UNIVERSIDAD CARLOS III DE MADRID

# *TESIS DOCTORAL*

# *Systemic Risks: Measures and Determinants*

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“What we know about the global financial crisis is
that we don’t know very much.”
Paul A. Samuelson (1915-2009)

# Abstract

In this Thesis, I study the measurement and the determinants of systemic risk, paying special attention to the role of the Credit Default Swaps (CDSs) either as financial instruments containing valuable information about the soundness of the reference institutions or as a market whose distress contributes to potential systemic shocks on the economy. The measurement of systemic risk is addressed from two perspectives, aggregate and individual contribution to systemic risk where the former refers to the level of systemic risk in the overall economy and the last to the individual contribution of each financial institution to the overall systemic risk. The analysis of the determinants of the individual contribution of financial institutions to systemic risk focuses on the effect of their portfolio holdings of derivatives. Finally, I study the liquidity commonalities and their determinants in the corporate CDS worldwide markets. The main participants in these markets are systemically important financial institutions (SIFIs) and so, abrupt changes in the market liquidity could cause systemic shocks on the overall economy and as a consequence, adverse effects on the global stability. Next, I summarize the main findings of the three chapters of this Thesis.

In Chapter 2 I adopt an aggregate perspective to estimate and compare two groups (macro and micro) of high-frequency market-based systemic risk measures using European and US interbank rates, stock prices and credit derivatives data from 2004 to 2009. Measures belonging to the macro group gauge the overall tension in the financial sector and micro group measures rely on individual institution information to extract joint distress. I rank the measures using three criteria: i) Granger causality tests, ii) Gonzalo and Granger metric, and iii) correlation with an index of systemic events and policy actions. I find that the best systemic measure in the macro group is the first

principal component of a portfolio of CDS spreads whereas the best measure in the micro group is the multivariate densities computed from CDS spreads. These results suggest that simple measures based on CDSs outperform measures based on interbank rates or stock market prices.

Chapter 3 relies on the banks individual contribution to systemic risk. In this chapter I estimate and compare five measures of such contributions to systemic risk and find that a new measure proposed in this chapter, Net Shapley Value, outperforms the others using a sample of 91 U.S. bank holding companies from 2002 to 2011. The Net Shapley Value of institution $j$ is defined as the weighted average of the marginal contribution to the subsystem's risk across all possible subsystems containing institution $j$ in which the portfolio can be split, apart from the subsystem composed of the institution $j$ in isolation. Using this measure, I study the impact of the banks' portfolio holdings of financial derivatives on the banks' individual contribution to systemic risk over and above the effect of variables related to size, interconnectedness, substitutability, and other balance sheet information. I find that the banks' holdings of foreign exchange and credit derivatives increase the banks contributions to systemic risk whereas holdings of interest rate derivatives decrease it. Nevertheless, the proportion of non-performing loans over total loans and the leverage ratio have much stronger impact on systemic risk than derivatives holdings. I also find that before the subprime crisis credit derivatives contributed to decrease systemic risk whereas during the crisis holdings of derivatives led to increase it. So, credit derivatives seemed to change their role from shock absorbers to shock issuers. This effect is not observed in the other types of derivatives.

Finally, in Chapter 4 I focus on the liquidity commonalities in the corporate CDS market and their determinants. The analysis of liquidity commonalities in this market is motivated by the fact that the CDS market contains value information to construct systemic risk measures, as shown in Chapter 2, and also because the banks' holdings of these derivatives have been found to be significant determinants of systemic risk, as documented in Chapter 3. In addition, the main participants in the CDS market are systemically important financial institutions (SIFIs). For these reasons, a high level of liquidity commonalities would imply that abrupt changes in the liquidity of the CDS market could cause systemic shocks on the overall economy and, in a context of an illiquid CDS market firms could not be able to timely manage their credit exposures. This study presents robust evidence suggesting the existence of significant liquidity commonalities. Using daily data for 438 firms from 25 countries that comprises the period 2005-2012, I find that these commonalities vary over time, being stronger in periods in which the global, counterparty, and funding liquidity risks increase. However, commonalities do not depend on firm's characteristics. The level of the liquidity commonalities differs across economic areas being on average stronger in the European Monetary Union. The effect of market liquidity is stronger than the effect of industry specific liquidity in most industries excluding the banking sector. Additionally, I document the existence of asymmetries in commonalities around financial distress episodes such that the effect of market liquidity is stronger when the CDS market price increases.

# Resumen

Esta Tesis se centra en la medición del riesgo sistémico y sus determinantes. Para ello se presta especial atención al papel desempeñado por los Credit Default Swaps (CDSs) bien como instrumentos financieros que contienen información relevante sobre la solvencia de las instituciones de referencia o como mercado cuyos problemas pueden desencadenar *shocks* sistémicos en la economía. La medición del riesgo sistémico se aborda desde dos diferentes perspectivas: a nivel agregado y a nivel individual analizando la contribución de cada institución al riesgo sistémico. La primera perspectiva se refiere a la medición del nivel de riesgo sistémico total en una economía o en una cartera de instituciones representativas de la economía. La segunda perspectiva, se refiere a la contribución al riesgo sistémico total de cada una de las instituciones que componen la cartera. El análisis de los determinantes del riesgo sistémico se aborda desde la perspectiva de la contribución individual al riesgo sistémico y estudia, principalmente, el efecto de la tenencia de derivados en la cartera de las instituciones financieras sobre su contribución a este riesgo. Dado que los dos análisis anteriores muestran que los CDS contienen información útil para la medición del riesgo sistémico y que han contribuido a crear efectos adversos sobre la estabilidad financiera, a continuación, se analiza el comportamiento de este mercado. Además, los principales participantes del mercado de CDS son instituciones financieras sistémicas (*systemically important financial institutions*, SIFIs) y, por lo tanto, cambios repentinos en la liquidez del mercado de CDS pueden provocar *shocks* sistémicos sobre la economía con efectos adversos sobre la estabilidad del sistema. En concreto, se analiza el riesgo de liquidez existente en este mercado a partir de la dependencia de la liquidez de los CDSs individuales de la liquidez global del mercado (*liquidity commonalities*) así como los determinantes de esta dependencia que puede resultar uno de los posibles

canales de propagación de *shocks* en este mercado. A continuación se resumen las principales conclusiones de los tres capítulos de la tesis.

En el Capítulo 2 se adopta la perspectiva agregada del riesgo sistémico para estimar y comparar dos grupos de medidas de riesgo sistémico (macro y micro) basadas en datos de alta frecuencia procedentes de los mercados de acciones, derivados e interbancario desde 2004 a 2009 en Europa y EEUU. Las medidas pertenecientes al grupo macro evalúan la tensión general existente en el sector financiero mientras que las medidas pertenecientes al grupo micro se basan en información de las instituciones financieras para inferir la tensión existente en estas instituciones de forma conjunta. Posteriormente se determina la bondad de las medidas estimadas de acuerdo a tres criterios: i) test de causalidad de Granger, ii) métrica de Gonzalo y Granger, y iii) correlación con un índice de eventos sistémicos y políticas emprendidas para mitigar dichos eventos. Los resultados muestran que la mejor medida de riesgo sistémico en el grupo macro es el primer componente principal de la cartera compuesta por los CDS de las principales instituciones financieras mientras que la mejor medida en el grupo micro se corresponde con las densidades multivariantes estimadas en base a los CDS de las instituciones analizadas. Estos resultados sugieren que las medidas más simples basadas en CDS son capaces de medir de forma más adecuada el riesgo sistémico que otras medidas alternativas basadas en tipos de interés o mercado de acciones.

El Capítulo 3 se centra en la contribución individual de las instituciones financieras al riesgo sistémico. Para este análisis se utiliza una muestra de 91 holdings financieros estadounidenses desde 2002 and 2011. En primer lugar, se estiman y comparan cinco medidas relativas a dicha contribución y se muestra que la nueva medida propuesta en este capítulo, Net Shapley Value, mide de forma más adecuada la contribución individual al riesgo sistémico. El Net Shapley Value de una institución *j* se define como la media ponderada de las contribuciones marginales al riesgo de cada sub-sistema, considerando todos los posibles sub-sistemas que contienen a la institución *j* en los que la cartera se puede dividir excepto el sub-sistema compuesto únicamente por la institución *j*. Usando esta medida, se estudia el impacto de la tenencia de derivados financieros en las carteras de las instituciones financieras sobre su contribución al riesgo sistémico controlando por el efecto de variables relacionadas con tamaño, conectividad, sustituibilidad y otras variables de balance. Los resultados muestran que la tenencia de derivados de crédito y de tipo de cambio en un determinado trimestre por un determinado banco conduce a un aumento en su contribución al nivel de riesgo sistémico de la economía un trimestre después. Por otro lado, la tenencia de derivados sobre tipo de interés y materias primas (*commodities*) tiene un efecto contrario y contribuyen a la reducción del riesgo sistémico. Sin embargo, la proporción de préstamos morosos sobre préstamos totales y el ratio de apalancamiento presenta un impacto mucho mayor sobre la contribución al riesgo sistémico que la tenencia de derivados. Además, en el caso de los derivados de crédito, se documenta el cambio en el papel estos derivados tras la crisis *subprime*. Así, antes de la crisis de las hipotecas basura los derivados de crédito contribuían a la reducción del nivel de riesgo sistémico mientras que durante la crisis se observa el efecto contrario. De ahí que se concluya que los derivados de crédito han pasado de ser instrumentos que favorecían la absorción y reducción de riesgos en el periodo de estabilidad a ser amplificadores de riesgos durante la crisis. Sin embargo, el efecto del resto de los derivados analizados permanece constante durante ambos periodos.

Para finalizar, el Capítulo 4 analiza la dependencia de la liquidez de los CDSs corporativos individuales de la liquidez global del mercado (*liquidity commonalities*) y sus determinantes. Este estudio se encuentra motivado por el hecho de que el mercado de CDS contiene información relevante para construir medidas de riesgo sistémico, como se mostró en el Capítulo 2, y porque las posiciones mantenidas en derivados de crédito contribuyen a explicar la contribución de las instituciones financieras al riesgo sistémico, tal y como se documentó en el Capítulo 3. Además, los principales participantes del mercado de CDS son SIFIs. Debido a todas estas razones, niveles elevados de *liquidity commonalities* pueden acarrear cambios repentinos en la liquidez del mercado de CDS que, a su vez, pueden generar *shocks* de carácter sistémico sobre la economía dado que en un contexto de iliquidez en el mercado de CDS las empresas no pueden adaptar sus exposiciones al riesgo de forma adecuada. Este capítulo presenta evidencia sólida en favor de la existencia de dichas *liquidity commonalities*. Usando una muestra compuesta por 438 empresas pertenecientes a 25 países durante el periodo 2005-2012, se encuentra que las *liquidity commonalities* varían a lo largo del tiempo y son más fuertes durante aquellos periodos en los que el riesgo global, de contraparte y liquidez de financiación se agudiza. Sin embargo, dichas *commonalities* no dependen de las características específicas de las empresas. Además, el nivel de las *liquidity commonalities* varía en las distintas áreas económicas consideradas en este análisis siendo, en media, más fuertes en la Unión Monetaria Europea. Por otro lado, el efecto de la liquidez de mercado es superior al de la liquidez de la industria en todos los casos salvo en el sector bancario. Por último, se muestra la existencia de asimetrías en las *commonalities* alrededor de episodios de estrés financieros de tal forma que el impacto de la liquidez de mercado es superior cuando los precios representativos del mercado de CDS aumentan.

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# Chapter 1 General introduction

In this Thesis, I study the measurement and the determinants of systemic risk, paying special attention to the role of the Credit Default Swaps (CDSs) either as financial instruments containing valuable information about the soundness of the reference institutions or as a market whose distress contributes to potential systemic shocks on the economy. The measurement of systemic risk is addressed from two perspectives, aggregate and individual contribution to systemic risk. The first one is studied in the Chapter 2 and refers to the level of systemic risk in the overall economy, which is also understood as a portfolio of institutions. The second one is studied in Chapter 3 and refers to the individual contribution of each financial institution to the overall systemic risk. In this chapter I also study the determinants of the individual contribution of financial institutions to the systemic risk, focusing on the effect of portfolio holdings of derivatives. In Chapter 4 I study the liquidity commonalities and theirs determinants in the corporate CDS worldwide markets. The importance of this analysis relies on the fact that the main participants in the CDS market are systemically important financial institutions (SIFIs) and so, abrupt changes in the market liquidity could cause systemic shocks on the overall economy and as a consequence, adverse effects on the global stability. Finally Chapter 5 concludes and summarizes the main contributions, policy implications and future research lines. Next, I summarize the main findings of the three chapters of this Thesis.

Chapter 2 provides a general overview of what is systemic risk. Systemic risk appears when generalized malfunctioning in the financial system threatens economic growth and welfare. The causes of malfunctions can be related to multiple mechanisms such as macro imbalances (e.g. excessive credit expansion in the private or public sector), correlated exposures (e.g. herding behavior), contagions, asset bubbles, negative externalities (e.g. banks too big to fall) or information disruptions (e.g. freezes in the interbank market). Given this lengthy but incomplete list of possible mechanisms influencing systemic risk, it seems safe to posit that more than one risk measure is needed to capture its complex nature, in particular, that policymakers charged with the responsibility of ensuring financial stability should rely on a wide array of measures.

The measurement of systemic risk can be addressed from two alternative perspectives, at aggregate level and individual contribution level (i.e., the individual contribution of each institution to the overall systemic risk). In this Chapter I, study the systemic risk measures at aggregate level whose aim is to provide a measurement of the level of system risk in the economy or in a certain portfolio. The measurement of aggregate systemic risk has been addressed from a wide variety of perspectives (see surveys by De Bandt and Hartmann (2000), Acharya, Pedersen, Philippon and Richardson (2011b) and International Monetary Fund (2011)). Essentially, two types of indicators are suggested: first, slow moving low-frequency indicators based on balance sheet aggregates or macroeconomic data and second, high-frequency indicators based on market prices and rates. However, little is known of the relative quality of the different measures.

In this chapter I study the quality of the different aggregate systemic risk measures, focusing on high-frequency, market-based indicators (daily prices and rates).[1] These measures are classified in two groups: macro and micro. The aggregate market or macro group gauges the overall tension in the financial sector and the micro or individual institution level relies on individual institution information to extract joint distribution

[1] The low-frequency measures focus on the evolution of macroeconomic (overall market) or balance sheet indicators (individual institution) in order to detect the buildup of possible imbalances or tensions in the economy and in the financial sector. These measures provide a global perspective but, by their very nature, the low-frequency indicators cannot inform policymakers of imminent financial distress. All those indicators are beyond the scope of this chapter.

distress at portfolio level. This information would help regulatory institutions to design a *toolkit* to prevent systemic risk episodes in which the micro group of measures can be used as an early warning indicator that will alert the regulator that an individual (systemically important) bank is in trouble. The macro group of measures will deliver the same message when a group of them are in dire straits.

Using a sample of the most important systemic actors, the biggest banks, in the two main economic areas (the Western Europe and the U.S.) from January 2004 to November 2009; I estimate the two previously mentioned groups of measures. The set of measures in the first category (macro) are i) the LIBOR spreads (LS), ii) the principal component analysis (PCA) of portfolios of CDS spreads, and iii) the systemic factor extracted from the CDS indexes (CDX and iTraxx) and their tranches. The measures in the second group (micro) are i) the systemic risk index (SI) based on structural credit risk models, ii) the multivariate densities (MD) computed from groups of individual bank's CDS spreads, and iii) the aggregate of individual co-risk (CR) measures. All the above measures belong to different branches of literature and in most cases systemic risk is measured using alternative specifications. So, for every measure I consider all these alternative specification.

Then, I compare the estimated measures as follows. First I select the best performing category within each measure using their correlation with an index of systemic events and policy actions as the basic criterion. For instance, the LS measure contains two categories, LIBOR-OIS and LIBOR-TBILL. The former has the highest correlation with the index and therefore it is the one I use for the subsequent analysis. I then compare the best performing categories within each group (macro and micro) using two additional criteria: i) Granger causality tests, and ii) Gonzalo and Granger (GG) metric. The first criterion gives information about whether measure X is a leading indicator of measure Y. The second criterion relates to each measure with a common component, which may be interpreted as the underlying systemic risk trend in the economy. The intuition is that if measure X contributes to this common component to a greater extent than measure Y, then X is preferable. The performance of each measure is judged by their scores on each of the three criteria. For instance, to rank the measures according to the Granger causality test I give a score of +1 to measure X if X Granger-causes measure Y and I give a score of -1 to X if X is caused in the Granger sense by Y. By doing this, the best measure gets the highest positive score and the worst measure the highest negative score. I apply the same procedure to the correlation index and the GG metric. Finally, I add the scores provided by the three criteria for each measure.

I document that the best high-frequency, market-based systemic risk measure in the macro group, in both U.S. and in Europe portfolios, is simply the first principal component of a portfolio which contains the CDS of the main banks (PCA). The worst measure is the one based on the LIBOR-OIS spread. The best measure in the micro group in both economic areas is the multivariate densities (MDs), that is again based essentially on bank's CDS, while the worst is the aggregate of co-risk (CR) measures. According to these results, I document that measures based on credit derivatives (CDSs) seem to perform better than measures based on interbank rates or stock market prices. Therefore the high-frequency credit derivatives market-based measures are the best indicators in our sample to warn that a systemic event or crisis is close at hand. This result holds both in the case of measures in the macro group as well as those measures in the micro group. It certainly seems that signals of impending financial distress that come from the CDS market are clearer and louder than the ones coming from other markets.

In Chapter 3, I study systemic risk measures that provide a measurement of the individual contribution of each financial institution to the overall systemic risk and theirs determinants. This information could help to the banking regulatory institutions not only to improve currently available systemic risk measures and warning flags but also to develop a taxation system on the basis of the externalities generated by a banks' impact on systemic risk. Additionally, it could help securities market regulators in understanding the contribution of traded financial instruments, for instance financial derivatives, to systemic risk in order to consider new regulatory initiatives. Finally, investors should be concerned with the extent to which derivatives holdings affect the systemic impact of a given bank in order to assess the appropriate reward required to bear this kind of risk. Stulz (2009) pointed out the lack of rigorous empirical studies on the social benefits and costs of derivatives and in particular their role in the financial crisis 2007-09. So, this chapter aims to improve our understanding of these social costs and benefits examining whether the use of financial derivatives was a relevant factor in the destabilization of the banking system during the recent financial crisis. For this aim I combine two analyses; I first measure the banks' individual contributions to systemic risk and then, I estimate the effects of their holdings of financial derivatives on the banks' contributions to systemic risk.

To assess the banks' contributions to systemic risk I use the following five measures: $\Delta$CoVaR, $\Delta$CoES, Asymmetric $\Delta$CoVaR, Gross Shapley Value (GSV) and Net Shapley Value (NSV). The $\Delta$CoVaR is the difference between the Value at Risk (VaR) of the banking system conditional on bank $i$ being in distress minus the VaR of the banking system conditional on bank $i$ being in its median state. The $\Delta$CoES applies the same idea but using the Expected Shortfall instead of the VaR (see Adrian and Brunnermeier, 2011). The Asymmetric $\Delta$CoVaR represents a variation of the standard $\Delta$CoVaR specification that allows for asymmetries in this specification (see López, Moreno, Rubia and Valderama, 2011). The GSV measures the average contribution to systemic risk of bank *i* in all possible groups in which the whole financial system can be divided (see Tarashev, Borio, and Tsatsaronis, 2010). Finally, I propose an alternative measure to the GSV called NSV in which I get rid of the idiosyncratic component present in the former measure by subtracting from the GSV the VaR of the bank *i*.

I estimate these five measures for a subset of the 91 biggest U.S. bank holding companies for the period that spans from 2002 to 2011. Then, I compute the correlation of the systemic risk measures with an index of systemic events and run a Granger causality test between pairs of measures. I document that the NSV presents the closest association with the index and Granger causes more frequently the other measures.[2]

Then, using this measure of systemic risk as the dependent variable, I document that derivatives holdings act as leading indicators of systemic risk contributions. Concretely, banks' holdings of credit and foreign exchange derivatives have an increasing effect on systemic risk whereas holdings of interest rate and commodity derivatives have a decreasing effect. Additionally, disclosing the effect of the positions held in derivatives I find that usually derivatives held for trading have a significant effect, either positive (foreign exchange) or negative (interest rate, commodity) whereas derivatives held for purposes other than trading do not significantly affect systemic risk. In the case of credit derivatives, I find that being net protection buyer increases systemic risk. The results also show that before the subprime crisis credit derivatives contributed to decrease systemic risk whereas during the crisis holdings of derivatives led to increase it.

[2] Chapter 2 documents that measures based on CDS information provide more reliable information to measure aggregate systemic risk. However, in order to estimate the individual contribution of each financial institution to the overall systemic risk we cannot systematically use CDS information because of the lack of traded CDS for medium and small financial institutions.

However, the way foreign exchange, interest rate, equity and commodity derivatives influence systemic risk remains unchanged. Finally, on top of that I find that the variables with the highest economic impact on systemic risk are the proportion of non-performing loans to total loans and the leverage ratio, and in fact, their economic impact is higher than the one corresponding to derivatives holdings.

In Chapter 4 I study the liquidity commonalities in the corporative Credit Default Swap market around the 2007-2012 financial crisis. According to the main conclusions in Chapters 2 and 3, Credit Default Swaps are key instruments in understanding systemic risk either at aggregate or individual contribution levels. Additionally, during the 2007-2012 financial crisis, we have witnessed severe episodes of liquidity shortage in many markets being this shortage especially noticeable in the CDS market because of the uncertainty about the net amount, the structure, and the counterparty risk of such exposures. As a consequence, many firms have had difficulties to timely manage their credit risk exposures. This situation posed important challenges at the individual level but also from a global stability perspective. These facts point out the importance of considering the extent to which the shortage of liquidity has spread over the different contracts traded in the CDS market, and the factors that affect such scarcity.

This Chapter focuses on factors that may affect this shortage in market liquidity, and specifically the extent to which liquidity commonalities in the CDS market are of material importance in this regard. Liquidity commonalities can be defined as the co-movement of individual liquidity measures with market- and industry-wide liquidity. The objective of this Chapter is to provide new evidence on the co-movement in liquidity for the CDS market, which was firstly documented by Pu (2009), from a threefold perspective: firstly, the analysis of the time-varying behavior of the commonalities putting special emphasis on the financial crisis events; secondly, the use of different economic areas and industries for the analysis of such commonalities; and, thirdly the analysis of the factors influencing this co-movement at both aggregate and firm levels.

The typology of the participants in the CDS market, the high degree of concentration, and the role of credit derivatives during the financial crisis affecting both the financial sector and real economy make the analysis of the existence and the behavior of liquidity commonalities in the CDS market a topic of special relevance for regulators, risk managers, and investors. The fact that the main participants in the CDS market are systemically important financial institutions (SIFIs) facilitates that any shock affecting credit derivatives could revert directly on these institutions and could have implications in terms of financial stability. It is worth mentioning that the liquidity risk derived from the typology of the banks participating in the CDS market could be exacerbated by the high degree of concentration of the market activity in the hands of a few SIFIs acting as market participants. This high degree of market concentration may have implications in terms of the impact of large shocks on market liquidity. In fact, Mayordomo and Peña (2012) show that liquidity commonalities have significant effects on the pricing of the CDS of European non-financial firms and on the co-movements among CDS prices during the recent financial crisis.

The analysis of the determinants of the commonalities in liquidity is also certainly a timely topic because, as remarked by Dewatripont et al. (2010), developing a better understanding of what drives illiquidity at the individual and aggregate levels should stand high on the agenda of economists and policy makers alike.

I contribute with several findings to the empirical literature on liquidity commonalities. I document the existence of significant co-movements between single-name CDS liquidity and market-wide liquidity. Market commonalities are stronger than industry commonalities in most industries, with the exception of the banking sector. The liquidity commonalities are still present when I analyze separately the CDSs of companies located in different economic areas, but the degree of commonality differs across them.

Moreover, the liquidity commonalities are time-varying and increase in times of financial distress characterized by high counterparty, global, and funding liquidity risks but they do not depend on firms' specific characteristics. In this line, I find that the Lehman Brothers collapse and the Greek bailout requests triggered a significant increase in commonalities. In fact, the results suggest the existence of asymmetries in commonalities around these episodes of financial distress, such that the effect on market liquidity is stronger when the CDS market price increases. Finally, I find that liquidity commonalities provide additional information relative to the three aforementioned aggregate risks around these periods. All these results are robust to alternative liquidity measures and are not driven by the CDS data imputation method or by the firms with the highest CDS prices.

As a last remark, this Thesis was elaborated in a way that any of the following chapters can be read independently. In this sense, Chapters 2, 3, and 4 present complete researches that, although based on systemic risk and its relation to the CDS market, consider different research questions and lead to independent conclusions.

# Chapter 2 Systemic risk measures: The simpler the better?

## 2.1. Introduction

Systemic risk appears when generalized malfunctioning in the financial system threatens economic growth and welfare. The causes of this malfunction are multiple and therefore a single measure of systemic risk may neither be appropriate nor desirable. The financial system plays a fundamental role in the global economy as the middleman between both agents who need to borrow and those who are willing to lend or invest and is naturally linked to all economic sectors therefore, if the financial system does not work properly, its problems have a strong impact on the real economy. For this reason, policymakers, regulators, academics and practitioners should pay close attention to the soundness and stability of this sector.

The causes of malfunctions can be related to multiple mechanisms such as macro imbalances (e.g. excessive credit expansion in the private or public sector), correlated exposures (e.g. herding behavior), contagions, asset bubbles, negative externalities (e.g. banks too big to fall) or information disruptions (e.g. freezes in the interbank market). Given this lengthy but incomplete list of possible mechanisms influencing systemic risk, it seems safe to posit that more than one risk measure is needed to capture its complex nature, in particular, that policymakers charged with the responsibility of ensuring financial stability should rely on a wide array of measures. These measures should detect at least two kinds of situations and cover two different groups of potential systemic risk's detectors. They should warn of a persistent build-up of imbalances within the financial sector or be able to capture the abrupt materialization of systemic risk. With regard to the potential systemic risk's group detector, measures should be based on the aggregate market level (e.g. interbank rates, stock market and CDS indexes) or at the level of individual institutions. For the sake of clarity we will refer to those groups as macro and micro group, respectively. These kinds of indicators should be underpinned by measurable patterns of systemic stability which form the basis for early warning and correcting. If a systemic risk measurement indicates that destabilizing systemic events are looming, preventive policies such as stricter financial regulation and more rigorous supervision may be justified.

In the years leading up to the crisis in August 2007, we witnessed some of the above mentioned malfunctions. Explosive growth in the US subprime market, unprecedented increase in credit in private sector in the UK, Ireland and Spain, generalized external imbalances in many Western countries and of course, once the crisis started, the Lehman Brothers bankruptcy and persistent stress in the European and US banking sectors are examples of the most salient events. As a consequence, from 2007 to 2009, macroeconomic indicators such as real GDP growth or government deficits were strongly eroded in many countries.[3]

Measuring systemic risk has been addressed from a wide variety of perspectives (see surveys by De Bandt and Hartmann (2000), Acharya, Pedersen, Philippon and Richardson (2011b) and International Monetary Fund (2011)). Essentially, two types of indicators are suggested: first, slow moving low-frequency indicators based on balance sheet aggregates or macroeconomic data and second, high-frequency indicators based on market prices and rates. However, little is known of the relative quality of the

[3] For instance, the annual GDP growth rate decreased from 3.09% in 2007 to -4.09% in 2009 in the European Union while in the US this rate decreased from 2.14% to -2.45%. Regarding the government deficits, 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%. Meanwhile, in the same period the unemployment rate increased from 7.8% in January 2007 to 9.4% in November 2009 in the European Union and from 4.6% to 10% in the US during the same period.

different measures. In this paper we focus on systemic risk measures based on high-frequency, market-based indicators (daily prices and rates) for the two potential systemic risk's group detectors mentioned above (aggregate market or macro and individual institution or micro). The measures we study in this paper are near-coincident indicators of financial stress and could be useful in alerting regulators of imminent and serious strains on the financial system.

The selection of the financial institutions to be included in the study is a critical issue. Billio, Getmansky, Lo, and Pelizzon (2010) found that banks may be more central to systemic risk than non-bank financial institutions engaging in banking functions. Tarashev, Borio and Tsatsaronis (2010) convincingly argued that larger size implies greater systemic importance, that the contribution to system-wide risk increases disproportionately to relative size, and that a positive relationship between size and systemic importance leads a robust result. Thus, we restrict our sample to the biggest banks according to the size's criteria proposed by the BIS, IMF and FSB (2009). Thereby concentrating on some of the most important systemic actors: the biggest banks in the two main economic areas (the Western Europe and the US). Our sample spans from January 2004 to November 2009 and comprises the 20 biggest European and 13 biggest US banks.[4]

[4] Regarding the relative size of systemic risk in large European and US banks, ex-ante it is not easy to say much about its size because measures have to be contextualized. The question should be how much systemic risk is the banking sector able to assume before collapsing. Given that systemic risk measures cover a sufficiently long time (which cover tranquil periods and systemic events) we can use these measures to estimate the thresholds that determine different stress regimens. For instance, on the basis of econometric tools such as thresholds-VAR models the different regimes (normal times, stress times) of the time series can be identified. When a given measure rises above the critical value separating the two regimes, the regulator should carry out an assessment of the situation. Additionally, depending on the measures on stress (i.e., aggregate vs. individual institution level) the policy actions should differ. At the aggregated level macro measures may be called for (interest rates moves, restrictions on aggregate credit growth) whereas at the individual institution level tailored measures are more appropriate (new equity issuances, restrictions on specific trading activities) to decrease the stress

We employ two groups of measures. The first group gauges the overall tension in the financial sector and the second relies on individual institution information to extract joint distribution distress at portfolio level. The set of measures in the first category (macro) are i) the LIBOR spreads (LS), ii) the principal component analysis (PCA) of portfolios of CDS spreads, and iii) the systemic factor extracted from the CDS indexes (CDX and iTraxx) and their tranches. The measures in the second group (micro) are i) the systemic risk index (SI) based on structural credit risk models, ii) the multivariate densities (MD) computed from groups of individual bank's CDS spreads, and iii) the aggregate of individual co-risk (CR) measures. All the above measures belong to different branches of literature and in most cases systemic risk is measured using alternative specifications. So, for every measure we consider all these alternative categories. The comparison procedure is as follows. We first select the best performing category within each measure using their correlation with an index of systemic events and policy actions as the basic criterion. For instance the LS measure contains two categories, the LIBOR-OIS and the LIBOR-TBILL. The former has the highest correlation with the index and therefore it is the one we use for the subsequent analysis. We then compare the best performing categories within each group using two additional criteria: i) Granger causality tests, and ii) Gonzalo and Granger (GG) metric. The first criterion gives information about whether measure X is a leading indicator of measure Y. The second criterion relates to each measure with a common component, which may be interpreted as the underlying systemic risk trend in the economy. The intuition is that if measure X contributes to this common component to a greater extent than measure Y, X is preferable. The performance of each measure is judged by their scores on each of the three criteria. For instance, to rank the measures according to the Granger causality test we give a score of +1 to measure X if X Granger-causes measure Y and we give a score of -1 to X if X is caused in the Granger sense by Y. By doing this, the best measure gets the highest positive score and the worst measure the highest negative score. We apply the same procedure to the correlation index and the GG metric. We then add the scores provided by the three criteria for each measure.

We find that the best high-frequency, market-based systemic risk measure based on the macro group, in both US and in Europe portfolios, is simply the first principal component of a portfolio which contains the CDS of the main banks (PCA). The worst measure is the one based on the LIBOR-OIS spread. The best measure based on micro group in both economic areas is the multivariate densities (MDs) again based essentially on bank's CDS and the worst is the aggregate of co-risk (CR) measures. According to these results, measures based on credit derivatives (CDSs) seem to perform better than measures based on interbank rates or stock market prices. Therefore the high-frequency credit derivatives market-based measures are the best indicators in our sample to warn that a systemic event or crisis is close at hand. This result holds both in the case of measures in the macro group as well as those measures in the micro group. It certainly seems that signals of impending financial distress that come from the CDS market are clearer and louder than the ones coming from other markets.

The paper is divided into six sections. Section 2.2 reviews literature and presents the systemic risk measures. Section 2.3 describes the data set. Section 2.4 summarizes the empirical estimates of the systemic risk measures. In Section 2.5, we compare the measures using three criteria. Section 2.6 outlines some suggestions for policymakers and concludes.

## 2.2. Literature review

Until recently, risk management in the financial industry has usually focused on individual institution's market, credit and operational risks and ignores systemic risk. In this vein, the Basel I (1988) and Basel II (2004) Capital Accords advise risk management policy on the basis of the banks' portfolios, ignoring interconnection among banks. However, as the 2007-2009 crisis has shown, this firm-specific perspective is not sufficient to appropriately ensure the soundness of the financial system. This is because the risk it poses the system is greater than the sum of the risk faced by individual institutions.[5] Nevertheless, this issue is addressed in the new Basel III (2011) Accord in which capital buffers are improved (quality and quantity) and a macro-prudential overlay proposed to deal with systemic risk.

As mentioned before some (low-frequency) measures should warn of the persistent build-up of imbalances in the economy within the financial sector and some other measures (high-frequency) should be able to capture the abrupt materialization of systemic risk, both at aggregate market level as well as at the level of individual institutions. The low-frequency measures focus on the evolution of macroeconomic (overall market) or balance sheet indicators (individual institution) in order to detect the buildup of possible imbalances or tensions in the economy and in the financial sector. These measures provide a global perspective but, by their very nature, the low-frequency indicators cannot inform policymakers of imminent financial distress. For instance, some macroeconomic variables and balance sheet aggregates continue to present a positive profile well after a systemic stress is detected. Examples of the low-frequency approach are Borio and Lowe (2002) and Borio and Drehmann (2009), who

[5] See speech by Jaime Caruana, General Manager of the Bank for International Settlements, "Basel III: towards a safer financial system" September 2010.

proposed measuring the financial unwinding of imbalances by means of price misalignments in some key indicators like inflation-adjusted equity prices or private sector leverage. Schwaab, Koopman and Lucas (2011) developed a set of coincident measures and forward looking indicators based on macro-financial and credit risk factors. All these low-frequency measures provide useful tools to the macro-prudential policy but are beyond the scope of this paper.

Our focus in this article is on the high-frequency measures. At the macro group of measures, interbank interest rates provide a general vision of the sentiment in the credit markets on daily basis. This use of LIBOR spreads is a prevalent practice amongst practitioners' and regulatory circles alike, for example, these measures were employed by Brunnermeier (2009), and by the IMF's Global Financial Stability Report (2009). Therefore, the LIBOR spreads constitutes the first measure at macro group level. We distinguish between two categories the 3-month LIBOR rate and the 3-month overnight interest swap spread (LIBOR-OIS, hereafter) and the 3-month LIBOR rate and 3-month Treasury bills spread (LIBOR-TBILL, hereafter).[6] Although similar, there are important conceptual differences between them. The LIBOR represents the unsecured average interest rate at which banks lend money and hence, contains liquidity risk and the bank's default risk. The OIS is equivalent to the average of the overnight interest rates expected until maturity and is almost riskless. So, LIBOR-OIS reflects liquidity and default risk. On the other hand, Treasury bill rates show the rates that an investor earns on Treasury bills. In times of stress, most lenders only accept Treasuries as collateral, pushing down Treasury rates. Hence, LIBOR-TBILL captures not only liquidity and default risk but also the additional fact that, during periods of turmoil, investors lend against the better form of collateral, Treasury bills, thereby also measuring the "flight to

[6] This measure is also known as the TED spread.

quality" effect. These spreads should be closely linked to systemic risk because they assess whether financial institutions are able to perform their activities or are impaired by any shock that affects liquidity, default or "flight to quality". Nevertheless, it is important to bear in mind that short-term rates are policy targets and as such are subjected to regulatory pressure.[7] This may affect their usefulness as systemic risk indicators as suggested by the well-known Goodhart's Law.

Credit Default Swap (CDS) spreads have been extensively used in literature to measure systemic risk. Longstaff and Rajan (2008) carried out a principal component analysis of changes in the CDS spreads for the individual firms in the CDX index in an effort to understand whether clustering default risk is linked to the industry. They find that the first principal component is a dominant factor that drives spreads across all industries. Using a similar methodology, Berndt and Obreja (2010) studied the CDS returns of all European public firms with active CDS and found that the first factor captures 53% of the total variance. Following this line, the second measure we employ in this paper at the macro group level is the first principal component of the banks' CDS spreads that compose our two reference portfolios (US and European). This component is linked to systemic risk since CDS spreads measure the default risk of the reference institution and hence, the first component contains the common driver of this default risk in the whole portfolio, measuring the impairment risk of the portfolio.

Other researchers use more complex procedures based on CDS indexes and their tranches. Huang, Zhou and Zhu (2009) proposed creating a synthetic collateralized debt obligation (CDO) whose underlying portfolio consists in debt instruments issued by banks to measure the systemic risk in the banking system through the spread of the

[7] For example, the Federal Reserve introduced the Term Auction Facility (TAF) on 12 December 2007 with the aim of narrowing the LIBOR-OIS spreads (In, Cui and Maharaj, 2012).

tranche that captures losses above the threshold of the 15%, however their main insights are based on a non-traded instrument. Bhansali, Gingrich and Longstaff (2008) extracted the idiosyncratic, sector and economy-wide (systemic) factors from US (CDX) and European (iTraxx) prices of indexed credit derivatives and their tranches. To such an end, they modeled the realized credit losses for underlying portfolios using a linearized three-jump model where each jump corresponded to the idiosyncratic, sector-wide and systemic factors and they differ in their frequency and their impact of the realized losses.[8] By using the risk-neutral pricing equation they broke down the indexes into the above mentioned risks. Following this line, the third measure in the macro group we study in this paper is based on Bhansali et al. (2008). This measure is naturally linked to systemic risk as it provides a market perception of having a large number of simultaneous defaults.

