The Sovereign Nature of Systemic Risk

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Abstract

We present a methodology to empirically investigate systemic risk, fragility and contagion in financial networks. We use this methodology to measure the sovereign and banking components of systemic risk in Europe and to study their interaction. Our econometric framework provides a way to quantify the impact and spillover rates of systemic shocks within and across the two networks. We find that sovereign systemic shocks have a large and persistent impact on the probability of a collective banking default. Conversely, banking systemic shocks have a smaller and more transitory impact on sovereign risk. We show that the most fiscally constrained governments are the most vulnerable to sovereign systemic shocks. Finally, we provide evidence on how bank exposure to these fiscally fragile governments drives contagion across the two networks.

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Keywords: Systemic Risk, Contagion Risk, Banking Risk, Sovereign Risk, Fiscal Space, Narrative Approach

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1 Introduction

Systemic risk is the risk of a breakdown or major dysfunction in financial markets. Recent research has mainly focused on the identification of large and highly interconnected financial institutions. The failure of these institutions can have a disastrous impact on the entire financial system and economic activity (Adrian and Brunnermeier (2011), Acharya et al. (2010), Brownlee and Engle (2010), and Acharya, Engle, and Richardson (2012), among others). However, if we look at the recent banking and sovereign bailouts in Europe we realize that default risk of governments has become closer and closer to that of their domestic banks. This phenomenon has already been documented by Acharya, Drechsler, and Schnabl (2011), who argue that the increasing correlation between sovereign risk and banking risk is the result of a risk transfer from banks to their local governments, following a bailout. Figure 1 shows this phenomenon by plotting the 1-year rolling-window correlation between sovereign credit spreads and equally-weighted average credit spreads of domestic banks for Spain, the U.K., Germany and the U.S. In Europe, these correlations have been increasing since 2008 and have reached levels of about 70 percent during the European debt crisis. However, the picture also highlights strong comovements in bank-country correlations *across* European countries, signaling the existence of a source of fragility that drives up the probability of a collective default involving all European banks and governments. Moreover, such a phenomenon is not observed in the U.S., suggesting that this source of fragility is not relevant for the U.S. economy. In this paper we conjecture that, since governments are in charge of bailing out banks, systemic risk may have a risk component that pertains to the network of governments. In particular, we measure independently sovereign systemic risk and banking systemic risk to study their interaction.[1] We then investigate the source of fragility and contagion risk within and across networks.

When studying systemic risk, the main concern is how to quantify it. A proper measurement is a complex task as it requires the knowledge of the probability of the occurrence of a rare and disastrous event, the degree to which the shock is propagated through the system (i.e. understanding the linkages between financial markets and the macroeconomy), and the magnitude of the losses. To this end, we introduce a methodology that measures systemic risk according to a credit portfolio

[1] In the rest of the paper we use the labels "sovereign risk" and "banking risk" to refer to the risk of a collective default of the sovereign and the banking systems, respectively. In the literature, sovereign risk usually refers to the risk that a *single* country defaults. Here it has a wider meaning.

approach. We form portfolios of sovereign and bank liabilities and measure systemic risk as the price an investor would pay for hedging tail losses on these portfolios. We call it *systemic insurance price* (SIP)[2]. This measure is similar to the senior tranche of a collateralized debt obligation (CDO) that triggers when the loss on the portfolio is greater than 10 percent. We show that this methodology can replicate real traded prices, such as the senior tranche on the iTraxx Europe, with a correlation in weekly levels (changes) of approximately 80 (77) percent. This finding rules out concerns about model misspecification and guarantees that our SIP is a measure market participants are interested in, as it reflects market information.

We investigate how the two networks interact by focusing on the impact and propagation rate of systemic shocks from one network to the other. In particular, we conjecture that shocks to countries are more important for systemic risk than shocks to banks, because weaker countries are less able to fully serve as rescuers for the banking system. In particular, we test how "sovereign shocks" and "banking shocks" impact both the sovereign and the banking risk components. In our terminology, a sovereign (banking) shock is a shock that hits the sovereign (banking) system *directly,* and is identified from daily relevant news. In some cases, the shock is generated by institutions such as the European Union (EU), the European Central Bank (ECB) and rating agencies that have the power to mitigate or exacerbate the risk in financial markets, through actions or announcements. In other cases, the shock is generated by social unrest, such as protests or strikes.

To test our conjecture we use a structural vector autoregressive (VAR) where shocks are identified with the narrative of the events, similar to Romer and Romer (1989). This approach enables us to disentangle sovereign and banking structural shocks from ordinary ones. In particular, we quantify both the size of structural shocks and their spillover rates across the banking and sovereign systems. We find that shocks to sovereign risk have large and persistent impact on systemic risk. In particular, a negative sovereign shock increases sovereign risk by 12.4 percent with a spillover rate on the banking system of 88 percent. Conversely, shocks to banking risk have a smaller, more transitory impact on sovereign risk. Indeed, a negative banking shock increases banking risk by 11.8

[2]Such an approach has been introduced by Huang, Zhou, and Zhu (2009) and labeled "distress insurance premium" (DIP). We change the name in "systemic insurance price" to avoid a possible confusion between insurance premium and risk premium studied in the asset pricing literature. This re-labeling will be useful for the analysis we present in section 6.

percent on average and spills over to sovereign risk with a rate of 32 percent. Moreover, this shock dies off two days after impact. The systemic relevance of sovereign shocks supports our hypothesis that systemic risk has a significant sovereign component. Therefore, monitoring banking risk only does not provide a complete picture of the source of systemic risk.

To further explore the nature of sovereign shocks, we decompose our risk-neutral measure into a default-risk component and its associated risk premium. Such a decomposition will shed light on the relevance of sovereign shocks for banking risk. We find that these shocks have a larger impact on the banking default risk than on its risk premium.

We further conjecture that the main source of fragility in Europe comes from fiscally constrained countries, unable to provide outside assistance to the banking system in case of a large negative shock. We measure the fragility of a country as flexibility for fiscal maneuver and as the level of indebtedness. Fiscal flexibility, or "fiscal space", measures the difference between a theoretical government debt limit and its actual debt load. Therefore, a government with low or close-to-zero fiscal space cannot use conventional fiscal tools (issuing new debt and/or increasing taxes) to support extraordinary expenses, such as a banking bailout. Because fiscal space is derived from a model, we use sovereign indebtedness, defined as debt-to-GDP ratio, as a model-free variable that captures the debt-load dimension of the fiscal space. Using a portfolio sorting approach, we quantify systemic risk of three sub-systems of countries sorted by their fiscal space and debt-to-GDP ratios. We find that sovereign shocks have the largest impact on low-fiscal-space and highly indebted governments, such as Portugal, Italy, Ireland, Greece and Spain (PIIGS). In particular, the impact of sovereign shocks is doubled (tripled) for the lowest-fiscal-space (most-indebted) governments. Conversely, these measures of fragility do not capture heterogeneity in the exposure of sovereign risk to banking shocks.

Given these findings, we further investigate the spillover channels from the sovereign to the banking system. Sovereign shocks can impact banks through their liabilities and/or their assets: Governments provide implicit guarantees to banks (liability-side effect) and banks hold sovereign debt (asset-side channel). Using a portfolio sorting approach, we form three sub-systems of banks sorted by their exposure to governments with very low fiscal space and high indebtedness. We find that sovereign shocks are amplified for banks that are highly exposed to fiscally constrained governments. Moreover, to disentangle the liability-side and asset-side effects, we split the highest-exposed banks into domestic and foreign. Indeed, foreign banks can only be exposed to the most indebted countries through the asset side, while domestic banks are also exposed through the liability side (implicit guarantees). We find a significant heterogeneity in the response of the two portfolios to sovereign shocks. Specifically, the impact of sovereign shocks on foreign banks is statistically different from that on domestic banks. These results suggest exposure to the weakest economies drives contagion risk from the sovereign to the banking system.

In summary, the main contribution of our paper is methodological: We provide a platform to empirically investigate systemic risk in economic networks. In our empirical analysis, we focus on Europe because recent developments in European credit markets provide us with a natural framework to think about fragility in the sovereign system. However, our analysis can be extended both geographically and across sectors. Indeed, we apply our methodology to the U.S. economy and, differently from Europe, we find a weak comovement between banking and sovereign systemic risk. Even though we do not provide an empirical explanation of such a difference across the two macro-systems, this empirical finding paves the way to new research questions, such as studying spillover effects across geographical areas.

A second contribution is empirical: Our results suggest that, in Europe, there is a sovereign component of systemic risk that dominates the banking one. Our methodology can help policy-makers identify the dominant source of systemic risk and implement macroprudential policy to specifically target the dominant risk component. Moreover, our empirical results can serve as a guide for future macroeconomic models that aim at formalizing the propagation of shocks across economic networks.

Literature Review and Contribution. Recent papers on systemic risk have focused on its measurement and on the information it conveys about the macroeconomic cycle.

Two main approaches have been proposed to measure systemic risk: A structural method that uses a contingent claims analysis *à la* Merton (1974), where the equity is a call option on the bank's assets (see Lehar (2005), Gray, Merton, and Bodie (2008), and Gray and Jobst (2011), among others), and a reduced-form method that exploits the information content of the tail distribution of asset returns. The methodology we present in this paper is in line with the second approach, as we use both credit and stock market information to quantify the main components of systemic risk: The probability of default, the loss given default, and the degree of interconnectedness in the system. Our measure was first introduced by Huang, Zhou, and Zhu (2009), Huang, Zhou, and Zhu (2012), and Black et al. (2013) who quantify systemic risk of major U.S. and European banks during the sub-prime financial crisis. However, we improve on their analysis by (i) focusing on the economic significance of this measure, (ii) showing that it replicates real traded prices and (iii) using it to investigate fragility and contagion risk.

