-1}}\right)$$

(4)

Following the practice in the RiskMetrics framework, parameter λ is set equal to 0.94. This

methodology enables us to estimate a variance-covariance matrix (Σ_t) for each period. This

matrix is employed to predict the future value of the bank by means of Monte Carlo

simulations. The underlying idea is that firm asset values can be modelled through a

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[26] Parameters are estimated on a weekly basis. Lehar estimates those parameters on a monthly and yearly basis in 2005 and 2006, respectively.

[27] Using total liabilities of the firm implies that all the debt is insured. Although this is a simplification, given the bailout practices, this could be a reasonable assumption, as Laeven (2008) states.

[28] Regarding total liabilities, data is available yearly and has been transformed by linear interpolation into weekly data. Similar procedures are also employed by Allenspach et al. (2006) and Chan-Lau et al. (2004), who transform the series by either linear or quadratic interpolation to monthly data.

multivariate Geometric Brownian motion. By means of Ito's Lemma, the evolution of V_t can be defined as:

$$V_T = V_0 \exp\left\{ \mu T - \frac{\sigma^2}{2}T + X \right\}$$ (5)

where $X = N_m(0,I)u$ and u is obtained by Cholesky Decomposition of the variance-covariance matrix (i.e. $\Sigma = u'u$). Hence, for each week, we obtain V_t, σ_t and μ_t, which come from Merton's model. After that, we simulate 50,000 multinomial normal distributions with a distribution function following a Normal distribution $N_m(0,I)$ for each period to simulate different paths of V.[29]

The systemic risk measure is computed as the probability that banks with total assets of more than a given percentage (ε) of all bank assets go bankrupt. Formally,

$$V_{j,t+1} < B_{j,t+1} \forall j \in J \subset F, \sum_{j \in J} V_{j,t} < \xi \sum_{i \in F} V_{i,t}$$ (6)

where $V_{j,t+1}$ is the value that we have already simulated, while we consider $B_{j,t+1} = B_{j,t}$. This measure is called SIV. Figure 3 depicts the probability that 5, 10 and 15, 20 and 25% (i.e., five different values for ε) of the all considered banks go bankrupt for the next six months in the European (Panel A) and US (Panel B) banking system. In general, European and US systemic risk measures behave in a similar way. Before 2008, those measures were zero or almost zero for all ε, although the smallest one (i.e., $\varepsilon = 0.05$), albeit different from zero, is usually at very low levels.[30] Since the summer of 2008, a year after the subprime crisis started, those probabilities increased sharply. European measures jumped noticeably to a high level up to March 2009. After this date, there was a downward trend. On the contrary, US measures have followed a smoothly increasing trend and have maintained a similar level since October 2008. Table 3 contains the descriptive statistics for those measures. As can be

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[29] See Lehar (2005) for the details of the simulation.
[30] However, US banks endured a significant stress period in 2005.

seen in Panel A of Table 3, on average, European measures show higher values for small ε while US measures have higher values for large ε.

Lehar (2005) also proposes an additional measure (SIN) that looks at the number of banks that default instead of the value of the firms. The formal definition is the following:

$$V_{j,t+1} < B_{j,t+1} \forall j \in J \subset F, \#J > \xi \# F \tag{7}$$

Figure 4 shows these measures. The behavior of these measures is very similar to the previous one although the probabilities are in general lower than in the case of SIV.

Lehar's measure combines two sources of data, market and accounting information. This is attractive given the multidimensional character of systemic risk. On the other hand, he makes use of the original structural model of Merton (1973), whose assumptions are usually too simplistic in comparison with real-world banks' capital structure and therefore the estimated asset value might be biased.[31]

d. CDO indexes and their tranches

The fourth set of measures is based on CDO indexes and their tranches. Huang et al. (2009) propose creating a synthetic CDO whose underlying portfolio consists of debt instruments issued by banks to measure the systemic risk of the banking system through the spread of the tranche that captures losses higher than 15%. Bhansali et al. (2008) extract the idiosyncratic, systematic and systemic risks from U.S (CDX) and European (iTraxx) prices of indexed credit derivatives by means of a linearized three-jump model. In this section, we report the estimation of the systemic risk measure according to Bhansali et al. (2008). The reason is that the measure of Huang et al. (2009) is based on a non-existent product and hence we cannot determine its market value. This is especially important when we are

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[31] It is assumed that the firm has issued two types of securities: equity and debt. The equity receives no dividends. The debt is a pure discount bond where a payment of B is promised at time T.

considering CDO, whose theoretical valuation is extremely dependent on the assumptions about the joint loss distribution.

Bhansali et al. (2008) employ a linearized version of the Longstaff et al. (2008) model in which the proportion of portfolio losses realized in a credit portfolio (L) is represented as a three-jump model,

$$L = \gamma_1 N_1 + \gamma_2 N_2 + \gamma_3 N_3 \tag{8}$$

where $L_0 = 0$, the γ_i denote jump sizes and N_i are independent Poisson counters that correspond to the number of jumps. Regarding the independent Poisson, constant intensities λ_i over a period T are assumed and hence, the probability of "j" jumps for the i-th Poisson process P_{ij} is as follows:

$$P_{ij} = \frac{e^{-\lambda_i T} (\lambda_i T)^j}{j!} \tag{9}$$

The risk-neutral pricing equation implies that the coupon can be solved by setting the premium leg (left hand side) equal to the protection leg (right hand side) such that,

$$C \int_0^T D(t)(1 - E[L(t)]) dt = \int_0^T D(t) E[dL] dt \tag{10}$$

where D(t) denotes the discount factor. The authors propose fitting this model to both the CDO indexes and their tranches in order to get the jump sizes and intensities to each Poisson counter (one to each series). Once γ_i and λ_i have been estimated, they decompose the CDO indexes into three different spreads. Those spreads are in the following form:

$$\text{Idiosyncratic} \equiv S_1 = \frac{\gamma_1 \lambda_1}{1 - (\gamma_1 \lambda_1 + \gamma_2 \lambda_2 + \gamma_3 \lambda_3) A} \tag{11}$$

$$\text{Systematic} \equiv S_2 = \frac{\gamma_2 \lambda_2}{1 - (\gamma_1 \lambda_1 + \gamma_2 \lambda_2 + \gamma_3 \lambda_3) A} \tag{12}$$

$$\text{Systemic} \equiv S_3 = \frac{\gamma_3 \lambda_3}{1 - (\gamma_1 \lambda_1 + \gamma_2 \lambda_2 + \gamma_3 \lambda_3) A} \tag{13}$$

where $A = \int_0^T D(t)t dt \Big/ \int_0^T D(t)dt$. See Bhansali et al. (2008) and Longstaff et al. (2007) for a complete description of the model and the estimation process.

Figure 5 depicts the evolution of the European (Panel A) and US (Panel B) spreads. Before the subprime crisis, the CDO indexes and their tranches were mainly driven by the idiosyncratic component, the systemic and systematic spreads remaining almost negligible. At the beginning of the crisis, the systemic spreads increase substantially, achieving the first peak during the Bearn Stearns' episode (see Appendix A1), in which the systemic spreads are higher than the idiosyncratic spreads in both economic areas. Up to the Lehman Brothers episode, the European and US spreads behaved similarly. After that episode, the European and US spreads behaved in a different way. From the Lehman episode to March 2009, in Europe, the systemic spread captures half of the iTraxx IG 5y's[32] behavior, whereas in the US, the systematic spread explains a higher proportion of the CDX IG 5y. Since March 2009, the idiosyncratic spread has explained most of the iTraxx IG 5y while in the US it has remained at the same level.[33] Table 4 contains the descriptive statistics for the three spreads. In both economic areas, we observe that, on average, the higher spread is related to the idiosyncratic component followed by the systemic and systematic components.

e. Multivariate density

Another set of measures assesses the systemic risk through recovering the multivariate density of the analyzed portfolio. Within this line, we follow Segoviano et al. (2009), who propose a set of banking stability measures based on distress dependence, which is estimated by the Banking System Multivariate Density (BSMD).[34] BSMD is the key element for measuring banking stability and is estimated by means of Consistent

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[32] Note that by construction, the idiosyncratic, systematic and systemic spreads add up the CDO index spreads.
[33] At the end of the sample period, three jumps appear on the US spreads, corresponding to periods in which out-the-roll series are employed (see Section 3).
[34] The authors propose three different categories of measures: (a) common distress in the banks of the system; (b) distress between specific banks; (c) distress in the system associated with a specific bank.

Information Multivariate Density Optimizing (CIMDO) methodology (see Segoviano, 2006). CIMDO methodology is characterized by the CIMDO-copula function, which is able to capture both linear and non-linear distress dependences and allows changes throughout the economic cycle.[35] Once the BSMD is recovered, the authors propose two measures for common distress in the banking system: the Joint Probability of Distress (JPoD) and the Banking Stability Index (BSI).

The estimation of the BSMD becomes harder as we increase the number of banks under analysis. In order to overcome this problem, we analyze this measure using "reduced portfolios" according to three criteria: (a) level of CDS spread; (b) level of liabilities; (c) level of the liabilities over market value ratio. For each period of time, we choose the three banks which are at the top of each classification and estimate the corresponding BSMD. Estimating the systemic risk measures over the "reduced portfolio" instead of over the whole portfolio is an approximation. However, we believe that the "reduced portfolios" could appropriately measure the systemic risk of the European and US banking systems because these categories (i.e., level of CDS spread; level of liabilities; level of the liabilities over market value ratio) usually give reliable indications about the soundness of the bank's financial position.

The procedure for estimating these measures could be divided into two steps. The first one consists of recovering the BSMD by means of CIMDO-copula while the second one concerns the estimation of the common distress measures.

To recover the BSMD, we use the CIMDO-methodology. With this approach, a posterior multivariate distribution "p" (i.e., the CIMDO density) is obtained by using an optimization procedure by which a prior density "q" is updated with empirical information via a set of constraints based on the probability of defaults. According to the CIMDO density, the

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[35] By means of CIMDO-copula, the authors overcome the drawbacks of the characterization of distress dependence of financial returns with correlations, which has been one of the most popular approaches for measuring systemic risk.

BSMD is the posterior density that is the closest to the prior distribution and that is consistent with the empirically estimated PoDs of the banks making up the "reduced portfolios".

The optimal solution is represented by the following posterior multivariate density:

$$\hat{p}(x,y,z) = q(x,y,z)\exp\left\{-\left[1+\hat{\mu}+\hat{\lambda}_1\chi_{[x_d^x,\infty)}+\hat{\lambda}_2\chi_{[x_d^y,\infty)}+\hat{\lambda}_3\chi_{[x_d^z,\infty)}\right]\right\} \quad (14)$$

where $q(x,y,z)$ and $p(x,y,z)$ are the prior and posterior multivariate distributions and χ is an indicator variable which takes 1 in the defined interval and zero otherwise.[36]

This methodology takes the structural approach (Merton 1973) as the departing point. Assuming that its basic premises and economic intuition are correct, the initial hypothesis is that the portfolio follows a multivariate distribution, $q(x,y,z)\in\Re^3$, which is a Normal distribution $N(0,I)$ where I is the identity matrix.

To recover the Lagrange multipliers (i.e., $\hat{\mu},\hat{\lambda}_1,\hat{\lambda}_2,\hat{\lambda}_3$), we solve the next system of equations of each period of time:

$$\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\int_{x_d^x}^{\infty}\hat{p}(x,y,z)dxdydz = PoD_t^x$$

$$\int_{-\infty}^{\infty}\int_{x_d^y}^{\infty}\int_{-\infty}^{\infty}\hat{p}(x,y,z)dxdydz = PoD_t^y \quad (15)$$

$$\int_{x_d^z}^{\infty}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\hat{p}(x,y,z)dxdydz = PoD_t^z$$

$$\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\hat{p}(x,y,z)dxdydz = 1$$

where PoD_t^i refers to the probability of default of each individual bank (among the three selected) at period t. The intuition is that the BSMD must satisfy the observed default probabilities for each bank.

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[36] x_m^i is the default threshold which is defined as

$$x_d^i = \Phi^{-1}\left(1-PoD_m^i\right)$$

where PoD_m^i is the average of the PoD for the previous 6 months and Φ^{-1} stands for the inverse of the standard normal CDF.

Once we get the Lagrange multipliers on the basis of Equation (15), the BSMD is easily recovered by plugging the estimated Lagrange multipliers (i.e. $\hat{\mu}, \hat{\lambda}_1, \hat{\lambda}_2, \hat{\lambda}_3$) into Equation (14). We repeat this process for each period and portfolio to obtain the BSMD of each portfolio over time.

After that, we estimate the two measures of common distress:

Joint Probability of Default (JPoD): This measure represents the probability of all banks in the portfolio (i.e., the three selected banks) becoming distressed. The JPoD not only contains changes in the individual banks' PoD but also captures changes in the distress dependence among banks, which increases in times of distress. This measure is defined as:

$$\int_{x_d^z}^{\infty} \int_{x_d^y}^{\infty} \int_{x_d^x}^{\infty} \hat{p}(x, y, z) dx dy dz = JPoD \tag{16}$$

Figure 6 shows the evolution of the JPD for European and US reduced portfolios. Up to the start of the subprime crisis, the JPD was almost zero. However, in the crisis period, there is a substantial increment of this risk. As can be seen in Panel A of Table 5, in both cases, the "reduced portfolio" that has higher risk is the one associated with the spread. On average, the spread portfolio's JPD is 0.53 and 1.93 b.p. for the European and US portfolios, respectively. Regarding the liabilities and ratio portfolios, these averages are around 0.11 and 0.14 for Europe and 0.44 and 0.98 for US portfolios, respectively. The reason the spread portfolio displays a higher level of risk could be related to the close relationship that CDSs and systemic risk have maintained throughout the crisis. Three periods of stronger distress can be seen in Figure 6: March and October 2008 and March 2009. Our results are consistent to the ones of Segoviano et al. (2009) during the comparable period, although in our case, the probabilities are lower than theirs.