Within the second group of measures, the micro group, a popular tool to model systemic risk is to use the structural model originally proposed by Merton (1973). Using this tool, Lehar (2005) proposed a systemic risk measure based on the probability of default of a given proportion of the banks in the financial system. This probability of default is linked to the relationship between a banks' asset value and its liabilities. The procedure to estimate this measure consists in recovering the bank's asset portfolio and correlations through Merton's model and an exponentially weighted moving average (EWMA) model, respectively. Then a simulation is carried out to infer future bank's asset portfolio and compare them with their liabilities according to different criteria thus constructing two systemic risk indexes: systemic risk index based on the expected value of bank's asset portfolio (SIV) and the expected number of defaulted banks (SIN). Similar approaches have been taken by amongst others Allenspach and Monnin (2009)

[8] Idiosyncratic factor is characterized by having a large frequency and small impact on portfolio losses while systemic factor is characterized by very small frequency and strong impact.

and Gray, Merton, and Bodie (2008). Following this line, the first measure, at individual institution level, we consider is Lehar's (2005) which represents the structural model approach.[9] The proposed categories (SIV and SIN) are linked to systemic risk as they assess the probability of the impairment of part of the portfolio either in terms of the value or the number of impaired banks.

Recovering the multivariate density distribution of a portfolio of institutions has also been proposed as an alternative measure of systemic risk, as systemic risk can be considered the probability of being at the tail of the joint distribution. Segoviano and Goodhart (2009) modeled the so-called banking system multivariate density (i.e., joint probability distribution of the banks that compose the portfolio, BSMD) by means of the consistent information multivariate density optimizing methodology (Segoviano, 2006). Once the BSMD is recovered, the authors proposed two categories of measures for common distress in the banking system: the joint probability of distress (JPoD) and the banking stability index (BSI). The former category represents the probability of all banks in the portfolio becoming distressed. The second category represents the expected number of banks that will become distressed, conditional on the fact that at least one bank is distressed. This approach has been considered by other authors, for example, Zhou (2010) proposed a different procedure to estimate the systemic risk measure based on Segoviano and Goodhart by means of extreme value theory. Following this approach, the second measure at micro group estimated in this paper is based on Segoviano and Goodhart (2009).

Finally, other researchers have proposed measures that quantify the individual contribution of each institution in the portfolio to the systemic risk. Adrian and

[9] We estimate these measures as indicated by Lehar (2005) in order to be consistent with the original methodology.

Brunnermeier (2008) proposed 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 $\Delta CoVaR_i$. A similar perspective was taken by Acharya et al. (2010) or Brownlees and Engle (2010) amongst others. The third measure we consider at micro group in this paper consists of the sum of the Adrian and Brunnermeier (2008) measure across banks in the portfolio.

## 2.3. Data

Our analysis of systemic risk is focused on two portfolios which contain the largest banks in Western Europe (including non-Eurozone) and United States (US). 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 for which we have information about CDS spreads, liabilities and equity prices.[10] Our final sample is composed of 20 European banks and 13 US banks and is summarized in Table 2.1, which also contains the average portfolio weights on the basis of their average market capitalization during the sample period.

The main data inputs 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

[10] 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.

or DataStream depending on the data availability in both data sources. Additionally, other aggregate market variables are required, for instance, the 3-month and 10-year LIBOR, swap rates and Treasury yields. We employ interest rates from the two economic areas: US and the Eurozone.[11, 12] These variables are obtained from Reuters. Moreover, CDS index spreads are also employed: the US CDS index investment grade spreads (CDX IG 5y) and the European (iTraxx Europe 5y) as well as their tranches. Index spreads and their tranches come from Markit.

**Table 2.1 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 | 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 | 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 | The Netherlands | 0.05 | Suntrust | 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 | | | |

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 (before

[11] 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.

[12] 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 analysed 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.

2007) and crisis periods (2007-2009). However, the sample period used for the CDS indexes is slightly shorter due to data restrictions. Concretely, CDX IG 5y spans from March 2006 to November 2009 while iTraxx Europe 5y spans from March 2005 to November 2009.[13]

## 2.4. Empirical results

In this section we show the empirical results of the computation of the systemic risk measures discussed. It is worth remembering that we employ two groups of measures, measures in the first category are supposed to gauge the overall tension in financial markets whereas measures in the second rely on the individual institution information to extract the joint distress at portfolio level. The first group is composed of three measures: i) the LIBOR spreads (LS), ii) the principal component analysis (PCA) of the portfolio of CDS, and iii) the systemic factor extracted from the CDS indexes (CDX and iTraxx) and their tranches. The primary information comes from interbank interest rate spreads and CDS. Stress in the interest rate spreads directly affects to the soundness and stability of the financial institutions, while the information extracted from the CDS provides insights on the market perception of the joint default risk of the considered institutions.

The second group is composed of three measures: i) the systemic risk index (SI) based on structural credit risk models, ii) the multivariate densities (MD) computed from groups of individual bank's CDS spreads, and iii) the aggregate of individual co-risk (CR) measures.[14] These measures combine accounting, equity and CDS information at

[13] Regarding the use of the CDS indexes, 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.

[14] "Co-risk management" measure refers 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.

an individual level. Table 2.2 summarizes the measures and the corresponding categories as well as their main characteristics in terms of basic information, objective and relation with systemic risk.

### *2.4.1. Macro group*

#### *2.4.1.1. LIBOR spreads*

Figure 2.1 depicts the evolution of the LIBOR spreads. We observe a remarkable difference between the pre-crisis and crisis periods. As the subprime crisis started in August 2007, two phases of the crisis can be distinguished, the first phase spans from August 2007 to August 2008 and is characterized by a general increment in the level and volatility of the spreads. Noting that, the US LIBOR-TBILL reacts earlier and in a more volatile way in comparison with the other spreads. The second phase of the crisis starts with a generalized sharp widening after the Lehman Brothers bankruptcy.[15] The US LIBOR-TBILL hits 458 b.p. followed by the US LIBOR-OIS which reached 363 b.p. (see Panel A of Table 2.3 for the descriptive statistics). After that episode, all spreads gradually contracted, ending the sample period at pre-crisis levels. This behavior was possibly related to the Fed, ECB and other central banks' program to flood the market with cheap money, pushing down interest rate spreads after massive intervention.

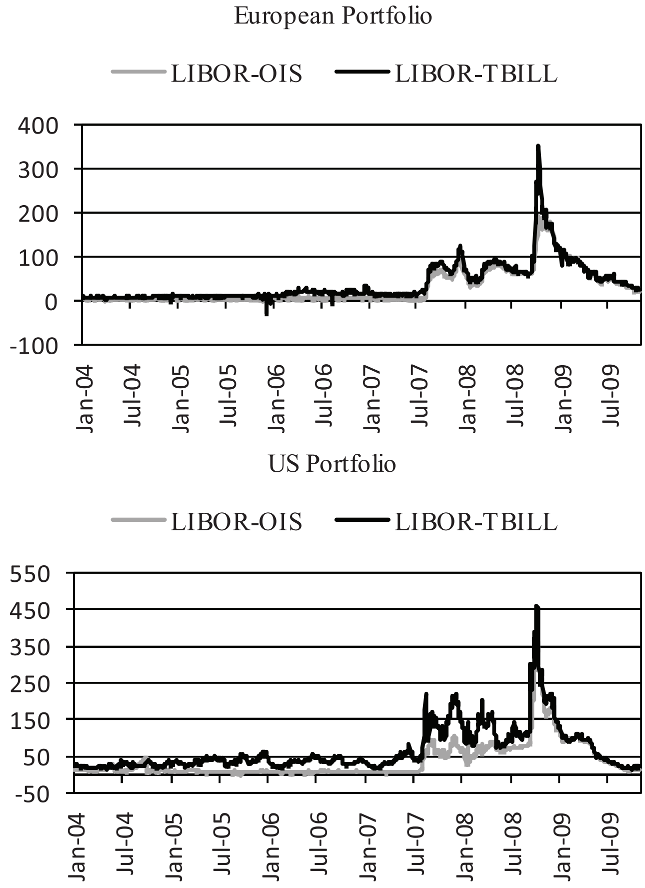
#### *2.4.1.2. Principal component analysis of CDS portfolios*

Figure 2.2 shows the evolution of the European and US first principal components (FPCs) during the whole sample period and Panel B of Table 2.3 their main descriptive statistic. From January 2004 to July 2007, both components remained almost flat. When

[15] The Lehman Brother bankruptcy sparked off a wave of bankruptcies and bail-outs in the US and Europe.

the crisis started in August 2007, and up March 2009, both variables follow an upward trend in which three peaks are clearly visible: March 2008, September 2008 and March 2009. Both FPCs are largely similar but in the later period, from September 2008 to December 2008, given the high stress in the US markets after the bankruptcy of the Lehman Brothers, the US factor is higher. After the Lehman Brothers bankruptcy, a number of bad news events accumulated in the last quarter of 2008 and first quarter of 2009 and consequently, systemic risk skyrocketed.[16]

**Figure 2.1 Systemic risk measures based on LIBOR spread**
This figure represents the spreads between LIBOR and the Overnight Interest Rate (LIBOR-OIS) and between LIBOR and Treasury Bills (LIBOR-TBILL) for the European and US portfolios. These variables are measured in basis points.




In March 2009, the launch of the Term Asset-Backed Securities Loan Facility (TALF) with the potential to generate up to $1 trillion of lending for businesses and households

[16] To give an example, the number of "problem banks" increased from 171 institutions with $116 billion of assets at the end of the third quarter of 2008, to 252 insured institutions with $159 billion in assets at the end of fourth quarter of 2008. The FDIC also announced that there were 25 bank failures and five assistance transactions in 2008, which was the largest annual number since 1993. See http://timeline.stlouisfed.org/index.cfm?p=timeline for the complete timeline of the crisis.

decreased the overall tension in the markets. After March 2009, both FPCs decreased noticeably and at the end of the sample period, the levels of these variables returned to a level similar to that at the beginning of 2008, but still clearly above pre-crisis levels.

**Table 2.2 Description of the systemic risk measures**
This table summarizes the main characteristics of the systemic risk measures in terms of: (i) theoretical approach; (ii) author; (iii) group (macro/micro) (iv) category; (v) data requirements; (vi) objective of the measure; and (vii) relationship with systemic risk.
[a] We do not report the field "author" when it is a widely employed measure.
[b] We use the definition of systemic risk jointly provided by the FSB, IMF and BIS (2009).

| Measure | Author[a] | Group | Category | Data requirements | Objective | Relationship with systemic risk[b] |
|---|---|---|---|---|---|---|
| LIBOR spread (LS) | | Macro | • LIBOR OIS<br>• LIBOR TBILL | Short term LIBOR, swap rates and Treasury yields | To measure the distress in the interbank market.<br>• LIBOR OIS: Liquidity and default risk<br>• LIBOR TBILL: Liquidity, default risk and "flight to quality" effect | The higher the liquidity and default risk, the higher is the systemic risk. "Flight to quality" effect also increases as systemic risk increases. |
| Principal component analysis (PCA) | | Macro | First principal component (FPC) | Credit default swap (CDS) spreads of the portfolio European and US banks | To measure the common factor that drives the CDS spreads (spreads are considered as indicators of the default probability) | The higher the common factor that explain the default probability, the higher the systemic risk |
| CDS indexes and tranches (CDS) | Bhansali, Gingrich and Longstaff (2008) | Macro | They propose to measure of systemic risk from indexes of CDSs | CDS index and tranches of the CDX and iTraxx Europe. These indexes are composed by the most liquid firms but not all firms are financials. | To assess the risk of a massive economy wide default scenarios embedded in index tranche prices | The higher the risk of a massive economy wide default, the higher the systemic risk |
| Systemic risk index based on structural credit risk model (SI) | Lehar (2005) | Micro | • SIV: Measure based on the value of expected default institutions<br>• SIN: Measure based on the number of expected default institutions | • Market capitalization of individual banks<br>• Balance sheet information<br>• Correlation among bank returns | To measure the default probability of certain proportion of the total system | The higher the probability of a joint default, the higher the systemic risk |
| Multivariate Densities (MD) | Segoviano and Goodhart (2009) | Micro | • JPoD: Joint probability of default<br>• BSI: Banking stability index | • CDSs of selected banks<br>• Banking system's portfolio multivariate density (BSMD): distress interdependence structure | To measure the common distress in the banking system.<br>• JPoD: Measures the probability of all the banks in the portfolio becoming distress<br>• BSI: Reflects the expected number of banks becoming distressed given that at least one is in distress | • The higher the JPoD, the higher the systemic risk<br>• The higher the BSI, the higher the probability of contagion and hence, the higher the systemic risk |
| Aggregate co risk (CR) | Adrian and Brunnermeier (2008) | Micro | • AΔCoVaR: Sum delta co value at risk<br>• AΔCoES: Sum delta co expected shortfall | • Equity prices and returns of considered banks<br>• Market information such as: VIX/VDAX, 3M Libor OIS, change in TBill 3M, 10Y 3M TBill, Banking Index and accounting information | • ΔCoVaRi measures how the system's VaR change when bank i is in distress (spillover of institution i to the system)<br>• AΔCoVaR measures the aggregate spillover effect<br>• The same concept applies to AΔCoES | • The higher the AΔCoVaR, the higher the contagion of distress and the higher the systemic risk<br>• The higher the AΔCoES, the higher the contagion of distress and hence, the higher the systemic risk |

### Table 2.3 Descriptive statistics of the macro group

This table reports the descriptive statistics of the measures belonging to the macro group. Panel A contains the LIBOR spreads: LIBOR-OIS and LIBOR-TBILL for the European and US portfolios, measured on basis points. Panel B refers to the principal component analysis measure (PCA) and contains the first principal component (FPC) of the European and US CDS portfolios. Panel C reports the descriptive statistics for CDS indexes and their tranches approach. Panel C.1 reports the economy-wide or systemic (I), sector-wide (II) and idiosyncratic (III) spreads which are extracted from both CDS indexes and their tranches of the corresponding economic area (i.e., the Europe and the US) measured on basis points. The left hand side refers to the European spreads whose reference index is the iTraxx Europe 5y and the right hand side refers to the US spreads whose reference index is the CDX IG 5y. Panel C.2 contains the average portfolio losses implied by the model (jump size). The descriptive statistics cover the mean, standard deviation, median, maximum and minimum value. Sample start and final dates are reported.

Panel A: LIBOR spreads

| | European portfolios | | US portfolios | |
|---|---|---|---|---|
| | LIBOR-OIS | LIBOR-TBILL | LIBOR-OIS | LIBOR-TBILL |
| Mean | 30.39 | 39.26 | 36.96 | 66.02 |
| SD | 39.44 | 44.54 | 50.66 | 62.41 |
| Median | 5.70 | 17.53 | 10.90 | 39.14 |
| Maximum | 194.33 | 351.63 | 363.88 | 458.80 |
| Minimum | -1.85 | -29.79 | -1.06 | 14.24 |
| Start date | 01/01/04 | | 01/01/04 | |
| Final date | 04/11/09 | | 04/11/09 | |

Panel B: Principal component analysis

| | First principal component of the European portfolio | First principal component of the US portfolio |
|---|---|---|
| Mean | 0.00 | 0.00 |
| SD | 4.52 | 3.55 |
| Median | -2.68 | -1.92 |
| Maximum | 15.08 | 12.52 |
| Minimum | -3.53 | -2.84 |
| Start date | 01/01/04 | 01/01/04 |
| Final date | 04/11/09 | 04/11/09 |

Panel C: CDS indexes and their tranches

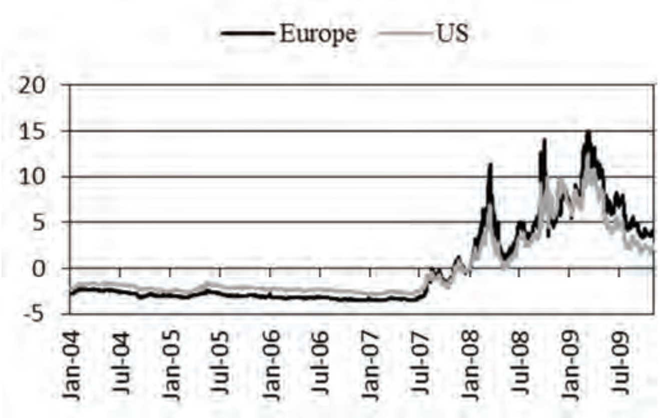
Panel C.1: Descriptive statistics of the estimated spreads

| | European CDS index | | | US CDS index | | |
|---|---|---|---|---|---|---|
| | I | II | III | I | II | III |
| Mean | 29.95 | 10.96 | 36.57 | 31.55 | 29.87 | 44.67 |
| SD | 40.87 | 12.92 | 17.78 | 26.31 | 41.14 | 17.78 |
| Median | 8.28 | 2.10 | 30.25 | 27.86 | 11.31 | 41.60 |
| Maximum | 164.96 | 50.71 | 99.41 | 105.62 | 182.84 | 145.24 |
| Minimum | 0.09 | 0.63 | 17.12 | 1.25 | 0.74 | 24.51 |
| Start date | 25/02/05 | | | 22/03/06 | | |
| Final date | 04/11/09 | | | 04/11/09 | | |

Panel C.2: Jump size

| | European CDS index | | | US CDS index | | |
|---|---|---|---|---|---|---|
| | I | II | III | I | II | III |
| Mean | 0.663 | 0.082 | 0.014 | 0.708 | 0.081 | 0.011 |

**Figure 2.2 Systemic risk measures based on principal component analysis**
This figure represents the first principal component factor of the European and US portfolios of single CDS.



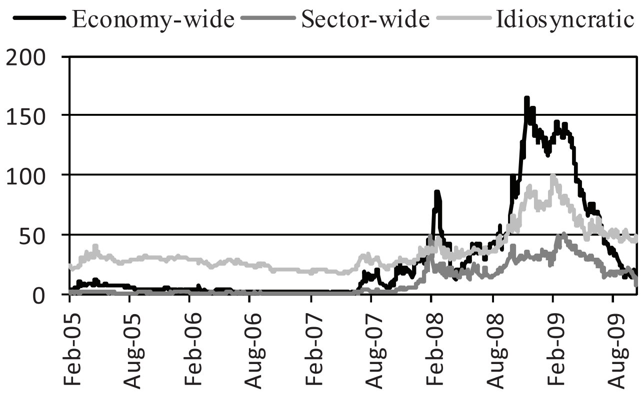

*2.4.1.3. CDS indexes and their tranches*

Figure 2.3 depicts the evolution of the idiosyncratic, sector-wide and economy-wide (systemic) component extracted from the CDX IG 5y and the iTraxx Europe 5y indexes.[17] Before the subprime crisis, the CDS indexes were mainly driven by the idiosyncratic component being the systemic component around zero. At the beginning of the crisis, the systemic spreads increased substantially, achieving a first peak during the Bearn Stearns episode, in which they were higher than the idiosyncratic spreads in both economic areas. Up to the Lehman Brothers episode, the European and US systemic risk spreads showed an upward trend. After that, they behaved differently, in Europe from the Lehman episode to March 2009, the systemic spread explains half of the iTraxx Europe 5y's behavior, whereas in the US, the sector-wide spread explains a higher proportion of the CDX IG 5y. The idiosyncratic spread has explained most of the iTraxx Europe 5y since March 2009, while in the US it has remained at the same level.[18] The discrepancy between the behavior of the CDX IG 5y and iTraxx Europe 5y could be due to the lower amount of financial institutions included in the US index.

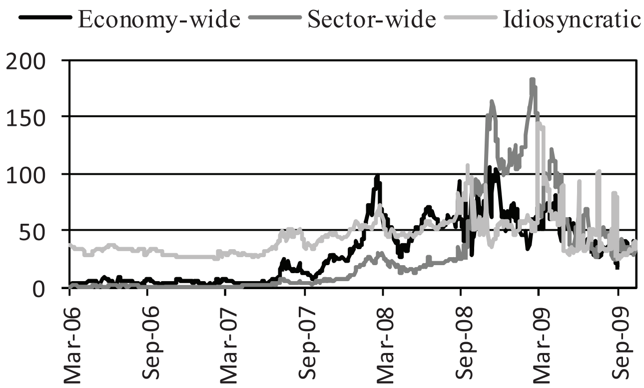
[17] Note that by construction, the idiosyncratic, sector-wide and systemic spreads add up the CDS index spreads.
[18] At the end of the sample period, three jumps appear on the US spreads, corresponding to periods in which out-the-roll series are employed (see Section 1.3).

**Figure 2.3 CDS indexes and their tranches**
This figure depicts the idiosyncratic, sector-wide and economy-wide (systemic spreads) which are extracted from both CDS indexes of the corresponding economic area and their tranches for the European and US portfolios. These variables are measured in basis points.

European Portfolio




US Portfolio




Panel C.1 of Table 2.3 contains the descriptive statistics for the three spreads. Panel C.2 reports the average portfolio losses implied by the model in the three considered shocks, we observe similar output in both portfolios. An idiosyncratic shock generates a loss of a 1% of the notional, while sector-wide and systemic shocks generate losses of 8% and 68%, respectively.

### *2.4.2. Micro group*

#### *2.4.2.1. Systemic risk indicators based on structural models*

In this measure two alternative categories have been proposed: SIV and SIN. The first assesses the probability that banks with total assets of more than a given percentage (ε) of all banks assets go bankrupt in a 6 month horizon and this is depicted on Panel A of

Figure 2.4. Five different thresholds have been chosen (i.e.,$\varepsilon = 5, 10, 15, 25$ and $50\%$), European and US systemic risk variables behave in a similar way. Before 2008, they were close to zero for all ε. In the second semester of 2008 these probabilities sharply increased reaching the 100% for the thresholds at 5% and 10%. Then, the probability that in the subsequent 6 months the value of the defaulted banks is above the 10% of the whole portfolio value is 1. This extremely high stress remained in both portfolios up to March 2009. Then, there was a downward trend in the US portfolio while European measures experienced another increase in systemic risk after August 2009.

The second category, SIN, is defined as the probability of more than a given number of banks going bankrupt within a six month horizon where this number is a proportion of the whole number of banks in the portfolio. Panel B of Figure 2.4 shows their descriptive statistics. We do not find notable differences between the SIN and SIV categories.

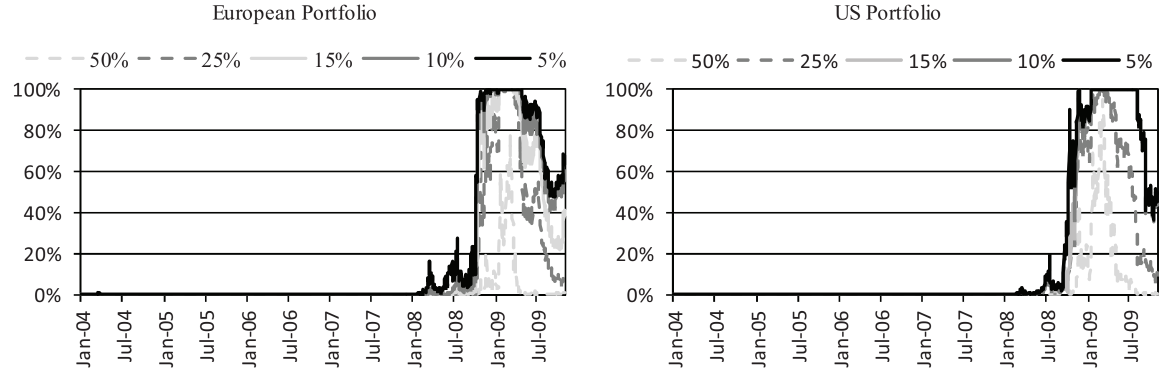
*2.4.2.2. Multivariate densities*

This measure relies on the process of recovering a multivariate density that models the default risk of whole or part of the portfolio. Segoviano and Goodhart (2009) recovered this density (the so-called banking system multivariate density, BSMD) through the CIMDO methodology (Segoviano, 2006). However, the estimation of the BSMD becomes harder as we increase the number of banks under analysis. 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 at the top of each classification and estimate the corresponding BSMD. Estimating the systemic risk measures on the reduced portfolio instead of using the whole portfolio is an approximation. However, we consider that the reduced portfolios can 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.

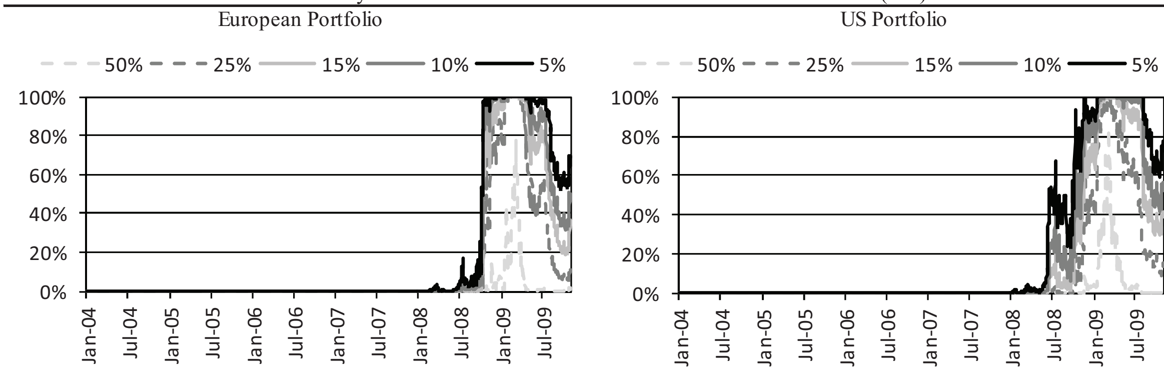
**Figure 2.4 Systemic risk measure based on structural models**

This figure depicts the systemic risk index based on the value of defaulted assets (Panel A) and systemic risk index based on the number of defaulted banks (Panel B) categories for different default thresholds (50, 25, 15, 10 and 5%). These variables are measured on percentage points.

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




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

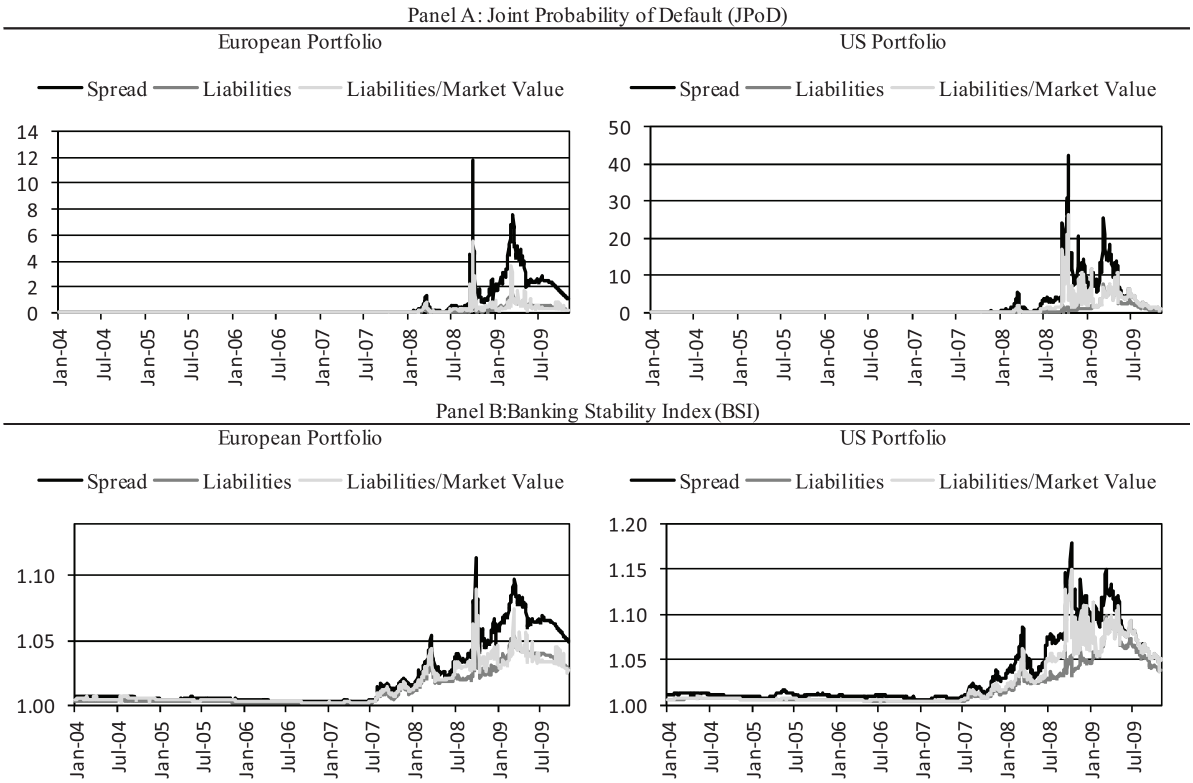



This measure allows us to estimate two different categories: the joint probability of distress (JPoD) and the banking stability index (BSI). The former represents the probability of all banks in the portfolio becoming distressed, this is depicted in the Panel A of Figure 2.5. In broad terms, up to the start of the subprime crisis the JPoDs were zero, then they soared across the reduced portfolio until March 2009, being the one based on CDS the highest (see Panel B.1 of Table 2.4). One possible explanation is that

CDS' price default risk is calculated on a daily basis while liabilities are measured on annual basis and reflect default risk with an inbuilt delay. In the US portfolio the joint default probability is noticeably larger than in the European portfolio. Our results are consistent with Segoviano and Goodhart (2009) although in our case, the probabilities are lower than theirs.

**Figure 2.5 Systemic risk measure based on multivariate densities**

This figure depicts the joint probability of default (Panel A) and banking stability index (Panel B) categories 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 is measured in basis points.




The banking stability index (BSI) represents the expected number of banks to become distressed, conditional on the fact that at least one bank has become distressed. Due to the number of components in a reduced portfolio, it is an index that ranges between 1 and 3. Value 1 refers to the situation in which the stress in one institution causes no effect on the others. As can be seen in Panel B of Figure 2.5, up to July 2007, this measure is almost 1. After that point, the distress between institutions skyrockets until March 2009. As in the previous category, the CDS reduced portfolio shows higher levels of stress in the US than in the European portfolio (see Panel B.2 of Table 2.4). Our results are again in line with the findings of Segoviano and Goodhart (2009).

#### *2.4.2.3. Aggregate of co-risk management measures*

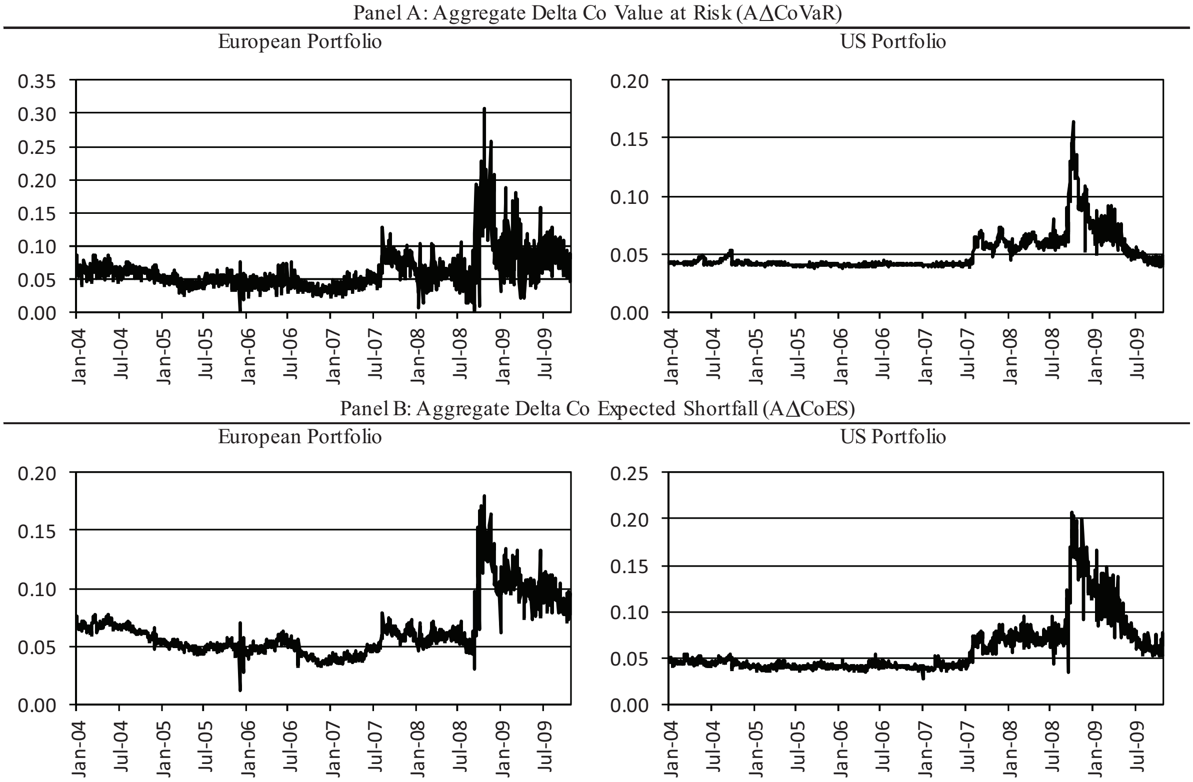
The last systemic risk measure is based on the standard risk management tools: value-at-risk (VaR) and expected shortfall (ES). The methodology proposed by Adrian and Brunnermeier (2008) estimates the individual contribution of each institution to the systemic risk of the portfolio. We compute the individual ΔCoVaR on the institutions of the European and US portfolio and add them up for each portfolio. This measure is called aggregated delta CoVaR (AΔCoVaR).

Panel A of Figure 2.6 shows the evolution of the AΔCoVaR. As is also the case with other systemic measures, both measures remain almost flat up to July 2007. Then, we are able to distinguish between three periods: the beginning of the crisis, which is characterized by the Bear Stearns episode and presents a moderate increase in AΔCoVaR as well as in its volatility; the Lehman episode, which generated the highest level of distress in both portfolios; and the post-Lehman bankruptcy period, in which AΔCoVaR goes down to a level similar to the one at the beginning of 2008.

Additionally, we apply the “co-risk” methodology to the ES through quantile regression. The ES might provide additional insights with respect to the VaR due to the VaR not being a coherent measure (Artzner, Delbaen, Eber and Heath (1999)). Panel B of Figure 2.6 shows the evolution of the AΔCoES. Its behavior is similar to that observed for the AΔCoVaR.

**Figure 2.6 Aggregate of co-risk management measure**

This figure represents the aggregate delta co-value-at-risk ($A\Delta CoVaR$, Panel A) and aggregate delta co-expected-shortfall ($A\Delta CoES$, Panel B) categories for the European and US portfolios.




## 2.5. Comparing measures

Once we have estimated the six systemic risk measures we then compare them to identify the measures that provide quicker and most reliable information to detect systemic events. We first select the most informative variables for those measures that involve more than one category. The selection criterion is based on the correlation of each systemic risk measure on a variable that contains several events and policy actions that occurred during the crisis. We then compare within groups (macro and micro) the selected systemic risk measures and rank them according to three criteria: i) Granger causality tests, ii) Gonzalo and Granger (GG) metric, and iii) the correlation with an index of systemic events and policy actions.

## Table 2.4 Descriptive statistics of measures micro group

This table reports the descriptive statistics of the measures belonging to the micro group. Panel A contains the systemic risk indexes based on structural credit risk models for alternative default thresholds (50, 25, 15, 10, and 5%): systemic risk indexes based on the value of assets (Panel A.1) and systemic risk indexes based on the number of defaulted banks (Panel A.2). Panel B contains the multivariate densities computed from groups of individual bank's CDS spreads: joint probability of default (Panel B.1) and banking stability index (Panel B.2). Within each economic area, three reduced portfolios are considered: CDS spread, liabilities and liabilities over market value ratio. Each portfolio is composed of the three banks at the top of each classification. Panel C contains the aggregate of individual co-risk measures: aggregate delta co-value-at-risk ($A\Delta CoVaR$) and aggregate delta co-expected-shortfall ($A\Delta CoES$). The sample period spans from January 2004 to November 2009.