With contagion at the heart of systemic risk, recent papers have proposed several measures to capture spillover and externalities across financial institutions.[3] Brunnermeier et al. (2009) and Adrian and Brunnermeier (2011) propose a conditional value-at-risk (CoVaR) model, which measures the value-at-risk of a financial institution conditional on the institution being in distress.[4] The CoVaR method is measured by changes in the total market asset value of all publicly traded financial institutions, and is able to capture externalities and fundamental comovements across markets.[5] The economic mechanism behind these externalities is the fire-sale channel, which implies that during distress times, institutions do not take into account the price impact their individual fire-sales will have on asset prices in a future liquidity crunch. In other words, during crises, fire-sale prices are driven by the need for financial institutions as a group to deleverage.[6] Brownlee and Engle (2010) and Acharya, Engle, and Richardson (2012) introduce the SRISK index, which measures the expected capital shortage of a financial institution conditional on a significant market

[3]Contagion is meant to be a particular strong propagation of failures from one institution, market or system to another (De Bandt and Hartmann (2000))

[4]Other empirical works on contagion have focused on measuring the degree of interconnectedness of the system. Kritzman et al. (2011) propose the absorption ratio, which is "the fraction of the total variance of a set of asset returns explained or "absorbed" by a fixed number of eigenvectors". Such a measure enables them to capture how much a market is unified or tightly coupled. Billio et al. (2012) propose and investigate five measures of systemic risk that are designed to capture some aspect of the four L's of systemic risk: Liquidity, leverage, linkages and losses. To this end, they propose measures such as correlation, return illiquidity, principal component analysis, regime-switching models and Granger causality tests. Acharya, Engle, and Richardson (2012) propose the Dynamic Conditional Correlation model (Engle (2002)) to capture the time-varying nature of the degree of contagion.

[5]Adams, Füss, and Gropp (2012), Wong et al. (2011), Gauthier, Lehar, and Souissi (2012) are other studies that use CoVaR to estimate systemic risk of banking systems.

[6]Stein (2009), Korinek (2011) and Brunnermeier and Sannikov (2014) formalize the fire-sale channel in a theoretical framework.

decline. Such a measure is based on the fact that externalities are generated by the propensity of financial institutions to be undercapitalized when the financial system as a whole is undercapitalized. Engle, Jondeau, and Rockinger (2014) modify the SRISK measure to allow for global, regional and countrywide factors, and perform an empirical analysis on a large set of European financial institutions.[7] Both of these approaches use realized equity returns and thus measure systemic risk under the physical probability measure. In a departure from these studies, we use a risk-neutral measure derived from traded credit spreads.[8] Risk-neutrality may be a crucial aspect of systemic risk for the policymaker, because it corrects for the risk aversion of the market. Indeed, systemic risk is priced in the market not only when there is a serious risk of a catastrophic breakdown, but also when risk aversion is high, and shows up in the marginal utility of the representative investor. Moreover, we also exploit a technique to decompose our systemic insurance price into a default-related component and its associated risk premium (Zhang (2003), Remolona, Scatigna, and Wu (2007), Pan and Singleton (2008), and Longstaff et al. (2011), among others) to further explore the interplay between sovereign and banking systems.

Fiscal space is a recent term introduced in economics to estimate the flexibility of a government in absorbing large negative shocks by using conventional fiscal policy tools. This term is also called "fiscal fatigue" and has been modeled and estimated by Ghosh et al. (2013) and Ostry et al. (2010) to study debt sustainability in advanced economies.[9] To the best of our knowledge, we are the first in using the concept of fiscal space to better identify the fragility of a system of governments and how shock impact those countries.

In summary, recent works have focused mainly on the risk of contagion across financial institutions *within* the same system. To the best of our knowledge, our paper is the first in considering the risk of contagion *across* financial systems by decomposing systemic risk into the sovereign and the banking components. Additionally, we provide insight for the first time into a decomposition

[7] Other studies have focused on the European financial system. Allen, Bali, and Tang (2012) highlight the importance of the risk of macroeconomic contagion that makes both regulators and governments concerned about systemic risk. To this end, they propose an aggregate measure of systemic risk to predict future real economic declines using the cross-section of equity returns of both European and Asian financial institutions. Acharya and Steffen (2013) use the SRISK measure to rank systemically important European banks (SIFI) at different points in time.

[8] Giglio (2011) uses credit spreads to derive bounds of systemic risk with a non-parametric approach.

[9] The concept of fiscal space is mainly related to the research on the primary balance of governments in advanced and emerging economies (Bohn (1998) and Mendoza and Ostry (2008)).

of our systemic risk measure into a default-related component and its associated risk premium for a deeper understanding of the nature of such a risk. Finally, we identify structural systemic shocks through the narrative approach of Romer and Romer (1989) to test empirically how they impact on the two components of systemic risk, in an attempt to shed light on the complex and unexplored relation between the two.

Structure of the paper. The paper proceeds as follows: In Section 2 we introduce the methodology used to measure the systemic credit risk; in Section 3 we present the data and demonstrate how our measure can replicate a traded asset; in Section 4 and 5 we quantify the two components of systemic risk in Europe and present the empirical framework; in Section 6 we show how to decompose systemic risk into systemic distress and default risks; Section 7 investigates channels of contagion, and Section 8 concludes the paper.

2 Systemic Credit Risk Measure

Measuring systemic risk is a complex task because it requires the knowledge of the probability of a collapse of an entire macro region. This probability depends upon the degree of interconnectedness of entities in the region, as even a small negative shock can have a large impact if the system is highly interconnected. To this end, in this section we present a methodology that quantifies systemic risk and can be readily applied to any system or sub-system whose risk requires a closer investigation.

Assume a hypothetical investor holds a portfolio of liabilities of N entities. We compute a systemic risk indicator as the hypothetical insurance price the investor is willing to pay for hedging against catastrophic losses. We define "catastrophic" as a loss that exceeds 10 percent of total liabilities in the portfolio.[10] To give a sense of the economic magnitude of the aforementioned loss, when the European debt crisis reached its maximum peak in the summer of 2011, the outstanding debt of European countries amounted to about 10.4 trillion. A loss of 10 percent would wipe out almost a full 9 percent of European GDP.[11]

[10] The subsequent results are robust to different threshold levels such as 15 or 20 percent.

[11] Eurostat reports that the GDP of the European Union (25 countries) in 2011 amounted to about 12.1 trillion.

Systemic risk is measured as the expected total loss on such a portfolio, conditional on losses being greater than a threshold x. More specifically, let $L_t = \sum_{i=1}^{N} L_{i,t} w_{i,t}$ be the total loss of the portfolio as the weighted sum of the losses on each debt's entity i at time t, $L_{i,t}$, with weights $w_{i,t} = Debt_{i,t} / \sum_i Debt_{i,t}$. Then, the T-year systemic insurance price (SIP) at time t is:

$$\mathbf{SIP}_t\,(T) = E^{\mathbb{Q}}[L_{t+T} \times \mathbb{1}\,\{L_{t+T} \geq x\}] \tag{1}$$

where x is set to 10 percent of the total liabilities and $\mathbb{Q}$ indicates that the expectation is taken under the risk-neutral probability measure. Using a risk neutral measure to price systemic risk has the advantage of correcting the actual systemic default risk by the market price of risk, that captures agents' attitudes toward risk. Indeed, the risk of a catastrophic breakdown is priced in the market when risk aversion is high and shows up in the marginal utility of the representative investor. Therefore, studying systemic risk only under the physical measure misses the important weight of market risk aversion that is in play during periods of high distress. Moreover, this measure computes the risk of a portfolio of liabilities that, differently from equity, can be bailed out in case of distress.

SIP can also be thought of as the capital buffer the investor needs to hedge catastrophic losses. Indeed, SIP is similar in spirit to a collateralized debt obligation (CDO), as it is a claim against a portfolio of debts that embeds the joint default probability of the entities. A CDO is priced in tranches split by attachment points that define the range of losses within which the contract triggers. Attachment points are expressed as a percentage of the notional, M-N, which refer to the lower, N, and upper, M, boundaries of the losses. Each tranche has its own price, and the one that suffers the largest losses is called super-senior tranche. Therefore, our measure is similar to a CDO_{10-55} in that we price only losses greater than the 10 percent threshold and less than the loss given default, that we assume at 55 percent without a loss of generality.[12] A detailed overview on CDOs is provided by Longstaff and Rajan (2008) and Bhansali, Gingrich, and Longstaff (2008).

Senior or super-senior tranches have been used as a proxy for the "economic catastrophe risk", which refers to those institutions (or bonds) that default only under harsh economic conditions

[12] See Appendix A.1 for a detailed explanation.

(Coval, Jurek, and Stafford (2009), Berndt and Obreja (2010)). That said, our measure resembles the characteristics of such a risk, as a loss of 10 percent or greater can only be the result of a shock or event that occurs infrequently with disastrous consequences, most likely due to a high degree of interconnectedness.