Banking Stability Index (BSI): This measure represents the expected number of banks to become distressed, conditioned on the fact that at least one bank has become distressed. Hence, the higher this number is, the higher the instability. This measure is defined as:

$$BSI = \frac{P(X \geq x_d^x) + P(Y \geq x_d^y) + P(Z \geq x_d^z)}{1 - P(X < x_d^x, Y < x_d^y, Z < x_d^z)} \qquad (17)$$

This measure is an index which takes values between 1 and 3 due to the number of components in a "reduced portfolio". The value 1 refers to the situation in which the stress in one institution causes no effect on the others. As can be seen in Figure 7, up to July 2007, this measure is almost 1. After that point, the distress between institutions is intensified. Panel B of Table 5 reports the descriptive statistics. There we observe that as in the JPD, the "CDS reduced portfolio" shows higher levels of stress. Our results are again in line with the findings of Segoviano et al. (2009).

f. "Co-risk management" measures

Our last set of systemic risk measures are based on the traditional risk management tools like Value-at-Risk (*VaR*) and Expected Shortfall (*ES*). Adrian et al. (2009) propose estimating institution *i*'s Co-Value-at-Risk (*CoVaR_i*) as the whole system (i.e., portfolio)'s *VaR_s* conditioned on institution *i* being in distress (i.e., being at its unconditional *VaR_i* level). On the basis of *CoVaR*, they calculate the marginal contribution of institution *i* to the overall systemic risk as the difference between *CoVaR* and the unconditional whole system's *VaR*, which is denoted as $\Delta CoVaR_i$. Therefore, $\Delta CoVaR_i$ allows us to determine how much an institution adds to overall systemic risk. Additionally, the authors argue that their methodology can be easily extended to other risk management tools like *ES*. The Expected Shortfall is the basis of the systemic risk measure proposed by Acharya et al. (2010a). They propose a taxation system which is determined by the financial firm's *ES* (i.e., its losses in the tail of the aggregate sector distribution). However, they do not provide

a tool for monitoring the evolution of the level of the systemic risk in the system (i.e., portfolio) on a daily or weekly basis, and hence, we base our analysis on the "co-risk management" measures of Adrian et al. (2009).

Adrian et al. (2009) based their analysis on the growth rates of the market value of total financial assets (X_t^i), which are defined as:

$$X_t^i = \frac{ME_t^i \cdot LEV_t^i - ME_{t-1}^i \cdot LEV_{t-1}^i}{ME_{t-1}^i \cdot LEV_{t-1}^i} \tag{18}$$

where ME_t^i denotes the market value of institution i and LEV_t^i is the ratio of total assets to book equity. In order to estimate this growth rate for the whole portfolio, we calculate the total market weighted sum of the X_t^i across all institutions, which is:

$$X_t^{portfolio} = \sum_i \frac{ME_{t-1}^i \cdot LEV_{t-1}^i}{\sum_j ME_{t-1}^j \cdot LEV_{t-1}^j} X_t^i \tag{19}$$

VaR and *CoVaR* are estimated by means of quantile regression (Koenker and Bassett, 1978). The time-variant measures are based on the following system of equations:

$$
\begin{aligned}
X_t^i &= \alpha^i + \beta^i M_{t-1} + \varepsilon_t^i \\
X_t^{portfolio} &= \alpha^{portfolio} + \beta^{portfolio} M_{t-1} + \varepsilon_t^{portfolio} \\
X_t^{portfolio} &= \alpha^{portfolio|i} + \beta^{portfolio|i} M_{t-1} + \gamma^{portfolio|i} X_t^i + \varepsilon_t^{portfolio|i}
\end{aligned}
\tag{20}
$$

where M_t^i is a set of state variables. Due to the fact that we are considering two different portfolios (European and US), we employ two sets of state variables. The European one is composed of VDAX, the LIBOR-OIS referring to the Eurozone (see Section 4.b), the change in 3-month term Treasury Eurozone bill[37], the difference between 10-year and 3-month Treasury rates, the difference between a BBB-rated 10-year bond and 10-year Treasury rates and the banking index return[38] of European banks. For the US portfolio, we

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[37] See Section 3 for a detailed description.
[38] Banking Indexes are return indexes which represent the theoretical aggregate growth in value of the constituents of the indexes. (Source, DataStream)

use VIX, the LIBOR-OIS of the US, the change in the 3-month Treasury bill, the difference between 10-year and 3-month Treasury rates, the difference between a BAA- rated 10-year bond and 10-year Treasury rates and the banking index return of US banks. In order to perform the quantile regression, we assume a confidence level of 5% (i.e., $\alpha = 0.05$). This is like estimating a *VaR* at 5%.

Once the coefficients of Equation (21) have been estimated through quantile regression, *VaRs* and *CoVaR* are estimated as follows:

$$VaR_t^i = \hat{\alpha}^i + \hat{\beta}^i M_{t-1}$$
$$VaR_t^{portfolio} = \hat{\alpha}^{portfolio} + \hat{\beta}^{portfolio} M_{t-1} \qquad (21)$$
$$CoVaR_t^i = \hat{\alpha}^{portfolio|i} + \hat{\beta}^{portfolio|i} M_{t-1} + \hat{\gamma}^{portfolio|i} VaR_t^i$$

Subsequently, the marginal contribution of institution *i* to the overall systemic risk, which is called Delta Co-Value-at-Risk ($\Delta CoVaR_i$), is calculated as the difference between $CoVaR_i$ and the unconditional *VaR* of the whole system,

$$\Delta CoVaR_t^i = CoVaR_t^i - VaR_t^{portfolio} \qquad (22)$$

This measure allows us to determine how much systemic risk is associated with each bank in the portfolio. In order to obtain a global measure (up to now this systemic risk measure has been associated with each institution) to monitor the level of systemic risk in the whole portfolio, we aggregate the $\Delta CoVaR_i$ of each bank, using two different criteria: first, equally weighted, and second, using weights proportional to market capitalization.

Figure 8 shows the evolution of the $\Delta CoVaR_i$ for the European (Panel A) and US (Panel B) portfolios. As is also the case with other systemic measures, both measures remain almost flat up to July 2007. Then, we distinguish three periods: the beginning of the crisis, which is characterized by the Bearn Stearns episode and presents a moderate increase in $\Delta CoVaR_i$ as well as in its volatility; the Lehman Brothers episode, which generates the highest level of

distress in both portfolios; and the post-Lehman Brother bankruptcy, in which $\Delta CoVaR_i$ goes down to a level similar to the one at the beginning of 2008.

Panel A of Table 6 reports the descriptive statistics of these measures. Within each economic area, two measures are estimated: equally weighted and weighted by market capitalization. In both portfolios, the former measure presents higher $\Delta CoVaR_i$ and is more volatile. However, within the European portfolio, the measures are closer than within the US portfolio.

Additionally, we apply the "co-risk" methodology to the *ES* through the quantile regression. The *ES* might provide additional insights with respect to the *VaR* due to the fact that the *VaR* is not a coherent measure (Artzner, Delbaen, Eber and Heath (1999)). Figure 9 shows the evolution of the $\Delta CoES_i$. Panel A refers to the European portfolio and Panel B to the US portfolio. Their behavior is similar to the behavior observed for the $\Delta CoVaR_i$. Panel B of Table 6 reports their descriptive statistics. We observe that, on average, the US weighted average measure of $\Delta CoES_i$ is bigger than the European one.

Moreover, under both co-risk measures, we may observe that equally weighted systemic risk measures suggest higher systemic risk levels than the ones weighted by market capitalization. In the latter case, the results suggest that the largest banks (i.e., the banks with the highest market capitalization) are not necessarily the ones which generate the most systemic risk (see Table 6).

5. Comparing Measures

In this section, we choose the more informative variables within each group, regressing the measures against the influential events that have marked the main episodes of the crisis. Then we establish a common metric to be able to compare all of them. The common metric is achieved by standardizing the different systemic risk measures. Finally, we run a "horse

race" to rank the systemic risk measures according to their performance in a causality test, price discovery and McFadden R-squared.

a. Choosing measures in each group

Up to now several measures have been proposed within each group. However, most of them may provide redundant information. In this subsection, we choose the variables that provide more information within each group and economic area.

To choose the most informative variables about systemic risk we use of an influential events variable. This variable is a dummy which reflects most important adverse news during the financial crisis.[39] Then we run logistic regressions, using each systemic risk measure as an explanatory variable, and choose the systemic risk measures with the highest McFadden R-squared.

Given that the frequency of the measures differs, we construct two influential events variables on both a daily and weekly basis. The former is a dummy variable that equals 1 on the event day as well as on the days before and after and is equal to zero otherwise. The other one is a categorical variable that ranges between 0 and 3, which represents the number of events within the corresponding week (i.e., number 3 captures three or more events while 0, 1 and 2 capture the corresponding number of events).

Regarding the daily measures (i.e., Principal Component Analysis, Libor spreads, CDO indexes and their tranches, multivariate density copulas and "co-risk management" tools), we run logit regressions, while for the weekly measure (i.e., structural models), we make use of multinomial logit regressions. In this framework, there is not any R-squared equivalent to the one of Ordinary Least Squared (OLS) (Long, 1997). However, to evaluate the goodness-of-fit for a logistic model, pseudo R-squared has been developed. Higher values of pseudo R-squared indicate better model fitting, although they cannot be

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[39] A detailed description of the influential events considered can be found in Appendix A1.

interpreted as in OLS R-squared. Our selection criterion is based on the McFadden R-squared[40] because it has appropriate statistical properties.

For each group of measures, we run several logistic regressions in which the independent variable is lagged up to 14 days and 2 weeks, respectively.[41] After that, we compute the average R-squared for each variable. Finally, we choose those variables that provide better average fit within each group and economic area.

Table 7 summarizes the average McFadden R-squared. The degree of fit provided by the systemic risk measures is not very high. The highest for Europe (US) is LO (LT) with R-squared of 13% (15%).[42] Structural models and "co-risk management" tools do not give particularly good results, especially in Europe, with R-squared ranging from 1% to 10%. In these groups, the selected variables are the SIN05 (SIV10) and $\Delta CoES$ ($\Delta CoES$ and $\Delta CoVaR$)[43] in Europe (US). Similar fits are provided by the CDO-based measure in both economic areas. Regarding multivariate density variables, BSI whose "reduced portfolio" is based on the liabilities over market value ratio (BSI) usually has the best fit.

b. Horse race

In this subsection, we rank the selected variables across groups within each economic area. Firstly, we compare the evolution of the selected measures by portfolios. In order to carry out a comprehensive comparison, we establish a common metric. As Nardo, Saisana, Saltelli and Tarantola (2005) detail, there are several procedures for determining a common

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[40] McFadden R-squared is calculated as:

$$R^2 = 1 - \frac{\ln \hat{L}(M_{Full})}{\ln \hat{L}(L_{Intercept})}$$

where M_{Full} refers to the full model and $M_{Intercept}$ to the model without predictors. $\hat{L}$ is the estimated likelihood.
[41] Results do not change substantially when other lags are considered.
[42] In order to construct LIBOR-TBILL in Europe, we employ a "hypothetical" Treasury yield, which is the weighted average of the Treasury yield of Eurozone members. The consequence of the lack of a European Treasury bill is that the LIBOR-TBILL does not capture the fact that in time of stress, Treasuries become especially valuable. On the contrary, LIBOR-TBILL provides more information in the US market, in which the tight relationship between bad news and Treasury bills becomes apparent.
[43] Due to the difference between $\Delta CoES$ and $\Delta CoVaR$, we choose both to perform the horse race.

metric.[44] However, due to the nature of our dataset, we standardize all measures so as to get a comparable measure. Once we have standardized the variables, we rank the systemic risk measures within each economic area according to three criteria: (i) causality test; (ii) price discovery analysis; (iii) McFadden R-squared.

Panel A of Figure 10 depicts the evolution of the standardized European variables since 2007. From the beginning of the period up to the start of the subprime crisis, no variable gives signal of an increase in systemic risk, remaining flat up to that date. During the crisis, the PCA variable, BSI and CDO behave similarly, although the last measure achieves its maximum just before the Lehman Brothers episode while the other two measures get it during that episode. Regarding the variable SIN05, we have transformed the original weekly variable into a daily variable to make the comparison easier.[45] This measure does not show any change up to April 2008. The measure LO shows the quickest reaction after the start of the subprime crisis. Finally, the $\Delta CoES$ measure is very volatile. Just before the Lehman Brothers bankruptcy (see Appendix A1), it sharply increased, staying at high levels up to December 2008.

Panel B of Figure 10 depicts the standardized US systemic risk measures. We rule out the pre-crisis period as well as the $\Delta CoVaR$ in order to have a clearer picture during the crisis period.[46] In this figure, we can see that apart from LT measure, the European and US systemic risk measures (Principal Component Analysis, structural credit risk model, CDO indexes and their tranches, multivariate densities and "co-risk" management measures) perform very similar in both portfolios. Regarding LT, it seems to be a leading indicator at the beginning of the crisis. Moreover, after the Lehman Brothers episode, this measure dramatically drops, finishing the sample period at levels similar to the pre-crisis period.

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[44] In the context of computing composite indicators among countries, they propose the following strategies: ranking indicators, standardization, re-scaling and distance to the reference country, among others.
[45] We use the same value for each week.
[46] In this subsection, we show that according to our three classifications, $\Delta CoES$ takes a better position in the horse race than $\Delta CoVaR$.

The first result that we find is the lack of early indicators (measures that warn about systemic risk before the hit takes place). Apart from LT and $\Delta CoES$ in the US (although the second case is less clear), no measure could be employed as an early indicator. This fact is especially serious in certain measures like the ones which are based on structural models.[47] The second characteristic that we find is that Libor Spreads are useful (mainly LT) while they are not subject to economic policies. Once they become a political-economic tool, their behavior is misleading and they do not appropriately measure the pressures of the financial system.