Panel A: Systemic risk indicators based on structural models

Panel A.1: Systemic risk index based on the value of assets (SIV)

| Proportion (ε) | European portfolio | | | | | US portfolio | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 0.5 | 0.25 | 0.15 | 0.1 | 0.05 | 0.5 | 0.25 | 0.15 | 0.1 | 0.05 |
| Mean | 0.02 | 0.10 | 0.13 | 0.15 | 0.17 | 0.03 | 0.11 | 0.15 | 0.16 | 0.16 |
| SD | 0.08 | 0.25 | 0.30 | 0.33 | 0.34 | 0.13 | 0.27 | 0.33 | 0.34 | 0.34 |
| Median | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Maximum | 0.78 | 1.00 | 1.00 | 1.00 | 1.00 | 0.95 | 1.00 | 1.00 | 1.00 | 1.00 |
| Minimum | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

Panel A.2: Systemic risk index based on the number of defaulted banks (SIN)

| Proportion (ε) | European portfolio | | | | | US portfolio | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 0.5 | 0.25 | 0.15 | 0.1 | 0.05 | 0.5 | 0.25 | 0.15 | 0.1 | 0.05 |
| Mean | 0.01 | 0.10 | 0.13 | 0.15 | 0.17 | 0.02 | 0.09 | 0.14 | 0.16 | 0.19 |
| SD | 0.08 | 0.25 | 0.30 | 0.33 | 0.35 | 0.09 | 0.24 | 0.30 | 0.33 | 0.36 |
| Median | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Maximum | 0.78 | 1.00 | 1.00 | 1.00 | 1.00 | 0.84 | 1.00 | 1.00 | 1.00 | 1.00 |
| Minimum | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

Panel B: Multivariate densities

Panel B.1: Joint probability of default (JPoD)

| | European reduced portfolios | | | US reduced portfolios | | |
|---|---|---|---|---|---|---|
| Portfolios | CDS spread | Liabilities | Liabilities/MV | CDS spread | Liabilities | Liabilities/MV |
| Mean | 0.56 | 0.11 | 0.14 | 1.94 | 0.44 | 0.98 |
| SD | 1.24 | 0.22 | 0.33 | 4.46 | 1.10 | 2.40 |
| Median | 0.00 | 0.00 | 0.00 | 0.02 | 0.00 | 0.00 |
| Maximum | 11.78 | 1.42 | 5.58 | 42.49 | 7.89 | 26.45 |
| Minimum | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

Panel B.2: Banking stability index (BSI)

| | European reduced portfolios | | | US reduced portfolios | | |
|---|---|---|---|---|---|---|
| Portfolios | CDS spread | Liabilities | Liabilities/MV | CDS spread | Liabilities | Liabilities/MV |
| Mean | 1.02 | 1.01 | 1.01 | 1.03 | 1.02 | 1.02 |
| SD | 0.02 | 0.01 | 0.01 | 0.04 | 0.02 | 0.03 |
| Median | 1.01 | 1.00 | 1.00 | 1.01 | 1.01 | 1.01 |
| Maximum | 1.11 | 1.05 | 1.09 | 1.18 | 1.10 | 1.15 |
| Minimum | 1.00 | 1.00 | 1.00 | 1.01 | 1.00 | 1.00 |

Panel C: Aggregates of co-risk management measures

| | AΔCoVaR | | AΔCoES | |
|---|---|---|---|---|
| | European portfolio | US portfolio | European portfolio | US portfolio |
| Mean | 0.06 | 0.05 | 0.06 | 0.06 |
| SD | 0.03 | 0.02 | 0.02 | 0.03 |
| Median | 0.05 | 0.04 | 0.06 | 0.05 |
| Maximum | 0.31 | 0.16 | 0.18 | 0.21 |
| Minimum | 0.00 | 0.04 | 0.01 | 0.03 |

### *2.5.1. Comparing the categories of each measure*

The selection of the most informative systemic risk category of measures is done on the basis of the influential events variable (IEV). This is a categorical variable that captures the main events and policy actions that occurred during the financial crisis based on the Federal Reserve Bank of St. Louis' crisis timeline.[19] The IEV takes value 1 whenever there is a systemic event, under the hypothesis that those events should increase systemic risk variables; and -1 whenever there is a policy action, under the hypothesis that policy actions should decrease systemic risk variables. Otherwise it takes value zero.

For each systemic risk category of measure we run multinomial regressions, using as explanatory variable the estimated systemic risk category lagged up to 2 weeks (in order to avoid penalizing discounted information) and the IEV as the dependent variable.[20]

$$IEV_t = \alpha + \beta Systemic\ Risk_{i,t-k} + \varepsilon_t \qquad \text{where } k = 0,\dots,10 \qquad (2.1)$$

Next, the goodness of fit of each regression is estimated. However, 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 multinomial regression, a pseudo R-squared has been developed. Our selection criterion is based on the McFadden R-squared calculated as:

$$R^2 = 1 - \frac{ln\hat{L}(M_{Full})}{ln\hat{L}(M_{Intercept})} \qquad (2.2)$$

where $M_{Full}$ refers to the full model and $M_{Intercept}$ to the model without predictors. $\hat{L}$ is the estimated likelihood.

[19] Timeline crisis can be accessed via http://timeline.stlouisfed.org/.
[20] Results do not change substantially when other lags are considered. Detailed results are available on request.

Finally, for every category of measure we compute the average McFadden R-squared (across the different lags), which constitute our selection criteria to determine the category that better fit within each measure.

Due to data restrictions, the systemic risk measures based on CDS indexes and their tranches do not span the whole sample period (i.e., from January 2004 to November 2009). So, for consistency in the comparison of measures we run Equation 2.1 using a sample period from March 2006 to November 2009 which is the shortest available sample period and corresponds to the US portfolio CDS.

Table 2.5 summarizes the average McFadden R-squared. In this subsection we focus on those measures that provide more than one category which are LIBOR spreads (LS), systemic indicator based on structural model (SI), multivariate densities (MD) and co-risk (CR) measures.

The LS measure contains two categories: LIBOR-OIS and LIBOR-TBILL. We observe that in both economic areas the LIBOR-OIS spread has the highest average McFadden R-squared (11.60% and 10.18% in the European and US portfolio, respectively). Hence, the "flight to quality" that is contained in the LIBOR-TBILL but not in the LIBOR-OIS apparently does not add additional information on systemic risk fluctuations. The reason could be related to the fact that the flight to quality appears when the crisis intensifies.

Regarding the SI measure, it contains ten categories which correspond to two different indexes (i.e., SIN and SIV) and five default thresholds (i.e., 50, 25, 15, 10, and 5%). For every category and portfolio we observe that the systemic risk indicators with the highest McFadden R-squared are the ones with the lowest stress level (i.e., 5%). This implies that categories which capture the stress of a relatively small fraction of the system outperform other measures. In the European portfolio, the SIV category has the highest R-squared (15.16%) while in the US portfolio the SIN category has the highest R-squared (14.31%). The discrepancy could be due to the different portfolio compositions given that while in the European portfolio the size of all banks is similar, in the US portfolio Bank of America, Citigroup and JP Morgan Chase account to more than 60% of the portfolio value (see Table 2.1). Therefore, it is not surprising that a category based on the number of defaulted institutions such as SIN performs better for the US portfolio while a category based on the value of defaulted institutions such as SIV performs better for the European portfolio.

**Table 2.5 McFadden R-squared**

This table reports the average McFadden R-squared for all estimated measures. For each systemic risk measure, we compute individual multinomial regressions in which we consider the independent variable lagged up to a maximum of 10 days (i.e., two weeks). Then, we calculate the average of the McFadden R-squared for each measure across lags. Within each approach, we report this information for the European and the US portfolio.

| Measure | Portfolio | Category | | | | |
|---|---|---|---|---|---|---|
| LIBOR spread (LS) | European | LIBOR OIS | LIBOR TBILL | | | |
| | | 0.1161 | 0.0833 | | | |
| | US | LIBOR OIS | LIBOR TBILL | | | |
| | | 0.1019 | 0.0554 | | | |
| Principal component analysis (PCA) | European | FPC | | | | |
| | | 0.1842 | | | | |
| | US | FPC | | | | |
| | | 0.1963 | | | | |
| CDS indexes and tranches (CDS) | European | CDS | | | | |
| | | 0.1688 | | | | |
| | US | CDS | | | | |
| | | 0.1336 | | | | |
| Systemic risk index based on structural credit risk model (SI) | European | SIN50 | SIN25 | SIN15 | SIN10 | SIN05 |
| | | 0.0508 | 0.1337 | 0.1446 | 0.1462 | 0.1434 |
| | | SIV50 | SIV25 | SIV15 | SIV10 | SIV05 |
| | | 0.0540 | 0.1320 | 0.1452 | 0.1490 | 0.1516 |
| | US | SIN50 | SIN25 | SIN15 | SIN10 | SIN05 |
| | | 0.0628 | 0.1215 | 0.1306 | 0.1369 | 0.1431 |
| | | SIV50 | SIV25 | SIV15 | SIV10 | SIV05 |
| | | 0.0839 | 0.1424 | 0.1207 | 0.1346 | 0.1378 |
| Multivariate densities (MD) | European | BSI Spread | BSI Liabilities | BSI Ratio | | |
| | | 0.1694 | 0.1523 | 0.1644 | | |
| | | JPoD Spread | JPoD Liabilities | JPoD Ratio | | |
| | | 0.1264 | 0.1132 | 0.1049 | | |
| | US | BSI Spread | BSI Liabilities | BSI Ratio | | |
| | | 0.1913 | 0.1575 | 0.1698 | | |
| | | JPoD Spread | JPoD Liabilities | JPoD Ratio | | |
| | | 0.1439 | 0.0975 | 0.1098 | | |
| Aggregate co risk (CR) | European | AΔCoVaR | AΔCoES | | | |
| | | 0.0696 | 0.1347 | | | |
| | US | AΔCoVaR | AΔCoES | | | |
| | | 0.1006 | 0.1485 | | | |

For each portfolio, the MD approach offers six categories which correspond to two definitions of the systemic risk variable (i.e., BSI and JPoD) and three alternative ways to select the portfolios (i.e., according to the level of CDS spread, liabilities and ratio liabilities over market value). We observe that BSI categories consistently outperform the JPoD measures. This could be related to the fact that the definition of the JPoD (i.e., the probability of all banks in the portfolio becoming distressed) goes one step further than the systemic risk even if we compute the measure on a reduced portfolio of three banks. Regarding the BSI categories, the highest R-squared are 16.94% and 19.13% in the European and US portfolios, respectively and correspond to the CDS reduced portfolio. The reason being that CDS' price default risk while the other criteria are weaker related to the short run default.

Regarding the CR measure, two categories have been estimated: $A\Delta CoVaR$ and $A\Delta CoES$. We observe that in both portfolios $A\Delta CoES$ outperforms the $A\Delta CoVaR$ and its average R-squared is 13.47% and 14.85% in the European and US portfolios respectively. However, this result is not surprising due to the well-known problems of the VaR measure as a risk management tool (see Artzner et al. (1999)) and which do not appear in the ES measure.

Summing up, we chose the following categories in the macro group both for Europe and US: FPC (PCA), LIBOR-OIS (LS) and systemic factor (CDS). In the micro group we choose: SIV at 5% (Europe, SM), SIN at 5% (US, SM), BSI (MD), and $A\Delta CoES$ (CR). For the sake of the clarity of exposition, from now on we just refer to the measure's name (e.g., LS or MD) instead of using the detailed name.

### *2.5.2. Horse race*

In this subsection we rank the previously selected measures within each group and economic area according to three criteria: i) Granger causality test; ii) GG metric; iii) McFadden R-squared. The first criterion enables us to point out measures that act as leading indicators with respect to other measures, the second criterion correlates each measure to the underlying systemic risk trend in the economy, and the third criterion compares each measure with the main systemic events and policy actions.

In the Granger causality test and the GG metric we compare pairs of measures with different metrics, in order to carry out a comprehensive comparison, we establish a common metric by standardizing the measures. Moreover, to be consistent in that comparison, all analyses are restricted to the sample period March 2006 to November 2009.

*2.5.2.1. Granger causality test*

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

$$\Delta Y_t = \alpha + \sum_{i=1}^{p} \beta_{yi} \Delta Y_{t-i} + \sum_{i=1}^{p} \beta_{xi} \Delta X_{t-i} + \varepsilon_t \qquad (2.3)$$

where $\Delta$ is the first-difference operator and $\Delta X$ and $\Delta Y$ are stationary variables. We reject the null hypothesis that $X_t$ does not Granger cause $Y_t$ if the coefficients $\beta_{xi}$ are jointly significant based on the standard F-test.

We carry out the Granger causality test by pairs of measures within each economic area. Before conducting this analysis we run a unit root test to determine the order of integration and we conclude that all the measures are I(1) and hence, we take first differences to work with stationary variables. The number of lags is determined using the Schwarz information criterion on the corresponding vector autoregressive (VAR) equation.

Table 2.6 summarizes the p-values for each Granger causality test as well as the corresponding ranking scores, which are based on the p-values at a confidence level of 1%. To rank the measures we give a score of +1 to measure X if X Granger causes another measure Y and we give a score of -1 to measure X if X is caused in the Granger sense by Y. By doing this, the best measure gets the highest positive score and the worst measure the highest negative score.[21] We observe that PCA is the best measure in the aggregate market category obtaining final scores of +2 and +1 in the European and US portfolios, respectively. The PCA measure is followed by CDS and LS in both portfolios. When we compare the measures in the individual institutions category, we observe several reciprocal Granger causalities in both portfolios and so, there is no clear winner. In summary, at the aggregate market level measures based on CDSs are leading indicators of measures from other markets but, no clear ranking appears at the level of individual institutions.[22]

#### *2.5.2.2. Gonzalo and Granger metric*

The second classification is based on Gonzalo and Granger (1995, GG hereafter) metric. This analysis allows us to determine, by pairs of measures, the relative contribution of each measure to the unobserved factor that is the driving force in the cointegration. In

[21] This ranking procedure is related with the well-known Condorcet voting method. The Marquis de Condorcet, a prominent reformer who became a secretary of the revolutionary French National Assembly in 1791, suggested dividing elections into a series of one-on-one contests, so that every candidate is directly compared with every other. If there is a candidate who wins every such match, it is clear who should be the over-all winner of the tournament. However to avoid some of the problems of the Condorcet approach we also allow for negative as well as positive scores.

[22] The Granger Causality test is designed to handle pairs of variables, and may produce misleading results when the true relationship involves three or more variables. To deal with this problem we run a VAR specification where the dependent variable is the vector of the six measures and as explanatory variables we introduce the dependent variable lagged up to four periods. We next test whether all the lags of each explanatory variable $i$ are jointly significant for each dependent variable $j$ where $i \neq j$ using the F-test. To rank the measures, we count the number of times that a variable Granger causes (+1) and is caused (-1). The results are not materially different from the ones obtained in the baseline test. Results are available upon request.

our framework we define that factor as the systemic risk common trend in the economy. Formally, the GG metric is based on the following VECM specification:

$$\Delta X_t = \alpha\beta' X_{t-1} + \sum_{i=1}^{p} \Gamma_i \Delta X_{t-i} + \varepsilon_t \qquad (2.4)$$

where $X_t$ is a vector of I(1) time series, $\beta'$ is the cointegrating vector, and $\varepsilon_t$ is a white noise vector. The elements of $X_t$ can be explained in terms of the common trend ($f_t$) plus some I(0) components:

$$X_t = A_1 f_t + \widetilde{X}_t \qquad (2.5)$$

where $A_1$ is any basis of the null space of $\beta'$ $(\beta' A_1 = 0)$.

**Table 2.6 Granger causality test**

This table reports the p-value of two null hypotheses (Ho: I, variable 2 does not Granger cause variable 1; Ho: II, variable 1 does not Granger cause variable 2), and the corresponding ranking scores for the two groups: macro and micro. Measure X scores +1 if it Granger causes another measure at 1% of confidence level and -1 if it is Granger caused by another measure. Panel A and B refer to the European and US portfolio, respectively.

Panel A: European portfolio

Panel A.1: p-value

| | Macro | | | Micro | | |
|---|---|---|---|---|---|---|
| Variable 1 | LS | LS | PCA | SI | SI | MD |
| Variable 2 | PCA | CDS | CDS | MD | CR | CR |
| Ho: I | 0.006 | 0.568 | 0.385 | 0.000 | 0.000 | 0.000 |
| Ho: II | 0.094 | 0.108 | 0.000 | 0.000 | 0.000 | 0.000 |

Panel A.2: Ranking scores

| | Macro | | | Micro | | |
|---|---|---|---|---|---|---|
| Variable | PCA | LS | CDS | SI | MD | CR |
| Scoring | 2 | -1 | -1 | 0 | 0 | 0 |

Panel B: US portfolio

Panel B.1: p-value

| | Macro | | | Micro | | |
|---|---|---|---|---|---|---|
| Variable 1 | LS | LS | PCA | SI | SI | MD |
| Variable 2 | PCA | CDS | CDS | MD | CR | CR |
| Ho: I | 0.000 | 0.000 | 0.023 | 0.000 | 0.497 | 0.006 |
| Ho: II | 0.000 | 0.513 | 0.000 | 0.000 | 0.000 | 0.000 |

Panel B.2: Ranking scores

| | Macro | | | Micro | | |
|---|---|---|---|---|---|---|
| Variable | PCA | CDS | LS | SI | MD | CR |
| Scoring | 1 | 0 | -1 | 1 | 0 | -1 |

GG imposes two restrictions that are sufficient to identify the common trend ($f_t$):

1. $f_t$ are linear combinations of $X_t$.

2. $A_1 f_t$ and $\widetilde{X}_t$ form a Permanent-Transitory decomposition.

The long memory component $f_t$ is defined as follows:

$$f_t = \alpha'_{\perp} X_t \tag{2.6}$$

where the parameter α ($\alpha_1$ , $\alpha_2$ ) is a vector which includes the parameters that multiply the error correction term and $\alpha'_{\perp}\alpha = 0$ hence $\alpha_{\perp}$ takes the form $\alpha_{\perp} = (-\alpha_2/\alpha_1, 1)$. Therefore, the relative weights with which the time series $i$ (where $i$ = 1, 2) enters the long-memory component are defined from the following metric:

$$GG_1 = \frac{\alpha_2}{-\alpha_1 + \alpha_2}; \qquad GG_2 = \frac{-\alpha_1}{-\alpha_1 + \alpha_2} \tag{2.7}$$

This GG metric allows us to identify the contribution of each measure to the systemic risk common trend in the economy.[23] To rank the estimated measures we use the fact that the GG metric is bound between 0 and 1. We assign a score of +1 to measure X if the measure X contributes more to the systemic risk common trend factor (i.e., its GG metric is larger than 0.5) than the measure Y which gets -1 and we assign a score of -1 to measure X and a score of +1 to measure Y otherwise.

Before conducting this analysis we check that all the measures are I(1) and are cointegrated. Regarding the former requirement we perform an unit root test and we conclude that all the measures are I(1). Concerning the last requirement we conduct the Johansen cointegration test by pairs of measures and find that all pairs are cointegrated at 10% significance level apart from the pairs LS-SI, LS-MD, LS-CR and CDS-SI in the European portfolio and the pairs LS-PCA, PCA-SI, PCA-MD and SI-CDS in the US portfolio. Table 2.7 reports the GG metrics for European and US systemic risk measures and the corresponding ranking scores. In the aggregate market category there is not a

[23] The analysis of the systemic risk common trend factor is beyond the scope of this paper and is left for future research.

clear winner. One potential explanation for this result is that in the European portfolio the effects of different measures cancel each other out and the final score for the three measures is par for the course. In the individual institutions category, the results are the same for Europe and US, MD has the higher score (+2) followed by SI (0) and CR (-2). So, in summary, at the aggregate market level no clear ranking appears but at the level of individual institutions measures based on CDSs contribute more to the common underlying systemic risk trend.

**Table 2.7 Gonzalo and Granger metric**

This table reports Gonzalo and Granger metric (GG metric) and the corresponding ranking scores for the two groups: macro and micro. Measure X scores +1 if it has values larger than 0.5 in the corresponding GG metric and scores -1 otherwise. Panel A and B refer to the European and US portfolio, respectively.

| Panel A: European portfolio | | | | | | |
|---|---|---|---|---|---|---|
| Panel A.1: GG metric | | | | | | |
| | Macro | | | Micro | | |
| Variable 1 | LS | LS | PCA | SI | SI | MD |
| $GG_{variable\ 1}$ | 0.448 | 1.000 | 0.180 | 0.324 | 0.856 | 1.000 |
| Variable 2 | PCA | CDS | CDS | MD | CR | CR |
| $GG_{variable\ 2}$ | 0.552 | 0.000 | 0.820 | 0.676 | 0.144 | 0.000 |
| Panel A.2: Ranking Scores | | | | | | |
| | Macro | | | Micro | | |
| Variable | LS | PCA | CDS | MD | SI | CR |
| Scoring | 0 | 0 | 0 | 2 | 0 | -2 |
| Panel B: US portfolio | | | | | | |
| Panel B.1: GG metric | | | | | | |
| | Macro | | | Micro | | |
| Variable 1 | LS | LS | PCA | SI | SI | MD |
| $GG_{variable\ 1}$ | 0.424 | 0.865 | 0.951 | 0.217 | 0.630 | 1.000 |
| Variable 2 | PCA | CDS | CDS | MD | CR | CR |
| $GG_{variable\ 2}$ | 0.576 | 0.135 | 0.049 | 0.783 | 0.370 | 0.000 |
| Panel B.2: Ranking scores | | | | | | |
| | Macro | | | Micro | | |
| Variable | LS | PCA | CDS | MD | SI | CR |
| Scoring | 1 | 1 | -2 | 2 | 0 | -2 |

*2.5.2.3. McFadden R-squared*

Table 2.5 contains the average McFadden R-squared. We compare the systemic risk measures in pairs, assigning a score of +1 to the measure with the highest R-squared and -1 to the lowest. Table 2.8 reports the final scores. Regarding the classification at macro group, we observe a similar behavior in the European and US portfolios. That is, the PCA stays at the top of both portfolios with a score of +2 while LS appears at the bottom with a score of -2. With respect to the micro group, there is a clear winner in both portfolios MD (+2) while there is not a common loser across portfolios. Summing up, at macro and micro group, measures related to CDS are more closely correlated with the systemic risk event indicator than measures from other markets.

**Table 2.8 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 and B refer to the European and US portfolio, respectively.

Panel A: Ranking scores at European portfolio

| | Macro | | | Micro | | |
|---|---|---|---|---|---|---|
| Variable | PCA | CDS | LS | MD | SI | CR |
| Scoring | 2 | 0 | -2 | 2 | 0 | -2 |

Panel B: Ranking scores at US portfolio

| | Macro | | | Micro | | |
|---|---|---|---|---|---|---|
| Variable | PCA | CDS | LS | MD | CR | SI |
| Scoring | 2 | 0 | -2 | 2 | 0 | -2 |

*2.5.2.4. Final ranking*

Table 2.9 summarizes the final scores in the European (Panel A) and US (Panel B) portfolios. Regarding the classification in the macro group, both in the European and US portfolios, the PCA measure tops the ranking (+4) and the LS appears at the bottom (-3 and -2, respectively). In the micro group we also observe a common pattern across portfolios in which MD is the winner (+4) and CR is at the bottom of both portfolios (-4 and -3 in the European and US portfolios, respectively). Therefore, adding up the three criteria we conclude that measures based on CDSs outperform alternative systemic risk measures based on stock prices and interbank rates.

## 2.6. Conclusions

In this paper, we estimate and compare a set of high-frequency market-based systemic risk measures which are classified in two groups: macro and micro. Measures in the first group give information on how much systemic risk there is as a whole in the system and measures in the second group rely on individual institution information to gauge joint distress at portfolio level. The empirical application uses data on European and US financial markets and largest banks in the period from 2004 to 2009.

**Table 2.9 Horse race**

This table reports the ranking scores for the European and US banks using the three criteria: (i) Granger causality test; (ii) Gonzalo and Granger metric; (iii) McFadden R-squared. We also report the final score, which is the sum of the scores across classifications. Panel A and B refer to the European and the US portfolio, respectively.

Panel A: European portfolio

| Criteria | Granger causality test | GG Metric | McFadden R-squared | Final Score |
|---|---|---|---|---|
| Panel A.1: Macro | | | | |
| PCA | 2 | 0 | 2 | 4 |
| CDS | -1 | 0 | 0 | -1 |
| LS | -1 | 0 | -2 | -3 |
| Panel A.2: Micro | | | | |
| MD | 0 | 2 | 2 | 4 |
| SI | 0 | 0 | 0 | 0 |
| CR | 0 | -2 | -2 | -4 |

Panel B: US portfolio

| Criteria | Granger causality test | GG Metric | McFadden R-squared | Final Score |
|---|---|---|---|---|
| Panel B.1: Macro | | | | |
| PCA | 1 | 1 | 2 | 4 |
| CDS | 0 | -2 | 0 | -2 |
| LS | -1 | 1 | -2 | -2 |
| Panel B.2: Micro | | | | |
| MD | 0 | 2 | 2 | 4 |
| SI | 1 | 0 | -2 | -1 |
| CR | -1 | -2 | 0 | -3 |

Our overall results suggest that the measures based on CDSs outperform measures based on the stock market and on the interbank market. Some of the economic reasons behind these results follow; most banks have several traded claims (stocks, bonds, CDS) that contain information on the individual and joint probability of default and therefore on systemic risk. Equity prices do not provide direct information on these probabilities and therefore one specific model (structural or otherwise) must be employed to compute the implied default probabilities. Although there are some encouraging results in this line as documented in Forte and Peña (2009) and in Liao, Chen and Lu (2009), much more work is needed before this approach can be relied upon by policymakers. Both CDSs and bond prices could be a more promising alternative because their spreads and yields, respectively, give a direct measure of these default probabilities. However corporate bonds suffer from lack of standardization which provokes illiquidity and market segmentation. In fact the prominent role of CDS may be due to their standardized nature, their higher liquidity and the professionalized market in which they are traded. The CDS market is almost entirely institutional with hardly any retail presence. Furthermore, the empirical evidence suggests that the CDS market leads the credit rating agencies (Hull, Predescu and White, 2004) and the bond market (Blanco, Brennan, and Marsh, 2005). Also, Berndt and Obreja (2010) identify a common factor that explains around 50% of the variation in corporate CDS returns and show that this component is closely related to the super-senior tranche of the iTraxx Europe index, referred to the economic catastrophe risk indicator. The previous discussion helps to understand why measures based on CDSs work better in providing information on systemic risk which is a manifestation of extreme joint default risk in the financial sector.

A related question is how these measures can aid policymakers. The measures in this paper can be used as a tool to prevent systemic crisis. The micro group of measures can be used as an element of an early warning system that will alert the regulator that an individual (systemically important) bank is in trouble. The macro group of measures will deliver the same message when a group of them are in dire straits. The regulator can then step in before the impairment spreads to other banks and to the real economy. The specific mechanism can take different forms, for instance setting critical thresholds for the measures. When a given measure rises above that critical value, the regulator should carry out an assessment of the situation. If the market signals are indeed accurate and a systemic event comes into view, some form of intervention can ensue such as forcing the bank (if the signal comes from individual-institution based measures) or a group of banks (if the signal is from the aggregate indicator of the banking sector) to issue equity until the risk indicator moves back below the threshold. If the risk indicator does not fall below that threshold within a predetermined period of time, the regulator would intervene. Therefore, using historical figures as reference in combination with other similar information from other indicators (low-frequency measures), the policymaker can devise a set of warning flags triggering increasingly stronger regulatory and supervisory actions. Our suggestions are in agreement with the market-based corrective actions proposed by Bond, Goldstein and Prescott (2010) and by Hart and Zingales (2011).

A word of caution is in order. The success of the market-based corrective actions relies on the market's ability to collect relevant information quickly, and to make it known widely. Prices in the CDS market may sometimes give wrong signals (i.e. provide inaccurate prices) because some irrational exuberance or panic. Therefore the efficiency, transparency and quality of the CDS market become issues of paramount importance. By the same token it is crucial to guarantee that the CDSs are properly collateralized and transparently traded on an organized exchange. This guarantees that counterparty risk is largely eliminated, and the positions of the various parties are known. The current regulatory initiatives on this respect towards moving CDS trading to organized exchanges, which require better collateralization to protect the exchange's members, will certainly help to improve CDS prices' reliability.

# Chapter 3 Derivatives holdings and systemic risk in the U.S. banking sector

## 3.1. Introduction

Since the beginning of the current financial and economic crisis, the concern about systemic risk has increased, becoming a priority for regulatory authorities. These authorities realized that systemic risk is not a transitory problem and consequently, new institutional arrangements have been approved to address this challenging issue. The Financial Stability Oversight Council (FSOC) in the U.S. and the European Systemic Risk Board (ESRB) in the E.U. have been set to identify systemic risk, prevent regulatory loopholes, and make recommendations together with existing regulatory authorities. The concerns about systemic risk have also extended to securities markets regulators. Thus, the International Organization of Securities Commissions' (IOSCO) has also established a Standing Committee on Risk and Research to coordinate members' monitoring of potential systemic risks within securities markets.

In this setting it is crucial for the banking regulatory institutions to be able to analyze and understand the determinants of a banks' contribution to systemic risk. This information would help them not only to improve currently available systemic risk measures and warning flags but also to develop a taxation system on the basis of the externalities generated by a banks' impact on systemic risk. Additionally, securities market regulators are interested in understanding the contribution of traded financial instruments, for instance financial derivatives, to systemic risk in order to consider new regulatory initiatives. Finally, investors should be concerned with the extent to which derivatives holdings affect the systemic impact of a given bank in order to assess the appropriate reward required to bear this kind of risk. Stulz (2009) pointed out the lack of rigorous empirical studies on the social benefits and costs of derivatives and in particular their role in the financial crisis 2007-09. This paper aims to improve our understanding of these social costs and benefits examining whether the use of financial derivatives was a relevant factor in the destabilization of the banking system during the recent financial crisis.

The spectacular growth in banks' balance sheet over recent decades reflected increasing claims within the financial system rather than with non-financial agents. One key driver of this explosive intra-system activity came from the growth in derivatives markets and consequently in the growth of derivatives holdings in the banks' balance-sheets. A proportion of this growth may have been motivated by their use for hedging purposes justified by theory supporting the rationality of hedging decisions at individual bank level (e.g., Koppenhaver, 1985). This stance also finds support in empirical evidence suggesting the advantages of different hedging strategies for financial firms, again at individual level, see among others Jaffe (2003). However, another substantial proportion of this growth is due to proprietary trading activities by banks. Both activities, hedging and trading, are regarded as potentially useful and profitable by banks. However, it is well known that financial decisions that are rational at individual level can have negative consequences at system level. Is this also the case with respect to the banks' holdings of financial derivatives? The, admittedly very scarce, literature on this subject suggests that this might be the case, Calmès and Théoret (2010) find that off-balance-sheet activities reduce banks' mean returns, simultaneously increasing the volatility of their operating revenue and therefore increasing banks' systemic risk. Nijskens and Wagner (2011) report that the first use of credit derivatives is associated with an increase in a bank's risk, largely due to an increase in banks' correlations and therefore in their systemic risk. However, as far as we know, no evidence is available on the direct impact of derivatives holdings on the banks' individual contributions to systemic risk. Ours is a first attempt to fill this gap. For such aim, we combine two analyses; we first measure the banks' individual contributions to systemic risk and then, we estimate the effects of their holdings of financial derivatives on the banks' contributions to systemic risk.

To assess the banks' contributions to systemic risk we use the following five measures: ΔCoVaR, ΔCoES, Asymmetric ΔCoVaR, Gross Shapley Value (GSV) and Net Shapley Value (NSV). The ΔCoVaR is the difference between the Value at Risk (VaR) of the banking system conditional on bank *i* being in distress minus the VaR of the banking system conditional on bank *i* being in its median state. The ΔCoES applies the same idea but using the Expected Shortfall instead of the VaR (see Adrian and Brunnermeier, 2011). The Asymmetric ΔCoVaR represents a variation of the standard ΔCoVaR specification that allows for asymmetries in this specification (see López, Moreno, Rubia and Valderama, 2011). The GSV measures the average contribution to systemic risk of bank *i* in all possible groups in which the whole financial system can be divided (see Tarashev, Borio, and Tsatsaronis, 2010). Finally we propose an alternative measure to the GSV called NPV in which we get rid of the idiosyncratic component present in the former measure by subtracting from the GSV the VaR of the bank *i.*

We estimate these five measures for a subset of the 91 biggest U.S. bank holding companies for the period that spans from 2002 to 2011. We then compute the correlation of the systemic risk measures with an index of systemic events and run a Granger causality test between pairs of measures; and find that the NSV presents the closest association with the index and Granger causes more frequently the other measures.

Then, using this measure of systemic risk as the dependent variable, we examine six issues: (1) is there a relationship between the banks' holdings of financial derivatives and their contributions to systemic risk?; (2) is this relationship uniform across derivatives classes?; (3) is the impact on systemic risk the same irrespective of whether the derivative is held for trading or for other purposes?; (4) is the relationship between derivatives holdings and systemic risk sensitive to the emergence of the subprime crisis?; (5) in the case of credit derivatives, is their impact dependent on whether the bank is net protection seller or net protection buyer?; (6) besides derivatives, are there other balance sheet asset items which are significant contributors to systemic risk?.

We find the following results:

1. Yes. There is a significant relationship between the fair value of derivatives holdings of bank $j$ in quarter $t$ and the contribution to systemic risk of bank $j$ in quarter $t+1$. Therefore derivatives holdings act as leading indicators of systemic risk contributions.
2. No. Banks' holdings of credit and foreign exchange derivatives have an increasing effect on systemic risk whereas holdings of interest rate and commodity derivatives have a decreasing effect.
3. No. Usually derivatives held for trading have a significant effect, either positive (foreign exchange) or negative (interest rate, commodity) whereas derivatives held for other purposes do not significantly affect systemic risk.
4. Yes and No. We find that before the subprime crisis credit derivatives decreased systemic risk whereas after the crisis increased it. But the way foreign exchange, interest rate, equity and commodity derivatives influence systemic risk remains unchanged.

5. Yes. If the bank is net protection buyer its credit derivatives holdings increase its systemic risk.
6. Yes. Some variables (measured as ratios over total assets) are also leading indicators of systemic risk contributions. Increases in the following variables increase systemic risk contributions: total loans, net balance to banks belonging to the same banking group, leverage ratio and the proportion of non-performing loans (measured in this case, relative to total loans). On the other hand, increases in total deposits decrease systemic risk. The variables with the highest economic impact on systemic risk are the proportion of non-performing loans to total loans and the leverage ratio. In fact, their economic impact is higher than the one corresponding to derivatives holdings.

The rest of the paper is organized as follows. Section 3.2 describes the methodology. In section 3.3 we describe the data. Section 3.4 reports the main empirical findings. In section 3.5 we present some robustness tests, and we conclude in section 3.6.

## 3.2. Methodology

### *3.2.1. Systemic risk: measures and comparison*

We consider the following five measures of the individual contribution of banks to systemic risk: (i) ΔCoVaR, (ii) ΔCoES, (iii) Asymmetric ΔCoVaR, (iv) Gross Shapley Value (GSV) and (v) Net Shapley Value (NSV). The details of the characteristics and the estimation of the systemic risk measures can be found in Appendix B.[24]

[24] Acharya, Pedersen, Philippon and Richardson, (2011a, b) propose an alternative measure of the individual contribution to systemic risk called realized SES that measures the propensity of bank *i* to be undercapitalized when the whole system is undercapitalized. We exclude this measure from the discussion in the main text because, by construction, it is quarterly estimated and we cannot carry out the comparison with the considered five measures. Nevertheless, we estimate this measure, conduct the baseline regression to analyze the determinants of banks contributions to systemic risk and find that the results are fully in agreement with the main findings of this paper.

As in Chapter 2 we use two criteria to rank the five measures: (a) the correlation with an index of systemic events and policy actions, and (b) the Granger causality test. The first criterion compares the correlation of each measure with the main systemic events and policy actions and the second criterion points out the measures acting as leading indicators of systemic risk. Both criteria focus on different aspects of systemic risk and complement to each other to provide a robust diagnostic of the most reliable individual contribution to systemic risk measures.[25]

In the first criterion we use an influential event variable (IEV), which is a categorical variable that captures the main events observed and policy actions taken during the financial crisis based on the Federal Reserve Bank of St. Louis' crisis timeline.[26] The IEV takes value 1 whenever there is an event, under the hypothesis that those events should increase systemic risk, and is equal to -1 whenever there is a policy action, under the hypothesis that policy action's aim is to decrease systemic risk (and the action is usually successful). Otherwise it equals zero. The ranking method is based on the McFadden R-squared, a measure of goodness of fit. For each bank $i$ in the sample we run a multinomial regression in which the dependent variable is the IEV and the explanatory variable is the systemic risk measure $j$ for bank $i$ (where $j = 1, \dots, 5$ and $i = 1, \dots, 91$) and then estimate the McFadden R-squared. The comparison of the different pairs of systemic risk measures, referred to the same bank, is done by assigning a score of +1 to the measure with the highest R-squared and -1 to the one with the lowest. Finally, we add up the scores obtained for each measure across the 91

[25] In Chapter 2 we use an additional criterion based on the Gonzalo and Granger's (1995) methodology. To carry out this analysis, the pairs of systemic risk measures have to be cointegrated. However, this requirement is not satisfied in several of the pairs of measures and so, we do not consider it.
[26] Timeline crisis can be accessed via http://timeline.stlouisfed.org/.

banks.[27] By doing this, we avoid penalizing those measures that provide leading information and penalizing those events or political actions which have been discounted by the market before the event.

The second criterion is based on the Granger causality test (Granger, 1969). To rank the measures we give a score of +1 to a given measure X if X Granger causes another measure Y at 5% confidence level and -1 if X is caused in the Granger sense by Y. As a consequence, the best measure gets the highest positive score and the worst measure the highest negative score. Next, we add up the scores obtained by each measure across the 91 banks. Technical details on the procedure to compare the systemic risk measures can be found in Appendix C.

### *3.2.2. Determinants of systemic risk*

We implement a panel regression analysis in which the individual bank *i*'s contribution to systemic risk in quarter *t* is regressed on the following variables (all in quarter *t-1*): bank's holdings of derivatives, proxies for the standard drivers of systemic risk (size, interconnectedness, and substitutability), other balance sheet information and the aggregate level of systemic risk. We employ a Prais-Winsten regression with correlated panels, corrected standard errors (PCSEs) and robust to heteroskedasticity and contemporaneous correlation across panels. Our panel regression model is described by the following equation:

$$SR_{i,t} = \alpha + \sum_{n=1}^{N} \gamma_n Y_{n,i,t-1} + \sum_{m=1}^{M} \omega_m Z_{m,i,t-1} + \sum_{s=1}^{S} \beta_s X_{s,i,t-1} + Time\ Effects + \varepsilon_{i,t} \qquad (3.1)$$

where the dependent variable is the bank's *i* contribution to systemic risk as measured by the Net Shapley Value. The vector of variables $Y_{n,i,t}$ contains the proxies for the

[27] This ranking procedure is related to the well-known Condorcet voting method. However to avoid some of the problems of the Condorcet approach we also allow for negative as well as positive scores.

bank *i* size and its degree of interconnectedness and substitutability. The vector $Z_{m,i,t}$ contains variables related to other banks characteristics: balance-sheet quality and the aggregate level of systemic risk one and two quarters ago. The aggregate variables are obtained after aggregating the levels of systemic risk of the U.S. commercial banks (without considering the bank *i*), dealer-broker and insurance companies. The vector of variables $X_{s,i,t}$ refers to the banks' holdings of financial derivatives.