For the purpose of our analysis, we cannot use traded tranches for several reasons: They are only available for a short time period and for a basket of 125 European companies from different sectors. To our best knowledge, no tranche on sovereign CDS basket is traded, thus, inhibiting us from investigating the sovereign component of systemic risk. In addition to this, the measure we propose allows for the decomposition of the banking and sovereign systems in sub-systems, thus, suitable for studying the source of fragility and channels of contagion as presented in Section 7

3 Data

We measure systemic risk of two macro systems: The European sovereign system and the European banking system. The former is composed of 24 countries whereas the latter is comprised of 41 European banks. The number of entities for each portfolio is dictated by data availability; however, these 41 banks account for almost 70 percent of the total liabilities of the largest European banks[13]. For each system we collect credit default swap (CDS) spreads, total liabilities, public government debts and stock prices, over the daily period from January 1, 2001 to November 29, 2013.

We collect CDS spreads from Markit and range in maturity of 1-, 3-, 5-, 7- and 10-year. A CDS is an agreement between two parties: The buyer and the seller. The buyer pays a periodic premium, usually quarterly or semiannual, to hedge the underlying security, a loan or a bond, against the default of the issuer. Upon the default of the issuer, the seller commits herself to pay the amount the buyer will not recover from the bankruptcy procedure. At inception, one or both parties usually posts collateral, which leads to the assumption that counterparty risk is absent. Therefore, as a traded security, forward-looking information about the credit worthiness of the issuer is implicitly embedded in CDS contracts. For countries we use spreads with a complete restructuring (CR) clause, while for the European banks we use spreads with a modified-modified restructuring (MM)

[13] As of 2013 the consolidated banking data for EU large banks is €22.3 trillion, as reported by the European Central Bank (ECB).

clause. While the CR and MM clauses agree on the definition of credit events, they differ on the maturity of the deliverable obligation. According to the CR clause, any bond of maturity up to 30 years is deliverable. According to the MM clause, deliverable obligations against the contract must be limited to those with a maturity of 60 months or less after the termination date of the CDS contract. Our choice of data is constrained by availability and by concerns about liquidity. Stock market data has the same frequency as CDS spreads and is collected from Datastream. More specifically, we use local stock market indices for countries and individual stocks for banks. We then collect bank liabilities from Datastream and public central government debts from Eurostat.

Table 1 reports summary statistics for the 5-year sovereign CDS spreads, public debt, and domestic stock market prices over three subsamples: The 2001/2006 pre-crisis period, the 2007/2009 financial crisis, and the 2010/2013 European debt crisis.

Credit spreads in the pre-crisis period are very low except for some Eastern economies due to negative spillovers from the Ruble crisis that hit Russia at the end of the 1990s.[14] Supported by large borrowings from Western banks, these economies experienced flourishing growth in the mid-2000s, but suffered heavy losses during the subprime crisis in 2007/09 when banks significantly reduced lending activity. Indeed, in the 2007/2009 financial crisis period, Bulgaria, Estonia, Latvia and Lithuania recorded, on average, credit spreads greater than 200 basis points, which implies a 5-year risk-neutral default probability ranging from 17 percent for Bulgaria to 28 percent for Latvia - higher than those of the rest of Europe. The European debt crisis period shows a reverted scenario where Western developed economies experienced, on average, very high spreads. This scenario was mostly driven by the increasing indebtedness of countries such as Portugal, Italy, Ireland, Greece and Spain, the so-called PIIGS countries, as shown in the "Liab" column for each sub-sample. In addition to this, we use stock market prices as a proxy for the state of the local economy, as Levine and Zervos (1996) demonstrate a positive relation between stock market development and long-run economic growth. Therefore, the correlation between stock returns is a valid proxy for contagion risk across economies.[15]

[14] Jochum, Kirchgässner, and Platek (1999) show empirically how the correction in Russian stock prices in October 1997 had a pronounced influence on other Eastern European economies.

[15] Ang and Bekaert (2002) and Longstaff et al. (2011), among others, have shown that there is a tendency for correlations in financial markets to increase during crisis periods.

Table 2 reports the same statistics but for the European banking system. The pre-crisis period can be deemed as a period of calm for the European banking system, but the scenario is different during the financial and debt crisis periods. Similar to the most developed European countries, the debt crisis is the most turbulent period for the banking system, as credit spreads trended up dramatically and stock prices reached very low levels. We capture contagion risk among banks with the correlation in stock returns.[16] Comparing Table 1 with Table 2, we notice how the domestic banking systems of some countries, such as the most indebted ones, share the same high credit spreads, and negative slopes (for Greece) as their local government. These summary statistics point to the main argument of this paper that there is indeed a link between the two macro systems for which we provide an empirical explanation in the next sections.

Figure 2 plots the one-year rolling window average pairwise correlations of the stock returns of both banks and countries. Unlike credit default swap spreads that signal a low credit risk during the pre-crisis period, the average correlation in the banking system reaches a peak of about 50 percent in 2003, most likely due to the consequences of the dot-com bubble that collapsed in 1999/2001. At the beginning of 2006, we see a big spike that brings the contagion risk among banks to the level of 2003 before trending up to a maximum of 65 percent after the bankruptcy of Lehman Brothers at the end of 2008. The latter event is particularly significant in the sovereign system, as its contagion risk jumps up by 14 percent (from about 33 to 47 percent), which is 3.5 times the increase in banking contagion risk over the same period length. We will show that, during this event, sovereign risk jumps up, whereas banking risk goes down, signaling the risk transfer from the banks' balance sheets to those of countries (Acharya, Drechsler, and Schnabl (2011)). Also the debt crisis is characterized by varying contagion risk, with an increasing trend in the fall 2011, when political issues in Italy and Greece threatened the stability of the Union.

3.1 Systemic Insurance Price as a Real Price

Before employing any empirical analysis on our systemic risk measure, we test whether SIP represents the real price that would be traded, if such a CDO tranche of the underlying credit existed. Indeed, proving that our measure behaves like a real price makes it economically meaningful, as it

[16] For constant leverage, variations in equity (stocks) resemble variations in assets. Therefore, we measure the degree of interconnectedness among banks throughout their asset side.

proves that it is a number market participants or policymakers are interested in, because it reflects market expectations.

We use the methodology in Section 2 to price the super senior tranche (losses in the range 22-100 percent) on the 5-year iTraxx Europe CDX, which is a credit default swap on an equally-weighted basket of 125 companies from different sectors. It is mostly used to hedge credit risk of a portfolio as opposed to single-name CDS spreads that are more costly in terms of bid-ask spread. Tranches trade in series that cover a period of six months corresponding to the portfolio rebalancing frequency. We collect data on tranches from a J.P. Morgan proprietary database that span a short period from September 2011 to November 2012 (series s16, s17 and s18), but enough to test our measure.

Figure 3 plots both our SIP measure and the senior tranche on iTraxx Europe in basis points. The correlation in weekly levels and in first-differences between the two series is about 80 and 77 percent, respectively. This result suggests that our SIP is a viable measure to assess both contagion risk and credit risk of a system or sub-system.

4 Systemic Risk in Europe

So far we have introduced a methodology to measure systemic risk and have shown that it is a reliable way to price traded securities. Figure 4 plots the sovereign and the banking components of systemic risk over a 5-year horizon. This time horizon is chosen to price those persistent shocks to systemic risk that may have a delayed impact on the real economy. As an example, assume that on a specific day, monetary authorities announce that a pool of European banks has failed stress tests and need a strong recapitalization. Such a shock can have a negative impact on systemic risk and could spill over the real economy months after the impact, through a significant reduction of bank lending. Therefore, with the 5-year horizon we aim at capturing market expectations of systemically important and persistent shocks that have implications for the economic cycle.[17]

As already inferred from the summary statistics of 5-year CDS spreads, the pre-crisis period was a "normal" period with no systemic implications at stake. In the Summer of 2007, spillover

[17] In this paper we do not study implications of systemic risk for the real economy. However, our measure is suitable for this analysis as the insurance price, at low frequency, can convey information on the real economy.

from the US financial market spread throughout the European banking system and triggered a series of spikes in systemic risk. Immediately following the Lehman default, extraordinary liquidity measures and the UK and Irish bailouts led to a transfer in the riskiness from the banks' balance sheets to governments' budget balances. Indeed, contagion risk in the sovereign (banking) system jumped up by 14 (4) percent (Figure 2), whereas sovereign (banking) risk jumped up (down) and reached high levels of about 140 bps. In the period subsequent to this risk transfer, sovereign and banking risk moved together, signaling an important interplay between sovereign and banking risk.

Following the beginning of the debt crisis in 2010, both systemic risk measures trended upward, and reached a maximum level of approximately 350 basis points in the Summer of 2012. A sequence of political and economic events throughout Europe contributed to this rise in risk. At the end of 2009, doubts arose about the feasibility of the first bailout in European Union history, namely, the Greek bailout agreement that was reached in May 2010 after 4-months of negotiation among European politicians.