Once we have compared the standardized variables, we rank the systemic risk measures within each economic area.

i.   *Causality test*

The first classification is based on the Granger causality test (Granger, 1969). This test intuitively examines whether past changes in one variable, X_t, help to explain current changes in another variable, Y_t. If not, we conclude that Y_t does not Grange cause X_t. Formally, the Granger causality test was based on the follow regression:

$$\Delta X_t = \alpha + \sum_{i=1}^{p} \beta_{xi}\Delta X_{t-i} + \sum_{i=1}^{p} \beta_{yi}\Delta Y_{t-i} + \varepsilon_t \tag{23}$$

where Δ is the first-difference operator and ΔX and ΔY are stationary variables. We reject the null hypothesis that states Y_t does not Granger cause to X_t if the coefficients β_{yi} are jointly significant based on the standard F-test.

We perform the Granger causality test by pairs of measures within each economic area. The number of lags is determined on the basis of the Schwarz information criterion on the corresponding Vector Autoregressive (VAR) equation. In order to perform this analysis, we

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[47] We have estimated the probability that 5% of all banks considered go bankrupt for the next six months (SIV05). However, what we get is a lagged measure.

restrict the sample from January 2007 to the end of the sample period. We get the same results using both the standardized and non-standardized systemic risk measures.

Table 8 summarizes the p-values for each test as well as the number of lags employed in the test and the corresponding ranking score, which is based on the p-values at a confidence level of 1%; Table 11 contains the aggregated ranking scores for the horse race. Panel A of Table 8 refers to the European portfolio measures. To rank the measures, we give a score of +1 to measure X if X causes another measure Y and we give a score of -1 to measure X if X is caused by Y. The best measure gets the highest positive score and the worst measure the highest negative score. For instance, PCA causes BSI and $\Delta CoES$ but it is not caused by any other measure. Hence, PCA gets a final score of +2. LO gets a final score of +2, CDO scores +1, BSI scores par for the course, SIN5 scores -1 and, finally, $\Delta CoES$ scores -4.[48] Therefore, the best measures in this account are PCA and LO and the worst measure is $\Delta CoES$. Panel B shows the results of the US portfolio. Applying the same procedure as above, PCA scores +4, LT +2, SIV10 +1, $\Delta CoVaR$ scores par for the course, CDO -1 and, finally, $\Delta CoES$ and BSI both score -3.[49] Therefore, PCA is again the best measure and the worst measures are BSI and $\Delta CoES$.

ii. Price Discovery

The second classification is based on the Gonzalo and Granger's (1995) price discovery methodology. This analysis allows us to determine, by pairs of measures, which measures reveal information more efficiently to the market. Formally, this price discovery methodology is based on the following VECM specification:

$$\Delta X_t = \alpha\beta'X_{t-1} + \sum_{i=1}^{p}\Gamma_i X_{t-i} + \varepsilon_t \tag{24}$$

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[48] We observe that PCA, LO, CDO and BSI Granger cause at least two systemic risk measures while $\Delta CoES$ is Granger caused by all the measures considered.

[49] We observe that PCA, LT, SIV10 and CDO measures Granger-cause other systemic risk measures while $\Delta CoES$ and $\Delta CoVaR$ are Granger-caused by the rest of the measures.

where X_t is a vector which includes a pair of systemic risk measures and ε_t is a white noise vector. The parameter $\alpha = (\alpha_1, \alpha_2)$ is a vector which includes the parameters that multiply the error correction term. By means of the Gonzalo and Granger Permanent-Transitory (PT) component decomposition, we measure the market contribution to price discovery (price discovery metrics). The percentages of price discovery of systemic risk measure i (where i =1, 2) can be defined from the following metrics:

$$GG_1 = \frac{\alpha_2}{-\alpha_1 + \alpha_2}; \qquad GG_2 = \frac{-\alpha_1}{-\alpha_1 + \alpha_2} \qquad (25)$$

The vector α' represents the coefficients that determine the market contribution to price discovery. Thus, we conclude that a given market i leads the process of price discovery whenever its corresponding price discovery metric (GG_i, $i=1,2$) is higher than 0.5. The price discovery metric for an individual firm is defined such that it has a lower bound of 0 and an upper bound of 1.

Table 9 contains the GG metrics for European and US systemic risk measures, the number of employed lags and the corresponding ranking scores; Table 11 contains the aggregated ranking scores for the horse race. In both tables, Panels A and B refer to the European and US portfolio, respectively. Using the same procedure as above, the result for Europe is PCA +3, LO +3, CDO +2, SIN05 par for the course, BSI -3 and $\Delta CoES$ -5. Therefore, the best measures in this account are PCA and LO and the worst measure is $\Delta CoES$. This is in agreement with the results in the Granger causality test. The results for the US are PCA and SIV10 +5, BSI +2, LT, $\Delta CoES$ and CDO -2 and $\Delta CoVaR$ -6, and then the best measures are PCA and SIV10 and the worst is $\Delta CoVaR$.

iii.   McFadden R-squared

The last analysis is based on the McFadden R-squared. In Section 4.1, we make use of the logistic and multinomial regressions against an influential events variable to rule out those

variables which provide less information about the systemic events within each group of measures. In this section, we employ the McFadden R-squared to rank the systemic risk measures. This analysis provides a perspective different than the previous one because it is based on the relationship between the measures and the influential events instead of focusing on the relationship among variables.

Table 7 contains the average of McFadden R-squared. On the basis of the McFadden R-squared, we compare the systemic risk measures by pairs, assigning a score of +1 to the measure with the highest R-squared and -1 to the one with the lowest R-squared. For instance, in the European portfolio, LO has the highest McFadden R-squared (0.131) and hence its score is equal to +5 because its R-squared is higher in each of the five possible comparisons. Table 10 contains the ranking scores. The result for the European portfolio is LO +5, BSI +3, PCA +1, SIN05 -1, $\Delta CoES$ -3 and CDO -5. Therefore, the best measure in this ranking is LO and the worst is CDO. Regarding the US portfolio, LT gets the highest score (+6), followed by BSI (+4), $\Delta CoES$ (+2), $\Delta CoVaR$ (0). At the bottom of the ranking appear PCA (-2) and SIV10 (-4).

Table 11 summarizes the horse race among the systemic risk measures. In both Europe and the US, simple measures (PCA and Libor spreads) consistently rank in the top places in our three criteria. The message seems to be clear: the simpler the measure, the better its performance.

6. Conclusions

In this paper, we compute six different sets of systemic risk measures for a sample of European and US banks from January 2004 to November 2009. The six measures are based on i) Principal components of the bank's Credit Default Swaps, ii) Interbank interest rates, iii) Structural (Merton, 1973) credit risk models, iv) Collateralized Debt Obligations indexes

and their tranches, v) Multivariate densities computed from CDS spreads and vi) Co-Risk (*CoVaR*) measures. We then compare them using three different criteria: i) Causality tests, ii) Price discovery tests and iii) their relationship with an index of systemic events. We find that for the European market, the best indicator is the LIBOR-OIS spread followed by the Principal Component of the single-name CDSs, whereas the least reliable indicator is the Delta Co-Expected Shortfall. For the US market, the best indicator is the first Principal Component of the single-name CDSs followed by the LIBOR-TBILL spread, whereas the least reliable indicator is the systemic spread extracted from Collateralized Debt Obligations indexes and their tranches.

Measures based on complex models or convoluted statistical procedures do not perform particularly well in our sample. It seems that "model risk" is an issue when developing appropriate measures of systemic risk. Therefore, the implication for investors and regulators looking for reliable systemic risk indicators is to stick to simple, robust indicators based on credit derivatives and market data interest rates. Avoiding "model noise" seems to be a safe bet in this case.

Avenues for further research would be to study measures that combine information on CDS and interest rate variables. How to combine these measures with an individual bank's characteristics to build measures of the contribution of each individual bank to the overall systemic risk is a topic of special relevance.

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Appendix A1

This list summarizes most important negative events that have occurred during the subprime crisis.

2007

May 4: UBS shut down its internal hedge fund Dillon Read after suffering some large subprime-related losses.

June 20: Bear Stearns hedge funds involved in securities backed by subprime loans near shutting down.

August 1: Bear Stearns was hit by a legal claim stemming from the meltdown of two of its hedge funds, sending its shares, already under pressure from woes with a third fund, to a 19-month low.

August 6: American Home Mortgage Investment Corporation (AHMI) files Chapter 11 bankruptcy. Two days earlier, AHMI had laid off nearly ninety percent of its 7,000 employees. A German government-led bailout of IKB Deutsche Industriebank results in state-owned KfW assuming up to e1 billion in expected possible losses. Bear Stearns fires its co-president, Warren Spector. National City Home Equity, a unit of National City of Cleveland, stopped taking applications for new home-equity loans and lines of credit.

August 7: Numerous quantitative long/short equity hedge funds suddenly begin experiencing unprecedented losses as a result of what is believed to be liquidations by some managers eager to access cash during the liquidity crisis.

August 8: Mortgage Guaranty Insurance Corporation announces it will discontinue its purchase of Radian Group after suffering a billion-dollar loss of its investment in Credit-Based Asset Servicing and Securitization.

August 9: French investment bank BNP Paribas suspends three investment funds that invested in subprime mortgage debt, due to a "complete evaporation of liquidity in the market".

August 10: HomeBanc files for Chapter 11. Stock market downturn.

August 14: Sentinel Management Group suspends redemptions for investors and sells off $312 million worth of assets; three days later, Sentinel files for Chapter 11 bankruptcy protection. US and European stock indices continue to fall.

August 15: The stock of Countrywide Financial falls around 13% on the New York Stock Exchange after Countrywide says foreclosures and mortgage delinquencies have risen to their highest levels since early 2002.

August 16: Countrywide Financial Corporation narrowly avoids bankruptcy by taking out an emergency loan of $11 billion from a group of banks.

August 23: First Magnus Financial files for Chapter 11 bankruptcy protection.

August 26: Landesbank Baden-Württemberg (LBBW), the German public sector bank, agrees to buy Sachsen Landesbank for 250 million Euros. Sachsen LB is the second German bank that needed to be bailed out.

August 31: Ameriquest, once the largest subprime lender in the US, goes out of business.

September 5: Stock market downturn due to bad US economic data in the US.

September 11: Victoria Mortgages, which has a portfolio of 440 million Euros, declares that they have insufficient funds.

September 13: The Bank of England extends emergency funding to Northern Rock. The move came after investors withdrew support of Northern Rock amid worries that the institution could face short-term difficulties in raising the necessary capital in the wholesale market.

September 17: Stock market downturn.

September 21: Bear Stearns announces a 61% drop in earnings from the same quarter in 2006.

September 29: Affected by the spiraling mortgage and credit crises, Internet banking pioneer NetBank goes bankrupt.

October 1: the Swiss bank UBS announces that it lost $690 million US in the third quarter. Citigroup announces a 60% drop in earnings from the same quarter last year.

October 5: Merrill Lynch announces a $5.5 billion US loss as a consequence of the subprime crisis and the loss is later revised to $8.4 billion.

October 24: The $5.5 billion US loss announced by Merril Lynch on October 5 is revised to $8.4 billion, a sum that credit rating firm Standard & Poor's called "startling".

October 30: Merrill Lynch (ML) CEO, Stan O'Neal, resigns after an announcement that ML would writedown around $7.9 billion ($3.4 billion more than ML had predicted just three weeks earlier) in debt.

November 4: Citigroup CEO, Chuck Prince, resigns after an announcement that Citigroup may have to writedown up to $11 billion in bad debt.

November 21: Freddie Mac announces a $2 billion loss in mortgage defaults and credit losses. Shares in Freddie Mac dropped 28.7% and Fannie Mae dropped 24.8% upon the announcement.

November 23: Two French banks pledge $1.5 billion to bail out French bond insurer CIFG.

December 5: Fannie Mae faces capital problems because of the deteriorating US housing market.

December 19: Morgan Stanley announces $9.4 billion in writedowns from sub-prime losses.

December 20: Bear Stearns reports its first quarterly loss in its 84-year history, a sum of $854 million.

2008

January 15: Stock market downturn.

January 21: Stock market downturn.

February 28: AIG announces a $5.2 billion loss for the fourth quarter of 2007, the second consecutive quarter of losses. The largest portion of losses come from AIG writedowns of $11.12 billion (pre-tax) concerning their revaluation of a large credit default swap portfolio.

March 3: The UK's largest bank, HSBC, reports a $17.2 billion loss on writedowns of its US mortgage portfolio.

March 10: Rumors start to circulate on Wall Street that Bear Stearns could have liquidity problems. Investors believe rumors as financial stocks drop in value.

March 16: Bear Stearns is acquired for $2 a share by JPMorgan Chase in a fire sale, avoiding bankruptcy. The deal is backed by the Federal Reserve, providing up to $30 billion to cover possible Bear Stearns losses.

March 17: Stock market downturn.

April 1: UBS announces it will writedown $19 billion in the first quarter on its US holdings.

April 8: The International Monetary Fund's new estimate on credit crunch losses is projected upwards to $945 billion.

April 17: Merrill Lynch reveals first quarter losses of $1.96 billion and plans to cut 4,000 jobs worldwide.

April 18: Citigroup reports a $5.11 billion loss in the first quarter of 2008 off of a $12 billion writedown on subprime mortgage loans and other risky assets. The largest US bank also announces it will cut 9,000 more jobs.

May 9: AIG reports 1st quarter earnings results as a net loss of $7.81 billion. One of the principle factors of this loss was a first quarter writedown of $9.11 billion on the revaluation of their credit default swap portfolio.