### *3.2.3. Research questions*

We examine six issues that have not been addressed previously in literature regarding the role of derivatives holdings and their possible connections with systemic risk:

1. The first question to ask is whether the banks' holdings of financial derivatives contribute in any significant way to systemic risk. If this is indeed the case, then many other important questions come into play.
2. The next obvious question is whether this relationship is uniform across derivatives classes or are there differences in the impact between foreign exchange and interest rate derivatives, for example.
3. Given that our databases allow us to distinguish between derivatives held for trading or for other purposes, the next question is whether the impact on systemic risk is the same irrespective of the reason they are being held.
4. Given the abrupt change in market conditions since July 2007 a pressing question is to study whether the relationship between derivative holdings and systemic risk is sensitive to the emergence of the subprime crisis. The answer to this question could be very illuminating in the sense that some derivatives that were thought to play the role of shock absorbers before the crisis (this was the predominant view on the

derivatives industry in general)[28] may have changed their nature once the subprime crisis starts.

5. In the specific case of credit derivatives, one may think that a bank that is a net protection buyer and therefore is hedging its credit risk to some extent, should contribute to a lesser extent to the overall systemic risk. Testing whether this is indeed the case helps to understand the actual role of these controversial instruments.
6. Additionally, it seems natural to ask what other balance sheet asset items are significant contributors to systemic risk and in particular which ones have the biggest economic impact on systemic risk.

## 3.3. Data and explanatory variables

### *3.3.1. Data*

The Bank Holding Company Data (BHCD) from the Federal Reserve Bank of Chicago is our primary database.[29] Additional information (VIX, 3-monthTbill rate, 3-month repo rate, 10-year Treasury rate, BAA-rate bond, and MSCI index returns) is collected from DataStream and the Federal Reserve Bank of New York.

Our data set is composed of U.S. bank holding companies with total assets above $5billion in either the first quarter of 2006 or the first quarter of 2009. Therefore our focus is on relatively big banks in either the pre-crisis or the ongoing crisis period. Additional filters are banks for which we have information on their stock prices, banks that held at least one type of derivatives analyzed in this paper, and, we exclude banks

[28] "As is generally acknowledged, the development of credit derivatives has contributed to the stability of the banking system by allowing banks, especially the largest, systemically important banks, to measure and manage their credit risks more effectively" Greenspan (2005).
[29] http://www.chicagofed.org/webpages/banking/financial_institution_reports/bhc_data.cfm

that defaulted or were acquired before 2007.[30] Our final sample consists of quarterly information for 91 bank holding companies from March 2002 to June 2011.[31]

**Table 3.1 Descriptive Statistics of Bank Holding Companies**
This table reports the name of the 91 banks which form the sample and related information about their size (average market value in millions of U.S. dollars).

| id | Bank Holding | Market Value | id | Bank Holding | Market Value |
|---|---|---|---|---|---|
| 1 | Alabama National Bancorp | 1,063 | 47 | M&T Bank | 9,396 |
| 2 | Amcore Financial | 467 | 48 | Marshall & Ilsley | 6,824 |
| 3 | Associated Banc Corporation | 2,939 | 49 | MB Financial | 804 |
| 4 | Bancorpsouth | 1,636 | 50 | Mellon Financial | 16,300 |
| 5 | Bank of America | 140,000 | 51 | Metlife | 31,400 |
| 6 | Bank of Hawaii | 2,201 | 52 | National Penn Bancshares | 758 |
| 7 | Bank of New York Co | 27,000 | 53 | NBT Bancorp | 661 |
| 8 | Bank of New York Mellon | 38,100 | 54 | New York Community Bancorp | 4,612 |
| 9 | BB&T | 18,200 | 55 | Newalliance Bancshares | 1,492 |
| 10 | Bok Financial | 2,589 | 56 | Northern Trust | 12,300 |
| 11 | Boston Private Financial | 569 | 57 | Old National Bancorp | 1,318 |
| 12 | Capital One Financial | 16,900 | 58 | Pacific Capital Bancorp | 941 |
| 13 | Cathay General Bancorp | 1,095 | 59 | Park National | 1,230 |
| 14 | Central Pacific Financial | 510 | 60 | PNC Financial Services | 19,600 |
| 15 | Charles Schwab | 21,500 | 61 | Privatebancorp | 588 |
| 16 | Chittenden Corp | 1,119 | 62 | Provident Bankshares | 644 |
| 17 | Citigroup | 188,000 | 63 | Regions Financial New | 9,923 |
| 18 | Citizens Republic Bancorp | 970 | 64 | Sky Financial Group | 2,583 |
| 19 | City National | 2,681 | 65 | South Financial Group | 1,012 |
| 20 | Colonial Bancgroup | 1,758 | 66 | State Street | 19,000 |
| 21 | Comerica | 7,893 | 67 | Sterling Bancshares | 621 |
| 22 | Commerce Bancshares | 2,989 | 68 | Sterling Financial | 572 |
| 23 | Community Bank System | 571 | 69 | Suntrust Banks | 18,700 |
| 24 | Cullen Frost Bankers | 2,537 | 70 | Susquehanna Bancshares | 1,004 |
| 25 | CVB Financial | 878 | 71 | SVB Financial Group | 1,503 |
| 26 | East West Bancorp | 1,418 | 72 | Synovus Financial | 6,150 |
| 27 | FNB | 978 | 73 | TCF Financial | 2,986 |
| 28 | Fifth Third Bancorp | 21,300 | 74 | Texas Capital Bancshares | 547 |
| 29 | First Citizens Bancorporation | 411 | 75 | Trustmark | 1,488 |
| 30 | First Commonwealth Financial | 761 | 76 | United States Bancorp | 46,700 |
| 31 | First Horizon National | 3,939 | 77 | Ucbh Holdings | 921 |
| 32 | First Midwest Bancorp | 1,280 | 78 | UMB Financial | 1,310 |
| 33 | First National of Nebraska | 1,222 | 79 | Umpqua Holdings | 817 |
| 34 | Firstmerit | 1,935 | 80 | United Bankshares | 1,219 |
| 35 | Fulton Financial | 2,066 | 81 | United Community Banks | 721 |
| 36 | Glacier Bancorp | 765 | 82 | Valley National Bancorp | 2,390 |
| 37 | Greater Bay Bancorp | 1,315 | 83 | Wachovia Corp | 48,200 |
| 38 | Hancock Holding | 1,040 | 84 | Webster Financial | 1,762 |
| 39 | Harleysville National Corp | 450 | 85 | Wells Fargo and Company | 104,000 |
| 40 | Huntington Bancshares | 4,518 | 86 | Wesbanco | 530 |
| 41 | Iberiabank | 583 | 87 | Western Alliance Bancorp | 580 |
| 42 | International Bancshares | 1,405 | 88 | Whitney Holding Corp | 1,411 |
| 43 | Investors Bancorp | 1,480 | 89 | Wilmington Trust | 1,924 |
| 44 | Investors Financial Services | 3,005 | 90 | Wintrust Financial | 776 |
| 45 | JP Morgan Chase and Co | 117,000 | 91 | Zions Bancorporation | 5,051 |
| 46 | Keycorp | 10,200 | | | |

[30] We deal with bank mergers as in Hirtle (2008) who adjusts for the impact of significant mergers by treating the post-merger bank as a different entity from the pre-merger bank. This is the case of the case of the Bank of New York Company and Mellon Financial Corp.
[31] The BHCD provides information about 7.800 banks holdings that were alive before 2002.

Table 3.1 contains the 91 banks and information about their size (market capitalization in millions of dollars). In terms of size we observe a huge variance across banks under the analysis being by far Bank of America, Citigroup and JP Morgan the largest banks in the sample.

### *3.3.2. Explanatory variables*

Next we summarize the five groups of potential determinants of the banks' contribution to systemic risk (a detailed description can be found in Appendix A):

#### *3.3.2.1. Banks holdings of derivatives*

We consider five types of derivatives: credit, interest rate, foreign exchange, equity, and commodity. The holdings of derivatives are considered in terms of the fair value that is defined in the instructions of preparation of the BHCD as "the price that would be received to sell an asset or paid to transfer a liability in an orderly transaction between market participants in the asset's or liability's principal (or most advantageous) market at the measurement date". The holdings of derivatives are reported in the balance sheet with positive (asset side) or negative (liabilities side) fair values which refer to the amount of revaluation gains or losses from the ''marking to market'' of the five different types of derivative contracts.[32, 33] We focus on the total fair value (i.e., positive plus negative fair values) because it allows us to take into account the total exposures to the derivatives' counterparties and, at the same time, the counterparty risk. Alternatively to the fair value, we could use the notional amount outstanding; however according to

[32] Unlike other securities, derivative contracts involve two possible positions and positive fair values mean negative fair values on the counterparty. According to the Dodd-Frank Act, the required information to private funds advised by investment advisers to guarantee an appropriate monitoring of systemic risk in securities markets includes: amount of assets under management and use of leverage, trading and investment positions, types of assets held, or trading practices, among others contracts.

[33] The statement of Financial Accounting Standard No. 133 "Accounting for Derivative Instruments and Hedging Activities" requires all derivatives, without exception and regardless of the accounting treatment of the underlying asset, to be recognized in the balance sheet as either negative fair values (liabilities) or positive fair values (assets).

the Office of the Comptroller of the Currency (OCC) Quarterly Reports on Bank Trading and Derivatives Activities notional values can provide insight into potential revenue and operational issues but do not provide useful measure of the risk taken and so, could be meaningless from the systemic risk perspective.[34]

**Figure 3.1 Banks' holdings of derivatives relative to total assets**

This figure depicts the average ratio across banks of the fair value of derivatives holdings relative to total assets. The figure includes the following types of derivatives: interest rate, foreign exchange, credit, equity and commodity. The ratio is reported in percentages.

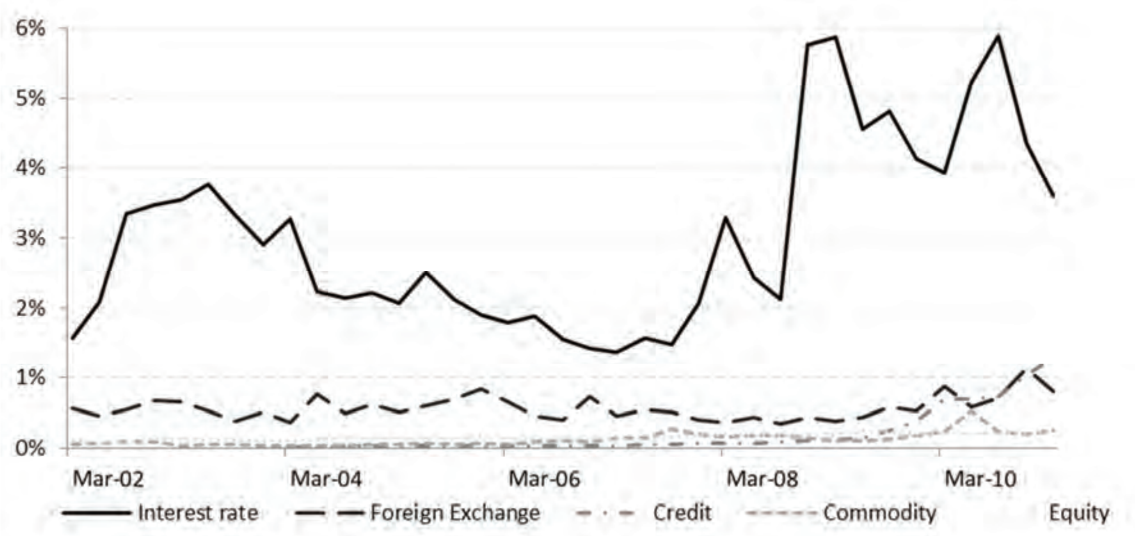



Figure 3.1 depicts the average fair values of the banks holdings of interest rate, foreign exchange, credit, equity and commodity derivatives over total assets. Interest rate derivatives represent the most widely used derivative during the whole sample period. Between 2003 and September 2007 they performed a downward trend that finished with the eruption of the subprime crisis in summer 2007. At the time of the Lehman Brothers collapse, the weight of interest rate derivatives more than doubled moving from 2% to 6% in one quarter. Since then, the holdings of interest rate derivatives have remained high and evolved within the 4-6% interval. Between 2002 and the Lehman Brothers episode, foreign exchange derivatives were the second most used derivatives and remained below 1% during almost the entire sample period. Credit derivatives

[34] The use of the derivatives fair value is a standard procedure in the literature (e.g. Venkatachalam, 1996; or Livne, Markarian and Milne, 2011).

performed a remarkable increase after summer 2007 and reached their maximum level in March 2009. In that period credit derivatives became the second most frequently used derivatives. Equity and commodity derivatives have lower weight in the sample. Equity derivatives did not experience large variations while commodity derivatives increased after the Bearn Stearns collapse probably coinciding with the increase in the commodity prices.

For the interest rate, foreign exchange, equity, and commodity derivatives we distinguish the effect of the holdings of derivatives held for trading from the ones held for purposes other than trading. Contracts held for trading purposes include those used in dealing and other trading activities accounted for at fair value with gains and losses recognized in earnings. Derivative instruments used to hedge trading activities are also reported in this category. For the credit derivatives we distinguish the effects of the holdings of derivatives in which the bank is the guarantor (protection seller) or the beneficiary (protection buyer).

Although previous literature about the effect of financial derivatives on systemic risk is scarce, some papers suggest the possible role of credit derivatives as determinant of systemic risk (see Stulz, 2004 and Acharya, 2011). Moreover, the hedging offered by derivatives could also lead banks to take more risk on the underlying asset. This fact could destabilize the banking sector if markets are not perfectly competitive (Instefjord, 2005).

*3.3.2.2. Size*

The impact of size on systemic risk is increasing and possibly non-linear as documented in Pais and Stork (2011). Tarashev, Borio and Tsatsaronis (2010) convincingly argue that larger size implies greater systemic importance, that the contribution to system-wide risk increases more than proportionately with relative size, and that a positive relationship between size and systemic importance is a robust result. The logarithm of the market capitalization (share price multiplied by the number of ordinary shares in issue) is used as the proxy for its size. This is a common practice in finance (e.g. Ferreira and Laux, 2007) and accounting (e.g. Bhen, Choi, and Kang, 2008) literature. We use market value instead of total assets to avoid any collinearity problem because banks' total assets have been employed to define and standardize most of the variables. We add the square of the size variable to our regression to control any potential non-lineal relation between size and systemic risk.

#### *3.3.2.3. Interconnectedness and substitutability*

Interconnectedness measures the extent to which a bank is connected with other institutions in such a way that its stress could easily be transmitted to other institutions. Substitutability can be defined as the extent to which other institutions or segments of the financial system can provide the same services that were provided by failed institutions. These two concepts are not easy to measure and there is therefore scarce evidence quantifying their effects on systemic risk.

As pointed out by Acharya, Pedersen, Philippon, and Richardson (2011a), the dimensions of systemic risk can be also translated into the following groups: size, leverage, risk, and correlation with the rest of the financial sector and economy. Due to the difficulty of measuring substitutability and interconnectedness, they are grouped in a more general group: correlation of the bank with the financial sector and economy.

To control for these dimensions we first employ some variables that could be more related to the interconnectedness dimension and then other variables related to the substitutability dimension. In the first group we consider the net balances to subsidiary banks and non-banks as a way to study the net position of a bank within the group. Additionally, this first dimension is captured by means of the correlation between the average daily individual bank's stock returns and the S&P500 index returns during the corresponding calendar quarter *t* (hereafter correlation with S&P500 index) in line with Allen, Bali, and Tang (2011).

In the second group we include variables related with the substitutability as reflected into the services that are provided by the banks, and we also distinguish between variables referred to the core and non-core banking activities. Brunnermeier, Dong and Palia (2011) find that non-interest to interest income variable (proxy for the non-core or non-traditional activities such as trading and securitization, investment banking, brokerage or advisory activities) has a significant contribution to systemic risk; we include this variable in our regressions. On the other hand, the amount of loans to banks and depository institutions relative to total assets and the total loans (excluding loans to banks and depository institutions) relating to total assets represent the bank's core or traditional activities. We distinguish between loans to the financial system and other loans enabling us to study whether they have different effects on systemic risk. Finally, we use the ratio of the bank's commercial paper holding relative to total assets as a proxy for the interbank activities given that we do not have direct information on the interbank lending. As Cummins and Weiss (2010) state, the inter-bank lending and commercial paper markets were critical in the subprime crisis. These variables could also indicate to some extent the degree of interconnectedness of a given bank given that the larger the total amount of the loans the larger is the expositions of a given bank to their borrowers. The difficulty of defining proxies related to the bank degree of substitutability could be one of the reasons that explain the scarcity of studies quantifying the effect of this dimension of systemic risk.[35] We define the variables referred to interconnectedness relative to the bank total assets.

#### *3.3.2.4. Balance sheet information*

We use several variables that refer to the balance sheet quality: (i) leverage, (ii) total deposits relative to total assets, (iii) maturity mismatch, and (iv) non-performing loans to total loans.

One of the dimensions proposed by Acharya, Pedersen, Philippon, and Richardson (2011b) is leverage, however true leverage is not straightforward to measure due to the limited market data breaking down off- and on-balance-sheet financing. According to them we define leverage as follows:

$$Leverage = \frac{book\ assets - book\ equity + market\ equity}{market\ value\ of\ equity} \tag{3.2}$$

As pointed out by Acharya and Thakor (2011) higher bank leverage creates stronger creditor discipline at individual bank level but it also increases systemic risk. However, some empirical analyses do not find significant effect of leverage on systemic risk (see Brunnermeier et al., 2011; or López, et al., 2011). Mizrach (2011) shows conventionally measured leverage as an unreliable indicator of systemic risk and suggests a more detailed examination of bank balance-sheets and asset holdings.

Other two potential explanatory variables are maturity mismatch and deposits to total assets. Thus, the higher the mismatch the more likely the bank is exposed to funding

[35] We are aware of only one study analyzing the effect of the substitutability dimension on systemic risk: Cummings and Weiss (2010). The authors study whether the U.S. insurers' activities create systemic risk and show that the lack of substitutability of insurers is not a serious problem. According to their results even a default of large insurers would not create a substitutability problem because other insurers could fill this gap. However, we consider that banking sector differs from the previous one and for this reason a positive effect of the substitutability dimension on the bank contribution to systemic risk cannot be ruled out.

stress. Deposits to total assets have two different interpretations. On the one hand during financial distress periods banks could rely more on deposits (see Boyson, Helwege, and Jindra, 2011). On the other hand, activities that are not traditionally associated with banks (outside the realm of traditional deposit taking and lending) are associated with a larger contribution to systemic risk and activities related to deposits taking are associated with a lower contribution to systemic risk. Total deposits could contribute to decrease systemic risk because they provide a shock-absorbing buffer.

Regarding the ratio of non-performing loans to total loans, the growth of credit and the easy access to financing observed before the subprime crisis could have increased substantially the role of this variable as a significant determinant of the bank's contribution to systemic risk.

*3.3.2.5. Aggregate systemic risk measure*

The aggregate systemic risk for each bank *i* is estimated as the sum of the individual contribution to systemic risk of all the banks with the exception of bank *i,* the 8 major broker-dealers, and the 23 major insurance companies. This variable captures the deterioration of the financial system's health. We use two lags of the aggregate measure of systemic risk to control by speed of adjustment to the aggregate level of risk and to absorb any lagged aggregated information transmitted into the current observation.

Table 3.2 reports the main descriptive statistics of the explanatory variables in the baseline analysis. We observe that the holdings of financial derivatives represent, on average, a small proportion of the total assets. They range from the interest rate derivatives, averaging 3.1% of total assets to commodity derivatives averaging only 0.1%. Net balances due to bank represent, on average, a lower proportion than net balances due to non-banks. The average correlation of the individual banks with

**Table 3.2 Descriptive Statistics**

This table reports the descriptive statistics (mean, median, standard deviation, maximum, minimum, and number of observations) of the five groups of determinants of systemic risk under analysis: *size* (log market value); *interconnectedness and substitutability* (commercial paper, loan to banks, total loans, non-interest to interest income, correlation with S&P500, net balances due to banks, net balances due to non-banks); *balance sheet* (leverage, maturity mismatch, total deposits and non-performing loans); *aggregate systemic risk; banks holdings of derivatives* (fair value of credit, interest rate, foreign exchange, equity and commodity derivatives).

| | *Mean* | *Median* | *Stard. Dev.* | *Max.* | *Min.* | *N. Obs.* |
|---|---|---|---|---|---|---|
| *Log market value* | 14.778 | 14.872 | 0.391 | 19.428 | 9.258 | 3154 |
| *Comercial paper/TA* | 0.002 | 0.002 | 0.002 | 0.095 | 0.000 | 3154 |
| *Loan to banks/TA* | 0.002 | 0.002 | 0.002 | 0.071 | 0.000 | 3154 |
| *Total loans/TA* | 0.611 | 0.615 | 0.043 | 0.937 | 0.012 | 3154 |
| *Non-interest to interest income/TA* | 0.500 | 0.493 | 0.125 | 5.305 | -0.648 | 3154 |
| *Correlation with S&P500* | 0.592 | 0.615 | 0.148 | 0.956 | -0.555 | 3154 |
| *Net balance to bank/TA* | 0.000 | 0.000 | 0.000 | 0.019 | -0.023 | 3154 |
| *Net balance to non-bank/TA* | 0.012 | 0.012 | 0.004 | 0.060 | 0.000 | 3154 |
| *Leverage* | 9.893 | 6.690 | 7.739 | 17.890 | 0.260 | 3154 |
| *Maturity mismatch* | 0.095 | 0.095 | 0.036 | 0.640 | 0.000 | 3151 |
| *Total deposits/TA* | 0.685 | 0.686 | 0.040 | 0.905 | 0.001 | 3154 |
| *Non-performing loans/Total loans* | 0.015 | 0.009 | 0.014 | 0.162 | 0.000 | 3154 |
| *Aggregate systemic risk measure* | 0.098 | 0.046 | 0.106 | 38.578 | 7.363 | 3154 |
| *Credit derivatives/TA* | 0.003 | 0.001 | 0.003 | 0.486 | 0.000 | 3154 |
| *Interest rate derivatives/TA* | 0.031 | 0.027 | 0.015 | 1.653 | 0.000 | 3154 |
| *Foreign exchange derivatives/TA* | 0.006 | 0.006 | 0.002 | 0.257 | 0.000 | 3154 |
| *Equity derivatives/TA* | 0.002 | 0.002 | 0.001 | 0.087 | 0.000 | 3154 |
| *Commodity derivatives/TA* | 0.001 | 0.001 | 0.001 | 0.206 | 0.000 | 3154 |

S&P500 index is quite large (0.6) which suggests a substantial interconnectedness of the banking system with the overall market. Average total loan and loan to banks represent around 61% and 0.2% of the total assets, respectively. The average ratio non-interest to interest income is close to 0.5 and average maturity mismatch is close to 10%. Finally, the balance sheet category, total deposits represent, on average, almost 70% of total assets.

## 3.4. Empirical results

### *3.4.1. Individual systemic risk measures and their comparison*

Panel A of Table 3.3 reports the main descriptive statistics of the individual quarterly measures. The signs for all the measures are set such that the higher the measure, the higher the bank's contribution to systemic risk. The measures are defined in basis points. We observe a common pattern in all of them with a huge difference between the mean and the maximum due to the big jump during Lehman Brothers episode.

We then rank the systemic risk measures according to the two criteria stated in Section 3.2.1 and Appendix C: (a) the correlation with an index of systemic events and policy actions and (b) Granger causality test. Panel B of Table 3.3 contains the final scores. Comparing the five weekly measures, we observe that under both criteria, the NSV obtains the highest score followed by the GSV. Therefore, for the baseline analysis we use the NSV as the proxy for the bank contribution to systemic risk. Some robustness checks using alternative measures of systemic risk are conducted in Section 3.5.

Other additional aspects of the different measures are worth mentioning. The co-risk measures strongly rely on the performance of the state variables and employ little firm specific information (i.e., information contained on stock prices, total assets and book

**Table 3.3 Systemic Risk Measures: Descriptive Statistics and Ranking**

This table reports the main descriptive statistics of the systemic risk measures and their ranking based on the average McFadden R-squared and Granger causality test. Panel A reports the descriptive statistics of five systemic risk measures in basis points: Net Shapley value (NSV), Gross Shapley Value (GSV), Co-risk measures (ΔCoVaR and ΔCoES), and asymmetric ΔCoVaR. They are reported on quarterly basis calculated at the last week of the corresponding quarter. Panel B reports the ranking scores for the systemic risk measures. The comparison of different pairs of systemic risk measures, referred to the same bank, based on the McFadden R-squared criterion is done by assigning a score of +1 to the measure with the highest R-squared and -1 to the lowest. The comparison based on the Granger causality test is done by applying the test to pairs of systemic risk measures, referred to the same bank, and giving a score of +1 to measure X if X Granger causes another measure Y at 5% confidence level and -1 if X is caused in the Granger sense by Y. Finally we add up the scores obtained by each measure across the 91 banks to obtain the one with highest score.

Panel A

| | *Mean* | *Median* | *Stard. Dev.* | *Max.* | *Min.* | *N. Obs.* |
|---|---|---|---|---|---|---|
| *Net Shapley Value* | 11.07 | 6.21 | 11.44 | 176.39 | -76.03 | 3154 |
| *Gross Shapley Value* | 93.22 | 82.33 | 49.34 | 546.15 | 6.08 | 3154 |
| *Delta co-value-at-risk* | 745.63 | 641.86 | 486.21 | 3205.45 | 22.69 | 3154 |
| *Delta co expected shortfall* | 454.96 | 396.00 | 306.43 | 2216.00 | -303.65 | 3154 |
| *Asymmetric Delta co-value-at-risk* | 765.25 | 660.07 | 488.35 | 4327.27 | -151.70 | 3154 |

Panel B

| | *Net Shapley Value* | *Gross Shapley Value* | *Delta co-value-at-risk* | *Delta co-expected-shortfall* | *Asymmetric Delta co-value-at-risk* |
|---|---|---|---|---|---|
| *McFadden R-squared* | 266 | 84 | -44 | -280 | -26 |
| *Granger causality test* | 13 | 10 | -20 | -1 | -2 |
| *Total* | 279 | 94 | -64 | -281 | -28 |

equity). So, these measures provide very similar output for different banks independent of the bank's risk profile. To give an example, the estimation of CoVaR for every bank $i$ (Equations B.1.1-B.1.3) is done using the growth rate of the market value of total financial assets (at system level) as the dependent variable; and a set of state variables and the growth rate of the market value of total financial assets of bank $i$ as explanatory variables. The results of the quantile regression shows that the coefficient measuring the impact of the market value of the total financial assets of bank $i$ on this measure of systemic risk is significant only for 11 of the 91 banks at 10% of significance level when quantile level is 1% ($q = 0.01$) and in zero cases when quantile level is 50%

($q = 0.5$). Therefore individual bank's CoVaR is largely determined by the same set of common variables. For this reason, we expect strong similarities across banks in terms of this systemic risk measure.[36]

Regarding the computation of the GSV for bank *i*, this measure includes the VaR of bank $i$ as an additional element in estimating the individual contribution to systemic risk. But in non-stress periods (where the individual contribution of bank $i$ to system risk is negligible) this measure is largely determined by the evolution of the VaR of bank $i$ which is a measure of the bank's individual risk.[37] To solve this shortcoming, we consider an alternative measure which is net of the impact of a proportion of the individual VaR, the Net Shapley Value. That is, we get rid of the bank's idiosyncratic risk and focus on the bank's contribution to systemic risk by subtracting the VaR from the GSV. Some robustness checks are carried out in Section 3.5.

### *3.4.2. Determinants of systemic risk: the effect of banks' holdings of derivatives*

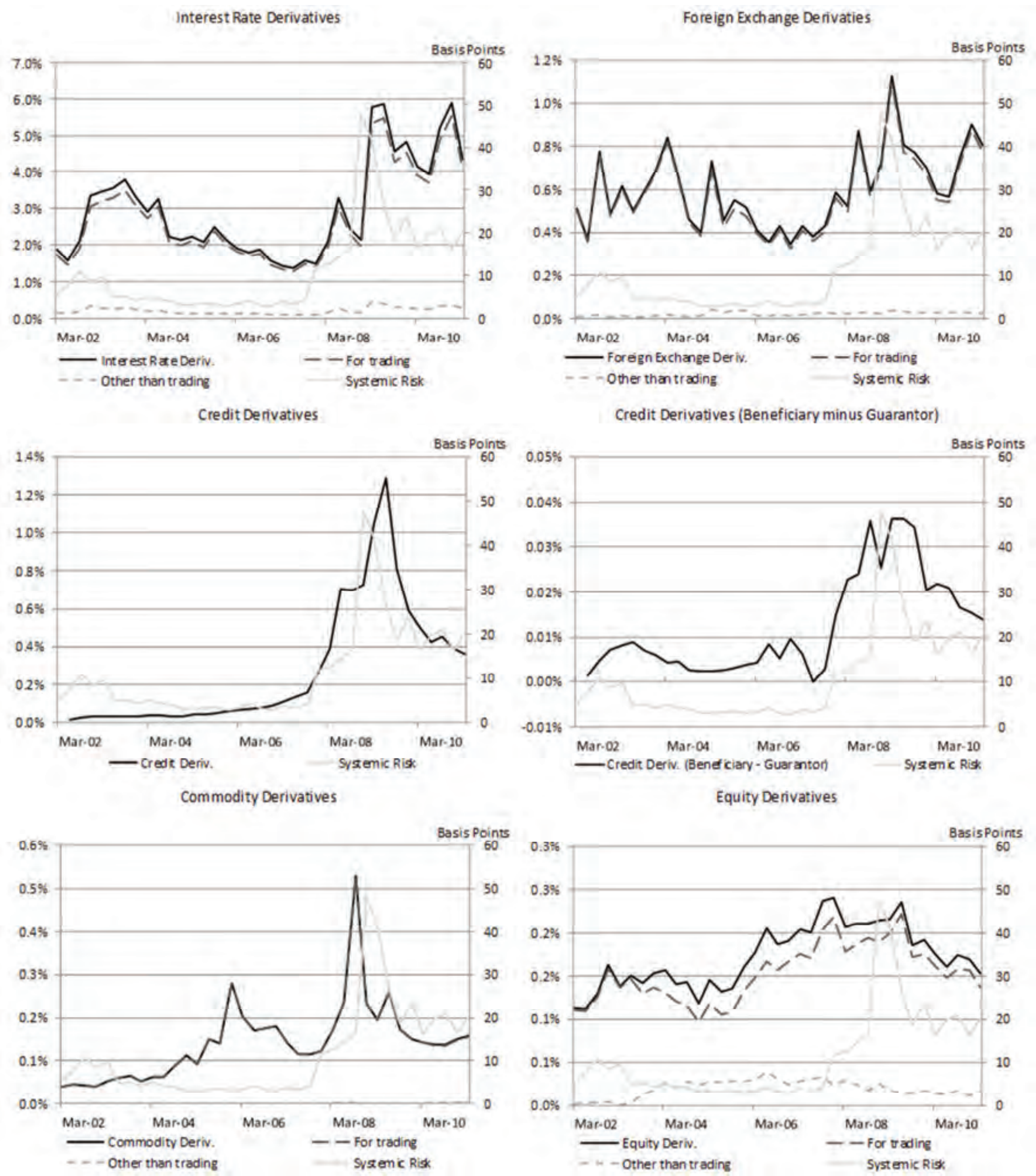
In addition to the banks' average contribution to systemic risk, Figure 3.2 depicts the average fair value of derivatives ratio held across banks for trading and for other purposes than trading relative to total assets. In the case of credit derivatives, we report the average holdings relative to total assets and the average difference between the fair value of credit derivatives in which the banks act as beneficiary (buy protection) and those in which they act as guarantor (sell protection). The series corresponding to the average bank holdings of derivatives are lagged one period (*t-1*) and the systemic risk measure is depicted at period $t$ such as they appear in regression (1). In general terms, we observe that trading positions are the most relevant for all the types of derivatives.

[36] To quantify these similarities, we estimate pairwise correlations between the individual VaR and the systemic risk measure for each bank. The average correlations are 0.98, 0.94 and 0.95 for the ΔCoVaR, ΔCoES and asymmetric CoVaR, respectively.

[37] We estimate the average correlation between the GSV and the VaR for each of the 91 banks. The average correlation for the period 2002-20011 is equal to 0.98 while this correlation drops to 0.75 using the NSV.

**Figure 3.2 Systemic risk measure and banks' holdings of derivatives held for trading and for purposes other than trading relative to total assets**

This figure depicts the average ratio across banks of the fair value of derivatives held for trading and for purposes other than trading relative to total assets (in percentages) in addition to the banks' average contribution to systemic risk (in basis points). The systemic risk measure is the average Net Shapley value across the 91 bank holdings (right axis). The figure includes the following types of derivatives (by order of appearance): interest rate, foreign exchange, credit, equity and commodity. In the case of credit derivatives, we report the average holdings relative to total assets and the average difference between the fair value of credit derivatives in which the banks act as beneficiary (buy protection) and those in which they act as guarantor (sell protection). The series corresponding to the average bank holdings of derivatives are lagged one period (*t-1*) and the systemic risk measure is depicted at period *t* such as they appear in the paper regressions.




The extensive use of derivatives for trading purposes could be due to banks moving towards innovative fee-producing activities as pointed out by Allen and Santomero

(2001). These trading activities have generated substantial revenues for large banks as can be observed in the OCC's Quarterly Reports on Bank Trading and Derivatives Activities but they have also led to large losses. Regarding credit derivatives, we observe that the beneficiary positions are on average larger than guarantor positions[38]. In interest rate and commodity derivatives panels, we observe that one quarter before the date corresponding to the most pronounced increase in systemic risk, holdings held for trading depict a downward trend, equity holdings for trading purposes remained stable during this systemic episode. The correlation between the holdings of interest rate and equity derivatives for trading purposes lagged one quarter on the one hand, and the systemic risk measure from the end of 2007 to the beginning of 2009 on the other hand; are negative and it is almost zero for case of the commodity derivatives. Finally, we find a closer relation between systemic risk and the positions in both credit and foreign exchange derivatives. We observe a slight increase in the holdings of the former and a significant increase in the latter one quarter before the main systemic event in the sample. Thus, the correlations of the holdings of these derivatives lagged by a quarter and the systemic risk measure during the period in which we observe the highest banks contributions to systemic risk were significantly positive.

We address the first, second and sixth research questions stated in Section 3.2 by means of Table 3.4, which shows the results of the estimation of Equation 3.1 (the baseline specification). Column 1 reports the estimated coefficients and their standard errors. Column 2 reports the standardized coefficient (i.e., the product of the coefficient and the standard deviation of the explanatory variable) and column 3 the economic impact of the statistically significant variables (i.e., the ratio of the standardized coefficient over the average value of the dependent variable).

[38] The implication is that net guarantors are other non-bank financial institutions (insurance companies, hedge funds)

**Table 3.4 Baseline Regression**

This table reports the results of the baseline unbalanced panel regressions. The dependent variable is the individual contribution to systemic risk measured as the Net Shapley Value which is measured in basis points. Our database is formed of 91 banks and spans from 1Q2002 to 2Q2011. We estimate the coefficients by means of a Prais-Winsten robust to heteroskedasticity, contemporaneous correlation across panels. Column 1 reports the results where bank holdings of derivatives are measured by means of the total fair value (sum of positive and negatives). Column 2 reports the standardized coefficient (i.e., the regression coefficient as in column 1 times standard deviation of the corresponding explanatory variable). Column 3 contains the standardized coefficient (as in column 2) over the mean of the dependent variable (in percentage) for the variables which are different from zero at 1 or 5% significance levels. The symbol *** (**) denotes the significance level at 1% (5%). The results correspond to the estimated coefficient and the robust standard errors.

| | (1) Coefficient [SE] | (2) Standardized coefficient | (3) Economic Impact (%) |
|---|---|---|---|
| *Log market value* $_{t-1}$ | 4.16<br>[2.51] | 1.627 | |
| *Log of squared market value* $_{t-1}$ | 0.09<br>[0.08] | 1.006 | |
| *Commercial paper* $_{t-1}$ */TA* | 30.62<br>[31.56] | 0.051 | |
| *Loan to banks* $_{t-1}$ */TA* | 19.71<br>[44.78] | 0.032 | |
| *Total loans* $_{t-1}$ */TA* | 9.67***<br>[2.84] | 0.416 | 3.755 |
| *Non-interest to interest income* $_{t-1}$ | 0.79<br>[0.83] | 0.099 | |
| *Correlation with S&P500* $_{t-1}$ | 2.36<br>[2.89] | 0.349 | |
| *Net balance to bank* $_{t-1}$ */TA* | 477.97***<br>[95.60] | 0.200 | 1.803 |
| *Net balance to non-bank* $_{t-1}$ */TA* | 23.38<br>[17.40] | 0.098 | |
| *Leverage* $_{t-1}$ | 0.15***<br>[0.04] | 1.161 | 10.486 |
| *Maturity mismatch* $_{t-1}$ | 0.21<br>[2.62] | 0.007 | |
| *Total deposits* $_{t-1}$ */TA* | 18.16***<br>[3.47] | 0.719 | 6.493 |
| *Non-performing loans* $_{t-1}$ */Total loans* | 136.40***<br>[44.56] | 1.955 | 17.655 |
| *Aggregate systemic risk measue* $_{t-1}$ | 67.13***<br>[16.82] | 7.147 | 64.550 |
| *Aggregate systemic risk measue* $_{t-2}$ | 27.54<br>[16.51] | 2.932 | |
| *Credit derivatives* $_{t-1}$ */TA* | 34.33***<br>[8.22] | 0.110 | 0.989 |
| *Interest rate derivatives* $_{t-1}$ */TA* | 11.51***<br>[2.78] | 0.168 | 1.517 |
| *Foreign exchange derivatives* $_{t-1}$ */TA* | 93.58***<br>[24.68] | 0.225 | 2.036 |
| *Equity derivatives* $_{t-1}$ */TA* | 39.55<br>[43.21] | 0.028 | 0.256 |
| *Commodity derivatives* $_{t-1}$ */TA* | 26.29**<br>[12.36] | 0.031 | 0.276 |
| *Constant* | 46.06**<br>[19.82] | | |
| *Time Effects* | Yes | | |
| Number of Observations | 2947 | | |
| Number of Groups | 91 | | |
| Min. Observations per Group | 13 | | |
| Avg. Observations per Group | 33.2 | | |
| Max. Observations per Group | 36 | | |
| R squared | 0.4904 | | |

There is a significant relation between the credit, interest rate, foreign exchange and commodity derivatives holdings of bank *i* in quarter *t* and the contribution to systemic risk of bank *i* in period *t+1*. Equity derivatives holdings do not affect systemic risk. Holdings of credit and foreign exchange derivatives have an increasing effect on systemic risk whereas holdings of interest rate and commodities derivatives have a decreasing effect. Foreign exchange derivatives have the highest economic impact on systemic risk.