Particularly important for systemic implications was the Summer/Fall of 2011, when political shocks in Greece, Italy, and Spain destabilized the European Union as a whole with the resignation of the Italian and Greek Prime Ministers and the possibility of national referendums on Euro-exit. During these events, the systemic insurance price reached a peak of 350 basis points per year in November 2011. At that time, the total debt of the 27 countries of the European Union (EU27) amounted to € 10.5 trillion, and a loss of 10 percent would have been triggered by a 30 percent selective default of the most indebted countries (Portugal, Greece, Spain, Italy and Ireland) whose total debt was in excess of € 3 trillion.[18] By that time, the EU had already bailed out Greece (May 2010 and October 2011 for a total of € 240 billion euros), Ireland (November 2010 for € 67 billion) and Portugal (May 2011 for € 78 billion) for a total of approximately € 385.5 billion, and was left with a safety-net of approximately € 364.5 billion.[19] This number is very close to that predicted by our measure, that is, € 365.9 billion, the hypothetical premium paid on the total debt of the EU27 countries at the end of 2011 to insure against large losses over the next 5 years. This finding highlights another interpretation of our systemic insurance price as a measure of capital

[18] The numbers are from Eurostat: Aggregate government statistics of EU27 for the last quarter of 2011.

[19] In 2010, the combination of the European Financial Stability Facility (EFSF), the European Financial Stabilization Mechanism (EFSM) and the IMF contribution amounted to € 750 billions.

requirements, and implies that the European Union had an adequate safety-net at the end of 2011. Indeed, as an ex-post analysis reveals, over the period 2012-13 the EU used an additional € 51.4 billion to rescue the Spanish banking system (July 2012) and Cyprus (May 2013). According to our measure, it would appear that the European Union maintained an adequate level of capital to absorb potentially large losses from the sovereign system.[20] Since most of the European Financial Stability Facility (EFSF) funding and other (implicit and explicit) guarantees come from individual countries, we can argue that a fiscally constrained system of governments may not be able to to "absorb" large losses from the banking system, thus, weakening it. In other words, governments could not be able to bail out the banking system.

The complex and unexplored relation between the sovereign and banking components leaves us without a clear picture about which one has the most significant impact on systemic risk. In an effort to shed more light on this relation, in the next section we introduce an empirical tool to test how sovereign and banking shocks affect the probability of a systemic collapse of both the European sovereign and banking systems.

5 Empirical Framework

In this section, we introduce the econometric tool used to study the impact of bank and sovereign shocks on systemic risk and present how we identify shocks through a coherent and systematic procedure. In our terminology, a sovereign (banking) shock is a shock that hits the sovereign (banking) system *directly* and is identified as the relevant news on a specific day. In some cases, the shock is generated by institutions such as the European Commission and the European Central Bank that have the power to mitigate or exacerbate the risk in financial markets through actions or announcements. In other cases, the shock is generated through social unrest such as protests or strikes that cause turmoil in a specific country and have a high potential to spread across the system. We provide further details about how we collect and identify these shocks in subsection 5.2. In particular, an interesting aspect of the narrative approach is that we can literally name economic and financial shocks and quantify both their magnitude and rate of transmission across

[20] At the time of the Spanish and Cypriot bailouts, the liabilities of the largest European banks amounted to € 25.5 trillion, which, according to our measure, requires a capital buffer of approximately € 854.6 billion.

the two systems.

Consider a bivariate vector autoregressive of order p, $VAR(p)$, of the form

$$y_t = \Phi_y(L)y_{t-1} + \Phi_x x_t + u_t,$$

where y_t is a vector containing the daily first differences of the sovereign and the banking systemic insurance price, $\Phi_y(L) = \sum_{j=1}^{J} \Phi_{y,j} L^{j-1}$ is a polynomial of 2×2 matrices in the J-lag polynomial operator, x_t is an m-dimensional vector of exogenous variables including the constant and a time dummy that is equal to one during the debt crisis (from 2010 on), and u_t is a vector of i.i.d. innovations. In a more compact form, this model can be written as

$$y_t = \Phi z_t + u_t, \tag{2}$$

where $z_t = [y_{t-1}^{\top}, ..., y_{t-J}^{\top}, x_t^{\top}]$ is a $p \times 1$ vector of both lagged endogenous and exogenous variables with $p = 2J + m$ and $\Phi = [\Phi_{y,1}, ..., \Phi_{y,J}, \Phi_x]$ as a $2 \times p$ matrix of coefficients. In the empirical implementation, we choose $p = 3$ as indicated by the Akaike Information Criterion.

As in structural VAR, we assume jointly correlated innovations u_t to capture spillover across the two systems. Following standard practice, we assume

$$u_t = B\varepsilon_t, \tag{3}$$

where ε_t is an i.i.d. vector of shocks with zero mean. The matrix B therefore reflects the impact and the rate of transmission of these shocks across systems.

5.1 Narrative Approach

Given the complex and relatively unexplored nature of the relation between sovereign and banking systemic risk, we cannot rely on statistical approaches to identify the off-diagonal elements of the matrix B. Cholesky ordering, exclusion restrictions, sign restrictions and long-run constraints do not have enough economic support to be used in this case. To get around this problem, we use a *narrative approach* similar to Romer and Romer (1989).[21] According to this approach, structural shocks are partitioned into two parts: Shocks of interest and "other" shocks. We modify this approach by further partitioning structural shocks into sovereign, banking and "other" shocks. The first two are called "exceptional" systemic shocks and reflect, to some extent, observable events, whereas the residuals are "ordinary" shocks. Specifically, we partition the matrix B into three $n \times 1$ vectors such that $B = \left[\beta^{sov}, \beta^{bank}, \tilde{\beta}\right]$ and $u_t = \beta^{sov}\epsilon_t^{sov} + \beta^{bank}\epsilon_t^{bank} + v_t$ with $v_t = \tilde{\beta}\tilde{\epsilon}_t$. β's are loadings that capture the conditional response of the two components of systemic risk to sovereign and banking shocks, ϵ_t^{sov} and ϵ_t^{bank}, respectively.

Estimating these loadings without restrictions is possible with the use of the narrative approach, whose main contribution is to find valid and orthogonal instruments for ϵ_t^{sov} and ϵ_t^{bank}. We define these instruments as signed indicators, $\mathbb{1}_{sov}$ and $\mathbb{1}_{bank}$, that take value of $+1$, -1 or 0, if there is a positive, negative or no shock on a specific day.

Before explaining how we measure instruments, we need to list some important conditions. In our case, the indicator variable will be valid instruments if they satisfy the following conditions:

$$\begin{aligned} E\left[\mathbb{1}_{bank}\epsilon^{bank}\right] &= \phi_{bank} \qquad E\left[\mathbb{1}_{bank}\tilde{\epsilon}\right] = 0 \\ E\left[\mathbb{1}_{sov}\epsilon^{sov}\right] &= \phi_{sov} \qquad E\left[\mathbb{1}_{sov}\tilde{\epsilon}\right] = 0 \end{aligned} \tag{4}$$

$$\begin{aligned} E\left[\mathbb{1}_{bank}\epsilon^{sov}\right] &= 0 \\ E\left[\mathbb{1}_{sov}\epsilon^{bank}\right] &= 0 \end{aligned} \tag{5}$$

where (4) assures that the instruments are reliable. In addition to this, (5) assures that the sovereign shock indicator is not an instrument for banking shocks and viceversa.[22]

Under these conditions, the joint correlated structural shocks can be written as

$$u_t = \beta^{sov}\mathbb{1}_{sov}\xi_{sov} + \beta^{bank}\mathbb{1}_{bank}\xi_{bank} + v_t \tag{6}$$

[21] Recently this approach has been used by Brutti and Sauré (2012), Mertens and Ravn (2011), Mertens and Ravn (2010), Romer and Romer (1997), and Romer and Romer (2007), among others.

[22] All these conditions are verified empirically. In particular, we estimate the VAR with either sovereign shocks only or banking shocks only. The coefficients do not change compared to the VAR with the two types of shocks. Results are not reported here but available upon request.

where $\beta^{sov} = \left[\beta^{sov\leftarrow sov}, \beta^{sov\leftarrow bank}\right]'$ and $\beta^{bank} = \left[\beta^{sov\leftarrow bank}, \beta^{bank\leftarrow bank}\right]'$ with $\beta^{Y\leftarrow X}$ being the impact of the X shock onto the component Y of systemic risk and ξ represent the average size of the exceptional event within networks to be estimated. Given that ϕ in (4) is not directly observable, we normalize the loading matrix such that sovereign (banking) shocks have a one-to-one impact on sovereign (banking) risk. Therefore, we can write (6) as

$$u_t = \begin{bmatrix} 1, & B^{sov\leftarrow bank} \\ B^{bank\leftarrow sov}, & 1 \end{bmatrix} \begin{bmatrix} \mathbb{1}_{sov}\xi_{sov} \\ \mathbb{1}_{bank}\xi_{bank} \end{bmatrix} + v_t \tag{7}$$

where $B^{sov\leftarrow bank} = \beta^{sov\leftarrow bank}/\xi_{bank}$ and $B^{bank\leftarrow sov} = \beta^{bank\leftarrow sov}/\xi_{sov}$ are the spillover rates *across* networks.

5.2 Shock Identification

In order to identify the instruments $\mathbb{1}_{sov}$ and $\mathbb{1}_{bank}$, we collect relevant daily news from a variety of sources such as the Financial Times, the Wall Street Journal, Wikipedia, BBC, Reuters, Bloomberg, rating agency websites, the ECB, Brugel, the Saint Louis Fed, and Stratfor. These websites or newspapers provide a detailed time line of the financial and European debt crises.

According to our selection criterion, a news is relevant when it is reported by multiple sources and includes: i) a policy announcement and/or action from central banks, the European Union Institutions, or individual countries; ii) actions by rating agencies; iii) social unrest; or iv) extraordinary events such as bankruptcy, bailouts and nationalizations.