July 8: Shares in Fannie Mae and Freddie Mac plunge around 20% as investors sell off their shares.

July 11: Indymac Bank, a subsidiary of Independent National Mortgage Corporation (Indymac), is placed into the receivership of the FDIC by the Office of Thrift Supervision. It is the fourth-largest bank failure in United States history, and the second-largest failure of a regulated thrift.

July 13: Investor speculation on the Freddie Mac and Fannie Mae bailout worsen the situation.

July 17: Major banks and financial institutions had borrowed and invested heavily in mortgage backed securities and report losses of approximately $435 billion.

July 31: Deutsche Bank reveals more writedowns, bringing the total so far to $7.8 billion for this year. Without figuring in the writedowns, the Deutsche corporate banking and securities division would have an income 16% less than the second quarter of last year.

August 7: AIG shares drop 19.1%, its biggest daily drop in 39 years, after the announcement of a higher-than-expected $5.4 billion loss for the second quarter. This loss was blamed on AIG's exposure to large subprime writedowns.

September 5: Stock market downturn.

September 7: Mortgage lenders Fannie Mae and Freddie Mac are rescued by the US government in one of the largest bailouts in US history.

September 10: Wall Street bank Lehman Brothers posts a loss of $3.9 billion for the three months to August.

September 15: Lehman Brothers files for Chapter 11 bankruptcy protection. Meanwhile, another US bank, Merrill Lynch, agrees to be taken over by Bank of America for $50 billion.

September 16: The US Federal Reserve announces an $85 billion rescue package for AIG.

September 17: Lloyds TSB announces it is to take over Britain's biggest mortgage lender, HBOS, in a £12 billion deal.

September 25: Washington Mutual is closed down by regulators and sold to JPMorgan Chase.

September 28: The credit crunch hits Europe's banking sector as the European banking and insurance giant Fortis is partly nationalized to ensure its survival.

September 29: In Britain, the mortgage lender Bradford & Bingley is nationalized. The Icelandic government takes control of the country's third-largest bank, Glitnir, after the company faces short-term funding problems.

The US House of Representatives rejects a $700 billion rescue plan for the US financial system - sending shockwaves around the world. It opens up new uncertainties about how banks will deal with their exposure to toxic loans and how credit markets can begin to operate more normally.

September 30: Dexia becomes the latest European bank to be bailed out as the deepening credit crisis continues to shake the banking sector.

October 6: Germany announces a $68 billion plan to save one of the country's biggest banks.

October 7: The Icelandic government takes control of Landsbanki, the country's second largest bank.

October 13: The UK government announces plans to nationalize the Royal Bank of Scotland (RBS), Lloyds TSB and HBOS.

The takeover of Wachovia by Wells Fargo is approved by regulators.

October 14: The US government unveils a $250 billion plan to purchase stakes in a wide variety of banks in an effort to restore confidence in the sector.

October 15: Stock market downturn.

October 24: The UK is on the brink of a recession.

November 14: The Eurozone officially slips into recession.

November 23: The US government announces a $20 billion rescue plan for Citigroup.

December 1: The US recession is officially declared.

December 11: Bank of America announces up to 35,000 job losses over three years following its takeover of Merrill Lynch.

The European Central Bank, as well as central banks in the UK, Sweden and Denmark, slash interest rates again.

December 19: President George W. Bush says the US government will use up to $17.4 billion of the $700 billion meant for the banking sector to help the Big Three US carmakers, General Motors, Ford and Chrysler.

2009

January 9: US jobless rate rises to 7.2% in December, the highest in 16 years.

January 13: German Chancellor Angela Merkel unveils an economic stimulus package worth about $67 billion to kick-start Europe's largest economy.

January 14: The UK government unveils a plan to guarantee up to £20 billion of loans to small and medium-sized firms.

January 15: The European Central Bank (ECB) cuts Eurozone interest rates by half a percentage point to 2%.

January 23: The UK has officially entered a recession.

March 2: Insurance giant AIG reports the largest quarterly loss in US corporate history: $61.7 billion in the final three months of 2008. The firm is also to receive an extra $30 billion from the US government as part of a revamped rescue package.

The beginning of the year represents the worst start to a year in the history of the S&P500, with a drop in value of 18.62%.

April 22: The IMF raises its forecast of total financial sector writedowns to $4 trillion. It says in its Global Stability Report that only $1 trillion has been written down so far, and that almost half the exposure is outside the US.

May 1: One of the "big three" US carmakers, Chrysler, enters bankruptcy protection after pressure from the US government.

May 8: Ten of the biggest US banks have failed their stress tests and need fresh capital, the US Treasury announces. It says they need to raise an additional $74.6 billion, with the Bank of America the most exposed.

June 1: The world's largest carmaker, GM, enters bankruptcy protection .

June 10: Global oil consumption falls for the first time since 1993 in 2008.

June 11: Japan's economy contracts at an annualized rate of 14.2% in the first three months of 2009, a record rate of decline.

July 15: The UK jobless rate increases to 7.6%, the highest in more than 10 years.

July 24: The UK economy contracts more than double the figure economists had expected.

August 3: HSBC reports this represents a 51% decline in profits in relation to the previous year, although the published figure was in line with analysts' predictions.

August 7: The Royal Bank of Scotland announces a £1 billion loss for the first half of 2009 and warns that the second half results are likely to be substantially weaker.

August 27: The US GDP fell annually by 1% in Q2 2009. The data serves as confirmation that the global financial crisis represents the longest running recession on record for the US economy as well as being the deepest since the Great Recession.

October 26: The European Commission has ordered ING to sell off its insurance and investment management business.

November 3: The UK Treasury announces that a further £33.5 billion will be injected into the Royal Bank of Scotland in order to ensure that the bank survives the current crisis, bringing the total government investment in the institution up to 84%.

Tables

Table 1: Composition of Bank Portfolios

This table shows the European and US banks which constitute the two portfolios under analysis. On the left hand side are the European banks as well as their main market and the average portfolio weights on the basis of their market capitalization during the sample period. On the right hand side, we summarize the same information for the US banks.

European Portfolio			US Portfolio		
Bank	Market	Average Portfolio Weights	Bank	Market	Average Portfolio Weights
Barclays Bank	United Kingdom	0.05	Bank of America Corp	US	0.20
BBVA	Spain	0.05	Capital One FC	US	0.03
BNP PARIBAS	France	0.06	Citigroup Inc	US	0.22
Commerzbank	Germany	0.01	Comerica	US	0.01
Credit Agricole	France	0.04	Harris Corp	US	0.01
Credit Suisse	Switzerland	0.05	JPMorgan Chase & Co	US	0.19
Danske Bank	Denmark	0.02	Keycorp	US	0.01
Deutsche Bank	Germany	0.04	Morgan Stanley BK NA	US	0.06
Dexia	Belgium	0.02	PNC	US	0.03
HSBC Bank	United Kingdom	0.16	State Street Corp	US	0.03
ING Bank	Netherlands	0.05	Suntrust BK	US	0.03
Intesa Sanpaolo	Italy	0.04	US BC	US	0.07
KBC	Belgium	0.02	Wells Fargo & Co	US	0.12
Lloyds TSB	United Kingdom	0.04			
Nordea Bank	Sweden	0.03			
RBS	United Kingdom	0.07			
Santander	Spain	0.08			
Societe Generale	France	0.04			
UBS	Switzerland	0.07			
Unicredito	Italy	0.05			

Table 2: Libor Spreads Descriptive Statistics

This table reports the descriptive statistics of the two Libor spreads: LIBOR-OIS (LO) and LIBOR-TBILL (LT) for the Eurozone and US, measured on basis points. It contains the mean, standard deviation, median, the first and third quartile, maximum and minimum value. Moreover, the frequencies of the data, number of observations and the initial and final date are also reported.

	LO EU	LT EU	LO US	LT US
Mean	30.398	39.283	36.992	66.072
SD	39.480	44.576	50.699	62.449
Median	5.700	17.525	10.900	39.150
Q1	4.488	9.907	7.487	27.770
Q3	56.857	63.369	60.938	93.918
Maximum	194.325	351.625	363.875	458.795
Minimum	-1.850	-29.787	-1.062	14.240
Frequency	Daily	Daily	Daily	Daily
N° Observation	1525	1525	1525	1525
Initial Date	01-01-04	01-01-04	01-01-04	01-01-04
Final Date	04-11-09	04-11-09	04-11-09	04-11-09

Table 3: Descriptive Statistics for the Systemic risk Index based on the Value of assets (SIV) and for the Systemic risk Index based on the Number of defaulted banks (SIN)

This table reports the descriptive statistics for the Systemic risk Indexes based on the Value of assets (SIV) and for the Systemic risk Indexes based on the Number of defaulted banks (SIN), for different proportions (0.25, 0.2, 0.15, 0.1 and 0.05). Panel A refers to the European (lhs) and the US (rhs) SIV and Panel B refers to the European (lhs) and the US (rhs) SIN. It contains the mean, standard deviation, median, the first and third quartile, maximum and minimum value. Moreover, the frequencies of the data, the number of observations and the initial and final date are reported.

Panel A: Systemic risk Index based on the Value of assets (SIV)

Proportion	European Portfolio					US Portfolio				
(ε)	0.25	0.2	0.15	0.1	0.05	0.25	0.2	0.15	0.1	0.05
Mean	0.041	0.069	0.103	0.143	0.192	0.035	0.065	0.106	0.168	0.265
SD	0.113	0.178	0.241	0.301	0.346	0.102	0.165	0.239	0.321	0.360
Median	0.000	0.000	0.000	0.000	0.004	0.000	0.000	0.000	0.002	0.082
Q1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.005
Q3	0.000	0.000	0.000	0.008	0.172	0.000	0.001	0.016	0.110	0.405
Maximum	0.606	0.819	0.931	0.992	1.000	0.616	0.820	0.930	0.990	1.000
Minimum	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Frequency	Weekly	Weekly	Weekly	Weekly	Weekly	Weekly	Weekly	Weekly	Weekly	Weekly
Number of Observatio	305	305	305	305	305	305	305	305	305	305
Initial Date	02-01-04	02-01-04	02-01-04	02-01-04	02-01-04	02-01-04	02-01-04	02-01-04	02-01-04	02-01-04
Final Date	30-10-09	30-10-09	30-10-09	30-10-09	30-10-09	30-10-09	30-10-09	30-10-09	30-10-09	30-10-09

Panel B: Systemic risk Index based on the Number of defaulted banks (SIN)

Proportion	SIN					SIV				
(ε)	0.25	0.2	0.15	0.1	0.05	0.25	0.2	0.15	0.1	0.05
Mean	0.039	0.061	0.093	0.124	0.202	0.061	0.122	0.155	0.166	0.219
SD	0.103	0.149	0.208	0.258	0.328	0.132	0.242	0.256	0.262	0.317
Median	0.000	0.000	0.000	0.003	0.040	0.000	0.000	0.008	0.012	0.063
Q1	0.000	0.000	0.000	0.000	0.014	0.000	0.000	0.000	0.001	0.005
Q3	0.000	0.001	0.009	0.025	0.185	0.007	0.014	0.163	0.173	0.218
Maximum	0.502	0.667	0.810	0.926	1.000	0.550	0.754	0.775	0.782	0.911
Minimum	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Frequency	Weekly	Weekly	Weekly	Weekly	Weekly	Weekly	Weekly	Weekly	Weekly	Weekly
Number of Observations	305	305	305	305	305	305	305	305	305	305
Initial Date	02-01-04	02-01-04	02-01-04	02-01-04	02-01-04	02-01-04	02-01-04	02-01-04	02-01-04	02-01-04
Final Date	30-10-09	30-10-09	30-10-09	30-10-09	30-10-09	30-10-09	30-10-09	30-10-09	30-10-09	30-10-09

Table 4: Descriptive Statistics for CDO Index and Tranches Measures

This table reports the descriptive statistics of the Idiosyncratic, Systematic and Systemic spreads which are extracted from both CDO indexes of the corresponding economic area (i.e., the Eurozone and the US) and their tranches measured on basis points. The left hand side refers to the European spreads and the right hand side refers to the US spreads. They contain the mean, standard deviation, median, the first and third quartile, maximum and minimum value. Moreover, the frequencies of the data, number of observations and the initial and final date are reported.

	European CDO			US CDO		
	Systemic	Systematic	Idiosyncratic	Systemic	Systematic	Idiosyncratic
Mean	29.953	10.964	36.574	31.552	29.872	44.667
SD	40.890	12.924	17.785	26.328	41.163	17.789
Median	8.281	2.097	30.247	27.860	11.309	41.604
Q1	3.281	1.468	25.463	5.455	1.614	32.622
Q3	39.594	19.410	41.462	53.382	35.428	53.007
Maximum	164.963	50.714	99.409	105.624	182.840	145.240
Minimum	0.090	0.632	17.124	1.254	0.743	24.514
Frequency	Daily	Daily	Daily	Daily	Daily	Daily
N° Observation	1224	1224	1224	946	946	946
Initial Date	25-02-05	25-02-05	25-02-05	22-03-06	22-03-06	22-03-06
Final Date	04-11-09	04-11-09	04-11-09	04-11-09	04-11-09	04-11-09

Table 5: Descriptive Statistics of the Joint Probability of Default (JPD) and Banking Stability Index (BSI)

This table represents the descriptive statistics of the Joint Probability of Default (JPD) and Banking Stability Index (BSI) for the two economic areas: Europe and the US. Panel A contains the JPD and the information is reported on basis points; Panel B contains the BSI. Within each economic area, three "reduced portfolios" are considered: spread, liabilities and liabilities over market value ratio. Each portfolio is composed of the three banks at the top of each classification. It contains the mean, standard deviation, median, the first and third quartile, maximum and minimum value. Moreover, the frequency of the data, the number of observations and the initial and final date are reported.