The positive and significant effect of credit derivatives may be due to the fact that banks positions in credit derivatives are held for trading activities rather than for hedging loans (Minton, Stulz, and Williamson, 2009). These authors estimate that the net notional amount of these derivatives that is used for hedging loans is below 2% of the total notional amount of this type of derivatives and is less than 2% of their loans. In this line, Kiff, Elliot, Kazarian, Scarlata, and Spackman (2009) state that a large portion of CDS buyers do not hold the underlying bond but are either speculating on the default of the underlying reference or protecting other interests.

The positive and significant effect of the variable referring to the use of foreign exchange derivatives casts some doubts on the argument against increased regulation of the foreign exchange derivatives based on the assumption of the high level of transparency of the foreign exchange market and that they performed smoothly during the financial crisis. An extreme situation, such as the devaluation of the currency of a large country, could lead to high losses for important players in this market and could make the global shock that this devaluation would cause even worse. According to the BIS (2008) report on the progress in reducing foreign exchange settlement risk, the establishment and growth of the CLS Bank has achieved significant success however, a notable share of foreign exchange transactions are settled in ways that still generate significant potential risks across the global financial system and so, further action is required. However, the clearing process is concentrated in one clearing house (the CLS Bank) and this fact could have negative systemic implications (Duffie and Zhu, 2011).

In regards to the negative and significant effect of the holdings of interest rate derivatives; previous literature such as Brewer, Minton, and Moser (2000) and Carter and Sinkey (1998) suggest the use of these derivatives being more frequent in banks more exposed to interest rate risk. Thus, the Carter and Sinkley (1998) and Downing (2012) results support the hypothesis that banks use interest-rate derivatives to hedge interest rate risk. In fact, we find that the correlation between the 10-year U.S. Government bond yield and the holdings of interest rate derivatives is 0.91 indicating that the use of these derivatives is determined by decreases in the interest rate. This finding is in line with the one presented by Christoffersen, Nain, and Oberoi (2009) who show a negative relation between the use of interest rate derivatives and the interest rate movements. These authors argue that even if companies are able to anticipate the interest rate policy, it is possible that they cannot adjust the debt exposure; however they can adjust the swap exposures to reduce the cost of debt. This negative correlation could also be consistent with a higher cost of interest rate volatility during economic downturns.

The effects of the use of equity and commodity derivatives on banks' risk or performance have been scarcely addressed in previous literature. One reason explaining the lack of empirical studies on this topic could be the lower relative importance of the positions on equity and commodity derivatives as can be observed in Figure 3.1.

However, while the effect of the equity derivatives is not significant, commodity derivatives have a negative and significant effect on the dependent variable.

The holdings of commodity derivatives, as occurs with the other derivatives, could be justified by the search for higher yields in a low interest rate environment. Moreover, the increase in the use of commodity derivatives could be propitiated, as stated in Basu and Gavin (2010), by the movement from real estate derivatives to commodity derivatives coinciding with the appearance of the problems in the subprime market. Other theories suggest that banks could use commodity derivatives to hedge inflation risk, to take advantage of the increase in the commodity prices around the systemic event, or because they are negatively correlated with equity and bond returns (Gorton and Rouwenhorst, 2006). Basu and Gavin (2010) show that when commodity prices peak in June 2008, the correlation with the equity index was, on average, negative. In fact, we observe the highest holdings of commodity derivatives by banks in this period. After summer 2008 the correlation becomes extremely positive and holdings of commodity derivatives diminished substantially from their highest levels.

Regarding the effect of the size, substitutability, interconnectedness and balance-sheet related variables, we find that increases in the following variables increase systemic risk contributions: total loans, net balance to banks belonging to the same banking group, leverage ratio and the proportion of non-performing loans over total loans. On the other hand, increases in total deposits decreases systemic risk. The effect of the size related variables is not significant given that size is our primary criterion for sample selection. The variables with the highest economic impact on systemic risk are the proportion of non-performing loans to total loans and the leverage ratio. For instance, one standard deviation increase in the proportion of non-performing loans to total loans in quarter *t*, increases the bank's contribution to systemic risk in quarter *t+1* to 17% above its average level.

No other variable presents significant effects. In particular and in contrast to Brunnermeier et al. (2011) non-interest to interest income is not significant when derivatives holding are included in the equation. This discrepancy could be also due to the different sample, time periods, systemic risk measures, or explanatory variables employed in the two papers. Size effect is not significant, as expected, given the sample selection bias.[39] Finally, the aggregate systemic risk level in the previous quarter contributes positively and significantly to increase the individual contribution to systemic risk but the effect of aggregate systemic risk does not go beyond one quarter before the current one.[40]

Summing up, although the two variables with the highest economic impact on the bank's contribution to systemic risk are the non-performing loans relative to total loans and the leverage variables; the bank's holdings of financial derivatives also have significant effects but of a much lower magnitude.

Some literature has considered that the use of derivatives should not pose significant levels of risk to the economy or to individual corporations. For instance, Stulz (2004) concludes that we should not fear derivatives but have a healthy respect for them. He considers that losses from derivatives are localized but the whole economy gains from

[39] We have repeated the analysis using the logarithm of total assets and its square as alternative variables to proxy the bank size and find similar results.

[40] The use of these lagged measures enables us to mitigate the potential autocorrelation in the residuals. Nevertheless, we check whether there is significant first order autocorrelation in the residuals by means of individual tests for each bank. The coefficient for the first order autocorrelation is only significant in 25 out of the 91 banks being its average magnitude around 0.3 for these 25 banks. We conduct an additional test to discard the existence of first order correlation in the residuals. Thus, we calculate the average residual for each date across the 91 banks and regress this series on its lagged value. The estimated coefficient is not significantly different from zero and so, we do not find evidence in favor of the presence of autocorrelation.

the existence of derivatives markets. Hentschel and Kothari (2001) question whether corporations are reducing or taking risks with derivatives, their answer is “typically not very much of either”. The authors find an absence of higher risks due to the effect of derivatives (even among firms with large derivatives positions) which in their view shows that the concern over widespread derivative speculation is unfounded. Along this line, Cyree, Huang, and Lindley (2012) find that the effects of derivatives (interest rate, foreign exchange, and credit derivatives) on market valuation are not statistically distinguishable from zero in either good times or bad times.

Our results do not imply that the use of derivatives by banks is inconsequential as far as systemic risk is concerned. They do imply that their impact, albeit statistically significant, plays a second fiddle in comparison with traditional variables such as leverage or the proportion of non-performing loans over total loans. Furthermore, the use of derivatives could indirectly affect the systemic contribution of banks given that derivatives require limited up-front payments and enable banks to take more leveraged positions. Additionally, the use of derivatives could lead to diminished monitoring of loans when the banks are considered to have used the right hedging strategies.

To address research questions three and five we look at Table 3.5 in which we distinguish holdings of derivatives (interest rate, foreign exchange, equity and commodity, respectively) used for trading and for other purposes using two different variables. In the case of credit derivatives we use the difference between the fair values of the holdings in which the bank is the beneficiary (buys protection) and guarantor (sells protection).

Derivatives held for purposes other than trading do not significantly contribute to systemic risk. However, foreign exchange and interest rate derivatives for trading purposes and to lesser extent equity derivatives affect systemic risk.

**Table 3.5 Analysis of the held position**

This table reports the results of a variation in the baseline unbalanced panel regressions in which we focus on the held position on derivatives. For credit derivatives we study the difference between fair value of holdings in which the bank is the beneficiary and the holdings in which the bank is the guarantor. For interest rate, foreign exchange, equity and commodity derivatives we distinguish holdings used for trading and for purposes other than trading using two different variables. The dependent variable is the individual contribution to systemic risk measured as the Net Shapley Value which is measured in basis points. Our database is formed of 91 banks and spans from 1Q2002 to 2Q2011. We estimate the coefficients by means of a Prais-Winsten robust to heteroskedasticity, contemporaneous correlation across panels. Column 1 reports the coefficients relative to holdings of derivatives. Column 2 reports the economic impact in percentage. It is assessed as the standardized coefficient over the mean of the dependent variable and is reported for the variables which are different from zero at 1 or 5% significance levels. The symbol *** (**) denotes that the variable is significant at 1% (5%). The results correspond to the estimated coefficient and the robust standard errors.

| | (1) | (2) |
|---|---|---|
| | *Coefficient [SE]* | *Economic Impact (%)* |
| *Beneficiary minus Guarantor* $_{t-1}$ */ TA* | 932.01*** [357.42] | 1.242 |
| *Interest rate derivatives held for purposes other than trading* $_{t-1}$ */TA* | 224.71 [117.51] | |
| *Interest rate derivatives held for trading* $_{t-1}$ */TA* | 8.44*** [2.79] | 1.021 |
| *Foreign exchange derivatives held for purposes other than trading* $_{t-1}$ */TA* | 60.3 [242.19] | |
| *Foreign exchange derivatives held for trading* $_{t-1}$ */TA* | 102.63*** [26.09] | 2.098 |
| *Equity derivatives held for purposes other than trading* $_{t-1}$ */TA* | 105.07 [62.01] | |
| *Equity derivatives held for trading* $_{t-1}$ */TA* | 145.03** [58.43] | 0.737 |
| *Commodity derivatives held for purposes other than trading* $_{t-1}$ */TA* | 2498.5 [2,927] | |
| *Commodity derivatives held for trading* $_{t-1}$ */TA* | 18.65 [12.74] | |
| *Constant* | 57.15*** [19.22] | |
| *Control variables* | Yes | |
| *Time Effects* | Yes | |
| Number of Observations | 2947 | |
| Number of Groups | 91 | |
| R-squared | 0.4934 | |

We find a positive and significant effect of the variable representing the holdings of foreign exchange derivatives for trading purposes. Fan, Mamun, and Tannous (2009) suggest that the reduction in risk gained from using foreign exchange derivatives for hedging purposes is offset by the increase in trading activities. Banks could use this type of derivatives to hedge foreign exchange risk and be engaged in trading activities which would expose them to additional risk at the same time.

Contrary to the effect of foreign exchange derivatives, interest rate derivatives held for trading have a negative and significant effect on systemic risk. Hirtle (1997) shows that the increase in the use of interest rate derivatives by U.S. bank holdings, which served as derivatives dealers, correspond to a greater interest rate risk exposure during the period 1991-1994. This result could be reflecting that derivatives enhance interest rate risk exposure for bank holding companies. Additionally, banks mainly lend to firms using floating rates and for this reason, they could aim to increase their trading in interest rate derivatives when the interest rates begin to diminish. According to Stulz (2004), derivatives can create risk at a firm level if they are used episodically and with no experience in their use. However, interest rate derivatives are broadly used by banks. The most common interest rate derivative is based on swaps, which account for around 70%, and in particular the “plain vanilla” interest rate swap. Banks participating more heavily in interest-rate swaps have a higher loans to asset ratio (Brewer, Minton, and Moser, 2000) and stronger capital positions (Carter and Sinkey, 1998).

The fact that the equity derivatives held for trading purposes have a negative and significant effect could be due to the use banks made of these derivatives during the crisis. Thus, the maximum value of the fair value ratio of equity derivatives for trading relative to total assets is reached by September 2007 and since then; this ratio has remained stable and decreased at the end of the sample.

We observe that as banks act as a net beneficiary when participating in the credit derivatives markets, its contribution to systemic risk increases. Given that the protection seller could default, a buyer of a CDS contract assumes counterparty risk, so the concern of heightened counterparty risk around the Lehman Brothers collapse could explain this effect. Moreover, as pointed out by Giglio (2011), the buyer of protection could suffer even larger loses if the default of the reference entity triggers the default of the counterparty (double default), given that the buyer would have a large amount owed by the bankrupt counterparty. Even the presence of collateral may not be enough to solve this counterparty risk related to double default problem. According to Giglio (2011), the buyers of CDS were aware of this residual counterparty risk and considered that the best way to reduce it was to buy additional CDS protection against their counterparty, which increased the cost of buying CDS protection. Banks being net buyers of protection have lower capital ratios, higher ratios of risk-based assets to total assets, and are users of other types of derivatives (Minton, Stulz, and Williamson, 2009). On the other hand, the banks that are more profitable, more liquid, or have a higher ratio of deposits over total assets are less likely to be net protection buyers.

Finally we address the fourth research question by means of Table 3.6. As stated in section 3.2.3, we aim to test whether the relationship between derivatives' holdings and systemic risk is sensitive to the emergence of the subprime crisis. To do that, we split the fair value of the holdings of every derivative (credit, interest rate, foreign exchange, equity and commodity derivatives) in two variables: the first variable represents the holdings of derivatives multiplied by a dummy variable which is equal to one before the first quarter of 2007 (no crisis dummy) while the second variable is obtained by multiplying the holdings of derivatives and a dummy variable which equals one after the first quarter of 2007 (crisis dummy). Then, we estimate Equation 3.1 focusing on the role of every derivative before and during the crisis in separate ways. We observe a negative effect of the credit derivatives holdings on systemic risk before the subprime crisis but a positive and significant effect during the crisis which evidences a change of role of the credit derivatives. Credit derivatives behaved as shock absorbers before the subprime crisis but as credit issuers during the crisis. This change of role is not observed in other derivatives. The effect of interest rate derivatives holdings is negative and significant before and during the crisis. The effect of foreign exchange derivatives is always positive although non-significant before the crisis, but significant during the crisis. The holdings of commodity derivatives hedge systemic risk in both periods but significantly only before the crisis.

## 3.5. Robustness test

So far we have studied the factors that explain the individual contribution to systemic risk. At this point our main aim is to ensure the reliability of our previous analysis proposing alternative dependent and explanatory variables.

### *3.5.1. Alternative indicators of systemic risk*

We first consider an alternative specification of the NSV in which we include a synthetic bank constructed as the weighted average of the remaining banks that do not belong to the system and are not used to estimate the measure (column 2 of Table 3.7). The second measure represents a variation of the NSV in which we aggregate the information within a given quarter by summing up all the weekly estimated measures

**Table 3.6 Sensitivity to the subprime crisis**

This table reports the results of a variation in the baseline unbalanced panel regressions in which we distinguish the role before and during the crisis of every derivative in a separate way. The dependent variable is the individual contribution to systemic risk measured as the Net Shapley Value which is measured in basis points. Our database is formed of 91 banks and spans from 1Q2002 to 2Q2011. We estimate the coefficients by means of a Prais-Winsten robust to heteroskedasticity, contemporaneous correlation across panels. We split the holdings of derivatives in two variables: the first variable represents the holdings of derivatives up to the first quarter of 2007 and the second variable represents the holdings of credit derivatives after the first quarter of 2007. We consider the total fair value of credit (column 1), interest rate (column 2), foreign exchange (column 3), equity (column 4) and commodity (column 5) derivatives. The results presented correspond to the estimated coefficient relative to holdings of derivatives. The symbol *** (**) denotes the significance level at 1% (5%).

| | (1) | | (2) | | (3) | | (4) | | (5) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | *Coefficient* | *Economic Impact* | *Coefficient* | *Economic Impact* | *Coefficient* | *Economic Impact* | *Coefficient* | *Economic Impact* | *Coefficient* | *Economic Impact* |
| *Credit derivatives$_{t-1}$ /TA * no crisis dummy* | -115 82 | | | | | | | | | |
| *Credit derivatives$_{t-1}$ /TA * crisis dummy* | 24 16** | 0 74 | | | | | | | | |
| *Credit derivatives$_{t-1}$ /TA* | | | 42 13** | 1 22 | 1 13 | 0 03 | 23 12 | | 31 56*** | 0 91 |
| *Interest rate derivatives$_{t-1}$ /TA * no crisis dummy* | | | -10 69*** | -1 30 | | | | | | |
| *Interest rate derivativest-1 /TA * crisis dummy* | | | -12 78*** | -2 32 | | | | | | |
| *Interest rate derivatives$_{t-1}$ /TA* | -10 65*** | -1 40 | | | -8 67*** | -1 14 | -10 67*** | -1 41 | -11 37*** | -1 50 |
| *Foreign exchange derivatives$_{t-1}$ /TA * no crisis dummy* | | | | | 57 71 | | | | | |
| *Foreign exchange derivativest-1 /TA * crisis dummy* | | | | | 123 03*** | 4 03 | | | | |
| *Foreign exchange derivatives$_{t-1}$ /TA* | 94 58*** | 2 07 | 91 75*** | 2 01 | | | 94 73*** | 2 08 | 93 69*** | 2 05 |
| *Equity derivatives$_{t-1}$ /TA * no crisis dummy* | | | | | | | -65 31 | | | |
| *Equity derivativest-1 /TA * crisis dummy* | | | | | | | -6 75 | | | |
| *Equity derivatives$_{t-1}$ /TA* | -11 59 | | -45 79 | | -18 63 | | | | -39 84 | |
| *Commodity derivatives$_{t-1}$ /TA * no crisis dummy* | | | | | | | | | -37 54** | -0 28 |
| *Commodity derivatives$_{t-1}$ /TA * crisis dummy* | | | | | | | | | -13 48 | |
| *Commodity derivatives$_{t-1}$ /TA* | -22 72 | | -26 71** | -0 28 | -24 98** | -0 26 | -26 17** | -0 28 | | |
| *Constant* | 46 72** | | 46 79** | | 45 46** | | 44 75** | | 46 41** | |
| *Control variables* | Yes | | Yes | | Yes | | Yes | | Yes | |
| *Time Effects* | Yes | | Yes | | Yes | | Yes | | Yes | |
| Number of Observations | 2947 | | 2947 | | 2947 | | 2947 | | 2947 | |
| Number of Groups | 91 | | 91 | | 91 | | 91 | | 91 | |
| R-squared | 0 4908 | | 0 4905 | | 0 4922 | | 0 4906 | | 0 4905 | |

## Table 3.7 Alternative Dependent Variables

This table reports the results of a variation in the baseline unbalanced panel regression in which different specifications of the dependent variable (contributions to systemic risk) are considered while the explanatory variables employed do not change. Our database is formed of 91 banks and spans from 1Q2002 to 2Q2011. We estimate the coefficients by means of a Prais-Winsten robust to heteroskedasticity, contemporaneous correlation across panels. This table reports the results of using alternative contributions to systemic risk: (1) Net Shapley Value at the end of the quarter (baseline); (2) Net Shapley Value using the alternative approach at the end of the quarter; (3) sum of the Net Shapley Value for the corresponding quarter; and (4) Gross Shapley Value the end of the quarter. All dependent variables are measures on basis points. The results presented correspond to the estimated coefficient and the robust standard errors. The symbol *** (**) denotes that the variable is significant at 1% (5%).

| | (1) Coefficient [SE] | (2) Coefficient [SE] | (3) Coefficient [SE] | (4) Coefficient [SE] |
|---|---|---|---|---|
| *Log market value* $_{t-1}$ | 4.16* | 4.56* | 35.82 | 50.56*** |
| | [2.51] | [2.51] | [27.72] | [14.09] |
| *Log of squared market value* $_{t-1}$ | 0.09 | 0.1 | 0.52 | 1.36*** |
| | [0.08] | [0.08] | [0.92] | [0.45] |
| *Commercial paper* $_{t-1}$ */TA* | 30.62 | 21.28 | 551.55 | 126.32 |
| | [31.56] | [31.72] | [346.68] | [119.26] |
| *Loan to banks* $_{t-1}$ */TA* | 19.71 | 27.56 | 181.18 | 613.85*** |
| | [44.78] | [45.01] | [514.13] | [161.47] |
| *Total loans* $_{t-1}$ */TA* | 9.67*** | 9.97*** | 110.01*** | 44.83*** |
| | [2.84] | [2.86] | [32.80] | [14.29] |
| *Non-interest to interest income* $_{t-1}$ | 0.79 | 0.92 | 10.47 | 1.51 |
| | [0.83] | [0.83] | [7.80] | [2.24] |
| *Correlation with S&P500* $_{t-1}$ | 2.36 | 2.35 | 75.40** | 2.96 |
| | [2.89] | [2.89] | [35.22] | [12.94] |
| *Net balance to bank* $_{t-1}$ */TA* | 477.97*** | 447.92*** | 6,174*** | 2,015*** |
| | [95.60] | [92.88] | [1,162] | [505.89] |
| *Net balance to non-bank* $_{t-1}$ */TA* | 23.38 | 29.04 | 309.18 | 133.57 |
| | [17.40] | [17.74] | [200.89] | [82.80] |
| *Leverage* $_{t-1}$ | 0.15*** | 0.14*** | 2.43*** | 0.67*** |
| | [0.04] | [0.04] | [0.51] | [0.23] |
| *Maturity mismatch* $_{t-1}$ | 0.21 | 1.2 | 15.88 | 28.75** |
| | [2.62] | [2.65] | [32.46] | [11.58] |
| *Total deposits* $_{t-1}$ */TA* | 18.16*** | 18.41*** | 272.39*** | 91.69*** |
| | [3.47] | [3.47] | [38.30] | [13.23] |
| *Non-performing loans* $_{t-1}$ */Total loans* | 136.40*** | 136.01*** | 1,589*** | 621.52*** |
| | [44.56] | [44.18] | [473.29] | [208.39] |
| *Aggregate systemic risk measue* $_{t-1}$ | 67.13*** | 67.34*** | 217.16*** | 81.61*** |
| | [16.82] | [16.91] | [47.27] | [15.53] |
| *Aggregate systemic risk measue* $_{t-2}$ | 27.54* | 28.04* | 82.16* | 35.82** |
| | [16.51] | [16.59] | [44.88] | [15.67] |
| *Credit derivatives* $_{t-1}$ */TA* | 34.33*** | 34.09*** | 519.29*** | 157.80*** |
| | [8.22] | [8.26] | [115.95] | [35.51] |
| *Interest rate derivatives* $_{t-1}$ */TA* | 11.51*** | 11.52*** | 145.13*** | 79.00*** |
| | [2.78] | [2.78] | [35.40] | [12.78] |
| *Foreign exchange derivatives* $_{t-1}$ */TA* | 93.58*** | 95.98*** | 1,096*** | 491.97*** |
| | [24.68] | [24.79] | [235.50] | [94.39] |
| *Equity derivatives* $_{t-1}$ */TA* | 39.55 | 33.33 | 525.38 | 57.15 |
| | [43.21] | [43.06] | [511.51] | [224.77] |
| *Commodity derivatives* $_{t-1}$ */TA* | 26.29** | 26.08** | 413.13** | 223.01*** |
| | [12.36] | [12.38] | [170.97] | [66.36] |
| *Constant* | 46.06** | 49.83** | 526.94** | 516.99*** |
| | [19.82] | [19.78] | [215.78] | [110.02] |
| *Time Effects* | | Yes | | |
| Number of Observations | 2947 | 2947 | 3038 | 2947 |
| Number of Groups | 91 | 91 | 91 | 91 |
| Min. Observations per Group | 13 | 13 | 14 | 13 |
| Avg. Observations per Group | 33.2 | 33.2 | 33.4 | 33.2 |
| Max. Observations per Group | 36 | 36 | 37 | 36 |
| R-squared | 0.4904 | 0.4907 | 0.5795 | 0.4252 |

instead of using the end of quarter information (column 3 of Table 3.7). The third measure corresponds to the GSV (column 4 of Table 3.7).

Comparing columns 1 and 2, we find similar results for both definitions of the NSV. Therefore, our results are robust to the use of either the largest banks (column 1) or all banks in the form of a synthetic bank (column 2) to define the core banks that form the system. The only difference when we sum up the weekly NSV within a given quarter (column 3) with respect to results in column 1 is that the size (correlation with S&P500) are now non-significant (significant).

Regarding the GSV (column 4), which has been found to be the second most reliable measure, we find similar results to those obtained for the baseline specification. Nevertheless, some differences should be mentioned: the explanatory power of the regressors decreases (from 0.49 to 0.43), size now exhibits a significant convex shape, loans to banks and depositary institutions, and maturity mismatch are now positive and significant.

Additionally, we estimate the five systemic risk measures for a portfolio that consists of only the 16 largest banks and compare them on the basis of their relation to the IEV and Granger causality test, obtaining once again that the NSV is the most reliable measure. In fact, the pairwise correlation between the NSV estimated in the baseline analysis and the NSV using a portfolio of the largest 16 banks is, on average, 0.99.

### *3.5.2. Alternative explanatory variables*

As in Brunnermeier et al. (2011) we also use as an explanatory variable the lagged level of bank risk according to its VaR (defined in positive terms) instead of the aggregate lagged level of systemic risk. In this case, the R-squared increases from 0.49 to 0.53 and the effect of the VaR variable is positive and significant at any level of significance. The effect of the remaining explanatory variables is similar to those in the baseline regression. In view of this, our results are robust to the use of the bank's VaR to control for the level of risk in the previous quarter.

To take into account the effect of the degree of concentration in the banking sector, we include the Herfindahl-Hirschman index referred to the banks' total assets as an additional explanatory variable. This variable does not have a significant effect at any level of significance and both the coefficients and levels of significance of the explanatory variables are unchanged with respect to the results obtained in the baseline regression. [41]

### 3.6. Conclusions

The recent financial crisis has exposed the dangers lurking in oversized banking sector balance sheets. One major concern for regulators has been the astonishing growth in derivatives markets and consequently in the swelling of derivatives holdings in banks' balance-sheets. The aim of this paper is to address the extent to which this situation has increased systemic risk.

First, we propose an alternative measure of the individual contribution to systemic risk that is based on the Gross Shapley Vale and that we call Net Shapley Value. This measure allows us to get rid of the idiosyncratic component present in the last measure. Then, we compare alternative systemic risk measures and find that the Net Shapley Value outperforms the others. Using the Net Shapley Value as our proxy for systemic risk we find strong evidence of derivative holdings acting as leading indicators of banks' systemic risk contributions. However, their effects are not alike because credit and foreign exchange derivatives have a positive effect on systemic risk whereas holdings of interest rate and commodity derivatives have a negative effect. The derivatives impact on systemic risk is only found when the derivative is held for trading. Furthermore, we find that before the subprime crisis credit

[41] Detailed results of the alternative specifications are available upon request.

derivatives decreased systemic risk whereas after the crisis increased it. But foreign exchange, interest rate, equity and commodity derivatives influence systemic risk in the same way in both time periods.

Surprisingly, the data suggest that if a bank is net protection buyer its credit derivatives holdings increase its individual contribution to systemic risk. This fact casts doubt on the real role of these controversial instruments with respect to banks' contributions to systemic risk. The concern about heightened counterparty risk around the Lehman Brothers collapse could explain this effect.

Finally, other balance sheet variables are also leading indicators of systemic risk contributions. Increases in the following variables increase systemic risk contributions: total loans, net balance to banks belonging to the same banking group, leverage ratio and the proportion of non-performing loans (measured in this case relative to total loans), on the other hand, increases in total deposits decreases systemic risk. The variables with the highest economic impact on systemic risk are the proportion of non-performing loans to total loans and the leverage ratio. In fact, in terms of economic impact on systemic risk, the balance sheet items related to traditional banking activities (leverage, non-performing loans) have the stronger effect.

Our results provide some implications for regulators and bankers alike. The move toward increasing derivatives holdings might be endogenous to the banking industry, in the sense that it was first originated by banks themselves. In the last years banks shifted their activities from the traditional lending activities toward, a priori, more profitable ones, like trading derivatives. But the reasons for doing that are related to low profitability of traditional activities. Based on the endogeneity of this move toward activities that increased profitability at the price of higher exposure to market risks, our paper suggest that some of these activities, in particular trading in interest rate derivatives had actually reduced the contribution of individual banks to systemic risk. On the other hand, trading in foreign exchange and credit derivatives (during the crisis) had increased their contributions to systemic risk. So the claims that all derivatives have pernicious effects on the overall financial system are not borne out by the data. Therefore, the process of re-regulation that is under way in many countries should be carefully designed to avoid hindering activities that are actually diminishing systemic risk. Financial stability is a public good that can inform corporate investment and financing decisions and thus any new regulatory initiative should be very carefully designed to give the different instruments within an asset class, in this case, derivatives, the appropriate regulatory oversight.

On the other hand, given the empirical evidence reported in this paper, the economic impact of non-performing loans and leverage on systemic risk is much stronger than the derivatives' impact. Therefore the traditional banking activities related to these two items should be closely watched by regulators worried about systemic risk episodes.

# Chapter 4 Liquidity commonalities in the corporate CDS market around the 2007-2012 financial crisis

### 4.1. Introduction

One of the key issues highlighted by the ongoing financial crisis is the role of the shortage of liquidity in financial markets. In this period we have witnessed severe episodes of liquidity shortage in many markets being this shortage especially noticeable in the Credit Default Swap (CDS) market because of the uncertainty about the net amount, the structure, and the counterparty risk of such exposures. As a consequence, many firms have had difficulties to timely manage their credit risk exposures. This situation posed important challenges at the individual level but also from a global stability perspective. These facts point out the importance of considering the extent to which the shortage of liquidity has spread over the different contracts traded in the CDS market, and the factors that affect such scarcity.

This paper focuses on factors that may affect this shortage in market liquidity, and specifically the extent to which liquidity commonalities in the CDS market are of material importance in this regard. Liquidity commonalities can be defined as the co-movement of individual liquidity measures with market- and industry-wide liquidity. The objective of this paper is to provide new evidence on the co-movement in liquidity for the CDS market, which was firstly documented by Pu (2009), from a threefold perspective: first, the analysis of the time-varying behavior of the commonalities putting special emphasis on the financial crisis events; secondly, the use of different economic areas and industries for the analysis of such commonalities; and, thirdly the analysis of the factors influencing this co-movement at both aggregate and firm levels.

The typology of the participants in the CDS market, the high degree of concentration, and the role of credit derivatives during the financial crisis affecting both the financial sector and real economy make the analysis of the existence and the behavior of liquidity commonalities in the CDS market a topic of special relevance for regulators, risk managers, and investors. The fact that the main participants in the CDS market are systemically important financial institutions (SIFIs) facilitates that any shock affecting credit derivatives could revert directly on these institutions and could have implications in terms of financial stability. In this line, in Chapter 3 we show that the holdings of credit derivatives by U.S. banks affected their contributions to systemic risk, such that these derivatives behaved as shock absorbers before the financial crisis but changed their role to shock issuers during the crisis. It is worth mentioning that the liquidity risk derived from the typology of the banks participating in the CDS market could be exacerbated by the high degree of concentration of the market activity in the hands of a few SIFIs acting as market participants.[42] This high degree of market concentration may have implications in terms of the impact of large shocks on market liquidity. In fact, Mayordomo and Peña (2012) show that liquidity commonalities have significant effects on the pricing of the CDS of European non-financial firms and on the co-movements among CDS prices during the recent financial crisis.

The analysis of the determinants of the commonalities in liquidity is also certainly a timely topic because, as remarked by Dewatripont et al. (2010), developing a better understanding of what drives illiquidity at the individual and aggregate levels should stand high on the agenda of economists and policy makers alike.

[42] According to a survey of U.S. firms by Fitch (2009), 96% of credit derivative exposures at the end of the first quarter of 2009 were concentrated in five firms (JPMorgan, Goldman Sachs, Citigroup, Morgan Stanley, and Bank of America). In the same line, the European Central Bank (2009) reports that the five largest CDS dealers were counterparties to almost half of the total outstanding notional amount in April 2009; being the ten largest dealers counterparties to 72% of the trades and the Bank of International Settlements reports that globally, the ten largest dealers account for 90% of trading volume by gross notional amount, being the 30% of the global activity generated by just one bank (JP Morgan).

We contribute with several findings to the empirical literature on liquidity commonalities. We document the existence of significant co-movements between single-name CDS liquidity and market-wide liquidity. Market commonalities are stronger than industry commonalities in most industries, with the exception of the banking sector. The liquidity commonalities are still present when we analyze separately the CDSs of companies located in different economic areas, but the degree of commonality differs across them. Moreover, the liquidity commonalities are time-varying and increase in times of financial distress characterized by high counterparty, global, and funding liquidity risks but they do not depend on firms' specific characteristics. In this line, we find that the Lehman Brothers collapse and the Greek bailout requests triggered a significant increase in commonalities. In fact, the results suggest the existence of asymmetries in commonalities around these episodes of financial distress, such that the effect on market liquidity is stronger when the CDS market price increases. Finally, we find that liquidity commonalities provide additional information relative to the three aforementioned aggregate risks around these periods. All these results are robust to alternative liquidity measures and are not driven by the CDS data imputation method or by the firms with the highest CDS prices.

The rest of this article is organized as follows. Section 4.2 presents a literature review. In Section 4.3 we describe the liquidity measures and the methodology. Section 4.4 describes the data. Section 4.5 reports the empirical findings regarding the existence of liquidity commonalities. Section 4.6 reports the results of the determinants of these commonalities. In Section 4.7 we present some robustness tests, and we conclude in Section 4.8.

## 4.2. Literature review

The Acharya and Pedersen's (2005) liquidity-adjusted Capital Asset Pricing Model (CAPM) yields three effects, besides the covariance between the asset's return and the market return, that provide a characterization of the liquidity risk of a security. The first of these effects on expected returns is due to the covariance between a security's expected return and the market liquidity. The second effect on expected returns is due to the co-variation between a security's illiquidity and the market return. The third of these effects is that the return increases with the covariance between the asset's illiquidity and the market illiquidity given that investors want to be compensated for holding a security that becomes illiquid when the market in general becomes illiquid. This last component is the common factor in liquidity or liquidity commonalities documented in the stock market by Chordia et al. (2000), Hasbrouck and Seppi (2001), and Huberman and Halka (2001).

Our paper belongs to the growing literature on liquidity risk and follows the Chordia, et al.'s (2000) methodology to study the time-varying nature and the determinants of the liquidity commonalities in the CDS market. Thus, the other two liquidity risk components and the effect of the liquidity commonalities on the CDS premium are beyond the scope of this paper.

Several methodologies have been used to study the existence of liquidity commonalities.[43] A detailed comparison of the different estimators can be found in Anderson et al. (2010). These authors distinguish two classes of methodologies for the estimation of systematic liquidity: (1) weighted average estimators based on concurrent liquidity shocks (the one employed in our study), and (2) principal component estimators based on both concurrent and past liquidity shocks. Their results show that the two types of estimators are largely equivalent because the simpler estimators give, in most cases, similar results to the complex estimators under different evaluation criteria and liquidity measures. Following Chordia et al. (2000),

[43] There is a wide array of variables to measure liquidity but one of the most common liquidity measures employed in the fixed-income and the CDS literature is the bid–ask spread. In fact, Fleming (2003) finds that the bid–ask spread is the best measure of liquidity in the bond market. For this reason, the primary liquidity measure employed in our baseline analysis focuses on the bid–ask spread.

we use cross-sectional equally weighted averages to construct the market liquidity measure employed for the estimation of liquidity commonalities.

The existence of liquidity commonalities has been documented for many assets independently of the dimension of liquidity and the geographical area analyzed. The foremost market in which liquidity commonalities have been documented is the stock market (see Chordia et al., 2000; Hasbrouck and Seppi, 2001; Huberman and Halka, 2001; Brockman and Chung, 2002; Domowitz et al., 2005; Kamara et al., 2008; Kempf and Mayston, 2008; or Korajczyk and Sadka, 2008; among others). Liquidity commonalities across different stock markets located in different countries have also been documented by previous literature (see for instance Brockman et al., 2009; Karolyi et al., 2009; or Zhang et al., 2009).

There are also several examples of analysis of liquidity commonalities for other markets in addition to the stock market. Thus, Chordia et al. (2005) and Goyenko (2009) document the commonality in liquidity for stocks and bonds in the United States (U.S.) market. Liquidity commonalities are also documented by Marshall et al. (2010) in the commodities markets and by Cao and Wei (2010) in the options market. Cao and Wei (2010) find strong commonalities in the option market but these commonalities are lower than those of the stock market.

However in the case of the CDS market this topic has been barely addressed. Pu's (2009) is the first paper that considers explicitly the commonalities in the CDS market. This author finds a strong commonality across all liquidity measures in the CDS market and also in the bond market using monthly data from 2002 to 2005 for a sample of non-financial U.S. firms. The method employed by Pu (2009) to extract the common factors from each liquidity measure is an asymptotic principal component analysis.

Liquidity commonalities in the CDS market are also treated indirectly in other papers such as Bongaerts et al. (2011) and Jacoby et al. (2009). Bongaerts et al. (2011) derive and estimate a model for the pricing of liquidity in the CDS market. Among the variables considered is the level of liquidity commonalities that is obtained from a principal component analysis across CDS portfolios. The first factor of this analysis explains 16.6% of the liquidity variation. Jacoby et al. (2009) analyze the existence of liquidity spillover shocks across the CDS, corporate bond, and equity markets and find a dominant first principal component in the CDS market for the CDS liquidity measures considered. Other papers that study the determinants of bid-ask spread use market liquidity as an additional driver of individual CDSs' liquidity (e.g. Meng and ap Gwilym, 2008; or Tang and Yan, 2008).