To systematically collect relevant news, we identify two macro categories of shocks: The shock generator and the shock recipient.[23] The former includes the European Central Bank, the European Union, and rating agencies.[24] These are institutions with the power of reverting negative trends and of mitigating the risk in financial markets through announcements and actions, thereby generating shocks. Additionally, a shock can be generated by events of massive social unrest, political instability, or electoral uncertainty. The shock recipient is essentially the system *directly*

[23] We are only interested in the shock recipient. The shock generator is identified only as a guidance: Whenever there is a relevant news, we first ask who is its generator and then assign the shock to the recipient.

[24] In some cases we also include foreign institutions such as the Fed and US Treasury

affected by these shocks, as our empirical approach estimates the transmission rate across systems. In particular, we distinguish between banking and sovereign shocks. In our identification, a shock hits either the banking system or the sovereign system.

The narrative approach also requires us to identify the direction of each shock. As explained in section 5.1, we measure shocks using a categorical variable that takes a value of one (minus one) if the shock is supposed to mitigate (exacerbate) risk and decrease (increase) the probability of a collective default. Examples of positive shocks to sovereign risk are the announcements and approvals of austerity plans, bailouts by the EU, or upgrades (very rare) by rating agencies. Conversely, examples of negative shocks are social unrest, political instability or electoral uncertainty, rating downgrades or the request of a bailout. Table 3 reports the two macro categories of shocks with generators and recipients in panels A and B, respectively, along with the direction of the shock in squared brackets. The detailed timeline is provided in the online Appendix.[25]

We aim at identifying shocks *ex ante*, in the sense that we define the shock directions regardless of the realization of uncertainty in the credit security the following day. Therefore, our approach can be seen as a "generalization" of the classical event-study analysis. because we do not compare the pre-shock period with the post-shock period. As a practical example, on July 26, 2012, the European Central Bank president, Mario Draghi, declared that *to the extent that the size of these* [European] *sovereign premia hamper the functioning of the monetary policy transmission channel, they come within our mandate,* [...] *within our mandate, the ECB is ready to do whatever it takes to preserve the euro and believe me, it will be enough.* Such announcements are called by policymakers to stop market expectations of self-fulling debt crisis (Cole and Kehoe (2000) and Lorenzoni and Werning (2013)), therefore, we code it as a positive shock generated by the ECB and impacting directly on the sovereign system. As a counter-factual example, on October 2, 2014, Draghi announced new measures in the form of outright purchases of asset-backed securities and covered bonds in an attempt to revive lending in the Eurozone. Even if our sample period ends in November 2013, this announcement would have been coded as a positive shock generated by the

[25]The announcement or the implementation of a conventional monetary policy tool, such as an increase or decrease of the official interest rate, might be hard to assign to a specific recipient. However, most of these announcements/actions are during the financial crisis and are made by the U.S. authorities. Given that a decrease of the federal fund rate was aimed at restoring liquidity in the market, it can be thought of as a positive (direct) shock to European banks.

ECB that affects the banking system. As an ex-post analysis, markets all over Europe plunged on the news the day after the announcement, because the ECB did not provide any detail of the actual policy measures and, thus, was considered vague. In this sense, we identify shocks before (ex ante) their impact on the financial markets.[26]

5.3 The Sovereignty of Sovereign Shocks

In the empirical application, we employ a VAR of order three where the endogenous variables are daily changes in both the sovereign and banking systemic risk prices. The lags control for information that is already included in the market and that might invalidate the significance of our shocks. Using first difference has a clear economic interpretation: A reduction of the premium of 3 bps on a notional of $\$1,000,000$ means that we save \$300 per year to insure our portfolio against losses higher than $\$100,000$.[27]

Table 4 reports the coefficients in basis points estimated over the period from July 3, 2006 to November 29, 2013 and confidence intervals bootstrapped with $1,000$ simulations and with a 5-day block to account for the autocorrelation of the residuals. The average exceptional shocks, ξ_{sov} and ξ_{bank}, are negative and similar in magnitude, implying that a negative exceptional sovereign (banking) shock will increase sovereign (banking) risk by 11.88 (13.4) basis points, on average. Interestingly, the transmission rate of sovereign shocks to banking risk is 88 percent, almost three times larger than that of banking shocks to sovereign risk ($^{B^{bank\leftarrow sov}}/_{B^{sov\leftarrow bank}} \approx 2.75$). To look at these magnitudes from a different perspective, we see that ξ_{sov} and ξ_{bank} account for the 12.4 and 11.8 percent of their sample averages of sovereign and banking SIPs, respectively. These results suggest that shocks to sovereign risk have important implications for the stability of the system, especially for banking risk.

To further analyze these shock spillover rates, we measure their persistence by estimating the impulse response functions (IRFs) reported in Figure 5. The top two graphs report the impulse

[26] As an additional example, on March 15, 2010 the finance ministers of the EU agreed on a mechanism to aid the Greek economy. In our categorization, this is coded as a positive shock generated by the EU and received by the sovereign system. On February 10, 2012, Standard and Poors downgraded 37 Italian banks, which is coded as a negative shock generated by a rating agency and received by the banking system.

[27] From the investor perspective, changes in default derivatives, such as credit default swaps or CDO, are very important as they have to provide margins in case of large movements.

response functions, whereas the bottom graphs report their corresponding cumulative IRFs, together with the 95 percent bootstrapped confidence intervals (in red). Banking shocks significantly impact sovereign risk but are transitory. They die off two days after impact as shown by cumulative confidence intervals crossing the zero line. Instead, sovereign shocks persistently affect banking risk as cumulative confidence intervals never cross the zero line.

These results support our hypothesis that most of the relevant shocks that lead to significant variations in systemic risk are directly related to sovereign risk, and affect significantly the probability of a collective default of banks.

5.3.1 A Robustness Check

The VAR analysis presented so far assumes that the coefficients are constant across time. However, since our sample covers three different states of the system (pre-crisis, financial crisis and European debt crisis), the impact of shocks could be different over time. The fact that VAR is estimated on first-differences rather than levels could rule out the possibility of a "timing" bias in the estimation, because changes in SIP should already resemble the different conditional volatilities. Nonetheless, the timing issue could be the result of the different distribution of shocks across time, thus, a deeper investigation is needed. Given that we do not have any systemically relevant shock during the pre-crisis period, and that we only have banking shocks during the financial crisis, we estimate the structural parameters in equation 7 over the European debt crisis (from the end of 2010 to 2013). Almost the 50 percent of banking shocks are in this period.

Table 5 reports the estimated impacts and spillover rates. The average impacts, ξ_{sov} and ξ_{bank}, are the same as when the entire sample is considered (Table 4). Interestingly, the impact of banking shocks on sovereign risk, $B^{sov \leftarrow bank}$, increases from 32 to 54 percent, whereas $B^{bank \leftarrow sov}$ remains unchanged. However, the spillover rate of sovereign shocks is still higher than that of banking shocks and statistically significant from each other, if we look at confidence intervals ($B^{sov \leftarrow bank}$ ranges from 40 to 70 percent whereas $B^{bank \leftarrow sov}$ ranges from 74 to 101 percent). These results make our analysis more robust as they confirm the systemic importance of sovereign shocks onto banking risk. Moreover, the unchanged coefficient $B^{bank \leftarrow sov}$ corroborate our shock identification.

6 Sovereign Shocks: Risk Premium or Default Risk?

In the previous section we showed that sovereign shocks are more systemically relevant for systemic risk than banking shocks, due to their large and persistent impact on banking risk. Since our SIP is a risk-neutral price, we investigate whether the impact of these shocks is attributable more to default risk or its associated risk premium. In particular, we decompose both the sovereign and banking SIP into a default-related component and its associated risk premium. The risk premium pertains to the compensation investors require to be exposed to default risk. We can distinguish two types of credit risk premia: The distress risk premium and the jump-at-event risk premium. The former is the compensation for unforeseeable variations in the probability that a credit event will occur, whereas the jump-at-event risk premium is related to the unexpected (negative) jump in the price if the underlying security upon default. With the approach we present here we can only infer the distress risk premium that is associated to the mark-to-market risk investors face on their positions. Such a decomposition will provide more insight into the nature of systemic risk.

Given that SIP can be considered a traded price and is similar to the spread of the senior tranche on a collateralized debt obligation (CDO), we use a modified version of the Longstaff and Rajan (2008) model for decomposing it into risk premium and default probability. In particular, we model and estimate the dynamics of the systemic default intensity for each system, under the risk-neutral and physical probability measures. Distress risk premium is priced in the market if these dynamics differ under the two probability measures.

6.1 Longstaff and Rajan Model with Distress Risk

In this section we present the Longstaff and Rajan (LR) model to price directly total losses on a portfolio without assuming any dependence structure among the portfolio's entities.[28] We assume that our SIP is driven by one latent global factor: The systemic default intensity. The total loss

[28] A simple interpretation can clarify the concept. The expected total loss on a portfolio (RHS) is the sum of losses on single positions weighted by the joint default probability (LHS). This probability can be split into marginal default probabilities plus a copula that captures the default due to contagion risk. Since our measure gives a tradable price, we can price *directly* the RHS of this equation. This is the main idea behind the work of Longstaff and Rajan (2008).