Panel A: Joint Probability of Default						
	European Reduced Portfolios			US Reduced Portfolios		
Reduced Portfolios	Spread	Liabilities	Liabilities / Market Value	Spread	Liabilities	Liabilities / Market Value
Mean	0.5637	0.107	0.138	1.9386	0.443	0.976
SD	1.2438	0.221	0.326	4.4609	1.103	2.403
Median	0.0028	0.000	0.001	0.0195	0.004	0.005
Q1	0.0007	0.000	0.000	0.0099	0.002	0.002
Q3	0.3378	0.080	0.157	1.2126	0.193	0.377
Maximum	11.7754	1.420	5.585	42.4871	7.889	26.452
Minimum	0.0002	0.000	0.000	0.0025	0.001	0.001
Frequency	Daily	Daily	Daily	Daily	Daily	Daily
N° Observations	1525	1525	1525	1525	1525	1525
Initial Date	01-01-04	01-01-04	01-01-04	01-01-04	01-01-04	01-01-04
Final Date	04-11-09	04-11-09	04-11-09	04-11-09	04-11-09	04-11-09

Panel B: Banking Stability Index						
	European Reduced Portfolios			US Reduced Portfolios		
Reduced Portfolios	Spread	Liabilities	Liabilities / Market Value	Spread	Liabilities	Liabilities / Market Value
Mean	1.0205	1.012	1.014	1.033	1.0193	1.025
SD	0.0097	0.007	0.008	0.017	0.0081	0.012
Median	1.0066	1.004	1.005	1.013	1.0073	1.008
Q1	1.0041	1.002	1.003	1.010	1.0056	1.006
Q3	1.0327	1.020	1.025	1.051	1.0273	1.034
Maximum	1.1143	1.054	1.090	1.179	1.0986	1.149
Minimum	1.0028	1.001	1.002	1.006	1.0041	1.005
Frequency	Daily	Daily	Daily	Daily	Daily	Daily
N° Observations	1525	1525	1525	1525	1525	1525
Initial Date	01-01-04	01-01-04	01-01-04	01-01-04	01-01-04	01-01-04
Final Date	04-11-09	04-11-09	04-11-09	04-11-09	04-11-09	04-11-09

Table 6: Descriptive Statistics of the Co-Risk Management Measures

This table represents the descriptive statistics of the Co-Risk Management Measures. Panel A refers to the European and US portfolios' Delta Co-Value-at-Risk (ΔCoVaR). Within each portfolio, two measures are calculated: (i) equally weighted; (ii) weighted by marked capitalization. Panel B contains the information relative to the European and US portfolios' Delta Co-Expected-Shortfall (ΔCoES). It contains the mean, standard deviation, median, the first and third quartile, maximum and minimum value. Moreover, the frequency of the data, the number of observations and the initial and final date are reported.

Panel A: ΔCoVaR				
	European Portfolios		US Portfolios	
	Equally Weighted	Weighted by Market	Equally Weighted	Weighted by Market
Mean	0.0034	0.003	0.0039	0.003
SD	0.0017	0.002	0.0012	0.001
Median	0.0030	0.002	0.0033	0.003
Q1	0.0024	0.002	0.0031	0.002
Q3	0.0039	0.003	0.0044	0.003
Maximum	0.0180	0.015	0.0126	0.008
Minimum	-0.0009	-0.001	0.0029	0.000
Frequency	Daily	Daily	Daily	Daily
Nº Observations	1522	1522	1522	1522
Initial Date	05-01-04	05-01-04	05-01-04	05-01-04
Final Date	03-11-09	03-11-09	03-11-09	03-11-09
Panel B: ΔCoES				
	European Portfolios		US Portfolios	
	Equally Weighted	Weighted by Market	Equally Weighted	Weighted by Market
Mean	0.0034	0.003	0.005	0.003
SD	0.0013	0.001	0.002	0.002
Median	0.0031	0.002	0.004	0.002
Q1	0.0026	0.002	0.003	0.002
Q3	0.0038	0.003	0.005	0.004
Maximum	0.0113	0.010	0.016	0.012
Minimum	0.0016	0.001	0.002	0.000
Frequency	Daily	Daily	Daily	Daily
Nº Observations	1522	1522	1522	1522
Initial Date	05-01-04	05-01-04	05-01-04	05-01-04
Final Date	03-11-09	03-11-09	03-11-09	03-11-09

This table reports the average McFadden R-squared for the systemic risk measures belonging to: (i) Princial Component Analysis; (ii) Libor Spread; (iii) Structural Model; (iv) CDO indexes and their tranches; (v) Multivariate Density; (vi) Co-Risk groups of measures. For each systemic risk measure, we compute logistic regressions in which we modify the number of lags of the independent variable (the number of lags appears in the third column). Then we calculate the average of the McFaddend R-squared for each measure. Within each group, we report this information to the European and the US portfolio. The reported measures are: (i) PCA; (ii) LIBOR-OIS (LO) and LIBOR-TBILL (LT); (iii) Systemic risk Index based on the Number of defaulted banks (SIN) and on the Value of assets (SIV) for different percentages (25, 20, 15, 10 and 5); (iv) Systemic component extracted from the CDO indexes and their tranches; (v) Banking Stability Index (BSI) and Index (BSI) and Joint Probability of Default (JPD) for the three "reference portfolios": spread, liabilities and liabilities over market value ratio; (vi) Delta Co-Value-at-risk (ΔCoVaR) and Delta Co-Expected-Shortfall (ΔCoES) for the aggregations, Equally Weighted (EW) and Weighted by Market Capitalization (WCap).

Group	Portfolio	N° Lags					
PCA	European	14	PCA 0.1243				
	US	14	PCA 0.1092				
LIBOR SPREADS	European	14	LO 0.1314	LT 0.1263			
	US	14	LO 0.1184	LT 0.1520			
STRUCTURAL MODELS	European	2	SIN25 0.0265	SIN20 0.0301	SIN15 0.0382	SIN10 0.0470	SIN05 0.0577
		2	SIV25 0.0255	SIV20 0.0324	SIV15 0.0404	SIV10 0.0451	SIV05 0.0533
	US	2	SIN25 0.0092	SIN20 0.0171	SIN15 0.0273	SIN10 0.0407	SIN05 0.0575
		2	SIV25 0.0459	SIV20 0.0460	SIV15 0.0672	SIV10 0.0683	SIV05 0.0571
CDO	European	14	CDO 0.0453				
	US	14	CDO 0.0638				
MULTIVARIATE DENSITIES	European	14	BSI_Spread 0.1041	BSI_Liabilities 0.1074	BSI_Ratio 0.1259		
		14	JPD_Spread 0.0386	JPD_Liabilities 0.0365	JPD_Ratio 0.0457		
	US	14	BSI_Spread 0.1140	BSI_Liabilities 0.0783	BSI_Ratio 0.1170		
		14	JPD_Spread 0.0539	JPD_Liabilities 0.0179	JPD_Ratio 0.0614		
CO-RISK	European	14	ΔCoVaR_EW 0.0378	ΔCoVaR_WCap 0.0395	ΔCoES_EW 0.0538	ΔCoES_WCap 0.0460	
	US	14	ΔCoVaR_EW 0.1099	ΔCoVaR_WCap 0.1125	ΔCoES_EW 0.1036	ΔCoES_WCap 0.1129	

Table 8: Granger Causality Test

This table reports the p-value of the null hypothesis (Ho), the employed number of lags and the corresponding ranking scores. To rank the measures, we give a measure +1 if it Granger causes another measure at 1% of confidence level and -1 if it is Granger caused by another measure. Panel A refers to the European portfolio such that in Panel A.1 we report the p-values and in Panel A.2 we report the ranking scores. The measures considered are the First Principal Component of the European portfolio of single CDS (PCA); LIBOR-OIS (LO); Systemic risk Index based on the Number of defaulted banks (SIN); Systemic component extracted from the iTraxx IG 5y (CDO); Banking Stability Index (BSI) based on the liabilities over market value ratio; Delta Co-Expected-Shortfall (ΔCoES). Panel B refers to the US portfolio such that in Panel B.1 we report the p-values and in Panel B.2 we report the ranking scores. The measures considered are the First Principal Component of the US portfolio of single CDS; LIBOR-TBILL (LT); Systemic risk Index based on the Value of defaulted assets (SIV); Systemic component extracted from the CDX IG 5y (CDO); Banking Stability Index (BSI) based on the liabilities over market value ratio; Delta Co-Expected-Shortfall (ΔCoES); Delta Co-Value-at-Risk (ΔCoVaR).

Panel A: European Portfolio								
Panel A.1: P-Value								
Variable 1 (V.1)	PCA	PCA	PCA	PCA	PCA	LO	LO	LO
Variable 2 (V.2)	LO	SIN05	CDO	BSI	ΔCoES	SIN05	CDO	BSI
Ho: V. 2 does not Granger Cause V. 1	0.208	0.253	0.111	0.041	0.998	0.000	0.063	0.325
Ho: V. 1 does not Granger Cause V. 2	0.538	0.026	0.348	0.000	0.000	0.008	0.000	0.185
Number of Lags	2	1	1	4	4	5	2	4
Variable 1 (V.1)	LO	SIN05	SIN05	SIN05	CDO	CDO	BSI	
Variable 2 (V.2)	ΔCoES	CDO	BSI	ΔCoES	BSI	ΔCoES	ΔCoES	
Ho: V. 2 does not Granger Cause V. 1	0.109	0.457	0.000	0.000	0.076	0.026	0.348	
Ho: V. 1 does not Granger Cause V. 2	0.000	0.261	0.021	0.003	0.001	0.000	0.000	
Number of Lags	6	2	7	5	4	3	4	
Panel A.2: Ranking Scores								
Variable			PCA	LO	CDO	BSI	SIN05	ΔCoES
Scoring			2	2	1	0	-1	-4
Panel B: US Portfolio								
Panel B.1: P-Values								
Variable 1 (V.1)	PCA	PCA	PCA	PCA	PCA	PCA	LT	LT
Variable 2 (V.2)	LT	SIV10	CDO	BSI	ΔCoES	ΔCoVaR	SIV10	CDO
Ho: V. 2 does not Granger Cause V. 1	0.000	0.041	0.297	0.332	0.250	0.048	0.026	0.322
Ho: V. 1 does not Granger Cause V. 2	0.951	0.005	0.000	0.000	0.000	0.000	0.211	0.328
Number of Lags	3	5	2	3	4	7	5	2
Variable 1 (V.1)	LT	LT	LT	SIV10	SIV10	SIV10	SIV10	CDO
Variable 2 (V.2)	BSI	ΔCoES	ΔCoVaR	CDO	BSI	ΔCoES	ΔCoVaR	BSI
Ho: V. 2 does not Granger Cause V. 1	0.036	0.008	0.005	0.232	0.039	0.018	0.043	0.000
Ho: V. 1 does not Granger Cause V. 2	0.000	0.000	0.000	0.117	0.000	0.002	0.022	0.003
Number of Lags	4	4	5	5	5	5	5	4
Variable 1 (V.1)	CDO	CDO	BSI	BSI	ΔCoES			
Variable 2 (V.2)	ΔCoES	ΔCoVaR	ΔCoES	ΔCoVaR	ΔCoVaR			
Ho: V. 2 does not Granger Cause V. 1	0.000	0.099	0.000	0.000	0.000			
Ho: V. 1 does not Granger Cause V. 2	0.174	0.000	0.000	0.000	0.000			
Number of Lags	4	3	4	4	7			
Panel B.2: Ranking Scores								
Variable		PCA	LT	SIV10	ΔCoVaR	CDO	BSI	ΔCoES
Scoring		4	2	1	0	-1	-3	-3

50

This table reports the market contribution to the price discovery by means of Gonzalo and Granger permanent-transitory (PT) component decomposition, the number of lags employed in the analysis and the corresponding ranking scores. To rank the measures, we give a score of +1 if the measure gets values larger than 0.5 in the corresponding price discovery metric and -1 if it gets values lower than 0.5. Panel A refers to the European portfolio such that in Panel A.1 we report the Gonzalo and Granger permanent-transitory (PT) component decomposition and the employed number of lags and in Panel A.2 we report the ranking scores. The measures considered are the First Principal Component of the European portfolio of single CDS (PCA); LIBOR-OIS (LO); Systemic risk Index based on the Number of defaulted banks (SIN); Systemic component extracted from the iTraxx IG 5y (CDO); Banking Stability Index (BSI) based on the liabilities over market value ratio; Delta Co-Expected-Shortfall (ΔCoES). Panel B refers to the US portfolio. The measures considered are the First Principal Component of the US portfolio of single CDS; LIBOR-TBILL (LT); Systemic risk Index based on the Value of defaulted assets (SIV); Systemic component extracted from the CDX IG 5y (CDO); Banking Stability Index (BSI) based on the liabilities over market value ratio; Delta Co-Expected-Shortfall (ΔCoES); Delta Co-Value-at-Risk (ΔCoVaR).