The aim of this paper is not to study the effect the determinants of bid-ask spreads but to estimate the effect of market liquidity on the individual CDS liquidity according to the standard methodology of liquidity commonalities. We share some of the objectives pursued by Pu (2009) but in contrast to her analysis, our study is carried out using daily data that covers the recent financial crisis and documents both the time varying behavior of liquidity commonalities and their determinants during this crisis. Additionally, our paper exploits a much more extensive database which allows us to deal explicitly with the differences in terms of commonalities of the different economic areas besides the US, and also to include firms from all sectors.

Besides documenting the existence of commonalities in liquidity, other stream of the literature analyzes the drivers of such commonalities. In one of these papers, Coughenour and Saad (2004) find that the individual stock liquidity co-varies with specialist portfolio liquidity given that the specialist firms that participate in the stock market provide liquidity for more than one common stock. This co-variation increases with the risk of providing liquidity. The role of capital constraints on stock market liquidity commonality is documented by Comerton-Forde et al. (2010) and Brunnermeier and Pedersen (2009).

Brunnermeier and Pedersen (2009) find that the effect of funding constraints is particularly important during market downturns. Situations of market stress have also been found to affect liquidity commonalities. Thus, Kempf and Mayston (2005) find that the commonality in the stock market is much stronger in falling markets than in rising markets. Brockman and Chung (2008) find that commonality in order-driven markets (in their case the Hong Kong Stock Exchange) increases during periods of market stress.

As Anderson et al. (2010) suggest, the degree and variation of commonality in liquidity could also be affected by the concentration of market makers and the type of trading. In fact, Kamara et al. (2008) find that increases in institutional ownership are associated with increases in stocks' sensitivity to systematic liquidity shocks. These authors show that during the period 1963 2005 commonality in liquidity increased significantly for large-cap stocks, in which institutional investing and index trading were more concentrated, but declined significantly for small-cap stocks.

In the best of our knowledge ours is the first paper documenting the determinants of liquidity commonalities in the CDS market at both aggregate and firm levels. We find that the level of liquidity commonalities is related to a large extent to global risk factors and therefore this level seems to be a potentially useful instrument to monitor global risk.

## 4.3. Liquidity measures and methodology

### *4.3.1. Liquidity measures*

Our baseline liquidity measure is the relative quoted spread (RQS), for a given firm *j* at time *t* defined as:

$$RQS_{j,t} = \frac{Ask_{j,t} - Bid_{j,t}}{\frac{(Ask_{j,t} + Bid_{j,t})}{2}} \tag{4.1}$$

This measure has been widely employed in the previous literature and avoids any bias in the results due to the dependence on the level of the CDS premium or the degree of risk as could be the case when one uses the bid ask CDS spread in absolute terms. However, to ensure that the results do not depend solely on the liquidity specification we use other liquidity measures:

- The absolute bid ask spread (AQS) defined as the difference between CDS ask and bid prices without rescaling by the mid spread as in the RQS (Equation 4.1).
- Number of contributed quotes in a given day, which represents the depth of the consortium liquidity.
- Number of contributors: the number of contributors providing quotes, which represents the breadth of the consortium coverage.
- The gross and net weekly traded notional CDS amount outstanding and the number of contracts outstanding.[44]

### *4.3.2. Estimation methodology of liquidity commonalities*

#### *4.3.2.1. Baseline market model*

[44] For a single reference entity, the gross notional values are the sum of CDS contracts bought (or equivalent sold) for all warehouse contracts and the net notional values present the sum of the net protection bought by net buyers (or equivalently net protection sold by net sellers).

As in Chordia et al. (2000), we use the following "market model" time series regression that is estimated by means of Ordinary Least Squares (OLS):

$$DL_{j,t} = \alpha_j + \beta_{1j}\, DL_{M,j,t-1} + \beta_{2j} DL_{M,j,t} + \beta_{3j}\, DL_{M,j,t+1} + \beta_{4j} DS_{M,j,t-1} + \beta_{5j} DS_{M,j,t} + \beta_{6j} DS_{M,j,t+1} + \beta_{7j} DS_{j,t}^2 + \varepsilon_{t,j} \quad for\ j = 1, \ldots, 438 \tag{4.2}$$

where $DL_{j,t}$ represents the daily percentage changes of the relative quoted spread for firm $j$ ($RQS_{j,t}$). $DL_{M,j,t}$ and $DS_{M,j,t}$ are the percentage changes of the contemporaneous market liquidity and market CDS premium, respectively, and are obtained as an equally weighted average of the individual percentage changes in the liquidity measure ($DL_{j,t}$) and in the CDS prices ($DS_{j,t}$) of all the firms with the exception of firm *j*:[45]

$$DL_{M,j,t} = \frac{\sum_{i=1\ i \neq j}^{n} DL_{i,t}}{n-1} \text{ and } DS_{M,j,t} = \frac{\sum_{i=1\ i \neq j}^{n} DS_{i,t}}{n-1} \quad for\ j = 1, \ldots, 438 \tag{4.3}$$

We use one lag and one lead of the market liquidity percentage changes ($DL_{M,j,t-1}$ and $DL_{M,j,t+1}$) and the market CDS premium percentage changes ($DS_{M,j,t-1}$ and $DS_{M,j,t+1}$). These leads and lags are used to capture any lagged spurious dependence induced by an association between returns and spread measures. Finally, $DS_{j,t}^2$ denotes the square of the CDS premium return for firm *j* and it is employed to proxy for single-firm volatility.[46] The use of percentage changes rather than levels is due to two reasons: (i) our interest lies in testing whether liquidity co-moves and (ii) liquidity levels are more likely to follow non-stationary processes.

We estimate Equation 4.2 at two levels. On the one hand, we estimate the annual coefficients using daily information for every calendar year such that we have annual estimations of the

[45] The exclusion of one CDS avoids constraints on the average coefficients. If one uses all the CDS to compute the equally weighted average, the cross-sectional mean of the coefficients is constrained to exactly a unit. The potential effects of cross-sectional dependence on the estimated coefficients due to the use of each individual liquidity measure as a component of the explanatory variables for all the other regressions are investigated in the robustness test section.

[46] The average correlation between the square of the CDS premium return and the percentage changes of the relative quoted spread is 0.03 what confirms that the volatility measure is not related to liquidity.

commonalities from 2005 to 2011. On the other hand, we estimate the daily coefficients using 1-year rolling windows such that we obtain a daily measure of commonalities on the basis of the one year ago observations.

Additionally, we estimate Equation 4.2 by OLS with a new definition of the market liquidity and credit risk variables using value weighted averages instead of equally weighted averages as it was done in Equation 4.3:

$$DL_{j,t} = \alpha_j + \beta_{1j}\, DL_{WM,j,t-1} + \beta_{2j} DL_{WM,j,t} + \beta_{3j}\, DL_{WM,j,t+1} + \beta_{4j} DS_{WM,j,t-1} + \beta_{5j} DS_{WM,j,t} + \beta_{6j} DS_{WM,j,t+1} + \beta_{7j} DS^2_{j,t} + \varepsilon_{t,j} \quad for\ j = 1, \dots, 438 \tag{4.4}$$

where $DL_{WM,j,t}$ and $DS_{WM,j,t}$ represent the percentage changes in the value weighted market liquidity and market CDS premium variables. For every firm, the weights are proportional to its market value relative to the sum of market values of the 437 firms that form the considered market. As we are using firms from different countries the market values are uniformly defined in U.S. Dollars.[47]

The 438 reference entities employed in this paper correspond to 25 countries that we assign to 5 economic areas. Due to their heterogeneity, we alternatively construct the market liquidity and market CDS premium measures at economic area level (i.e., using only the firms that belong to the same economic area of firm $j$ in Equation 4.3. Then, we use these new measures as explanatory variables to estimate the liquidity commonalities by OLS according to the specification of Equation 4.5.

$$DL_{j,t} = \alpha_j + \beta_{1j}\, DL_{M,i,j,t-1} + \beta_{2j} DL_{M,i,j,t} + \beta_{3j}\, DL_{M,i,j,t+1} + \beta_{4j} DS_{M,i,j,t-1} + \beta_{5j} DS_{M,i,j,t} + \beta_{6j} DS_{M,i,j,t+1} + \beta_{7j} DS^2_{j,t} + \varepsilon_{t,j} \quad for\ j = 1, \dots, 438 \text{ and } \mathrm{i} = 1, \dots, 5 \tag{4.5}$$

[47] Market values converted to the common currency are directly downloaded from Datastream. This database uses the corresponding daily exchange rate to convert the market value in the domestic currency to USD.

where $DL_{M,i,j,t}$ and $DS_{M,i,j,t}$ represent the percentage changes in the equally weighted market liquidity and market returns variables of economic area *i*.

*4.3.2.2. Market model with asymmetries in liquidity commonalities*

We next split up the contemporaneous effect of the market liquidity variable into two effects depending on whether the market CDS returns have a positive or negative sign. For such aim, we use two interaction variables obtained as the product of the percentage changes in market liquidity and two different dummy variables: (i) a dummy $\left(d_t^{up}\right)$ that takes value one when the market CDS premium is going up at a given date; and (ii) a dummy $\left(d_t^{down}\right)$ that takes value one when the market CDS premium is going down. We use the same methodology as in Equation 4.2 but excluding the lagged and lead values of the changes in market liquidity from the estimation such that the new equation is defined as follows:

$$DL_{j,t} = \alpha_j + \beta_{1j}\, d_t^{up} DL_{M,j,t} + \beta_{2j} d_t^{down} DL_{M,j,t} + \beta_{3j}\, DS_{M,j,t-1} + \beta_{4j} DS_{M,j,t} + \beta_{5j} DS_{M,j,t+1} + \beta_{6\,j} DS_{j,t}^2 + \varepsilon_{t,j} \quad for\; j = 1, \dots, 438 \tag{4.6}$$

*4.3.2.3. Two variations of the standard market model*

We first examine in more detail the effect of liquidity commonalities using both market and industry equally weighted liquidity measures. We add lagged, contemporaneous, and leading industry liquidity variables to Equation 4.2:

$$DL_{j,t} = \alpha_j + \beta_{1j}\, DL_{M,j,t-1} + \beta_{2j} DL_{M,j,t} + \beta_{3j}\, DL_{M,j,t+1} + \beta_{4j} DS_{M,j,t-1} + \beta_{5j} DS_{M,j,t} + \beta_{6\,j} DS_{M,j,t+1} + \beta_{7j} DS_{j,t}^2 + \beta_{8j}\, DL_{I,j,t-1} + \beta_{9j} DL_{I,j,t} + \beta_{10j} DL_{I,j,t+1} + \varepsilon_{t,j} \quad for\; j = 1, \dots, 438 \tag{4.7}$$

where $DL_{I,j,t}$ is the percentage change in the industry liquidity, obtained using only the firms that belong to the same industry that firm $j$ in Equation 4.3. We consider 28 out of 41 industries distinguished by the Industry Classification Benchmark (ICB), which is available from Datastream.[48]

We then test the hypothesis that the reference entities with the highest credit risk could be the ones causing the commonality effect. For this reason, we add to the explanatory variable group collected in Equation 4.2 the percentage changes of the contemporaneous ($DL_{C,j,t}$), lagged ($DL_{C,j,t-1}$), and leading ($DL_{C,j,t+1}$) high credit risk firms' liquidity measure that is constructed using only the firms that belong to the top quartile according to their level of CDS prices in Equation 4.3:[49]

$$DL_{j,t} = \alpha_j + \beta_{1j}\, DL_{M,j,t-1} + \beta_{2j} DL_{M,j,t} + \beta_{3j}\, DL_{M,j,t+1} + \beta_{4j} DS_{M,j,t-1} + \beta_{5j} DS_{M,j,t} + \beta_{6j} DS_{M,j,t+1} + \beta_{7j} DS_{j,t}^2 + \beta_{8j}\, DL_{C,j,t-1} + \beta_{9j} DL_{C,j,t} + \beta_{10j} DL_{C,j,t+1} + \varepsilon_{t,j} \;\; for\; j = 1, \dots ,438 \qquad (4.8)$$

### *4.3.3. Estimation methodology of the determinants of liquidity commonalities*

We study the determinants of liquidity commonalties at aggregate and firm levels. To proceed with the former analysis we first estimate the individual monthly liquidity commonalities using daily information for every calendar month where the market model is a variation of Equation 4.2 in which we do not include the leads and lags of any variable:

$$DL_{j,t} = \alpha + \beta_{1,j} DL_{M,j,t} + \beta_{2,j} DS_{M,j,t} + \beta_{3,j} DS_{j,t}^2 + \varepsilon_{t,j} \quad \text{for j} = 1, \dots ,438 \qquad (4.9)$$

We next construct the monthly aggregate beta as the median of the firm's betas referring to the contemporaneous market liquidity ($\beta_{1,j}$ in Equation 4.9). Finally, we conduct the following analysis:

$$Median(\beta_1)_m = \eta_0 + \eta_1\, Risk\ Factor_m + \varepsilon_m \qquad (4.10)$$

[48] No information on CDS is available for the firms of the remaining 13 sectors in the ICB classification system

[49] The classification of a given firm among the firms in the top quartile according to the CDS premia is performed on an annual basis. Alternatively we could use credit ratings instead of CDS premia. Both measures should give an equivalent stratification. Nevertheless, we use CDS prices because according to previous literature (see Hull et al., 2004, among others), the CDS premia seem to anticipate the rating announcements.

in which we regress the aggregate betas for every month *m* on the monthly averages of three risk factors: global risk, global liquidity/ funding costs, and counterparty risk in the CDS market. We use a robust to heteroskedasticy OLS methodology to estimate the effect of the above variables.

The analysis of the determinants of the market liquidity on individual liquidity is carried out on the basis of the daily liquidity commonalities estimated in Equation 4.2 using 1-year rolling windows. Concretely, we use the sum of the betas for the lagged, contemporaneous and lead market liquidity measures as the dependent variable. As the liquidity commonalities are based on overlapping information, we run a Fama-MacBeth cross-sectional regression for every day in the sample to avoid time series dependencies and to exploit the cross-sectional dimension. The standard errors are corrected for autocorrelation using the Newey-West methodology.[50]

$$Sum\ Betas_{i,t} = \delta_0 + \delta_1 Firm\ Info_{i,t} + \delta_2 Country\ Info_{i,t} + \varepsilon_i \quad where\ \ t = 1, \dots, 1625 \qquad (4.11)$$

Among the determinants of the co-variation between the CDS and market illiquidity measures we use firm and country specific variables. Among the former variables, we use proxies for the firm size, leverage, level of credit risk, and firm shares' squared returns (volatility). Among the variables referred to the country of origin of the firm, we use proxies for the volatility of the stock indexes and 3-month interbank interest rate.

## 4.4. Data

The data consist of daily 5-year CDS information for 438 listed firms from 25 countries and span from 1 January 2005 to 31 March 2012.[51] Due to the variety of countries and to ensure a

[50] The number of lags employed in the Newey-West regressions must grow with the sample size to ensure consistency when the moment conditions are dependent. We use a lag length determined by the widely employed method of the number of observations raised to the power of 1/3 that is equal to 12 lags.
[51] The sample does not include sovereign or unlisted reference entities. The use of the 5-year maturity CDS contracts is due to the higher liquidity in these contracts. The reference entities belong to the following countries

minimum number of firms in subsequent analysis we group them into 5 economic areas: the U.S. (236 firms), the European Monetary Union (E.M.U., 108 firms), the United Kingdom (U.K., 41 firms), Japan (15 firms), and Others (28 firms).

CDS information is obtained from Credit Market Analysis (CMA), an independent CDS data provider that is part of the Chicago Mercantile Exchange. CMA sources its CDS data from a consortium consisting of around 40 members of the buy-side community (hedge funds, asset managers, and major investment banks) who are active participants in the CDS market. CMA is found to be one of the more reliable CDS data sources by Mayordomo et al. (2010).

The information reported by CMA includes: (i) bid/mid/ask CDS premia for the 0.5 to 10 year maturities; (ii) an observed/derived indicator, which indicates whether the published level was observed in the market or implied through a model using recently observed quotes;[52] (iii) the number of contributors, which is the number of contributors providing quotes; (iv) contributed quotes, which reports the number of contributed quotes on a given day. The number of contributors and quotes is only available from June 2008. The nature of the CMA data supposes an advantage for the use of the bid ask spread as a measure of liquidity, in addition to the other measures employed in the robustness test, because of the use of information from the buy sell sides.

The information for the gross and net notional CDS amount and the number of contracts outstanding for each reference firm is obtained from the Depository Trust and Clearing Corporation's (DTCC). These data are only available for 399 of the 438 firms since November 2008 and with a weekly frequency.

(the number of firms in each country in brackets): the United States (236), the United Kingdom (41), France (35), Germany (24), Japan (15), Canada (11), Italy (9), the Netherlands (9), Switzerland (7), Australia (6), Finland (6), Spain (6), Sweden (6), Hong Kong (5), South Korea (4), Belgium (3), Malaysia (3), Portugal (3), Ireland (2), Singapore (2), Austria (1), Denmark (1), Greece (1), New Zealand (1), and Norway (1).

[52] CMA considers a CDS price as observed when they receive three different prices from at least two members of its consortium. The CDS prices that do not fulfill this principle become derived prices.

Next, we briefly describe the information employed to construct the remaining variables and their sources. Information referring to global risk, which is proxied by the implied volatility index (VIX), is obtained from Reuters.[53] Due to the difficulty in obtaining data on institutional-level funding constraints, we proxy the funding costs by means of the difference between the 90-day U.S. AA-rated commercial paper interest rates for the financial companies and the 90-day U.S. T-bill which should be a proxy for the funding cost faced by AAA-rated financial investors. Both rates jointly with the 3-month interbank rate and the country stock indexes are obtained from Datastream. As in Arce et al. (2012), we compute the proxy for counterparty risk by means of the first principal component obtained from the CDS premium of the main banks acting as dealers in the market. The information on the banks CDSs is obtained from CMA. The first principal component series should reflect the common default probability that is an aggregate measure of counterparty risk.[54] The information on the firms' stock prices, market capitalization, total debt and total assets is obtained from Datastream.

Table 4.1 summarizes the most salient features of the descriptive statistics for related information to the sample of CDS contracts. For the sake of brevity we focus on the annual cross-sectional average of the mean, median and standard deviation (SD) from 2005 to 2011. We also provide information about 2012 which refers to the first quarter of that year. Looking at the CDS premium levels, we observe a gradual increase in the levels and their volatilities from 2005 to 2009 and this behavior is common in both the total sample and in the economic areas. In 2010 CDS prices perform on average a generalized drop. Average CDS prices

[53] According to Lustig et al. (2011) "the VIX seems like a good proxy for the global risk factor. The VIX is highly correlated with similar volatility indices abroad".
[54] We use the 14 main banks acting as dealers in the CDS market. The first PC for the series of CDS prices of the previous dealers explains 90% of the total variance.

increase again in all economic areas apart from the U.S. in 2011 as a consequence of the deterioration of the economic situation worldwide and especially in Europe.

**Table 4.1 Descriptive statistics**

This table summarizes the annual cross-sectional average of the mean, median and standard deviation (SD) of liquidity and credit risk measures for the whole sample of CDS contracts employed in our analysis from 2005 to 2012. It is divided into six categories: Total, U.S., E.M.U., U.K., Japan and Others, where the former refers to the 438 sample firms and the remainder categories refer to the firms belonging to that economic area (the exact number of firms is in brackets in the first column). Column (1) shows the individual CDS prices, Column (2) the quoted spreads, Column (3) the relative quoted spreads, and Column (4) the squared CDS premium return. The CDS quoted spread (relative quoted spread) is obtained as the CDS bid–ask spread (as the ratio of the CDS bid–ask spread to the CDS mid-price).

*Information relating to 2012 refers to the first quarter of that year.

| | | CDS Premium | | | Bid Ask Spread | | | Relative Bid Ask Spread | | | Squared CDS Return | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Mean | Median | SD | Mean | Median | SD | Mean | Median | SD | Mean | Median | SD |
| Total (438) | 2005 | 74.1 | 73.2 | 16.6 | 7.4 | 7.1 | 2.8 | 0.15 | 0.15 | 0.05 | 0.003 | 0.001 | 0.01 |
| | 2006 | 65.0 | 64.3 | 12.2 | 5.2 | 5.1 | 1.7 | 0.15 | 0.14 | 0.05 | 0.002 | 0.000 | 0.01 |
| | 2007 | 73.7 | 64.2 | 27.5 | 6.0 | 5.1 | 2.5 | 0.14 | 0.14 | 0.04 | 0.004 | 0.000 | 0.02 |
| | 2008 | 250.0 | 201.7 | 136.1 | 19.9 | 13.8 | 16.4 | 0.09 | 0.09 | 0.03 | 0.004 | 0.001 | 0.01 |
| | 2009 | 328.2 | 286.4 | 151.8 | 21.3 | 19.0 | 10.0 | 0.09 | 0.09 | 0.03 | 0.002 | 0.000 | 0.01 |
| | 2010 | 201.9 | 194.1 | 52.3 | 11.1 | 10.5 | 3.3 | 0.08 | 0.07 | 0.02 | 0.001 | 0.000 | 0.01 |
| | 2011 | 220.5 | 186.5 | 78.9 | 13.0 | 10.4 | 5.8 | 0.07 | 0.07 | 0.02 | 0.001 | 0.000 | 0.01 |
| | 2012* | 257.9 | 256.2 | 34.4 | 15.6 | 15.4 | 2.9 | 0.09 | 0.09 | 0.01 | 0.001 | 0.000 | 0.00 |
| U.S. (236) | 2005 | 90.5 | 89.7 | 20.7 | 9.0 | 8.8 | 3.4 | 0.15 | 0.15 | 0.05 | 0.003 | 0.001 | 0.01 |
| | 2006 | 80.2 | 79.6 | 14.6 | 6.0 | 5.7 | 1.9 | 0.14 | 0.13 | 0.05 | 0.002 | 0.000 | 0.01 |
| | 2007 | 95.4 | 84.3 | 35.4 | 7.2 | 6.1 | 3.1 | 0.14 | 0.13 | 0.04 | 0.004 | 0.000 | 0.02 |
| | 2008 | 316.2 | 254.6 | 173.4 | 24.5 | 16.8 | 21.7 | 0.08 | 0.08 | 0.03 | 0.003 | 0.001 | 0.01 |
| | 2009 | 421.7 | 364.6 | 200.6 | 23.8 | 21.1 | 10.8 | 0.09 | 0.09 | 0.02 | 0.002 | 0.000 | 0.01 |
| | 2010 | 254.8 | 241.8 | 72.5 | 13.0 | 12.3 | 3.7 | 0.08 | 0.07 | 0.02 | 0.001 | 0.000 | 0.01 |
| | 2011 | 244.7 | 206.4 | 91.6 | 13.1 | 10.6 | 5.4 | 0.08 | 0.07 | 0.02 | 0.001 | 0.000 | 0.01 |
| | 2012* | 289.3 | 291.3 | 37.7 | 15.8 | 15.7 | 2.8 | 0.09 | 0.09 | 0.01 | 0.001 | 0.000 | 0.00 |
| E.M.U. (99) | 2005 | 53.2 | 52.5 | 11.2 | 5.0 | 4.8 | 1.9 | 0.14 | 0.13 | 0.05 | 0.002 | 0.000 | 0.01 |
| | 2006 | 46.5 | 45.9 | 9.0 | 3.8 | 3.7 | 1.2 | 0.13 | 0.13 | 0.04 | 0.002 | 0.000 | 0.01 |
| | 2007 | 48.8 | 40.2 | 19.3 | 3.9 | 3.3 | 1.7 | 0.12 | 0.12 | 0.04 | 0.003 | 0.000 | 0.02 |
| | 2008 | 178.8 | 144.6 | 98.8 | 13.1 | 9.2 | 9.9 | 0.08 | 0.08 | 0.03 | 0.004 | 0.001 | 0.01 |
| | 2009 | 243.9 | 226.7 | 96.7 | 16.8 | 15.6 | 8.0 | 0.08 | 0.08 | 0.02 | 0.001 | 0.000 | 0.00 |
| | 2010 | 167.3 | 165.7 | 38.1 | 9.1 | 8.6 | 3.2 | 0.06 | 0.06 | 0.01 | 0.002 | 0.000 | 0.00 |
| | 2011 | 248.0 | 207.5 | 89.9 | 15.2 | 11.7 | 7.6 | 0.06 | 0.06 | 0.02 | 0.002 | 0.000 | 0.01 |
| | 2012* | 287.5 | 277.6 | 41.2 | 16.9 | 16.8 | 3.4 | 0.07 | 0.07 | 0.01 | 0.001 | 0.000 | 0.00 |
| U.K. (41) | 2005 | 62.4 | 62.3 | 12.6 | 6.0 | 5.7 | 2.2 | 0.15 | 0.14 | 0.06 | 0.003 | 0.000 | 0.01 |
| | 2006 | 52.4 | 50.6 | 10.2 | 4.7 | 4.6 | 1.6 | 0.16 | 0.15 | 0.06 | 0.002 | 0.000 | 0.00 |
| | 2007 | 57.9 | 50.0 | 20.7 | 4.9 | 4.3 | 2.1 | 0.13 | 0.13 | 0.04 | 0.003 | 0.000 | 0.01 |
| | 2008 | 182.4 | 147.6 | 96.3 | 14.5 | 10.6 | 10.0 | 0.09 | 0.08 | 0.03 | 0.003 | 0.001 | 0.01 |
| | 2009 | 212.0 | 186.5 | 97.6 | 18.6 | 15.4 | 10.1 | 0.10 | 0.09 | 0.03 | 0.001 | 0.000 | 0.00 |
| | 2010 | 130.6 | 127.8 | 25.1 | 8.8 | 8.6 | 2.4 | 0.07 | 0.07 | 0.01 | 0.001 | 0.000 | 0.00 |
| | 2011 | 149.2 | 135.0 | 33.5 | 10.5 | 8.7 | 4.2 | 0.08 | 0.07 | 0.02 | 0.001 | 0.000 | 0.01 |
| | 2012* | 153.9 | 152.7 | 20.8 | 13.3 | 13.2 | 2.5 | 0.10 | 0.10 | 0.02 | 0.001 | 0.000 | 0.00 |
| Japan (15) | 2005 | 40.0 | 34.0 | 18.2 | 7.1 | 5.3 | 5.1 | 0.26 | 0.25 | 0.07 | 0.004 | 0.000 | 0.01 |
| | 2006 | 35.2 | 33.8 | 8.8 | 6.0 | 5.5 | 2.2 | 0.23 | 0.22 | 0.07 | 0.002 | 0.000 | 0.01 |
| | 2007 | 31.0 | 27.7 | 9.4 | 6.3 | 5.5 | 2.3 | 0.29 | 0.29 | 0.07 | 0.005 | 0.000 | 0.03 |
| | 2008 | 122.5 | 95.1 | 74.5 | 20.8 | 15.6 | 14.2 | 0.22 | 0.20 | 0.09 | 0.007 | 0.001 | 0.02 |
| | 2009 | 197.6 | 141.0 | 118.9 | 33.7 | 27.5 | 20.1 | 0.22 | 0.21 | 0.08 | 0.003 | 0.000 | 0.01 |
| | 2010 | 87.3 | 85.7 | 17.9 | 9.9 | 9.3 | 3.1 | 0.12 | 0.12 | 0.03 | 0.001 | 0.000 | 0.01 |
| | 2011 | 103.7 | 94.0 | 28.4 | 10.6 | 8.8 | 4.4 | 0.11 | 0.10 | 0.03 | 0.002 | 0.000 | 0.01 |
| | 2012* | 125.8 | 124.3 | 14.3 | 13.1 | 12.8 | 1.9 | 0.11 | 0.11 | 0.01 | 0.002 | 0.000 | 0.01 |
| Others (47) | 2005 | 56.9 | 55.9 | 10.4 | 5.9 | 5.5 | 2.0 | 0.17 | 0.16 | 0.06 | 0.003 | 0.001 | 0.01 |
| | 2006 | 48.6 | 48.0 | 9.9 | 4.9 | 4.7 | 1.5 | 0.16 | 0.15 | 0.05 | 0.002 | 0.000 | 0.01 |
| | 2007 | 45.2 | 37.7 | 17.0 | 5.1 | 4.6 | 1.9 | 0.17 | 0.16 | 0.05 | 0.004 | 0.000 | 0.02 |
| | 2008 | 167.4 | 137.0 | 82.3 | 15.1 | 11.1 | 9.8 | 0.10 | 0.10 | 0.03 | 0.005 | 0.001 | 0.02 |
| | 2009 | 179.8 | 153.0 | 80.8 | 16.8 | 16.1 | 7.2 | 0.11 | 0.11 | 0.03 | 0.001 | 0.000 | 0.00 |
| | 2010 | 108.1 | 107.1 | 15.9 | 7.9 | 7.7 | 2.2 | 0.09 | 0.08 | 0.02 | 0.001 | 0.000 | 0.00 |
| | 2011 | 141.1 | 116.8 | 47.9 | 10.9 | 8.4 | 5.4 | 0.09 | 0.08 | 0.02 | 0.001 | 0.000 | 0.00 |
| | 2012* | 175.0 | 171.0 | 22.1 | 14.8 | 14.0 | 3.4 | 0.10 | 0.10 | 0.02 | 0.001 | 0.000 | 0.00 |

Focusing on the bid-ask spreads, measured in basis points, their behavior is in line with the CDS premium levels. Looking at the relative bid-ask spread, measured in percentage over average price, we observe a gradual decrease in levels and volatilities from 2005 to 2011. It implies that the liquidity in the CDS market tends to increase and its volatility to decrease what is consistent with the market growing in size over time. Table 4.1 also contains the squared of the CDS returns, which is used as a proxy of the individual volatility. We observe that the higher average volatility is achieved in 2007 and 2008.

Regarding additional properties of the daily percentage changes of the relative bid-ask spreads ($DL_{j,t}$) employed in Equation 4.2, this variable is equal to zero (no changes in the level of liquidity) for around 10% of the total number of observations. This occurs mainly at the beginning of the sample coinciding with the early stages of the CDS market. This figure supports the idea that results are not driven by the level of persistence in $DL_{j,t}$. In fact, the average autocorrelation of $DL_{j,t}$ is around -0.3 which suggests that autocorrelation is hardly a relevant issue in our analysis.

## 4.5. Empirical findings

### *4.5.1. Basic empirical evidence*

We first test the co-variation between single-name CDS liquidity and CDS market-wide liquidity per calendar year. Table 4.2 reports the results for the estimation of Equation 4.2 showing the cross-sectional averages of the slopes of the contemporaneous, lagged, and leading market liquidity measures and the t-statistics over the 438 firms in our sample.[55] The table also includes the proportion of individual positive slopes and the proportion of

[55] Given that the individual disturbances in Equation 3.2 are probably not normally distributed it is safer to concentrate on the average cross-sectional results, the distribution of which is probably close to Gaussian under some mild conditions.

individual positive and significant (critical value 5%) coefficients. Finally, we report the "sum" and "median", which refer to the cross-sectional average and median of the sum of the contemporaneous, lead, and lag betas, respectively. The coefficients are estimated year by year from 2005 to 2011.[56]

The results show a positive and significant contemporaneous effect of the CDS market liquidity variables on the individual liquidity measure, while the magnitude of the lagged and leading coefficients is much lower and the number of significant coefficients only exceeds 11% in 2010.[57] The contemporaneous effect reaches its maximum values in 2007 and 2008 (0.82 and 0.86, respectively), both of them being highly significant. High significant values are also found in 2010 and 2011 (0.78 and 0.79, respectively). On the other hand, the minimum effect of the liquidity commonality occurs in 2005 (0.57) and 2006 (0.59).

On the basis of the sum of the three coefficients we find a positive and significant effect of the CDS market liquidity on the individual liquidity measures over the eight years of the sample. The median follows the same trend but the estimated levels are lower. The explanatory power as measured by the R-squared is not very high, ranging from 4% in 2005 to 9% in 2010, but it is in line with other papers using the same methodology, such as Chordia et al.'s (2000) analysis of the stock market commonalities. This fact suggests that there are additional explanatory variables that this methodology is not identifying. An interesting result is the trend observed in the liquidity commonalities which seem to evolve over time according to the economic conditions. It suggests that liquidity commonalities could be state-dependent as it is documented in Figure 4.1, which contains the cross-sectional

[56] We do not estimate the commonalities in liquidity for 2012 because we only have information for the first quarter. However, we use the information of year 2012 in the later rolling windows estimation.
[57] In some years such as 2005, 2006, and 2009 only 19, 14, and 28% of contemporaneous coefficients are positive and significant, respectively. The maximum level of significance is achieved in 2008 (70%). Nevertheless, this significance is not the one that determines the level of significance of liquidity commonalities but the one referred to the aggregate ("Sum") effect whose t-statistic is shown at the bottom of this Table 3.2.

median of the sum of the contemporaneous, lead and lag daily coefficients using 1-year rolling windows. Note that in the subsequent analysis we use the median to avoid any potential extreme betas, although the correlation between the median and average betas obtained in the baseline analysis is equal to 0.95.

Panel A of Figure 4.1 shows the median of the sum of liquidity commonalities from 2006 to 2012 obtained using the baseline methodology (Equation 4.2) and an alternative methodology in which market measures are constructed by means of value weighted averages by firm capitalization (Equation 4.4). The first comment that applies is that both methods for computing the market measures give similar trends given that the correlation between the two measures is 0.94. The baseline methodology gives systematically stronger liquidity commonalities before January 2008. After this date, the commonalities are larger under the equally weighted specification but the differences are smaller than before January 2008. After the Greek's bailout requests, both methodologies provide very similar levels. A potential explanation is that the liquidity of some large firms is not representative of the market liquidity, especially before the main episodes of high risk, and so the co-variation of other CDS contracts with the new market liquidity measure decreases.

Looking at the baseline specification we observe that the lowest levels of liquidity commonalities occur during year 2006, which is a tranquil period. During the whole year 2007 there is a monotonic increasing trend. The high liquidity commonalities reached by the end of 2007 persist until summer 2009 when there is a decrease that persists until the end of the year. The levels of commonalities remain relatively constant until March 2010. From this date commonalities exhibit a remarkable increase that reaches its maximum value around May 2010, coinciding with the Greek rescue, and remains high until March 2011 when there is a significant drop. A new increase is observed by June-July 2011 coinciding with the

European Council of 21st July in which there was a failure to arrive at a clearly articulated and adequately funded agreement to guarantee the viability of Greece's public finances. Liquidity commonalities remain around this level until the end of the sample.

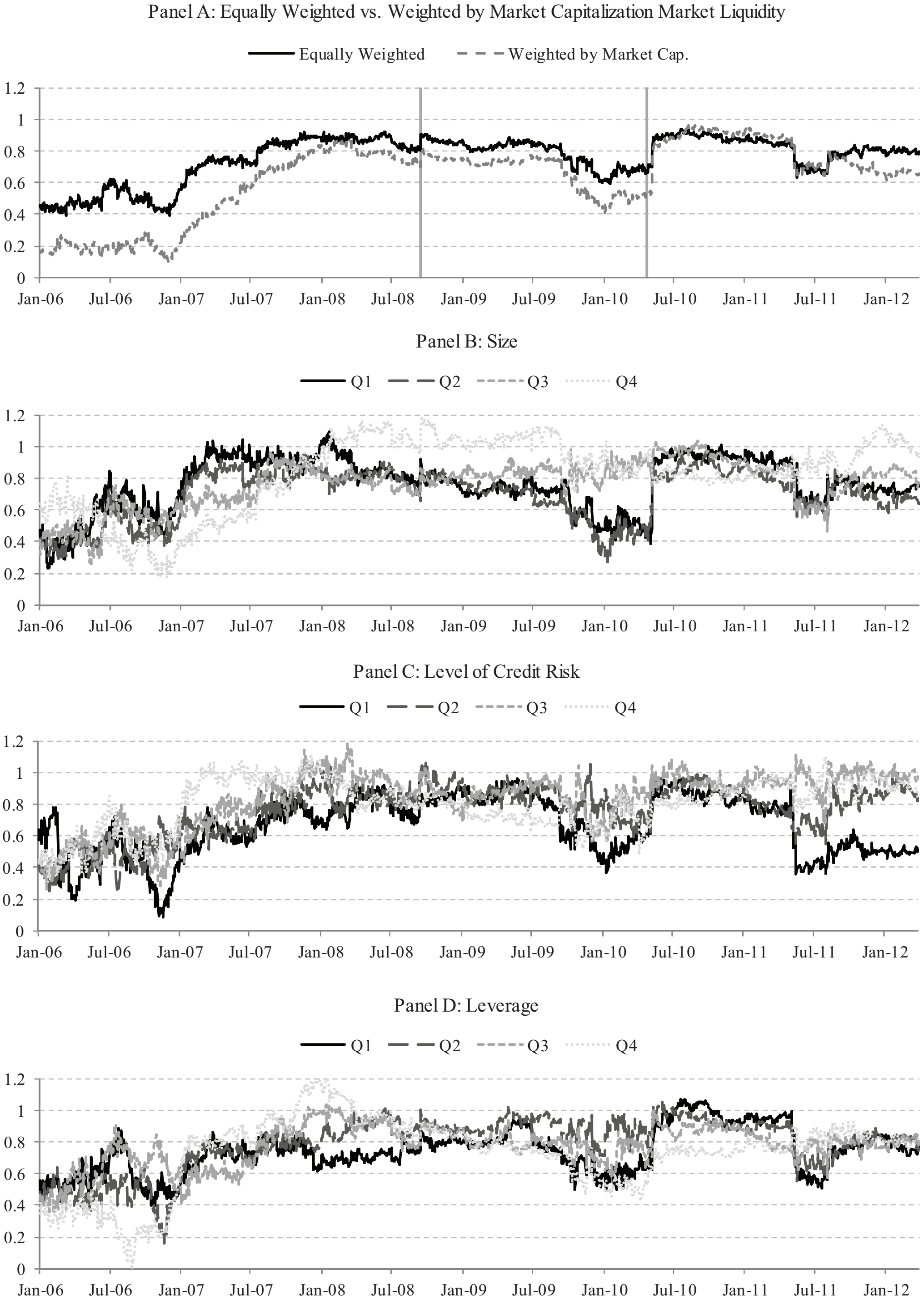
**Table 4.2 Baseline regression**

This table reports the effect of market liquidity on firm-specific liquidity. This table summarizes the cross-sectional averages of the slopes of the contemporaneous, lagged, and leading market liquidity measures that are estimated by Ordinary Least Squares (OLS) and the t-statistic. The table also reports the proportion of individual positive slopes and the proportion of individual positive and significant slopes (critical value 5%). "Sum" refers to the cross-sectional average of the sum of the contemporaneous, lead, and lag betas. We report the t-statistic for "Sum". "Median" refers to the cross-sectional median of the sum of the contemporaneous, lead, and lag betas.

| | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 |
|---|---|---|---|---|---|---|---|
| Contemporaneous | 0.57 | 0.59 | 0.82 | 0.86 | 0.68 | 0.78 | 0.79 |
| t-statistic | 12.65 | 14.41 | 21.68 | 26.36 | 17.96 | 24.68 | 21.73 |
| % Positive | 76.48 | 76.94 | 88.58 | 95.43 | 80.82 | 90.87 | 86.50 |
| % Positive & Significant | 18.72 | 14.38 | 44.75 | 69.63 | 28.08 | 53.20 | 57.21 |
| | | | | | | | |
| Lag | -0.02 | 0.02 | 0.08 | 0.00 | 0.02 | 0.04 | 0.02 |
| t-statistic | -0.49 | 0.56 | 2.93 | 0.07 | 0.49 | 1.61 | 0.75 |
| % Positive | 48.40 | 48.86 | 53.20 | 50.46 | 48.40 | 53.88 | 52.63 |
| % Positive & Significant | 3.20 | 7.99 | 9.36 | 7.99 | 6.62 | 15.75 | 11.90 |
| | | | | | | | |
| Lead | -0.03 | 0.02 | 0.07 | 0.02 | 0.03 | 0.07 | 0.05 |
| t-statistic | -0.60 | 0.44 | 2.52 | 1.04 | 0.94 | 2.25 | 1.90 |
| % Positive | 47.26 | 47.95 | 54.11 | 52.05 | 51.60 | 59.13 | 52.86 |
| % Positive & Significant | 6.16 | 6.39 | 8.22 | 7.53 | 5.48 | 11.64 | 8.47 |
| | | | | | | | |
| Sum | 0.52 | 0.63 | 0.97 | 0.88 | 0.73 | 0.89 | 0.86 |
| t-statistic | 8.29 | 10.15 | 24.09 | 28.16 | 13.06 | 24.50 | 23.74 |
| Median | 0.46 | 0.56 | 0.89 | 0.86 | 0.62 | 0.87 | 0.78 |
| | | | | | | | |
| Mean R-squared | 0.04 | 0.04 | 0.05 | 0.08 | 0.06 | 0.09 | 0.08 |

## Figure 4.1 Daily liquidity commonalities

This figure reports the daily effect of market liquidity on firm-specific liquidity using 1-year rolling windows (i.e., cross-sectional median of the sum of the contemporaneous, lead and lag market liquidity effects). Panel A contains the baseline methodology in which market liquidity and returns are obtained using equally weighted averages and an alternative methodology where measures are weighted by market capitalization. Vertical lines refer to the Lehman Brothers (September 15th, 2008) collapse and Greek's bailout requests (April 23rd, 2010). In Panels B to D we stratify the liquidity commonality effects of the baseline analysis in quartiles according to the size, level of credit risk and leverage.