L_t has the following dynamics (for \$1 of notional and with $L_0 = 0$):

$$\frac{dL_t}{1 - L_t} = \bar{\gamma} dN_t \tag{8}$$

where $\bar{\gamma} = 1 - e^{-\gamma}$, with a constant γ, is the jump size and N_t is an independent Poisson process with intensity λ. Integrating equation 8 we get the following general specification for the total loss:

$$L_t = 1 - e^{-\gamma N_t} \tag{9}$$

We assume a square-root CIR process for the risk-neutral intensity, that, under the physical measure is

$$d\lambda_t^{\mathbb{Q}} = \left(\alpha - \beta^{\mathbb{P}} \lambda_t^{\mathbb{Q}}\right) dt + \sigma_{\lambda_t^{\mathbb{Q}}} \sqrt{\lambda_t^{\mathbb{Q}}} dZ_t$$

where α is the mean reverting level, $\beta^{\mathbb{P}}$the mean reversion speed and $\sigma_{\lambda_t^{\mathbb{Q}}}$the instantaneous volatility. Applying a market price of risk of the form $\eta_t = \delta \sqrt{\lambda_t^{\mathbb{Q}}}$, the risk-neutral intensity under the risk-neutral framework preserves the same structure,

$$d\lambda_t^{\mathbb{Q}} = \left(\alpha - \beta^{\mathbb{Q}} \lambda_t^{\mathbb{Q}}\right) dt + \sigma_{\lambda_t^{\mathbb{Q}}} \sqrt{\lambda_t^{\mathbb{Q}}} dZ_t$$

because the market price of risk affects only the mean reversion speed, that is, $\beta^{\mathbb{Q}} = \beta^{\mathbb{P}} + \delta \sigma_{\lambda_t^{\mathbb{Q}}}$. The notation might be confusing, since we refer to the risk-neutral intensity under both probability measures, but this is necessary given that we can only infer the *pseudo* physical intensity from prices alone.[29] Indeed, we will define $E^{\mathbb{Q}}[L_t]$ and $E^{\mathbb{P}}[L_t]$ as risk-neutral loss and pseudo physical loss, respectively.[30]

Under this framework, we can price the SIP as a CDO with attachment points at 10 and 55

[29] Because defaults are rare events, Yu (2007), Pan and Singleton (2008), and Longstaff et al. (2011) emphasize that it is not possible to infer the true or objective default intensity from credit spreads alone. This is why in this framework we can only model the *pseudo* intensity of default, that is, the risk-neutral one under the physical measure. For additional details see Pan and Singleton (2008) and Longstaff et al. (2011).

[30] Standard results in probability theory state that, conditional on the path of the intensity, the probability of having i jumps, $N_T = i$, for $i = 0, 1, 2, ...$ is $\frac{P_i(\lambda, T)}{i!} = \frac{exp\left(-\int_0^T \lambda_t dt\right)\left(\int_0^T \lambda_t dt\right)^i}{i!}$ where $P_i(\lambda, T)$ satisfies a recursive partial differential equation that has a poly-affine closed-form solution. For technical details we refer to Karlin and Taylor (1981) and Longstaff and Rajan (2008, pp. 202-204). Once these probabilities are estimated, the expectation of a function $F(L_t)$ can be compute as follows $E[F(L_t)] = \sum_{i=0}^{\infty} \frac{P_i(\lambda, T)}{i!} F(L_t)$. In the practical application, few jumps are needed to capture the probability distribution, thus, we set $i = 10$.

percent, CDO_{10-55}.[31] Therefore, since an $N-M\%$ tranche will absorb losses that range from 10 to 55 percent, we will call this loss V_t as

$$V_t = \frac{1}{M-N}\left(\max\left(0, L_t - N\right) - \max\left(0, M - L_t\right)\right)$$

The buyer of such an insurance will pay an annualized premium on a quarterly basis, $S\left(T\right)$, to hedge losses greater than 10 percent and less then 55 percent over T years, whereas the seller commits to compensate the buyer for these losses. Therefore, the present value of the premium and contingent legs are $\frac{S_t}{4}\sum_{i=1}^{4T} D\left(i/4\right) E\left[1 - V_{i/4}\right]$ and $\sum_{i=1}^{4T} D\left(i/4\right) E\left[V_{i/4} - V_{(i-1)/4}\right]$, respectively. As swap contracts, it is worth zero at inception. Thus, setting the premium and contingent legs equal, we can simply invert the formula to get the credit spread.[32]

6.2 Market Estimation

We apply the quasi-maximum likelihood (Q-MLE) approach to estimate the model under the two probability measures.[33] The term "Quasi" stands for the fact that we do not use the distribution of the spreads to estimate them, but rather, we use the distributional assumption of the state variable, that is, the default intensity that moves spreads. An additional assumption of this approach is to have a maturity priced without error, so as we can invert the formula and extract the unobserved state variable. This approach is possible thanks to the availability of a term structure of our systemic insurance premium for the maturities, 1-, 3-, 5-, 7- and 10-year. We assume that the 5-year maturity is priced without error since it is deemed as the most liquid one, whereas the remaining maturities are

$$SIP_t\left(T\right) = f\left(\lambda_t^{\mathbb{Q}}\right) + \epsilon_t\left(T\right)$$

where $T = 1, 3, 7$ and 10, $f(\cdot)$ is the pricing function, and ϵ_t are normally-distributed pricing errors with zero mean and variance $\Omega = diag\left\{\sigma\left(1\right), \sigma\left(3\right), \sigma\left(7\right), \sigma\left(10\right)\right\}$. The model is jointly estimated

[31] To extract default probabilities from CDS spreads, we assume a loss given default of 55 percent without loss of generality. Therefore, SIP embeds losses in the range 10 to 55 percent.

[32] The daily risk-free discount functions are bootstrapped from constant maturity bonds collected from the H.15 release of the Federal Reserve system.

[33] The approach is widely used in the term structure literature and is referred to the dated works of Longstaff and Schwartz (1992) and Chen and Scott (1993), and to the recent works of Duffee (2002), Pan and Singleton (2008) and Longstaff et al. (2011)

according to the following joint density

$$\begin{aligned} f^{\mathbb{P}}\left(\lambda_t^{\mathbb{Q}}, \epsilon_t(T) | \mathcal{F}_{t-1}\right) &= f^{\mathbb{P}}\left(\lambda_t^{\mathbb{Q}} | \mathcal{F}_{t-1}\right) \times f^{\mathbb{P}}\left(\epsilon_t(T) | \lambda_t^{\mathbb{Q}}, \mathcal{F}_{t-1}\right) \\ &= f^{\mathbb{P}}\left(\lambda_t^{\mathbb{Q}} | \lambda_{t-1}^{\mathbb{Q}}\right) \times f^{\mathbb{P}}\left(\epsilon_t(T) | \lambda_t^{\mathbb{Q}}, \mathcal{F}_{t-1}\right) \end{aligned} \tag{10}$$

where the second equality comes from the Markovian assumption of the stochastic process. We then approximate the non-central Chi-Squared of the CIR process with the following Normal distribution

$$\nu_t | \lambda_{t-1}^{\mathbb{Q}} \sim \mathcal{N}\left(0, \left(e^{-\beta \Delta t} - e^{-2\beta \Delta t}\right) \frac{\sigma^2_{\lambda_t^{\mathbb{Q}}}}{\beta} \lambda_{t-1}^{\mathbb{Q}} + \left(1 - e^{-\beta \Delta t}\right)^2 \frac{\sigma^2_{\lambda_t^{\mathbb{Q}}}}{2\beta} \alpha\right)$$

that comes from the approximated density: $\lambda_t^{\mathbb{Q}} = e^{-\beta \Delta} \lambda_{t-1}^{\mathbb{Q}} + \left(1 - e^{-\beta \Delta t}\right) \alpha + \nu_t$.[34]

To perfectly identify the model, we assume that the jump size, γ, is equal to one, implying that variations in the systemic default intensity have a one-to-one effect on our measure of systemic risk. The set of parameters $\Theta = \left\{\alpha, \beta^{\mathbb{Q}}, \beta^{\mathbb{P}}, \sigma_{\lambda_t^{\mathbb{Q}}}, \sigma(1), \sigma(3), \sigma(7), \sigma(10)\right\}$ is then estimated by maximizing the sum of log-transformations of equation 10.

Table 6 reports the estimated parameters. The mean speed reversion β differs under the two probability measures for both sovereign and banking risk. This result implies that distress risk premium related to uncertainty about future arrival rates of systemic events is priced in the market.[35] Both $\beta^{\mathbb{P}}$ and $\beta^{\mathbb{Q}}$ are positive, thus the processes are not exploding under both probability measures. Moreover, the model fits the SIP well as shown by the small standard deviations across maturities.

Figure 6 plots the risk-neutral (black line) and pseudo (gray line) systemic insurance price for the sovereign system (top panel) and the banking system (bottom panel). As already inferred from parameter estimates, the distress risk premium is priced in the market as highlighted by the difference between SIPs under the two probability measures. On average, the distress risk premium for the sovereign (banking) system is 62.6 (57) percent of the actual SIP.

[34] For technical details see De Rossi (2010).

[35] Estimated parameters are not reported but available upon request.

6.3 The Impact of Systemic Shocks

We now test whether sovereign and banking shocks impact more on default risk or its associated premium. We perform an analysis similar to the one in section 5.3 with two separate bi-variate $VAR(3)$ for the distress risk premium and default risk.