Panel A: European Portfolio

Panel A.1: Gonzalo and Granger Permanent-Transitory Component Decomposition

Variable 1	PCA	PCA	PCA	PCA	PCA	LO	LO	LO
$GG_{variable\ 1}$	0.585	0.549	0.238	1.000	0.986	0.859	0.934	0.670
Variable 2	LO	SIN05	CDO	BSI	ΔCoES	SIN05	CDO	BSI
$GG_{variable\ 2}$	0.415	0.451	0.762	0.000	0.014	0.141	0.066	0.330
Number of Lags	20	25	15	25	16	6	11	15
Variable 1	LO	SIN05	SIN05	SIN05	CDO	CDO	BSI	
$GG_{variable\ 1}$	1	Na	0.616	0.890	0.937	0.872	1	
Variable 2	ΔCoES	CDO	BSI	ΔCoES	BSI	ΔCoES	ΔCoES	
$GG_{variable\ 2}$	0	Na	0.384	0.110	0.063	0.128	0	
Number of Lags	8	Na	20	20	15	17	17	

Panel A.2: Ranking Scores

Variable		PCA	LO	CDO	SIN05	BSI	ΔCoES
Scoring		3	3	2	0	-3	-5

Panel B: US Portfolio

Panel B.1: Gonzalo and Granger Permanent-Transitory Component Decomposition

Variable 1	PCA	PCA	PCA	PCA	PCA	PCA	LT	LT
$GG_{variable\ 1}$	0.886	0.496	0.873	1	0.764	0.947	0.219	0.425
Variable 2	LT	SIV10	CDO	BSI	ΔCoES	ΔCoVaR	SIV10	CDO
$GG_{variable\ 2}$	0.114	0.504	0.127	0	0.236	0.053	0.781	0.575
Number of Lags	18	17	17	25	15	18	16	20
Variable 1	LT	LT	LT	SIV10	SIV10	SIV10	SIV10	CDO
$GG_{variable\ 1}$	0.123	0.747	0.923	0.742	0.716	0.802	0.924	0.400
Variable 2	BSI	ΔCoES	ΔCoVaR	CDO	BSI	ΔCoES	ΔCoVaR	BSI
$GG_{variable\ 2}$	0.877	0.253	0.077	0.258	0.284	0.198	0.076	0.600
Number of Lags	20	14	10	23	25	20	15	20
Variable 1	CDO	CDO	BSI	BSI	ΔCoES			
$GG_{variable\ 1}$	0.284	0.802	0.641	0.930	0.759			
Variable 2	ΔCoES	ΔCoVaR	ΔCoES	ΔCoVaR	ΔCoVaR			
$GG_{variable\ 2}$	0.716	0.198	0.359	0.070	0.241			
Number of Lags	18	12	17	26	18			

Panel A.2: Ranking Scores

Variable	PCA	SIV10	BSI	LT	CDO	ΔCoES	ΔCoVaR
Scoring	5	5	2	-2	-2	-2	-6

Table 10: Ranking Scores by McFadden R-squared

This table contains the ranking scores according to McFadden R-squared. To rank the measures, we compare the McFadden R-squared by pairs and assign a score of +1 to the measure with the highest R-squared and -1 to the one with the lowest R-squared. Panel A refers to the European portfolio. The measures considered are the First Principal Component of the European portfolio of single CDS (PCA); LIBOR-OIS (LO); Systemic risk Index based on the Number of defaulted banks (SIN); Systemic component extracted from the iTraxx IG 5y (CDO); Banking Stability Index (BSI) based on the liabilities over market value ratio; Delta Co-Expected-Shortfall (ΔCoES). Panel B refers to the US portfolio. The measures considered are the First Principal Component of the US portfolio of single CDS; LIBOR-TBILL (LT); Systemic risk Index based on the Value of defaulted assets (SIV); Systemic component extracted from the CDX IG 5y (CDO); Banking Stability Index (BSI) based on the liabilities over market value ratio; Delta Co-Expected-Shortfall (ΔCoES); Delta Co-Value-at-Risk (ΔCoVaR).

Panel A: European Portfolio						
Variable	LO	BSI	PCA	SIN05	ΔCoES	CDO
Scoring	5	3	1	-1	-3	-5

Panel B: US Portfolio							
Variable	LT	BSI	ΔCoES	ΔCoVaR	PCA	SIV10	CDO
Scoring	6	4	2	0	-2	-4	-6

Table 11: Horse Race

This table reports the ranking scores of the systemic risk measures among three classifications: (i) Causality Test; (ii) Price Discovery; (iii) McFadden R-squared. We also report the final score, which is the sum of the scores among classifications. Panel A refers to the European portfolio. The measures considered are the First Principal Component of the European portfolio of single CDS (PCA); LIBOR-OIS (LO); Systemic risk Index based on the Number of defaulted banks (SIN); Systemic component extracted from the iTraxx IG 5y (CDO); Banking Stability Index (BSI) based on the liabilities over market value ratio; Delta Co-Expected-Shortfall (ΔCoES). Panel B reports the US portfolio systemic risk measures: the First Principal Component of the US portfolio of single CDS; LIBOR-TBILL (LT); Systemic risk Index based on the Value of defaulted assets (SIV); Systemic component extracted from the CDX IG 5y (CDO); Banking Stability Index (BSI) based on the liabilities over market value ratio; Delta Co-Expected-Shortfall (ΔCoES); Delta Co-Value-at-Risk (ΔCoVaR).

Panel A: European Portfolio				
	Causality Test	Price Discovery	McFadden R-squared	Final Score
PCA	2	3	1	6
LO	2	3	5	10
SIN05	-1	0	-1	-2
CDO	1	2	-5	-2
BSI	0	-3	3	0
ΔCoES	-4	-5	-3	-12
Panel B: US Portfolio				
	Causality Test	Price Discovery	McFadden R-squared	Final Score
PCA	4	5	-2	7
LT	2	-2	6	6
SIV10	1	5	-4	2
CDO	-1	-2	-6	-9
BSI	-3	2	4	3
ΔCoES	-3	-2	2	-3
ΔCoVaR	0	-6	0	-6

Figures

Figure 1: Systemic Risk Measures based on Principal Component Analysis

This figure represents the First Principal Component of the European and US portfolios of single CDS. These variables are measured on basis points.
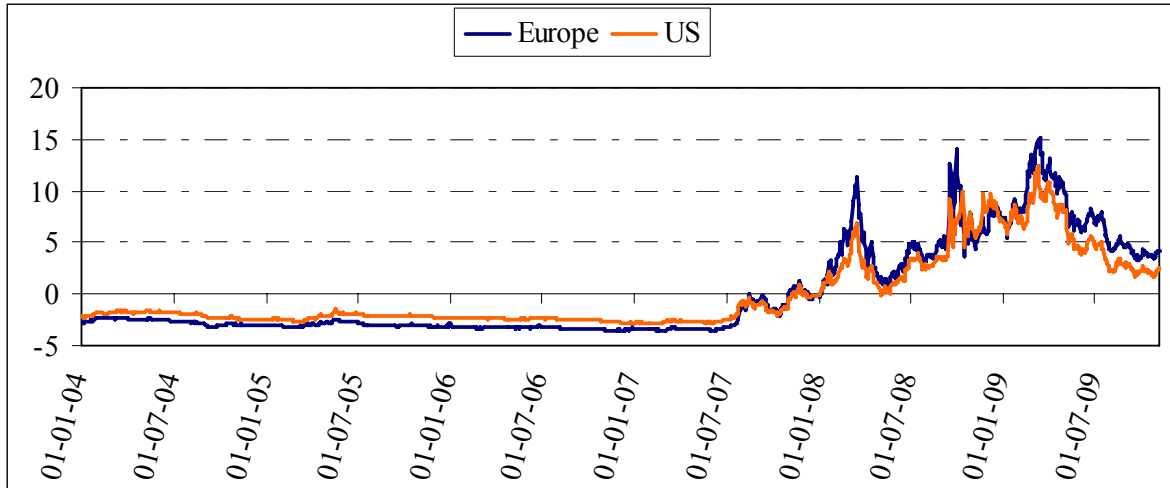
Figure 2: Systemic Risk Measures based on Libor Spreads

This figure represents the spreads between LIBOR and the Overnight Interest Rate (LO) and between LIBOR and Treasury Bills (LT). Additionally, we compute a "Natives Are Restless Factor" (NARF) as the difference between LT and LO. The dashed area represents the size of that factor. Panel A refers to the Eurozone portfolio and Panel B refers to the US portfolio. These spreads are measured on basis points.
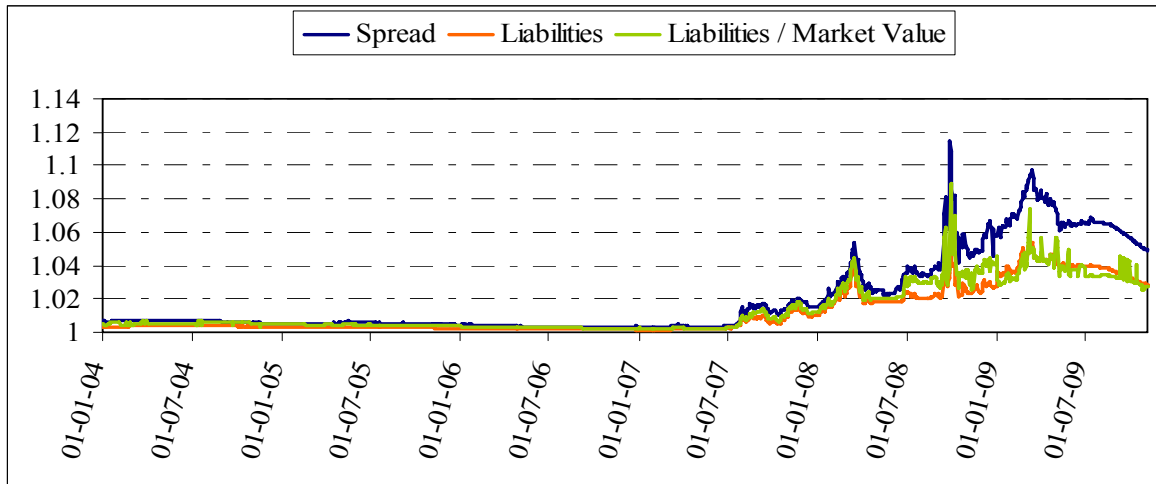
Panel A: European Portfolio
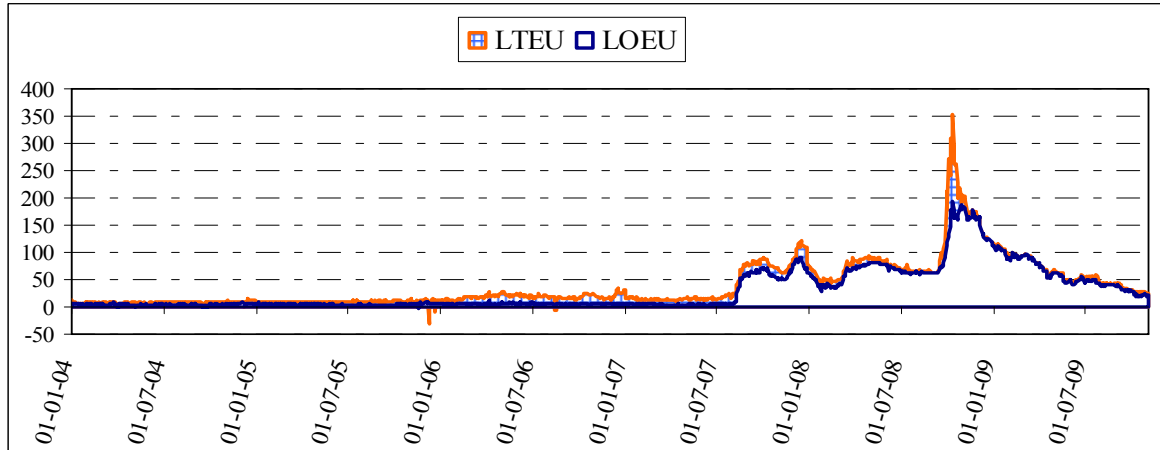
Panel B: US Portfolio
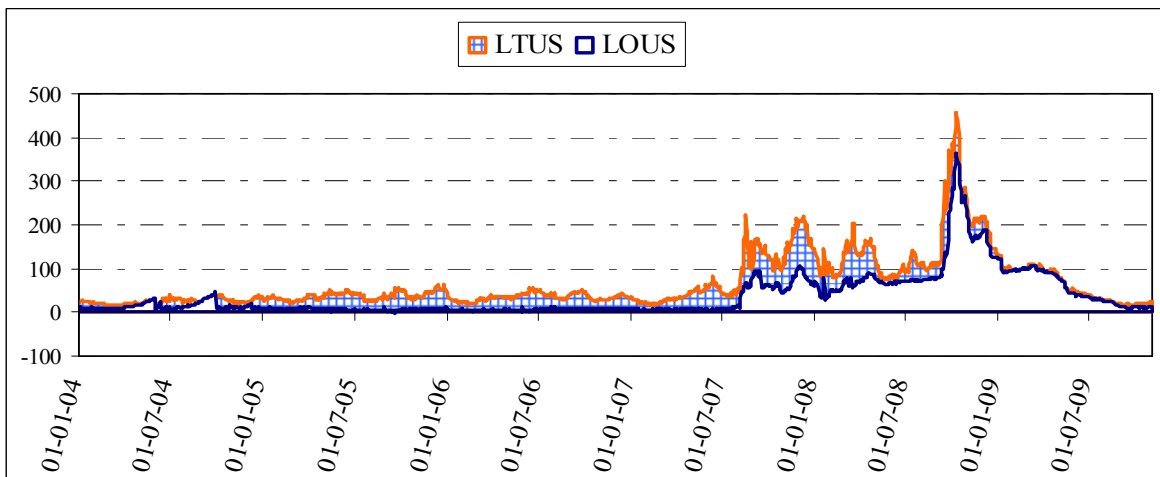
Figure 3: Systemic risk Index based on the Value of defaulted assets (SIV)

This figure depicts the SIV measure for different proportions which range from 25% to 5%. Panel A refers to the European portfolio and Panel B refers to the US portfolio.