In view of the pattern of the commonalities in liquidity, we next study whether there are significant changes around two relevant events related to the so-called subprime crisis (Lehman Brothers' collapse on September 15$^{th}$, 2008) and sovereign debt crisis (Greek's bailout requests on April 23$^{rd}$, 2010); on the basis of the liquidity commonalities obtained in the baseline analysis (Equation 4.2). For such aim, we carry out a mean test comparing the average of the liquidity commonalities one month before and after the relevant event. We find significant increases in liquidity commonalities after the two considered events supporting the idea that co-movements in liquidity strengthen around global shocks.

We next check whether the liquidity commonalities depend on several firm dimensions such as the size, the level of credit risk and the leverage. For such aim we stratify the liquidity commonality effects (the sum of the lagged, contemporaneous, and leading betas) in quartiles on the basis of the level of the three previous dimensions and check whether there are differences across the different stratified groups. Results are summarized in Panels B to D of Figure 4.1. We do not find a clear relation between the firm's total assets defined in USD (size) and the degree of liquidity commonality (see Panel B). Thus, the evidence does not support the hypotheses that the largest or the smallest firms have different liquidity commonalities. As in the case of size stratification, Panel C shows that there is not a clear relation between the level of credit risk and the effect of market liquidity. The firms with a stronger dependence on market liquidity do not necessarily exhibit higher levels of CDS prices. The same result is obtained in Panel D when firms are stratified according to their leverage defined as the ratio of total debt relative to total assets.

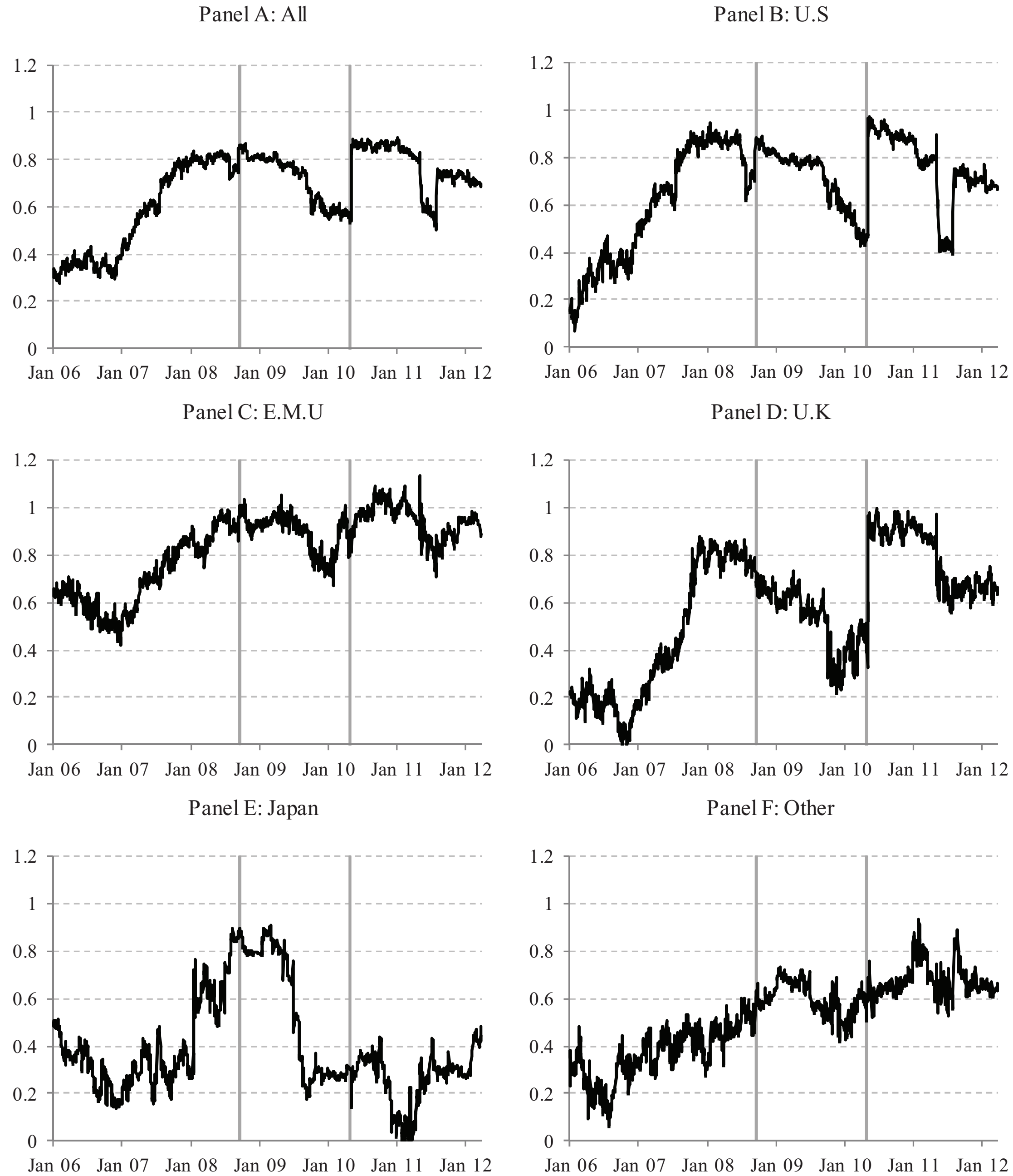
### *4.5.2. Empirical evidence by economic area*

Due to the heterogeneity of countries (25 in total), we alternatively construct the market liquidity and CDS premium measures at economic area level. The countries are then grouped into 5 economic areas. The cross-sectional median of the aggregate liquidity commonalities for each economic area are reported in Figure 4.2. Liquidity commonalities are still present when the analysis is carried out at economic area level but the degree of co-movement varies across economic areas. The highest level of liquidity commonalities in U.S. and U.K. corresponds to the first quarter of 2008 and May 2010 while the highest levels in the E.M.U. are reached after summer 2011 coinciding with the one of the hardest stages in the European sovereign debt crisis. In Japan the highest commonalities are reached in summer 2008 while in Others we do not observe a remarkable strength in commonalities.

As in the baseline estimation, we test whether there are significant changes in the liquidity commonalities at economic area level around the Lehman Brothers' and Greek's episodes through a test of means. After the Lehman Brothers' collapse the liquidity commonalities in the U.S., E.M.U. and U.K. significantly increase while there are not significant impacts on Japan and the Others economic areas. After the Greek's bailout requests, the level of commonalities increases significantly in the U.S. and U.K. from 0.4 to 1. This event also affects significantly to the level of commonalities in the E.M.U area but the increase was of a lower magnitude, mainly because liquidity commonalities were much higher there than in other economic areas prior to this event.  The effect of this event on Japanese firms is also positive and significant. Summing up, liquidity commonalities at economic area level significantly react to the main episodes of the subprime and sovereign crisis. The U.S. economic area seems to be the most sensitive to the events.

**Figure 4.2 Daily liquidity commonalities by economic area**

This table reports the daily effect of market liquidity on firm-specific liquidity using 1-year rolling windows (i.e., cross-sectional median of the sum of the contemporaneous, lead and lag market liquidity effects) being the market liquidity defined by economic area. Panel A depicts the cross-sectional median for all sample firms and Panel B to F depicts the cross-sectional median for firms belonging to the corresponding economic areas (United States, the European Monetary Union, the United Kingdom, Japan, and Others, respectively). Vertical lines refer to the Lehman Brothers (September 15th, 2008) collapse and Greek's bailout requests (April 23rd, 2010).




### 4.5.3. Asymmetries in liquidity commonalities

In this section we test the existence of asymmetries in liquidity commonalities. Concretely we study whether the level of liquidity commonalities depends on the upward or downward trend of the CDS prices. Results are shown in Figure 4.3. This figure shows that liquidity commonalities when the market CDS premium increases are larger around certain specific events. The first date for which this behavior is observed is December 2006 March 2007. The second episode around which this phenomenon is found is the collapse of Lehman Brothers. The two most significant episodes in which we find this asymmetric effect in commonalities are around May 2010 and July 2010, coinciding with the rescue of Greece and the European Council of 21st July. These results suggest the existence of asymmetries in commonalities around financial distress episodes such that the effect of market liquidity is stronger when the CDS market price increases, meaning that commonalities based on the information for these dates could be more informative around specific risky events.[58]

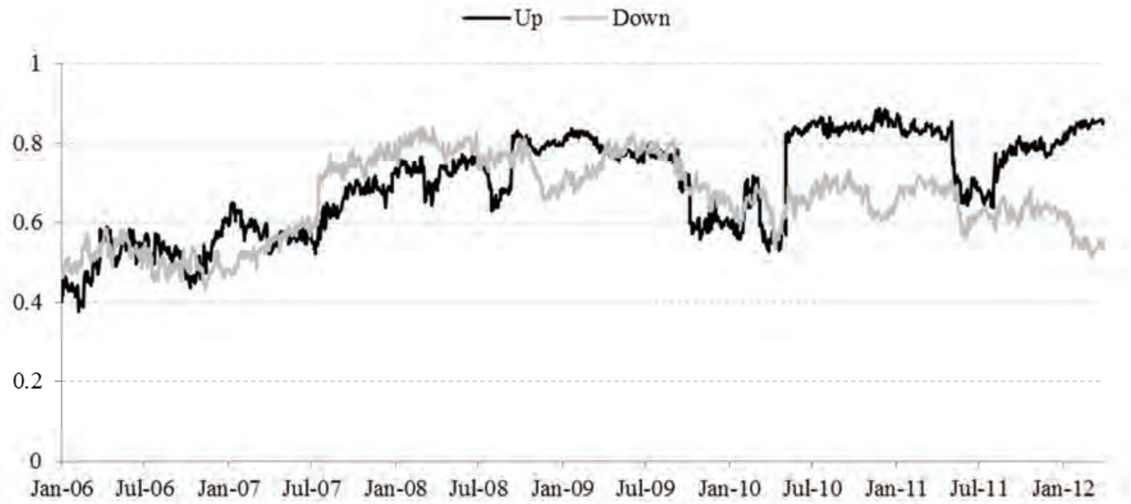
### *4.5.4. Industry and high CDS firms effects*

We first differentiate market liquidity from industry liquidity commonalities according to Equation 4.7. Table 4.3 reports the annual results referring to the liquidity commonalities to be compared with those obtained in Table 4.2. We find that the market commonality is stronger than the industry commonality but lower than in the baseline analysis because it is split up into the market and industry effects. Attending to the sum of the lagged, current, and leading coefficients, the industry commonality remains almost constant from 2005 to 2007 and increases in 2008 to remain almost invariable up to 2011. However, we find a significant increase in the market commonality from 2005 to 2007 and a decrease in 2008 and 2009 that are consistent with those obtained in Table 4.2. We obtain a new increase in the effect of market liquidity commonalities in 2010 followed by a decrease in 2011.

[58] We check the correlations between the variable for the market returns and the two market liquidity measures that represent both types of asymmetries and find that they are 0.40 and -0.45 for the up and down market returns references, respectively. Thus, there are not problems of collinearity derived from the joint use of market returns and the asymmetric liquidity measure.

**Figure 4.3 Analysis of Asymmetries**

This table reports the daily effect of market liquidity on firm-specific liquidity using 1-year rolling windows (i.e., cross-sectional median of the contemporaneous market liquidity effect) in which we split up the contemporaneous effect into two depending on whether the market CDS returns have a positive or negative sign. We use the baseline specification and interact the market liquidity measure with a dummy for positive changes in the CDS market returns and on the other hand with a dummy for negative changes in the CDS market returns. We also exclude the lagged and lead values of the changes in market liquidity.




We also test whether this pattern is common for all industries by stratifying the results at industry level and find that the banking industry is the only sector in which industry liquidity is significantly stronger than market liquidity for all the considered years. This finding could be explained by a strong effect of potential determinants of liquidity commonalities (such as global, liquidity or counterparty risks) that are specific of this sector. In fact, the main players in the CDS market are banks.[59]

We also study this effect over time in Figure 4.4, which contains the cross-sectional median of the sum of the contemporaneous, lead and lag daily coefficients of market and industry liquidity measures using 1-year rolling windows for all firms and for the banking and real estate sectors. In line with the previous finding we observe that market liquidity commonalities are stronger than the industry commonalities but the spread narrows from 2011 on. As obtained in the annual analysis, industry commonalities in the banking sector are

[59] Results are not reported for brevity but are available upon request.

**Table 4.3: Market and industry liquidity commonalities**

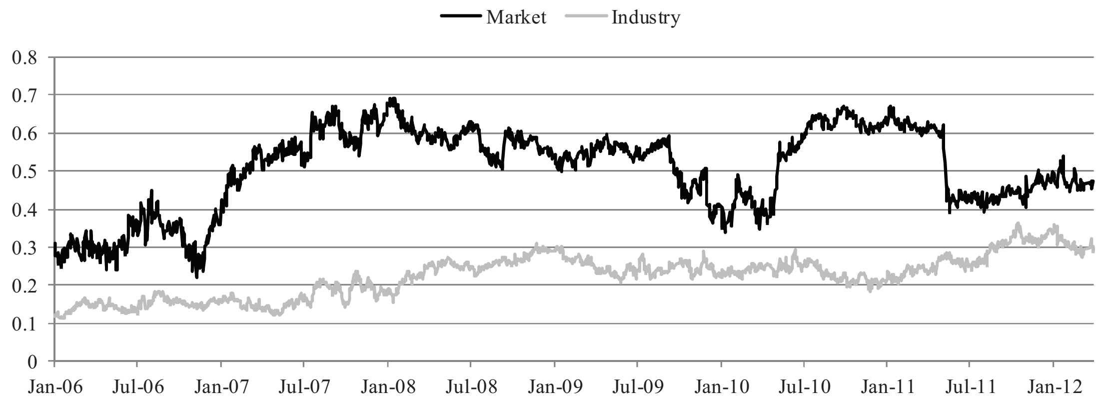
This table reports the effect of market and industry liquidity on firm-specific liquidity. This table summarizes the cross-sectional averages of the slopes of the contemporaneous, lagged, and leading market liquidity measures; the contemporaneous, lagged, and leading industry liquidity measures; and the t-statistic. The slopes are estimated by Ordinary Least Squares (OLS). We also report the proportion of individual positive slopes and the proportion of individual positive and significant slopes (critical value 5%). "Sum" refers to the cross-sectional average of the sum of the contemporaneous, lead, and lag betas. We report the t-statistic for "Sum". "Median" refers to the cross-sectional median of the sum of the contemporaneous, lead, and lag betas.

| | 2005 | | 2006 | | 2007 | | 2008 | | 2009 | | 2010 | | 2011 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Market | Industry | Market | Industry | Market | Industry | Market | Industry | Market | Industry | Market | Industry | Market | Industry |
| Contemporaneous | 0.35 | 0.24 | 0.36 | 0.26 | 0.59 | 0.24 | 0.60 | 0.28 | 0.40 | 0.30 | 0.51 | 0.28 | 0.46 | 0.32 |
| t-statistic | 8.03 | 12.05 | 8.86 | 13.97 | 15.89 | 14.56 | 16.57 | 14.47 | 9.95 | 15.51 | 15.10 | 12.16 | 12.33 | 16.11 |
| % Positive | 0.66 | 74.66 | 0.68 | 76.94 | 0.79 | 74.20 | 0.83 | 76.03 | 0.70 | 81.05 | 0.79 | 74.43 | 0.75 | 81.46 |
| % Positive & Signif. | 0.11 | 33.56 | 0.09 | 34.93 | 0.28 | 28.31 | 0.45 | 42.69 | 0.16 | 40.64 | 0.36 | 36.99 | 0.34 | 42.56 |
| Lag | 0.00 | -0.02 | 0.04 | -0.03 | 0.08 | 0.00 | -0.02 | 0.02 | 0.03 | 0.00 | 0.00 | 0.03 | -0.01 | 0.02 |
| t-statistic | 0.10 | -1.60 | 0.94 | -2.10 | 2.74 | -0.19 | -0.96 | 1.91 | 0.69 | -0.13 | 0.01 | 0.89 | -0.20 | 1.89 |
| % Positive | 50.00 | 41.55 | 48.63 | 42.69 | 53.65 | 50.00 | 49.54 | 52.28 | 49.77 | 49.32 | 52.74 | 50.46 | 51.26 | 51.03 |
| % Positive & Signif. | 4.57 | 3.88 | 8.68 | 5.25 | 8.68 | 6.85 | 5.48 | 6.85 | 7.31 | 6.85 | 12.33 | 6.62 | 10.07 | 8.92 |
| Lead | 0.00 | -0.02 | 0.06 | -0.03 | 0.08 | -0.01 | 0.00 | 0.02 | 0.04 | -0.01 | 0.06 | 0.01 | 0.01 | 0.03 |
| t-statistic | 0.04 | -1.48 | 1.35 | -2.54 | 2.74 | -0.61 | -0.20 | 2.20 | 1.07 | -0.50 | 2.08 | 0.59 | 0.55 | 1.61 |
| % Positive | 49.09 | 43.84 | 50.68 | 44.98 | 53.20 | 48.63 | 50.00 | 53.42 | 50.23 | 48.86 | 55.25 | 49.77 | 50.57 | 51.72 |
| % Positive & Signif. | 6.85 | 3.42 | 7.31 | 4.79 | 7.99 | 6.16 | 5.25 | 5.71 | 5.02 | 4.11 | 10.05 | 6.85 | 9.84 | 7.09 |
| Sum | 0.35 | 0.20 | 0.46 | 0.21 | 0.75 | 0.23 | 0.57 | 0.32 | 0.46 | 0.29 | 0.57 | 0.32 | 0.47 | 0.38 |
| t-statistic | 5.39 | 7.30 | 7.47 | 7.48 | 16.69 | 9.32 | 16.40 | 12.55 | 7.94 | 10.88 | 9.84 | 5.42 | 11.41 | 9.85 |
| Median | 0.31 | 0.12 | 0.36 | 0.16 | 0.65 | 0.17 | 0.53 | 0.29 | 0.41 | 0.22 | 0.64 | 0.21 | 0.49 | 0.34 |
| Mean R-squared | 0.07 | | 0.07 | | 0.08 | | 0.11 | | 0.09 | | 0.12 | | 0.11 | |

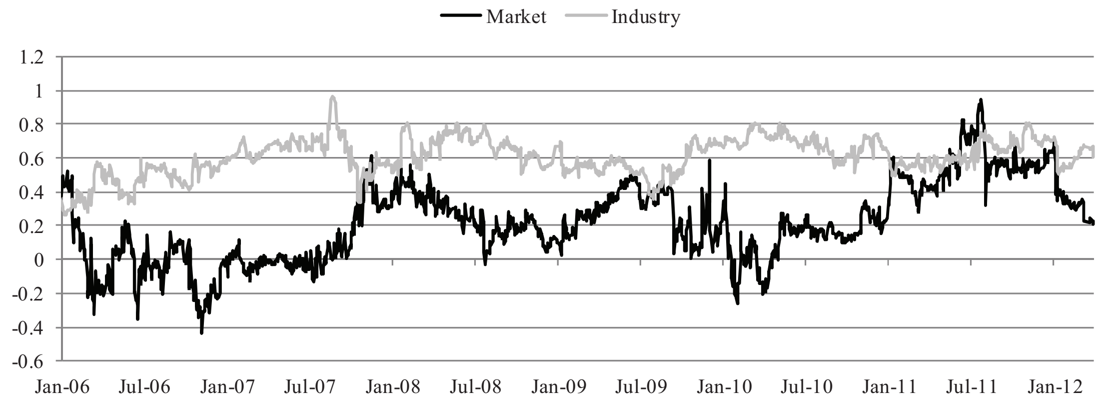
## Figure 4.4 Market vs. Industry Daily Liquidity Commonalities

This figure depicts the daily effect of market and industry liquidity on firm-specific liquidity using 1-year rolling windows (i.e., cross-sectional median of the sum of the contemporaneous, lead and lag liquidity effects) where industry liquidity measure is constructed as an equally weighted average of the relative bid-ask spreads for firms belonging to the same industry. Panel A reports the cross-sectional median of all sample firms and Panels B and C refer to banks and real estate investment trusts firms, respectively.

Panel A: All sample firms




Panel B: Banks




Panel C: Real Estate Investment Trusts

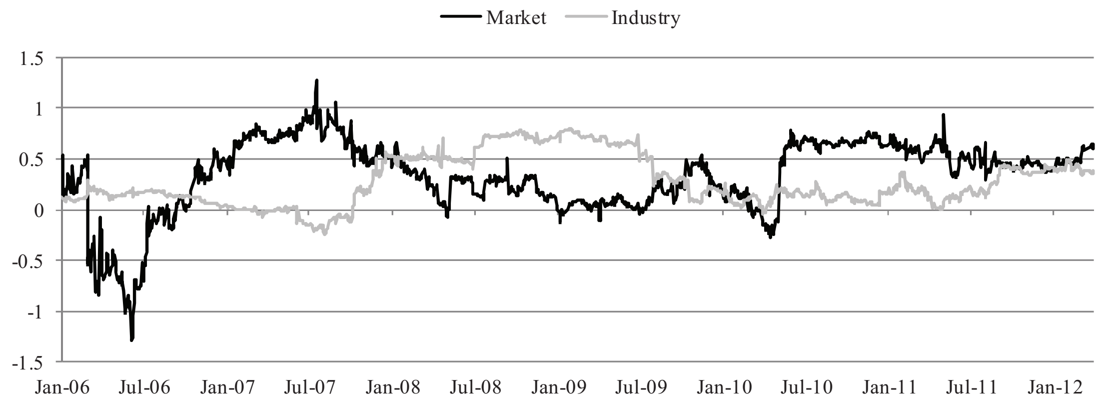
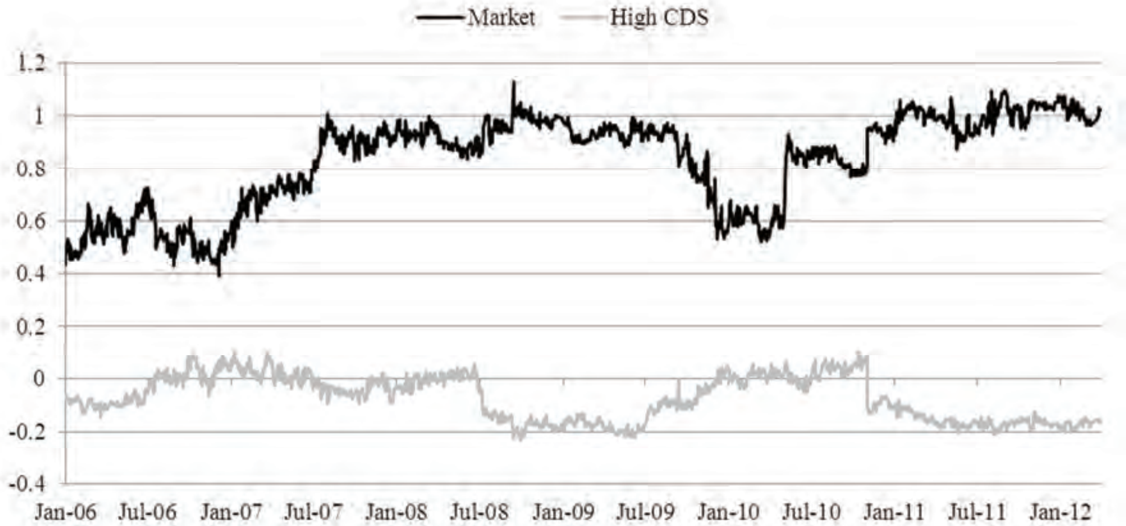


**Figure 4.5 Market vs. High CDS Daily Liquidity Commonalities**
This figure depicts the daily effect of market and high CDS liquidity on firm-specific liquidity using 1-year rolling windows (i.e., cross-sectional median of the sum of the contemporaneous, lead and lag liquidity effects) where high CDS liquidity measure is constructed as the equally weighted average of the relative bid-ask spreads of firms belonging to the top quartile according to their level of CDS prices.




stronger than market commonalities for the whole sample with the exception of some weeks around summer 2011. The effect of the real estate industry liquidity commonality is also interesting. In 2006 the commonality is driven by the market but this relation changes in 2007 and especially in 2008, coinciding with the subprime crisis, such that the industry commonality is significantly higher than the market commonality. This stronger effect of the industry liquidity could be related to the collapse of the U.S. housing bubble.

We next check whether the level of liquidity commonalities is influenced by a certain number of influential CDS single names. Our hypothesis is that the reference entities with the highest credit risk could be causing the commonality effect such that liquidity is conditioned by the firms with the highest CDS premia. We study this variation over time in Figure 4.5, which contains the median of the cross-sectional average of the sum of the contemporaneous, lead and lag daily coefficients of market and high CDS liquidity measures, as estimated in Equation 4.8, using 1-year rolling windows. The results suggest that liquidity commonalities are not driven by the liquidity of the reference entities with the highest CDS prices because it is close to zero during the whole sample.

## 4.6. Determinants of CDS liquidity commonalities and their role as indicators of global risk

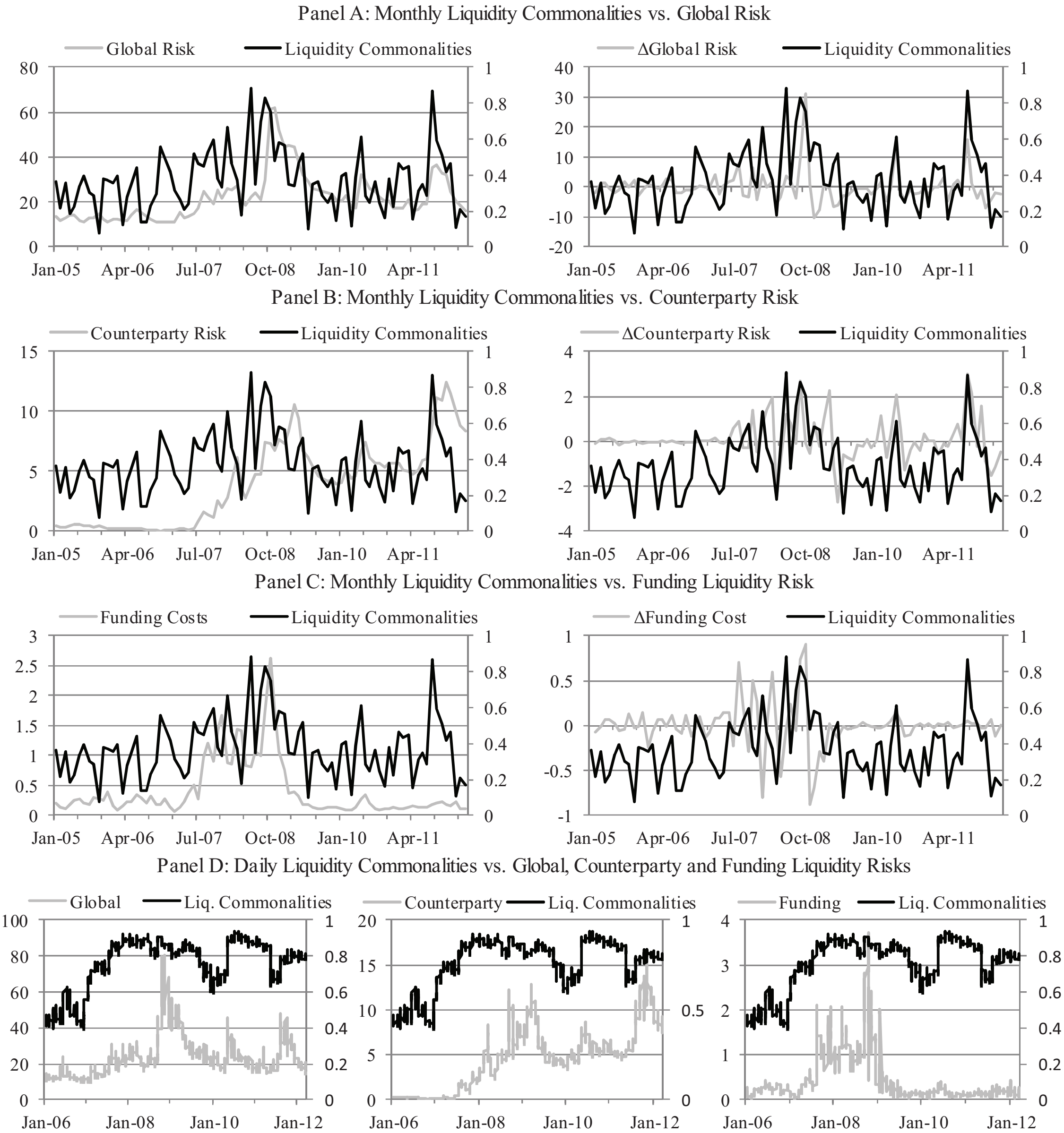
### *4.6.1. Determinants of liquidity commonalities at aggregate level*

In Figure 4.6 we depict the time series relation between the cross-sectional median of the individual monthly commonality betas (Equation 4.9) and the monthly average global (Panel A), counterparty (Panel B), and funding liquidity (Panel C) risks. Each panel contains two figures showing the risk measures in levels (left) and in first differences (right). The liquidity betas on the one hand, and the global, counterparty, and funding liquidity risks proxies either in levels or first differences on the other hand; are closely related. In fact, the correlation between the liquidity commonalities and the global risk expressed in levels and first differences are 0.42 and 0.43, and look similar to the ones with the counterparty risk (0.24 and 0.43). The funding liquidity risk in levels also shows a high correlation with the commonalities (0.45) but it is much lower in first differences (0.03). Panel D reports the daily series for the three global variables in levels and the daily median betas obtained using 1-year rolling windows. This figure reinforces the strong relation between the liquidity commonalities and the other variables. The correlations of daily betas with global, counterparty and liquidity risks are 0.50, 0.56, and 0.35, respectively.

After documenting the close relation between the commonalities in liquidity and the previous risks variables, we next analyze formally their relation according to Equation 4.10. We first check the order of integration of the above variables. The monthly averages of the global and counterparty risks are integrated of order one while the global funding costs and the betas series do not exhibit a unit root. Thus, we use the

**Figure 4.6: Firm's betas and global, counterparty and funding liquidity risks**

This figure depicts the series of liquidity commonalities and global, counterparty and funding liquidity risks. The right hand side axis of the figures in Panels A, B, and C refers to the monthly liquidity commonalities (i.e., cross-sectional median of the individual betas for each month) and the left hand side axis refers to the monthly average of global, counterparty and funding liquidity risks, respectively. Each panel contains two figures, on the left, risk variables are considered in levels and on the right in first differences. Finally and regarding Panel D, the right hand side axis of the three figures refers to the daily liquidity commonalities (i.e., cross-sectional median of the sum of the contemporaneous, lead and lag liquidity effects) and the left hand side axis refers to the global, counterparty and funding liquidity risks in levels. Daily and monthly betas are estimated according to Equations 4.2 and 4.9, respectively. Global risk is proxied with the VIX; counterparty risk is computed as the first principal component obtained from the CDS premia of the main banks that act as dealers in such a market; funding liquidity is defined as the difference between the 90-day U.S. AA-rated commercial paper interest rates for the financial companies and the 90-day U.S. T-bill.



first difference of the global and counterparty risk proxies as the explanatory variables. Panel A of table 4.4 reports the results. The first three columns include the effects of the three potential determinants of the liquidity commonalities individually. We observe that the liquidity commonalities' betas are well explained by the economy-wide variables. The first column confirms that the global risk has a positive and significant effect on the estimated betas. This variable has explanatory power as the R-squared of 25% suggests. One possible explanation is that the CDS market participants are strongly and homogenously affected by the shocks to the global economy, given the high degree of concentration of the market participants in this market. This result could also reflect the higher sensitivity of the CDS market to the global market factors. This result is in line with the findings of Kempf and Mayston (2005), among others, for the stock market in the sense that they find that commonality is much stronger in falling markets than in rising markets.

We next test how counterparty risk affects the degree of co-movement. The increase in counterparty risk could make it more difficult to find a counterparty to sell/buy protection, which lowers liquidity. The results of the second column show that as counterparty risk increases, liquidity commonalities also increase. The explanatory power of this variable is lower than the one of global risk but it is not negligible (16%).

Another potential global effect to consider as a determinant of liquidity commonalities is the role of capital constraints. The effect of such constraints on stock market liquidity commonality is documented by Comerton-Forde et al. (2010) and Brunnermeier and Pedersen (2009). We consider the capital constraints as a dimension of liquidity related to the overall funding constraints which should affect the investments in CDS. We find a positive and significant effect of the funding costs variable defined in levels. This variable has explanatory power (0.13) but lower than the ones for the two previous factors. The previous empirical evidence implies that as the funding cost increases, and as a consequence the liquidity risk also increases, so do the liquidity commonalities.

**Table 4.4 Determinants of liquidity commonalities**

This table reports the analysis of the determinants of liquidity commonalities at aggregate and firm levels. Panel A reports the effect of aggregate factors where we regress monthly aggregate betas on the monthly average of global, counterparty and funding cost risk, separately (columns I to III) and jointly (column IV), using OLS robust heteroskedasticy. Panel B reports the effect of individual factors where we run cross-sectional regressions by OLS for every date (1625) in the sample and calculate the average coefficient which is reported in the first column. The standard errors reported in brackets are the corrected for autocorrelation using the Newey-West methodology. These errors are obtained after regressing with Newey-West standard errors adjustment the loadings on each factor, which are shown in the first column, on a constant. The second column shows the change in the dependent variable after a change in the explanatory variable of one standard deviation (SD). The SD is obtained as the mean SD of the variable across all the firms. The third column is the ratio between the effect on the dependent variable of a change one SD in each regressor and the average beta across all the firms and over the whole sample. *** (** and *) indicates that the estimated coefficient is significant at a level of 1% (5% and 10%, respectively).