Table 7 shows the estimation results. Shocks to sovereign risk significantly impact both the banking default risk and its premium, with a greater impact on default risk. Therefore, sovereign shocks have more important implications for a collective default risk of banks than for the market risk aversion. Indeed, slightly overlapping confidence intervals of $B^{bank \leftarrow sov}$ in both panels suggest that the impact of sovereign shocks on default risk is significantly different than that on risk premia. Moreover, these results corroborate our shock identification in the sense that the selected shocks matter more for the structure of the system than for the market risk premium.

Figures 7 and 8 plot the impact over time of sovereign and banking shocks on the default-related components and its associated risk premia. Impulse response functions show that sovereign shocks are significantly persistent for both risk premium and default risk, with a larger impact on the latter. Conversely, banking shocks matter more for the market risk aversion toward sovereign risk than for sovereign default risk, as they do not die off quickly. In summary, these results show that sovereign shocks have a larger, more persistent impact on banking default risk rather than on its associated premium. In the next section we will investigate the source of fragility and contagion risk in the system.

7 Fiscal Fragility and Contagion

So far we have presented the aggregate analysis on the two systems. In particular, we have shown that sovereign shocks are more systemically relevant than banking shocks, and that they have a large and persistent impact on the banking default risk. However, it is reasonable to assume that these shocks are amplified by the fragility of the sovereign system. In this section we investigate the sources of this fragility. In particular, we test whether fiscal constraints capture cross-sectional heterogeneity in fragility. We measure fiscal constraints as flexibility for fiscal maneuver and as the level of indebtedness, and use a portfolio sorting approach to test whether sovereign shocks have a larger impact on the most fiscally constrained countries. We then investigate the spillover channels from the sovereign to the banking system.

Sovereign shocks can propagate to the banking system through two channels: The implicit guarantees a government provides on the liabilities of banks (the liability-side effect), and the value of bank assets (the asset-side effect). The latter includes both solvency and liquidity issues. Indeed, if a bank holds a sizeable amount of sovereign debt, a negative shock to the sovereign system will both reduce the asset value of the bank (the solvency effect), and increase its borrowing cost if sovereign securities are posted as collateral for further borrowing (the liquidity effect). To capture this heterogeneity, we sort banks on their asset exposure to the countries with the lowest fiscal space, over their total sovereign exposure. We expect that these banks are heavily affected by sovereign shocks. Moreover, we further split banks into (domestic) banks exposed to their highly fiscally constrained government and (foreign) banks exposed to these countries. In this way we are able to disentangle the asset-side channel from the liability-side channel, allowing for a deeper understanding of contagion risk.

To further explore channels of contagion, we use the debt-to-GDP ratio as another proxy to quantify how much a government is financially constrained. Such a variable captures the debt load-dimension of the fiscal space in a model-free setting.[36] The rationale behind this variable is the same as the one behind the fiscal space: A high level of debt implies that a government cannot issue more debt to finance its deficit to get back to a sustainable path. Thus, we expect that the most indebted countries should be mainly affected by systemic shocks. We then sort banks on their asset exposure to the most indebted countries, over their total sovereign exposure, to test both the asset-side and government implicit guarantees channels.

7.1 Fiscal Fragility

A highly fiscally constrained government may not be able to support large expenses such as a banking bailout. We measure the fiscal constraint by "fiscal space" that quantifies the budget space a government has "to provide resources for a desired purpose without jeopardizing the sustainability

[36]The fiscal space embeds four dimensions: The debt load, the real GDP growth rate, tax revenues and non-debt interest expenses.

of its fiscal position or the stability of the economy" (Heller (2005)). It is measured as the difference between the government debt limit and its actual debt-to-GDP ratio. The debt limit is the maximum debt load beyond which the sovereign default cannot be avoided, unless the government imposes structural fiscal reforms or asks for outside assistance. Therefore, no space or close-to-zero space suggests that the government budget has no room to spend without threatening macroeconomic stability. In Appendix B we show how fiscal space is estimated for our sample of European countries.[37] Moreover, because fiscal space is derived from a model, we use sovereign indebtedness, defined as debt-to-GDP ratio, as a model-free variable that captures the debt-load dimension of fiscal space.

We form two sets of three portfolios of countries sorted on their fiscal space and their indebtedness relative to GDP. Figures 9 and 10 plot the time series of systemic risk for the two sets of three portfolios. Governments with the lowest fiscal space and with the highest indebtedness are more systemically relevant than the rest of Europe. The probability of a collective default of these countries has increased dramatically since 2010 (black lines). Having no room for fiscal maneuver or being highly indebted preclude the possibility for governments to serve as strong lenders of last resort for their domestic banking systems, which in turn threatens the stability of the entire European Union.

For each portfolio i of countries, we run a bivariate $VAR\,(3)$ as in the aggregate case. In particular, for each VAR specification we have the systemic insurance price of portfolio i of countries and the aggregate banking SIP as endogenous variables. This implies that the two main vectors of the transmission matrix in (7) can be written as $\beta^{sov} = [\xi_{sov_i}, B^{bank\leftarrow sov}]'$ and $\beta^{bank} = [B^{sov_i\leftarrow bank}, \xi_{bank}]'$. We are now interested in identifying the first row of this matrix B, namely, ξ_{sov_i} and $B^{sov_i\leftarrow bank}$, that capture the size of sovereign shocks and the spillover rate of banking shocks on portfolio i. For a clearer interpretation of the magnitudes, ξ_{sov_i} is reported as a percentage of the size of the aggregate sovereign shock, ξ_{sov} (Table 4).[38]

[37] Fiscal space is estimated according to the historical fiscal response function of a government to lagged values of debt-to-GDP ratio. Therefore, a zero fiscal space suggests that the country should deviate significantly from the historical fiscal policy path to gain economic sustainability and restore its primary balance, in order to be able to absorb negative shocks such as wars, natural disasters or financial bailouts. Moreover, a zero fiscal space tells that conventional policy tools such as increasing taxes or issuing debt are not feasible given the historical fiscal path.

[38] This ratio is meaningful because aggregate shocks can be seen as a liability-weighted sum of disaggregated shocks.

Table 8, Panel A (Panel B), reports the estimation of shock impacts on countries sorted on their fiscal space (debt-to-GDP) together with t-statistics, 95 percent confidence intervals and pvalues. Portfolio 1 includes countries with the highest fiscal space and lowest indebtedness, whereas portfolio 3 includes countries with the lowest fiscal space and highest indebtedness. Sovereign shocks are sorted in an increasing order across the extreme portfolios and are strongly significant. Aggregate sovereign shocks are significantly doubled (tripled) for countries with the lowest fiscal space (highest indebtedness), as shown by the coefficient on the third portfolio equal to 195 percent (300 percent for highly indebted countries). Non overlapping confidence intervals of ξ_{sov_i}/ξ_{sov} across portfolios suggest that fiscal constraints capture cross-sectional heterogeneity in the fragility of countries.

Banking shocks have a significant impact on the three portfolios but the effect is not statistically different from each other, as highlighted by their confidence intervals of $B^{sov_i \leftarrow bank}$. Only 62 (75) percent of banking shocks impacts onto the low-fiscal-space (highly indebted) countries.

In summary, this set of results is in line with our hypothesis that high fiscally constrained governments increase fragility in the system, as they are largely affected by sovereign shocks. The scenario is worse if we think that these are shocks that heavily increase the default risk of the banking system rather than its associated distress risk premium.

7.2 Contagion Risk: Bank Exposure

In this section we study contagion risk from the sovereign to the banking system. Sovereign shocks can impact banks through their liabilities and/or their assets: Governments provide implicit guarantees to banks (liability-side effect) and banks hold sovereign debt (asset-side channel). As for countries, we use the portfolio sorting approach and form three sub-systems of banks sorted by their exposure to lowest-fiscal-space (most-indebted) countries. Bank exposure is collected from the 2010 stress test reports from the Bank of International Settlements website. The sorting is static as we only use the sovereign exposure as of 2010. Figures 11 and 12 plot the time series of the systemic insurance price for the three portfolios.

The three portfolios are well sorted on these variables, with the riskiest sub-systems (black lines) having the highest systemic risk. The gap between the time series of the three portfolios widens during the European debt crisis, when exposure to governments with close-to-zero fiscal space and with the highest indebtedness raised doubts about the feasibility of further bailouts and about the riskiness of banks' assets.

Similar to the previous section, we estimate a bivariate VAR(3) where we include each portfolio of banks and the sovereign SIP as endogenous variables. The two main vectors of the transmission matrix in (7) can be written as $\beta^{sov} = [\xi_{sov}, B^{bank_i \leftarrow sov}]'$ and $\beta^{bank} = [B^{sov \leftarrow bank}, \xi_{bank_i}]'$. We are now interested in identifying the second row of the transmission matrix B, namely, ξ_{bank_i} and $B^{bank_i \leftarrow sov}$, that captures the size of banking shocks and the spillover rate of sovereign shocks on portfolio i. For a clearer interpretation of the magnitudes, ξ_{bank_i} is reported as a percentage of the size of the aggregate sovereign shock, ξ_{bank} (Table 4).