Panel A: European Portfolio
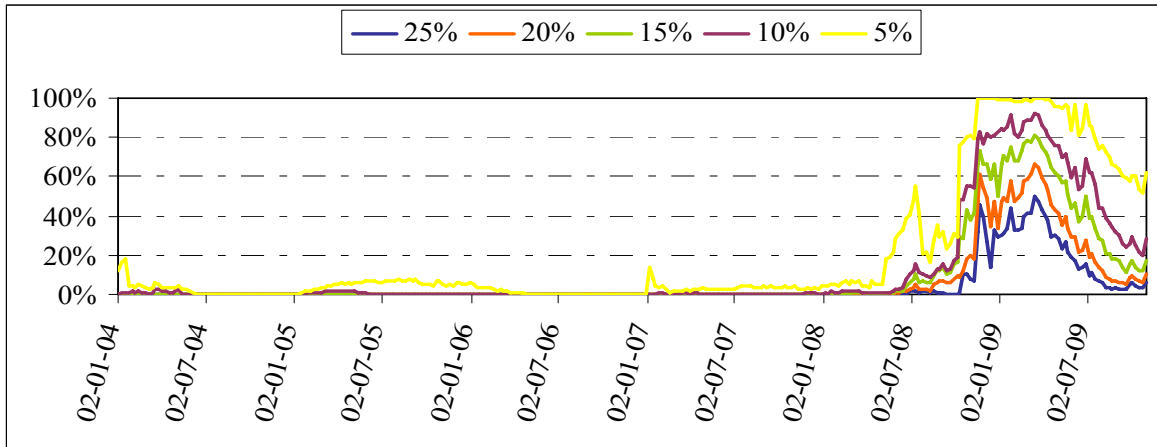
Panel B: US Portfolio
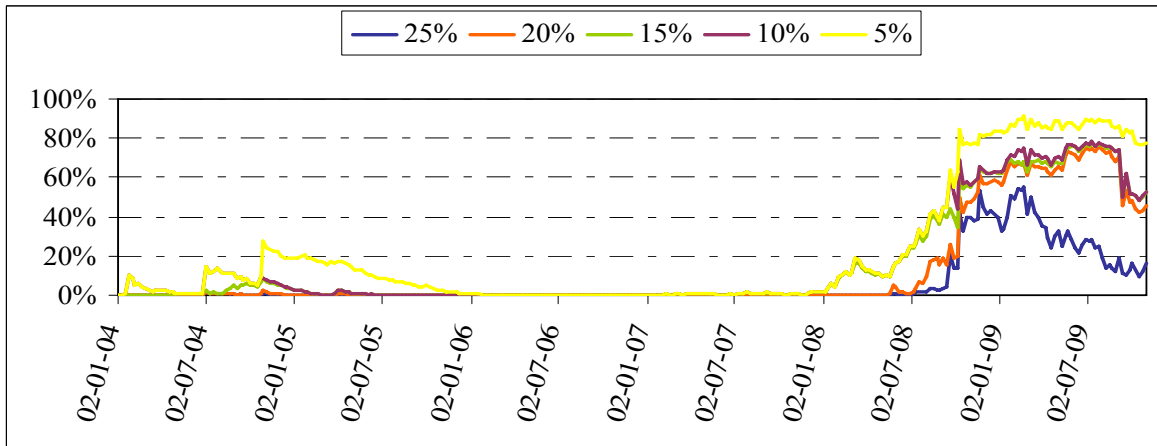
Figure 4: Systemic risk Index based on the Number of defaulted banks (SIN)

This figure depicts the SIN measure for different proportions which range from 25% to 5%. Panel A refers to the European portfolio and Panel B refers to the US portfolio.
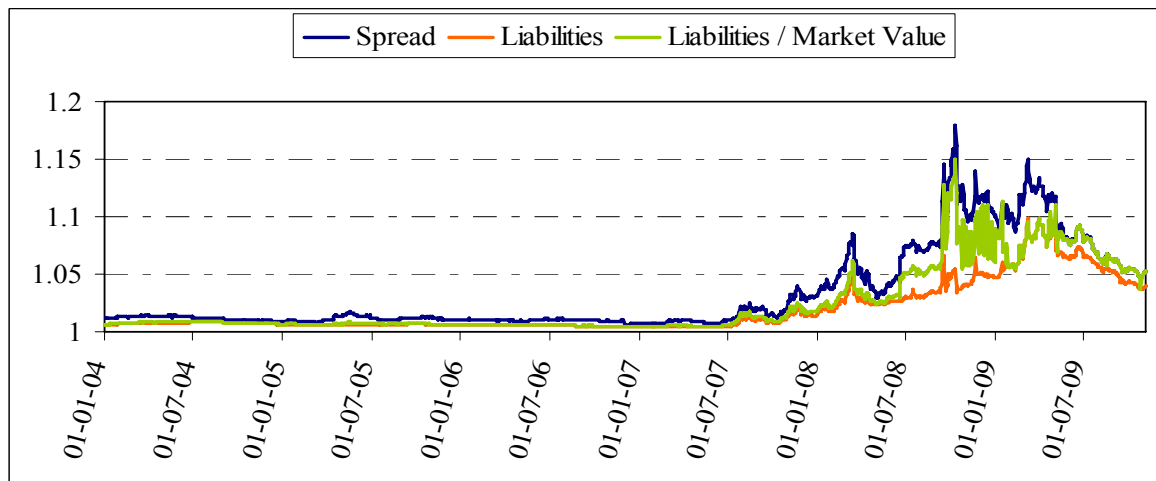
Panel A: European Portfolios
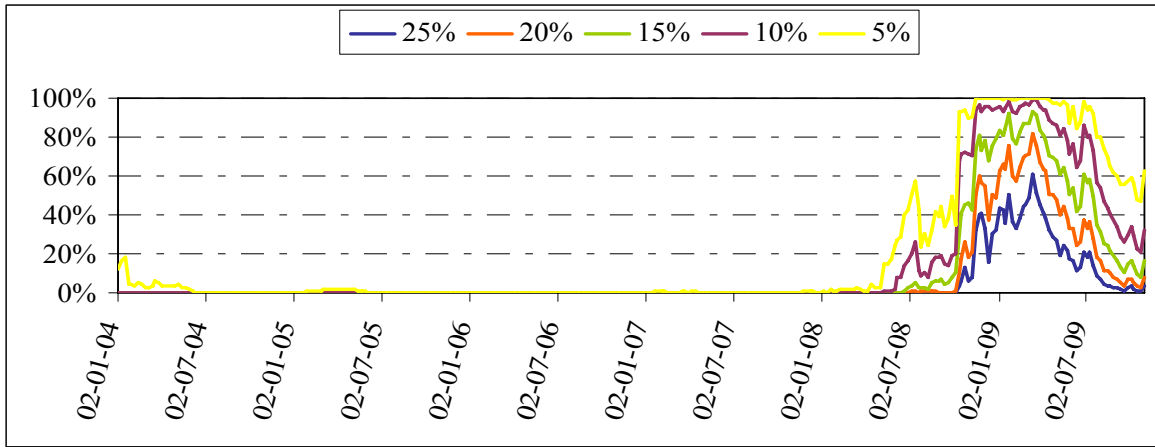
Panel B: US Portfolios
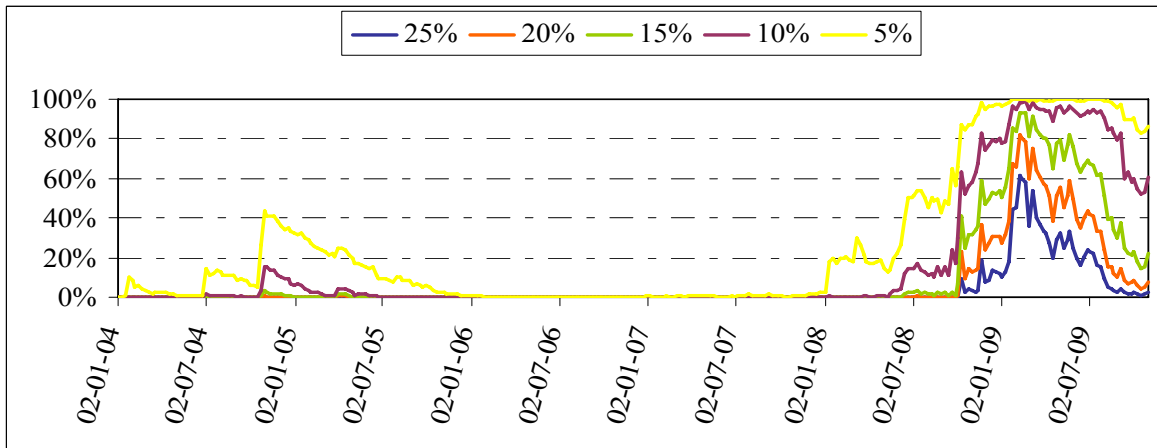
Figure 5: CDO Index and Their Tranches

This figure depicts the Idiosyncratic, Systematic and Systemic spreads which are extracted from both CDO indexes of the corresponding economic area and their tranches. Panel A refers to the European portfolios and Panel B refers to the US portfolios. These variables are measured in basis points.

Panel A: European Portfolios

Panel B: US portfolios
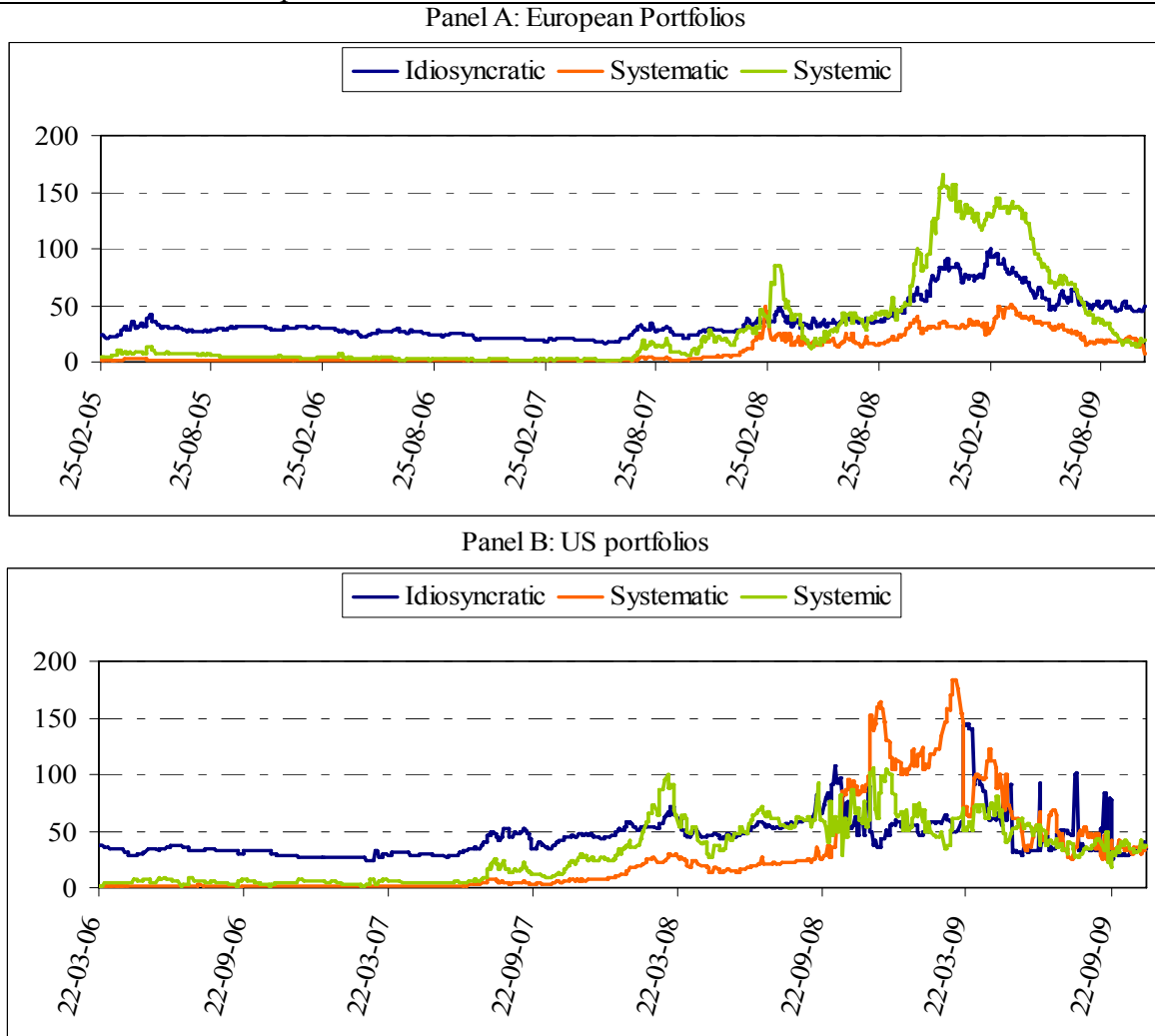
Figure 6: Joint Probability of Default (JPD)

This figure depicts the JPD measure for the different "reduced portfolios", spread, liabilities and the liabilities over market value ratio. Each portfolio is composed of the three banks at the top of each classification. Panel A refers to the European portfolios and Panel B refers to the US portfolios. This variable is measured in basis points.