Panel A: Determinants of liquidity commonalities at aggregate level

| | I | II | III | IV |
|---|---|---|---|---|
| ΔGlobal Risk | 0.020***<br>(0.00) | | | 0.013***<br>(0.00) |
| ΔCounterparty Risk | | 0.091***<br>(0.03) | | 0.048**<br>(0.02) |
| Global Funding Costs | | | 0.155***<br>(0.06) | 0.092**<br>(0.04) |
| Constant | 0.369***<br>(0.02) | 0.361***<br>(0.02) | 0.306***<br>(0.03) | 0.326***<br>(0.02) |
| Number of Observations | 84 | 84 | 85 | 84 |
| F(1,82) | 26.59 | 11.18 | 7.9 | 20.8 |
| Prob > F | 0.00 | 0.00 | 0.01 | 0.00 |
| R-Squared | 0.25 | 0.16 | 0.13 | 0.32 |

Panel B: Determinants of liquidity commonalities at individual level

| | Coefficient | 1 SD change | 1 SD change relative to |
|---|---|---|---|
| Size | -0.005<br>(0.00) | -0.002 | -0.002 |
| Leverage | 0.035<br>(0.05) | 0.001 | 0.002 |
| CDS premium | 0.000<br>(0.00) | 0.009 | 0.011 |
| Volatility stock price | 3.523<br>(5.85) | 0.012 | 0.014 |
| 3-month interbank rate | 0.049***<br>(0.01) | 0.093 | 0.115 |
| Volatility stock index | 32.939***<br>(5.38) | 0.248 | 0.304 |
| Constant | 0.323***<br>(0.06) | | |
| Average R-squared | 0.03 | | |

In the fourth column we use the three variables at the same time as explanatory variables and find similar results in terms of the degree of significance and the R-squared increases to 0.32. The results are also robust to other specifications.[60]

### *4.6.2. Determinants of liquidity commonalities at firm level*

In this section we study whether market liquidity has a different effect depending on firm characteristics or whether it is mainly determined by global factors. To do that, we study the determinants of liquidity commonalities in terms of firm level characteristics (leverage, credit-risk, volatility and size) and global levels of risk. The results for the estimation of Equation 4.11 are shown in Panel B of Table 4.4.

The firm's size measured as the log of market capitalization does not have a significant effect. Chordia et al. (2000) find that liquidity commonalities in the stock market are stronger in large firms, arguing that this pattern could be due to greater prevalence of institutional investors in large firms. On the contrary, participants in the CDS market are institutional investors, what could explain that the effect of the CDS market liquidity on single-name CDS is not significantly higher for large firms.

We also study the effect of leverage, defined as the ratio of total debt to total assets, and the level of credit risk, proxied by the CDS premium. The joint use of these two variables allows us to control by the fact that the investors might focus on either the market information or the balance-sheet information to infer the risk or distance to default of a firm. The results show that the leverage and CDS premium do not affect significantly the relation between the CDS liquidity and the market liquidity.

[60] Similar results are obtained when we use another global risk proxy as the VDAX index. We also repeat the analysis using the mean betas instead of the median and we find that the economic variables have positive and significant signs, although the estimated R-squared are lower. We repeated the regression using quarterly instead of monthly betas and obtained similar results.

Finally, we find that the volatility in the stock prices measured by the squared of the stock returns does not affect significantly the individual betas. Thus, a larger volatility does not make the firm CDS liquidity more dependent on market liquidity. In sum, there are not significant effects of the firm specific variables in line with the results shown in Figure 4.1.

There are many potential global risk variables to consider in the cross-sectional regression analysis. Our aim is to consider the effects of the three global variables employed in Section 4.6.1. Nevertheless, we can only include variables that are country specific being the effect of all other omitted global risk variables, such as counterparty risk, collected by the constant term. The same applies to the global risk variable. However, in this case we can use the standard deviation of the country stock indexes to take into account the effect of the country risk premium. Regarding the global funding costs referred to the constraints that global investors may face, we use the 3-month interbank rate for each country given that there is no information on the commercial paper for most of the countries forming the sample.

As expected in view of the results obtained in Section 4.6.1, we find positive significant effects for the two global variables employed in our regression. Additionally, the constant term is also positive and highly significant suggesting that other global risk variables lead to a larger exposition of CDS single-names liquidity to market liquidity. Thus, a change in the risk premium equal to one standard deviation would lead to an increase of 0.248 units of the beta referred to the commonalities. This increase is equal to 30.4% of the average level of beta. An increase of one standard deviation in the interbank rate would lead to an increase of 0.093 units of beta, or equivalently 11.5% of its average level. Similar changes in the firm specific variables have a more limited effect that never goes beyond 1.5% of the average level of liquidity commonalities.

### *4.6.3. Liquidity commonalities as indicators of global risk*

We next check whether the cross-sectional median of the individual liquidity commonalities provides additional informational with respect to the aggregate risk measures around the two most relevant periods of financial distress (Lehman and Greek events) by means of a Granger causality test. This test enables us to examine whether past information of liquidity commonalities helps to explain the current behaviour of the risk measures and vice versa. The results of Section 4.5.3 suggest that the asymmetric commonalities referred to the increases of CDS market prices perform particularly well around stress periods. Using an interval of three months before and after the previous events, we first run a Granger causality test between the baseline and the asymmetric commonalities and find that asymmetric commonalities Granger-cause the other measure around the two events.[61]

Using this asymmetric commonalities measure, we perform the same analysis with respect to the global, counterparty, and funding liquidity risks and find that commonalities Granger-cause the three risk measures around the Lehman Brothers' collapse but only the funding liquidity risk around the Greek's bailout requests. This result reinforces the role played by the CDS around the Lehman's collapse as shock issuers (see Chapter 3) and suggests a lower effect of this market around the Greek episode.

[61] Results are robust to longer intervals.

## 4.7. Robustness test

### *4.7.1. Alternative definitions of market liquidity*

The quoted bid-ask spreads suffer from well-known problems such as thin trading in the CDS market. It is not possible to use measures such as effective spreads as we do not have transaction level information but there are some additional measures of liquidity that we employ in this section to estimate Equation 4.2. Moreover, we use other methods to define the market liquidity rather than the relative spreads.[62] Individual CDS and market-wide liquidity measures are constructed under the specification of Equation 4.1.

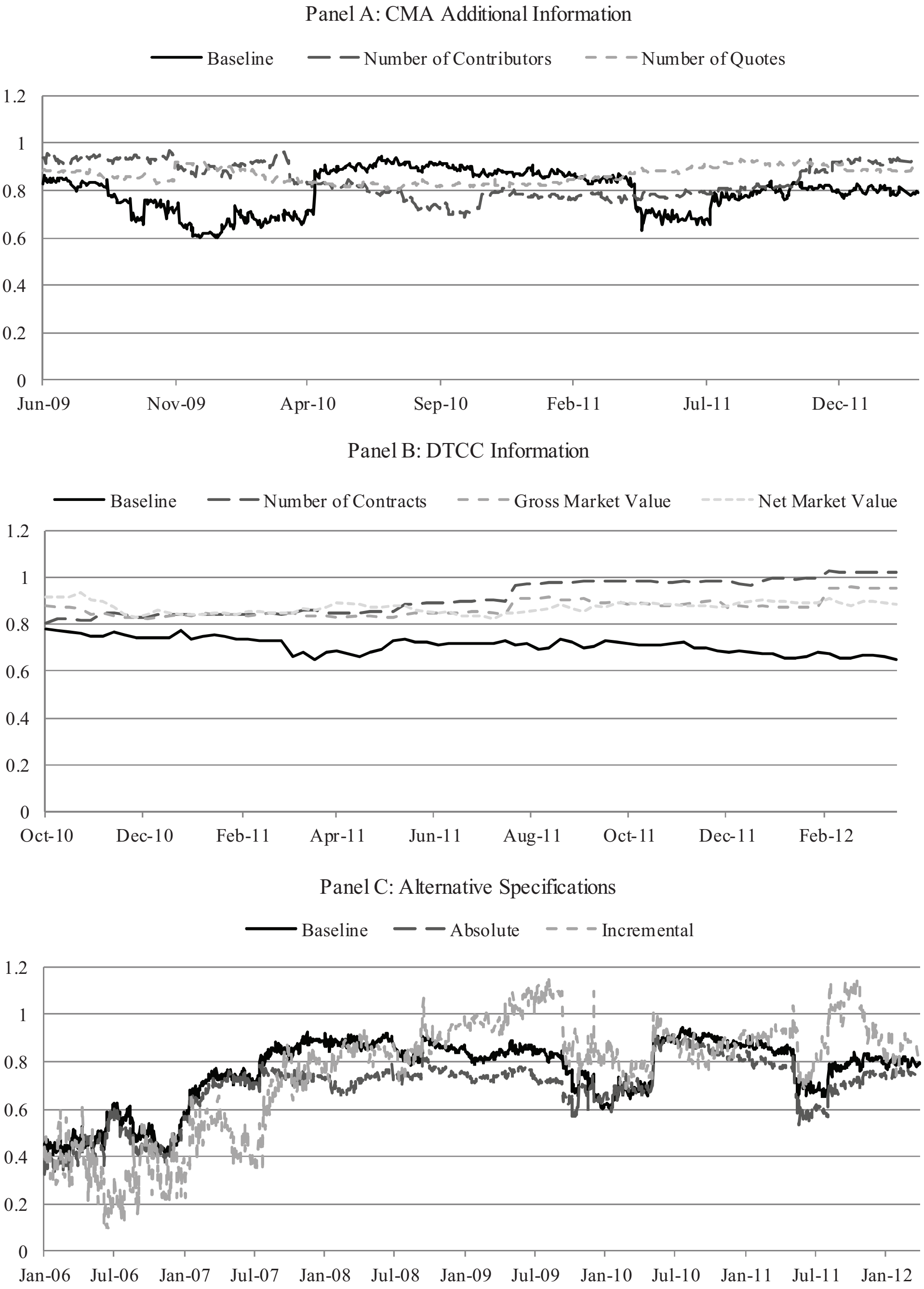
Figure 4.7 reports the cross-sectional median of the sum of the lagged, contemporaneous, and leading liquidity commonality coefficients for the different liquidity specifications using 1-year rolling windows. In Panel A we consider the number of contributors and quotes used to form the CDS prices as liquidity measures. Due to data availability, the sample spans from June 2009 to March 2012. We observe that the alternative liquidity measures provide very similar commonalities and in comparison to the baseline analysis they show even stronger commonalities apart from the interval between May 2010 and April 2011.

In Panel B we use as liquidity measures the DTCC information about the weekly traded gross and net nominal values and the number of contracts. Due to the data limitations the estimated measures span from October 2010 to March 2012 on weekly basis. We observe that these alternative liquidity measures provide similar commonalities among

[62] Given that intraday data are not available and our interest is to exploit the daily frequency, we do not consider the measures of liquidity that are based on the co-variations in prices. For the same reason, we cannot use as an alternative liquidity measure the days without changes in the CDS price within a given month as in Pu (2009).

## Figure 4.7 Alternative Liquidity Measures

This figure contains the effect of market liquidity on firm-specific liquidity using 1-year rolling windows (i.e., cross-sectional median of the sum of the contemporaneous, lead and lag market liquidity effects) for different liquidity measures. For comparability reasons, the baseline liquidity measure (relative bid-ask spread) is also depicted in all panels. In Panel A daily liquidity measures are based on additional information provided by CMA about the daily number of contributors and quotes used to form the CDS prices. In Panel B weekly liquidity measures are based on the DTCC information about the weekly traded gross and net nominal values and the number of contracts. In Panel C daily liquidity measures are based on the absolute bid-ask spread (absolute) and on first difference of the relative bid-ask spread (incremental). Sample length depends on the data availability.



them but they are systematically stronger than the ones in the baseline analysis and this difference widens at the end of the sample.[63]

In Panel C liquidity commonalities are obtained from (i) the absolute bid-ask spread and (ii) the first differences of the daily relative bid-ask spread instead of the percentage changes. Results are shown in Panel C. Up to July 2007 there is no difference between liquidity commonalities using the relative or absolute bid-ask spread. Then, the baseline liquidity measure exhibits stronger commonalities. Using the first difference of the relative bid-ask spread, the liquidity commonalities are systematically lower before 2008 and become stronger mainly during 2009 and at the end of 2011. Summing up, we estimate liquidity commonalities using alternative liquidity measures and in spite of some differences in levels, the results are in line to the baseline estimation: strong liquidity commonalities that are sensitive to the periods of global financial distress.

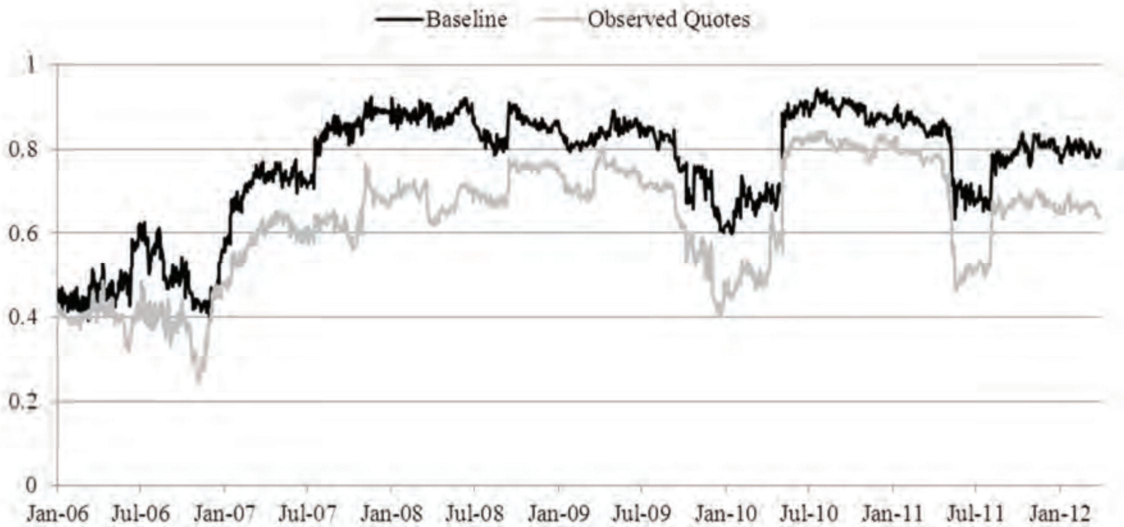
### *4.7.2. The effect of the derived quotes on liquidity commonalities*

Depending on the intraday market activity CMA denotes the prices as observed or derived. Observed prices reflect idiosyncratic liquidity but derived prices could be influenced by market or industry liquidity. The reason is that when there is no information on a specific company CMA uses information from the firm's peer group, which is constructed according to the firm's industry and rating. The percentage of derived prices over the total number of prices observed for the 438 firms and 8 years (823,878 observations) is 14.7%. We test whether the "derived" liquidity measures,

[63] Additionally, we take advantage of these measures of trading activity and estimate the baseline specification using only the more active firms according to the average gross amount outstanding of each single-name CDS over the period November 2008 – March 2012. Concretely, we repeat our analysis for the firms whose average gross amount outstanding is above the median and hence, the number of firms decreases to 219. The trend of the new liquidity commonalities measure is in line with the ones obtained using the baseline liquidity measure and the level of the commonalities is on average larger than the one under the baseline specification. In the sake of brevity, we do not report the results of this analysis but they are available upon request..

which correspond to the derived prices, have any influence on the liquidity commonalities. For this aim, we exclude the information referred to the derived quotes such that we only use the data points that were observed and repeat the baseline estimation as in Equation 4.2. Results are shown in Figure 4.8. The average level of liquidity commonalities for the whole sample period when using observed quotes is 0.63 while the average liquidity commonality in the baseline analysis is 0.76. The difference between these two figures is not significantly different from zero. This difference can be explained by the imputed values for the non-observed CDS quotes on the basis of industry/market liquidity measures that could reflect a more general dimension of liquidity rather than firm specific liquidity but also to the use of a lower number of observations.

**Figure 4.8 Observed vs. Derived Quotes**
This figure reports the daily effect of market liquidity on firm-specific liquidity using 1-year rolling windows (i.e., cross-sectional median of the sum of the contemporaneous, lead and lag market liquidity effects) using the baseline methodology where both, observed and derived are employed and alternative methodology where we exclude the information referred to the derived quotes.




### *4.7.3. Reliability of the t-statistics*

As Chordia et al. (2000) state, the reliability of the *t-statistics* depends on the estimation error being independent across the equations, which is a presumption equivalent to not having omitted a significant common variable. The standard deviations of the average $\beta$ corresponding to the liquidity commonality variable are obtained under the assumption that the estimated errors in $\beta$ are independent across the regressions and we now test the reliability of such an assumption. We check this following Chordia et al.'s (2000) method on the basis of the residuals obtained in Equation 4.2. According to this method, we regress the adjacent time series of the residuals (i.e. we regress the residuals for firm *2* on the ones for firm *1,* the residuals for firm *3* on the ones for firm *2,* and so successively). The two firms to be used in each regression are selected by alphabetical order, such as they appear in our sample. Thus, we run 437 regressions for 437 alphabetically ordered pairs of the total 438 firms as follows:

$$\varepsilon_{j+1,t} = \gamma_{j,0} + \gamma_{j,1}\varepsilon_{j,t} + \xi_{j,t} \quad for\ j = 1, \ldots, 437 \tag{4.12}$$

where $\varepsilon_{j,t}$ is the residual obtained in the baseline estimation for firm $j$ while $\varepsilon_{j+1,t}$ is the residual corresponding to firm *j+1*, which is the next in alphabetical order to *j*, $\gamma_{j,0}$ and $\gamma_{j,1}$ are the estimated coefficients, and $\xi_{j,1}$ is an estimated disturbance. The t-statistic for parameter $\gamma_{j,1}$ is the one that determines the existence of cross-equation dependence.

As it is observed in Table 4.5, we do not find evidence of cross-equation dependence given that the parameter $\gamma_{j,1}$ is not significantly different from zero. Given that the correlations between errors are very close to zero on average, the adjustment for cross-equation dependence should not materially affect the conclusions.

## 4.8. Conclusions

Corporate CDS individual liquidity measures co-move with the aggregate liquidity in the corporate CDS market. We present extensive empirical evidence based on data for

**Table 4.5 Reliability of the t-statistics**

This table reports the results of the test on the existence of cross-equation dependence, which affects the reliability of the t-statistics. We check this on the basis of the residuals obtained in Equation 4.2. We run 437 regressions for 437 pairs of the total 438 firms. The firms to be included in each regression are selected by alphabetical order, such as they appear in our sample. For each pair of residuals we regress the residual of firm *j+1* against the residuals of firm *j*. The t-statistic of the slope of this regression is the one that determines the existence of cross-equation dependence. The first row reports the average correlation coefficient between the pairs of residuals. The second and third rows show the sample mean and median t-statistics of the regression slope coefficient. The last two rows show the frequency of absolute t-statistics (for the slope) exceeding the 5% and 2.5% critical values. Due to the existence of two tails, double critical values (10% and 5%, respectively) are used.
*Information relating to 2012 refers to the first quarter of that year.

| | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012* |
|---|---|---|---|---|---|---|---|---|
| Average Correlation | 0.01 | 0.01 | 0.00 | 0.00 | 0.00 | 0.01 | 0.01 | 0.00 |
| Mean t-statistic | 0.13 | 0.14 | 0.07 | 0.09 | 0.06 | 0.10 | 0.11 | 0.03 |
| Median t-statistic | -0.01 | 0.04 | -0.06 | 0.02 | -0.08 | 0.05 | 0.08 | -0.03 |
| $\|t\|>1.645$ (%) | 16.48 | 16.70 | 17.62 | 27.46 | 17.62 | 18.54 | 16.02 | 16.70 |
| $\|t\|>1.96$ (%) | 9.38 | 11.21 | 11.21 | 19.45 | 12.81 | 12.59 | 10.30 | 9.38 |

the period 2005 2012 in support of this claim. The liquidity commonalities are still present when we analyze the co-movement of firms located in the same economic area, but the degree of commonality differs across them being the E.M.U. the region with the average stronger commonalities during the whole sample period. Regarding the effect of market and industry commonalities, the effect of the market is usually stronger than the one of the industry in most industries but there are some exceptions as the banking industry.

The liquidity commonalities are time-varying and increase in times of financial distress characterized by high counterparty, global, and funding liquidity risks. Nevertheless, the co-movement of the firm's liquidity with the market liquidity does not depend on firm's characteristics such as size, leverage, credit risk, or equity volatility but on global risk factors as the aforementioned. In this line, we find that the Lehman Brothers collapse and the Greek's bailout requests trigger a significantly increase in commonalities. In fact, the results suggest the existence of asymmetries in commonalities around these episodes of financial distress such that the effect of market liquidity is stronger when the

CDS market price increases. Finally, we find that liquidity commonalities provide informational efficiencies relative to the three previous aggregate risks around periods of financial distress originated or amplified by the CDS market such as Lehman Brothers collapse. All these results are robust to alternative liquidity measures and they are not driven by the CDS data imputation method (derived versus observed) or by the firms with high credit risk.

Some implications for traders, investors, and regulators follow. First, our results are consistent with inventory risk being the main source of the commonalities in liquidity. Second, the CDS market has a high probability of suffering sudden changes in aggregate liquidity. Third, and given that the degree of commonality differs across economic areas, the expected returns on CDSs of otherwise similar companies located in different countries might differ. Given that the expected returns before costs are related to trading costs; the higher the trading costs, the higher the expected returns. The more sensitive an asset is to the liquidity commonality component, the greater its expected return must be. Finally, regulators should consider whether the standardization of the CDS contracts and the implementation of a Central Counterparty Clearing House would alleviate the CDS market's relative propensity for abrupt changes in liquidity.

# Chapter 5 General conclusions, contributions and lines for further research

In this Thesis, I study the measurement and the determinants of the systemic risk, paying special attention to the role of the Credit Default Swaps (CDSs) either as financial instruments containing valuable information about the soundness of the reference institutions or as a market whose distress contributes to potential systemic shocks in the economy. These topics are highly relevant and timely from policymakers and investor perspectives and hence, some policy implications are also discussed along the chapters of this Thesis.

This thesis contributes to the systemic risk literature in three different ways:

1. It provides the first systematic comparison across aggregate systemic risk measures, showing the reliability of those simple measures based on CDS information.
2. It is the first study about the relationship between holdings of derivatives and the individual contribution of each institution to systemic risk, showing that derivatives holdings significantly affect to that risk but the impact varies across types of derivatives. I also document that the economic impact of leverage and non-performing loans ratios is much stronger than the one of derivatives.
3. It is the first worldwide study documenting the existence of liquidity commonalities in the corporate CDS market on a daily basis and their state-dependent nature, showing that they depend on global risk factors but not on firm-specific factors.

Overall I show that the measurement of systemic risk is a very hard task due, in part, to the complexity of the concept itself, which is still not fully understood. In this vein, the use of simple model based on CDS information provides some advantages. Among other reasons I would like to highlight that using simple models we avoid “model-specification” problems and unlike other traded claims (e.g., stocks or bonds) CDSs provide a standardized measures of the credit risk. Additionally, the use of interbank rates seems to be useless since they are target of monetary policy. Nevertheless, as I show in Chapters 3 and 4, CDSs may also become a potential source of instability when they are considered either as a financial instrument or as a market. Regarding the former, I document that holdings of credit derivatives significantly increase the contribution to systemic risk of that institution, emphasizing the importance of the disclosing of holdings on that and related instruments as well as the importance of the role of the CCPs. In relation to latter perspective, I show that the CDS market has a high probability of suffering sudden changes in aggregate liquidity and this probability is directly affected by aggregate risk factors, posing important challenges at individual level and from a global stability perspective because of the inability of firms to quickly manage their credit risk exposures and emphasizing, once again, the importance of the importance of the role of the CCPs.

Additionally, I also document the key role developed by the non-performing loan and the leverage ratio in order to understand the contribution to the overall systemic risk of the institution under study. In spite of the strong debate about the role of financial derivatives and their impact on the financial stability I find that the economic impact of those ratios is much stronger than the one of the financial derivatives, highlighting the importance of closely watch the business model taken by the financial institutions in order to avoid overexposures to systemic risk.

This Thesis contributes to increase the understanding about systemic risk; however the knowledge on systemic risk is still very limited. In order to improve our capabilities to deal with systemic risk further research is needed in at least two aspects; firstly, a systematic analysis on the causes that let systemic risk to mount up, paying special attention to the role of the financial firms business, design of the financial markets and the disclose of sensitive information; secondly, the development of efficient instruments to manage to the level of systemic risk.

# Appendices

**Appendix A**

In this appendix we provide a detailed description of the explanatory variables obtained from the database Bank Holding Company Data (Federal Reserve Bank of Chicago) that are employed in this paper:

*Fair value of credit derivatives*: this variable is defined as the sum of the total fair value (positive and negative) of the total gross notional amount in which the reporting bank is beneficiary or guarantor.[64]

*Fair value of interest rate, foreign exchange, equity and commodity derivatives*: this variable is defined as the sum of the total fair value of the total gross notional amount for each of the four previous types of derivative contracts held for trading and for purposes other than trading by the banks. The total fair value is obtained as the sum of the positive and negative fair values.[65]

*Commercial paper*: The total amount outstanding of commercial paper issued by the reporting bank holding company to unrelated parties. Commercial paper matures in 270 days or less and is not collateralized.

*Loan to banks*: this variable includes all loans and all other instruments evidencing loans (except those secured by real estate) to depository institutions chartered and headquartered in the U.S. and the U.S. and foreign branches of banks chartered and headquartered in a foreign country.

*Maturity mismatch:* this variable is defined as the ratio of short term debt relative to total assets.

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[64] Credit derivatives are off balance sheet arrangements that allow one party (beneficiary or protection buyer) to transfer the credit risk of the reference asset to another party (guarantor or protection seller).

[65] The total fair values are reported as an absolute value.

*Net balance to bank*: difference between all balances and cash due to related banks[66] and all balances and cash due from related banks. Due to accounts are liabilities accounts that represent the amount of funds currently payable to another account. Due from accounts are assets accounts that represent the amount of deposits currently held at another company.

*Net balance to non-bank:* this variable is the difference between all balances and cash due to related non-banks and all balances and cash due from related non-banks.[67]

*Non-interest to interest Income*: this variable is the ratio between the total non-interest income and total interest income. The former includes the sum of income from fiduciary activities, service charges on deposit accounts in domestic offices, and trading gains (losses) and fees from foreign exchange transactions, among others. The later includes interest and fee income on loans secured by real estate in domestic offices, interest and fee income on loans to depository institutions in domestic offices, credit cards and related plans, interest income from assets held in trading accounts, among others.

*Non-performing loans:* this variable is the sum of total loans, leasing financing receivables, debt securities and other assets past due 90 days or more.

*Total deposits*: this variable includes the amount of all noninterest-bearing deposits plus the time certificates of deposits of $100,000 or more held in foreign offices of the reporting bank.

*Total loans*: this variable includes all loans except to the commercial paper and the loans reported in the *loan to banks* variable.

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[66] Banks directly or indirectly owned by the top-tier parent bank holding company, excluding those directly or indirectly owned by the reporting lower-tier parent bank holding company.

[67] Nonbank companies directly or indirectly owned by the top-tier parent bank holding company, excluding those directly or indirectly owned by the reporting lower-tier parent bank holding company.

**Appendix B**

This appendix contains the details on the estimation of the five systemic measures that we consider in this paper. The systemic risk measures are estimated on a weekly basis. In order to conduct quarterly regression analysis we consider the last observation of the quarter. However, for the baseline measure we also consider the sum of the observations during the corresponding quarter as a robustness test.

### *B.1. Co-Risk measures*

Adrian and Brunnermeier (2011) based their analysis on the growth rate of the market value of total financial assets, $X_t^i$, which is defined as the growth rate of the product between the market value of institution $i$ and its ratio of total assets to book equity.[68] $VaR$ and $CoVaR$ are estimated by means of quantile regression (Koenker and Bassett, 1978). The time-variant measures are based on the following equations in weekly data:

$$\begin{aligned} X_t^i &= \alpha^i + \gamma^i M_{t-1} + \varepsilon_t^i \\ X_t^{system} &= \alpha^{system|i} + \beta^{system|i} X_t^i + \gamma^{system|i} M_{t-1} + \varepsilon_t^{system|i} \end{aligned} \qquad (B.1.1)$$

where $M_t^i$ is a set of state variables.[69] In order to perform the quantile regression, we assume a confidence level of 1% what implies to estimate a $VaR$ at 1%. Once the coefficients of Equation B.1.1 have been estimated through quantile regression, we replace them into Equation B.1.2 to obtain the $VaR$ and $CoVaR$.

$$\begin{aligned} VaR_t^i(q) &= \hat{\alpha}_q^i + \hat{\gamma}_q^i M_{t-1} \\ CoVaR_t^i(q) &= \hat{\alpha}_q^{system|i} + \hat{\beta}_q^{system|i} VaR_t^i(q) + \gamma_q^{system|i} M_{t-1} \end{aligned} \qquad (B.1.2)$$

Finally, 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 $CoVaR_i$

[68] At portfolio level, the growth rate of the market value of total financial assets is computed as a weighted average of the growth rates of the constituents of the portfolio lagged one period.

[69] This set is composed by VIX, *liquidity spread* (i.e., 3-month repo minus 3-month bill rate), change in 3-month Treasury bill rate, *slope of the yield curve* (i.e., 10-year Treasury rate minus 3-month bill rate), *credit spread* (i.e., 10 Year BAA rated bonds minus 10-year Treasury rate) and return of the MSCI index.

conditional on the distress of the institution (i.e., $q = 0.01$) and the $CoVaR_i$ conditional of the "normal" state of the institution (i.e., $q = 0.5$ )

$$\Delta CoVaR_t^i(1\%) = CoVaR_t^i(1\%) - CoVaR_t^i(50\%) \qquad (B.1.3)$$

On the basis of Equation B.1.3 we obtain the weekly $\Delta CoVaR_t^i$. We also apply this methodology to estimate co-expected shortfall ($CoES_i$) which is defined as the expected shortfall of the financial system conditional on $X^i \leq VaR_q^i$. See Adrian and Brunnermeier (2011) for the details.

### *B.2. Asymmetric CoVaR*

López, et al. (2011) propose to extend the $\Delta CoVaR_t^i$ methodology in order to capture asymmetries in the estimation of the co-value-at risk. They propose the following specification:

$$X_t^i = \alpha^i + \gamma^i M_{t-1} + \varepsilon_t^i$$
$$X_t^{system} = \alpha^{system|i} + \beta^{+system|i} X_t^i I_{(X_t^i \geq 0)} + \beta^{-system|i} X_t^i I_{(X_t^i < 0)} + \gamma^{system|i} M_{t-1} + \varepsilon_t^{system|i}$$
$$(B.2.1)$$

where $I_{(\cdot)}$is an indicator function that takes 1 if the condition of the subscript is true and zero otherwise. Under this specification, Adrian and Brunnermeier (2011) approach can be seen as an special case in which $\beta^{+system|i} = \beta^{-system|i} = \beta^{system|i}$. As in Adrian and Brunnermeier (2011), Equation B.2.1 is estimated using quantile regression at 1%. Then, $CoVaR_t^i$ is estimated according to Equation B.2.2:

$$VaR_t^i(q) = \hat{\alpha}_q^i + \hat{\gamma}_q^i M_{t-1}$$
$$CoVaR_t^i(q) = \hat{\alpha}_q^{system|i} + \hat{\beta}_q^{-system|i} VaR_t^i(q) + \gamma_q^{system|i} M_{t-1} \qquad (B.2.2)$$

### *B.3. Gross Shapley Value of Value-at-Risk*

In order to apply this methodology it is *sufficient* to define a "characteristic function" ($\vartheta$) which should define the system-wide VaR when it is applied to the entire system.

Once the characteristic function have been defined, the contribution of bank $i$ to the subsystem $S$ equals the difference between the risk of subsystem $S$ and the risk of the subsystem when bank $i$ is excluded from it $(S - \{i\})$. So, the Gross Shapley Value ($GSV_i$) equals to the expected value of such contribution when the $N!$ possible orderings may occur with the same probability. Mathematically $GSV_i$ is defined as,

$$GSV_i = \frac{1}{N}\sum_{n_s=1}^{N}\left[\frac{1}{c(n_s)}\sum_{\substack{S\supset i\\ |S|=n_s}}(\vartheta(S)-\vartheta(S-\{i\}))\right] \qquad (B.3.1)$$

where $\sum$ denotes the entire financial system, $S \supset i$ are all the possible subsystems in $\sum$ containing $i$, |S| represents the number of institutions in the subsystem and $c(n_s)$ comprises the number of all possible subsystem with $n_s$ institutions which is defined as $c(n_s) = \frac{(N-1)!}{(N-n_s)!(n_s-1)!}$.

In order to carry out the practical implementation of this methodology, we estimate the characteristic function as in Adrian and Brunnermeier (2011) (i.e., through quantile regression). The number of considered banks in the system implies the main challenge of this methodology. In this article we analyze 91 bank holding companies and hence, we would have to estimate 2.48E27 different subsystems. Given the unfeasibility of storing such amount of information we define a subset of the 15 largest banks in such a way that for studying every institution we consider 16 banks (i.e., the largest 15 banks plus the bank under study).[70] This modification enables us to reduce the size of our problem without biasing the results because those banks represent more than the 80% of the average total assets of the whole system.

[70] The selected banks are: Bank of America, Bank of New York Company, Bank of New York Mellon, BB&T, Charles Schwab, Citigroup, Fifth Third Bancorp, JP Morgan Chase and Company, Metlife, PNC Financial Services Group, State Street, Suntrust Banks, United States Bancorp, Wachovia Corporation and Wells Fargo and Company.

Additionally we estimate this measure in an alternative way in which the system (16 banks) is composed of the largest 14 banks, the bank under study and a "synthetic" bank created from the remaining 76 banks which are weighed by the market value of total financial assets. By creating this representative bank, we take all the available information of the system (including the information contained in the small banks). This approach will be considered as a robustness test.

### *B.4. Net Shapley Value of Value-at-Risk*

We now extend the expression for the GSV for a given bank *i* as presented in Equation B.3.1 to show that during non-stress periods the individual contribution of this bank to the aggregate systemic risk should be close to zero and consequently this measure will be governed by the individual VaR of bank *i*. To show this, we consider an economy that is composed by 4 banks ($n = 1, \dots, 4$). The possible subsystems and the GSV when we study the contribution of bank 1 to the risk of the economy would be:

Subsystems (S): $\{1\}, \{1,2\}, \{1,3\}, \{1,4\}, \{1,2,3\}, \{1,2,4\}, \{1,3,4\}, \{1,2,3,4\}$

$$\begin{aligned} GSV_1 = \frac{1}{4}\Big[ & VaR(\{1\}) + \frac{1}{3} \\ & * \Big(\big(VaR(\{1,2\}) - VaR(\{2\})\big) + \big(VaR(\{1,3\}) - VaR(\{3\})\big) \\ & + \big(VaR(\{1,4\}) - VaR(\{4\})\big)\Big) + \frac{1}{3} \\ & * \Big(\big(VaR(\{1,2,3\}) - VaR(\{2,3\})\big) + \big(VaR(\{1,2,4\}) - VaR(\{2,4\})\big) \\ & + \big(VaR(\{1,3,4\}) - VaR(\{3,4\})\big)\Big) \\ & + \big(VaR(\{1,2,3,4\}) - VaR(\{2,3,4\})\big)\Big] \end{aligned} \qquad (B.4.1)$$

In non-stress periods (no systemic risk) bank *i* does not contribute to the overall level of risk and the only term which would differ from zero would be VaR({1}). To check the extent of this problem we estimate the average correlation between the GSV and the

VaR for each of the 91 banks. The average correlation for the period 2002-20011 is 0.98. This suggests that GSV is not an appropriate measure in our sample due to their strong correlation with the bank's VaR.

In order to palliate this GSV's drawback we introduce an alternative measure which is free from the impact of the individual value-at-risk. The main reason justifying this adjustment being the $VaR_i$ measures bank $i$ specific market risk. But $VaR_i$ does not measure how much risk bank $i$ is adding to the whole system. This new measure is named as the Net Shapley Value ($NSV_i$). Mathematically, it is defined as:

$$NSV_i = GSV_i - \frac{1}{N} VaR_i \qquad (B.4.2)$$

Additionally, we estimate the NSV measure for a portfolio that consists of only the 16 largest banks. Note that considering 16 banks we can define the system on the basis of a whole portfolio of banks instead of focusing on a core subset of banks and adding individually the remaining smaller banks and obtain that the pairwise correlation between the NSV estimated in the baseline analysis and the NSV using a portfolio of the largest 16 banks is, on average, 0.99.

**Appendix C**

In this appendix we describe the methodology employed to compare the systemic risk measures described in Appendix B. As in Chapter 2 we use two criteria to compare the five individual contribution of bank to systemic risk measures: (i) the correlation with an index of systemic events and policy actions, and (ii) the Granger causality test.

To implement the first criterion we carry out a multinomial regression for each bank $j$ in sample, where the dependent variable is the influential event variable (IEV, a categorical variable that takes value 1 whenever there is an event; -1 whenever there is a political action; 0 otherwise) and the explanatory variable is the systemic risk measure.

$$IEV_t = \alpha + \beta SystemicRiskMeasure_{i,j,t-k} + \varepsilon_t \qquad (C.1)$$

The subindex $i$ refers to a given systemic risk measure (i.e., NSV, GSV, $\Delta CoVaR$, $\Delta CoES$ or asymmetric $\Delta CoVaR$), $j$ refers to bank under analysis ($j = 1, \ldots, 91$) and $k$ refers to the number of lags in the regression ($k = 0,1,2$).[71] Next, the McFadden R-squared for each regression is obtained as follows:

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

where $M_{Full}$ refers to the full model and $M_{Intercept}$ to the model without predictors, and $\hat{L}$ is the estimated likelihood.[72]

The second criterion is based on the Granger causality test (Granger, 1969). This test examines whether past changes in one variable, $X_t$, help to explain contemporary changes in another variable, $Y_t$. If not, we conclude that $X_t$ does not Granger cause $Y_t$. Formally, the Granger causality test is based on the following regression:

[71] Results do not change when other lags are considered.

[72] To evaluate the goodness-of-fit for a multinomial regression, several pseudo R-squared has been developed. We employ McFadden R-squared due to its appropriate statistical properties.

$$\Delta Y_t = \alpha + \sum_{i=1}^{p} \beta_{yi} \Delta Y_{t-i} + \sum_{i=1}^{p} \beta_{xi} \Delta X_{t-i} + \varepsilon_t \qquad (C.3)$$

where $\Delta$ is the first-difference operator and $\Delta X$ and $\Delta Y$ are stationary variables. We reject the null hypothesis that $X_t$ does not Granger cause $Y_t$ if the coefficients $\beta_{xi}$ are jointly significant based on the standard F-test.

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