Panel A: European Portfolios
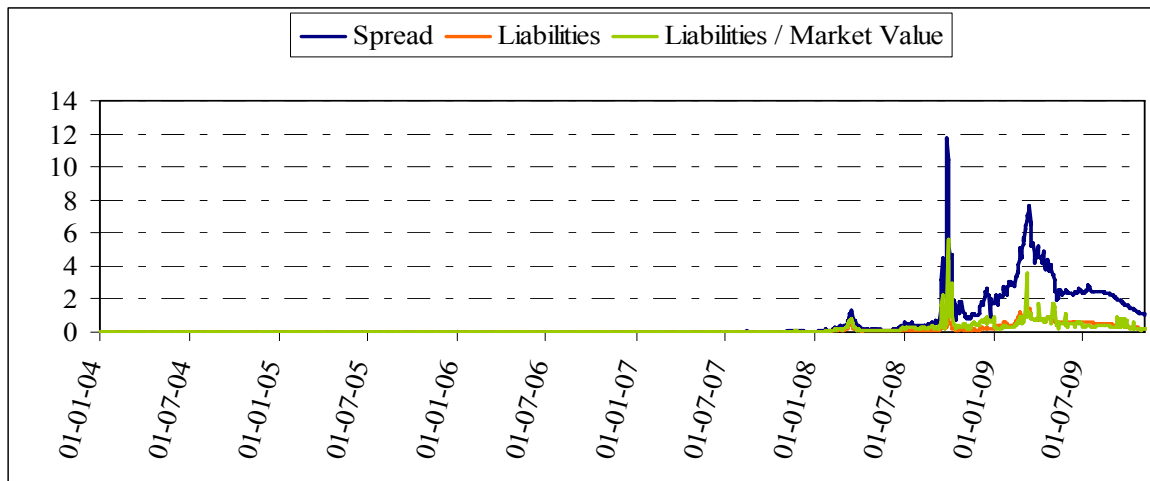
Panel B: US portfolios
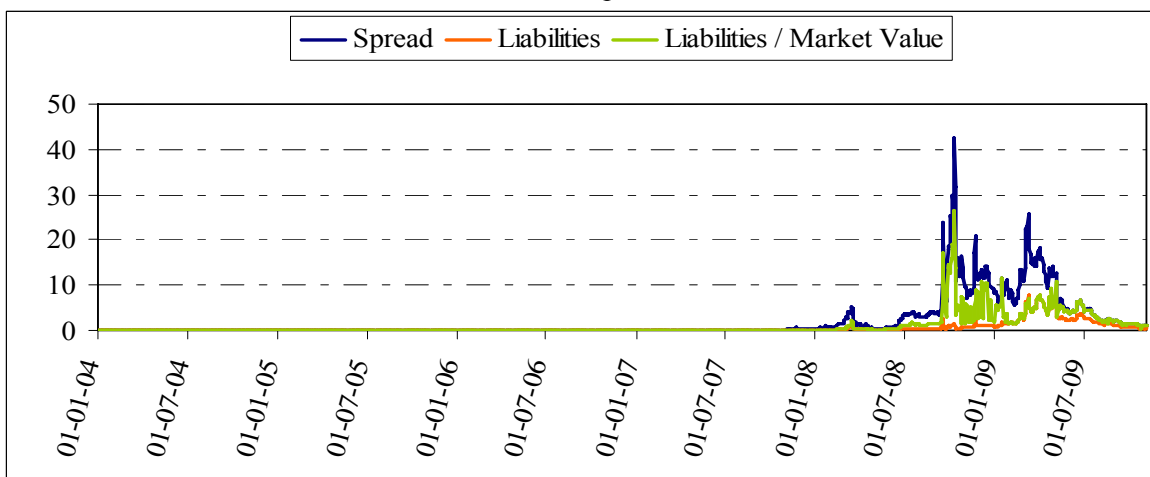
Figure 7: Banking Stability Index (BSI)

This figure depicts the BSI measure for the different "reduced portfolios", spread, liabilities and the liabilities over market value ratio. Each portfolio is composed of the three banks at the top of each classification. Panel A refers to the European portfolios and Panel B refers to the US portfolios.

Panel A: European Portfolios

Panel B: US Portfolios

Figure 8: Delta Co-Value-at-Risk

This figure represents the Delta Co-Value-at-Risk (ΔCoVaR) measure calculated as an equally weighted average and a weighted average by market capitalization. Panel A refers to the European portfolio and Panel B to the US portfolio.
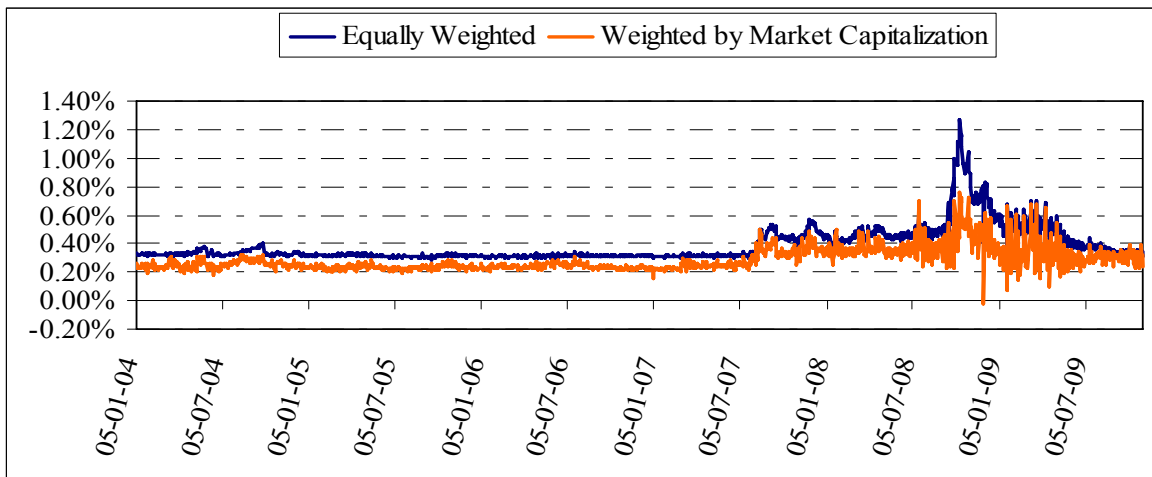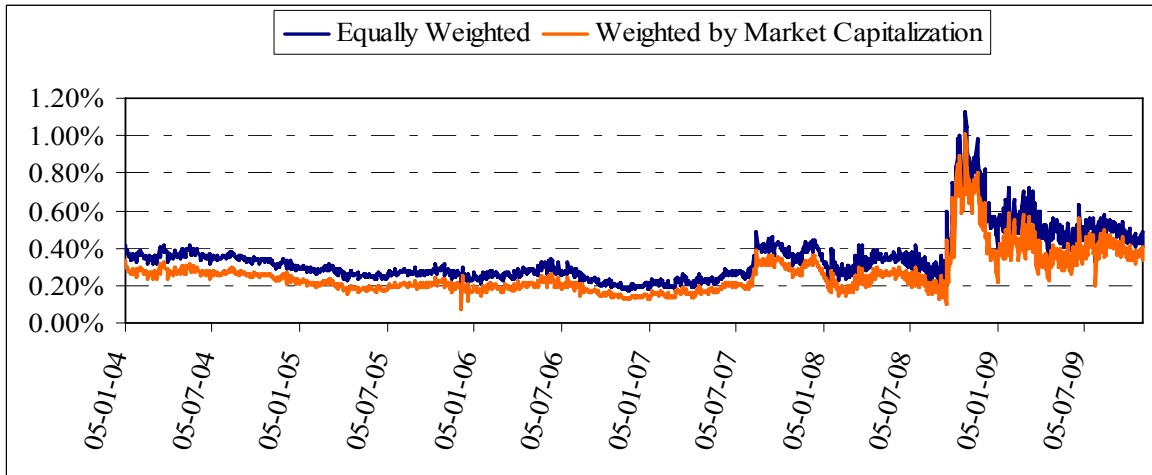
Panel A: European Portfolio
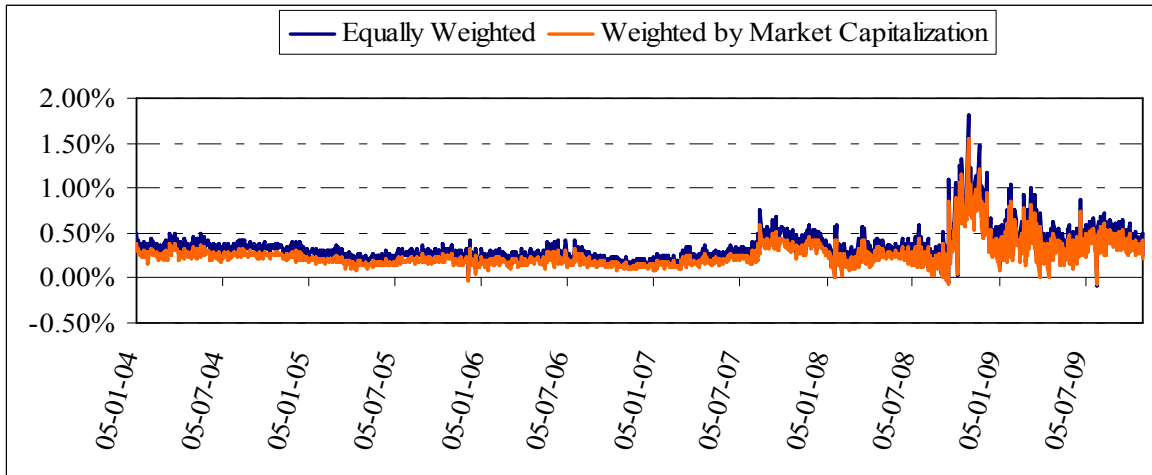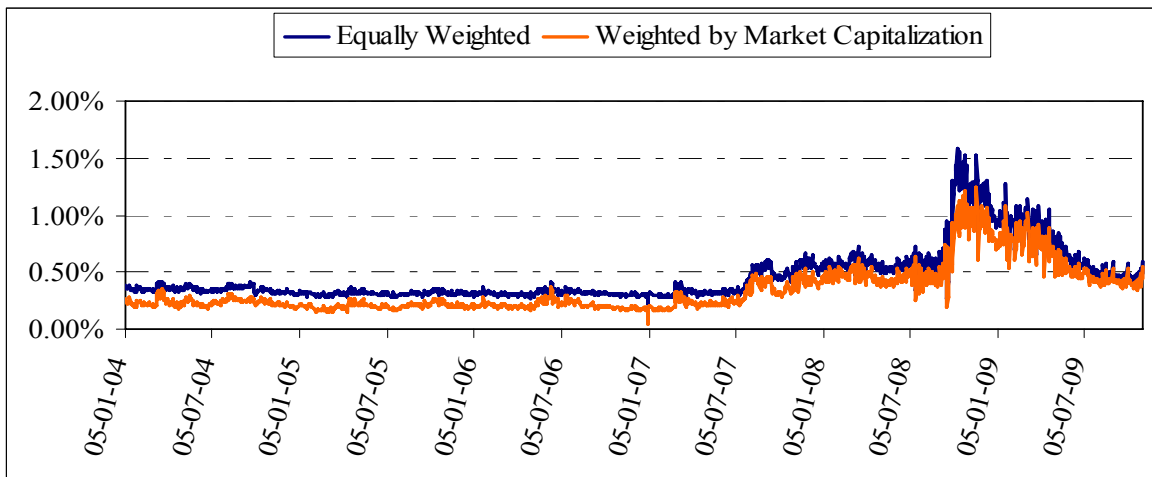

Panel B: US Portfolio

Figure 9: Delta Co-Extected-Shortfall

This figure represents the Delta Co-Expected-Shortfall (ΔCoES) measures calculated as an equally weighted average and a weighted average by market capitalization. Panel A refers to the European portfolio and Panel B to the US portfolio.

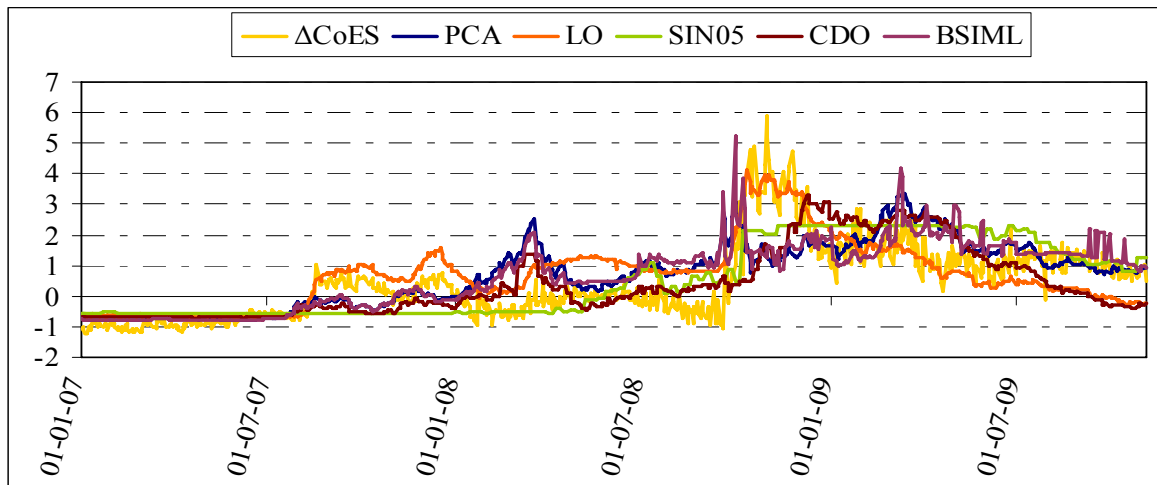Panel A: European Portfolio

Panel B: US Portfolio

Figure 10: Standardized Systemic Risk Measures

This figure depicts the evolution of the selected standardized systemic risk measures. Panel A reports the European portfolio measures: Principal Component Analysis (PCA), European portfolio measures: the First Principal Component of the European portfolio of single CDS (PCA); LIBOR-OIS (LO); Systemic risk Index based on the Number of defaulted banks (SIN); Systemic component extracted from the iTraxx IG 5y (CDO); Banking Systemic component extracted from the iTraxx IG 5y (CDO); Banking Stability Index (BSI) based on the liabilities over market value ratio; Delta Co-Expected-Shortfall (ΔCoES). Panel B reports the US portfolio systemic risk measures: the First Principal Component of the US portfolio of single CDS; LIBOR-TBILL (LT); Systemic risk Index based on the Value of defaulted assets (SIV); Systemic component extracted from the CDX IG 5y (CDO); Banking Stability Index (BSI) based on the liabilities over market value ratio; Delta Co-Expected-Shortfall (ΔCoES).

Panel A: European Portfolios

Panel B: US Portfolios