Table 9, panel A and B, reports the estimated shock impacts for the two sets of portfolios. Sovereign shocks on banks with the highest exposure to these governments have a spillover rate of 155 percent (182 percent for exposure to highly indebted countries). Non overlapping confidence intervals of the spillover rates, $B^{bank_i \leftarrow sov}$, across portfolios suggest that exposure to fiscally constrained countries capture well the heterogeneity in banking fragility. However, with such portfolios we cannot disentangle the asset-side from the liability-side channel. Therefore, we split the highest-exposed banks into domestic and foreign.[39] Foreign banks are only exposed to the most indebted countries through the asset side, whereas domestic banks are *also* exposed through the liability side. Results are reported in Panel C. The spillover rate of sovereign shocks, $B^{bank_i \leftarrow sov}$, is 91 percent for foreign banks and 153 percent for domestic ones, with slightly overlapping confidence intervals (foreign banks' spillover ranges from 67 to 120 percent, whereas domestic banks' spillover ranges from 110 to 210 percent). These results suggest exposure to the weakest economies drives contagion risk in the banking system, from sovereign to banking risk.

[39]For example, banks of the most indebted countries such as Italy, Ireland and Greece are considered "domestic". Instead, "foreign" refers to German or French banks exposed to these countries.

8 Conclusions

In this paper we have presented a methodology to empirically investigate systemic risk, fragility and contagion within and across economic networks. We have looked at Europe because it provides a natural framework to think about fragility in the sovereign system that can have consequences on the banking system. However, our methodology can be extended both geographically and across sectors, and can help policymakers identify sources of systemically relevant shocks. Moreover, our empirical results can serve as a guide for future macroeconomic models that aim at formalizing the propagation of shocks across economic networks.

We have also shown that in Europe there is a sovereign component in systemic risk that is relevant for the probability of a collective default of banks. Given our results, a possible and effective way to mitigate systemic risk in Europe is to intervene in the sovereign system through (i) announcements that have the power to stop self-fulfilling debt crisis (spirals of increasing government debt-load and its cost of borrowing), (ii) the implementation of austerity plans for low-fiscal space countries to restore room for fiscal maneuvers and (iii) a serious commitment to these plans and structural reforms to avoid fiscal ambiguity.

A Appendix: Systemic Risk

In section A.1 we present the portfolio approach we employ to measure the systemic insurance price and explain how rare events are estimated. In section A.2 we introduce the inputs of our measure of systemic risk and show how it is simulated.

A.1 Estimating Rare Events

The expectation in equation 1 embeds the small probability of large losses. Being a rare event, we employ a Bayesian technique to estimate such a probability. The estimation is proposed by Glasserman and Li (2005) and Grundke (2009) who apply the Importance Sampling (IS) technique to the pricing of credit portfolios. The IS approach twists the probability measure from which the loss paths are generated, such that "important" events are more likely. In other words, the twisting helps producing rare events even in a Normal-distributed setting. For a complete presentation of our measure, we explain the main concepts behind the procedure.

A.1.1 Portfolio Credit Risk: Exponential Twisting and Conditional Distribution

The portfolio approach described here is one of the classical *bottom-up* approaches, that is, it consists in piecing together information of the single entities or subsystems to give rise to a single or larger systems. In our case, an entity is the debt issued by a bank or a country.

Let us consider the following notation:

N: number of entities in the portfolio,

Y_i: default indicator (=1 if i-th entity defaults),

pd_i: marginal default probability of i-th entity,

$ELGD_i$: expected Loss Given Default of i-th entity,

$L = ELGD_1 Y_1 + ... + ELGD_N Y_N$: Aggregate portfolio loss,

T: maturity of the portfolio,

We then assume that both pd_i's and $ELGD_i$'s are known a priori. In particular, we extract default probabilities from credit default swap spreads, assuming a loss given default of 55 percent, and thus, a recovery rate of 45 percent. The latter assumption is in line with the industry practice as pointed out by Pan and Singleton (2008). Determining the amount an investor is going to recover upon default is a hard task, as it depends on the state of the economy (Altman et al. (2005) and Acharya, Bharath, and Srinivasan (2007)) and structural differences in the law systems across countries. Therefore, assuming it constant relieves us from large measurement errors.[40] Additionally, Moody's (2011) reports that, in 2010, the average recovery rate for senior unsecured (secured) bonds is 49.5 (62.5) percent as measured by post-default trading prices, whereas, over the period 1982-2010, such numbers are 36.7 and 50.8 percent, respectively. Thus, our assumption is in line with Moody's computation.

Simulating the loss distribution requires to know the dependence structure among the entities. Therefore, we use a Normal Copula model that, together with marginal probabilities, forms the joint default probability distribution. We follow Merton (1974) and Vasicek (1987) by assuming that an entity defaults on its obligations when its assets drop below a certain threshold. For a constant leverage structure, variations in the asset side are due to variations in the equity side. Thus, we use stock prices to proxy for the asset values so that an entity defaults the *first time* the stock return, $R_{i,t}$, falls below a threshold, $a_{i,t}(T)$ (defaulting in T years from time t). Let $Y_{i,t}(T) = \mathbf{1}\{R_{i,t} < a_{i,t}(T)\}$ be our default indicator, the threshold is extracted by inverting the risk-neutral marginal default probability, $pd_{i,t}(T)$, that is, $a_{i,t}(T) = \Phi^{-1}(pd_{i,t}(T))$, with Φ being the cumulative standard Normal distribution. As in Vasicek (1987), we assume a f-factor model for the stock log-return, where the latter depends on f-global factors M_t and entity-specific idiosyncratic components $Z_{i,t}$, that is,

$$R_{i,t} = B_{i,t}M_t + \sqrt{1 - B_{i,t}B_{i,t}^{\mathrm{T}}} \cdot Z_{i,t} \tag{11}$$

where $B_{i,t} = [\beta_{i,1,t}, ..., \beta_{i,F,t}]$ is the vector of loadings with $\beta_{i,f,t} \in [-1, 1]$ and $\sum_{f=1}^{F} \beta_{i,f}{}^2 \leq 1$.

Simple algebra shows that, substituting equation 11 into the default indicator, the conditional

[40] Some studies simulate the loss given default from either a beta or triangular distribution (Tarashev and Zhu (2008) and Huang, Zhou, and Zhu (2009)). In a previous version of the paper, we checked that the loss pricing was not significantly affected by the inclusion of a simulation approach. Thus, for computational speed and without loss of generality, we decide to set the loss given default to a fixed and reasonable value.

default probability, conditional on the realization of the global factors, $M_t = m_t$, is given by

$$\begin{aligned} PD_{i,t}(m_t, T) &= Pr\left(Y_{i,t}\left(T\right) = 1 | M_t = m_t\right) \\ &= Pr\left(R_{i,t} < a_{i,t}\left(T\right) | M_t = m_t\right) \\ &= Pr\left(B_i M_t + \sqrt{1 - B_i B_i^{\mathrm{T}}} \cdot Z_{i,t} < a_{i,t}\left(T\right) | M_t = m_t\right) \\ &= \Phi\left(\frac{a_{i,t}\left(T\right) - B_i m_t}{\sqrt{1 - B_i B_i^{\mathrm{T}}}}\right) \end{aligned} \tag{12}$$

We employ the IS technique to estimate the probability of a loss greater than the threshold, or simply the tail probability, $Pr(L \geq x)$. This procedure develops via two steps: In the first one, IS applies a twist to the original default probability when the simulated loss is not in the tail of the distribution. In other words, the initial marginal default probability at time t with maturity T of the entity i, $PD_{i,t}\left(T\right)$, is increased by a parameter θ, such that the twisted probability is now equal to

$$PD_{i,t}(\theta, T) = \frac{PD_{i,t}\left(T\right) exp(\theta \times ELGD_i)}{1 + PD_{i,t}\left(T\right)\left(exp(\theta \times ELGD_i) - 1\right)}$$

The choice of θ depends on whether the loss is in the tail or not. If $L > x$ a tail loss is not rare, so we set $\theta = 0$, that implies $PD_{i,t}(\theta, T) = PD_{i,t}\left(T\right)$. If $L < x$ a tail loss is rare, so θ is optimally chosen to minimize the second moment of the estimator $Pr(L \geq x)$. As shown in Glasserman and Li (2005), the optimal θ shifts up the loss distribution so that its new mean is the threshold, $E_\theta[L] = x$.

The second step of the IS procedure deals with the simulations of the loss distribution. Differently from the plain Monte Carlo technique, the second step of the IS methodology consists in simulating the factors from a Normal distribution with unit variance and an optimal mean for each factor f and time t, $\mu^*_{f,t}$.[41] Finally, for each realization (simulation) of the common factor, the conditional risk-neutral loss distribution is simply

[41] See Glasserman and Li (2005) for a detailed discussion of the procedure used to estimate the optimal $\mu_{f,t}$.

$$
\begin{aligned}
E^{Q}\left[L_{t+T}\times\mathbb{1}\left\{L_{t+T}\geq x\right\}|M=m\right] &= E^{Q}\left[L_{t+T}|L_{t+T}>x,M=m\right]\times\Pr\left\{L_{t+T}>x|M=m\right\}\\
&= \left[\sum_{i=1}^{N}Y_{i,t}\left(m,T\right)\times LGD_{i,t}\times w_{i,t}\right]\times\Pr\left\{L_{t+T}>x|M=m\right\}
\end{aligned}
$$

where $Y_{i,t}(m,T)\sim Bernulli\left(PD_{i,t}\left(m,T\right)\right)$.

The probability resulting from the two-step IS needs to be adjusted by the likelihood ratio that relates the original marginal probabilities to the twisted ones, the standard Normal distribution of the factors to the shifted one $N(\mu,1)$ and keeps the probability in the range $[0,1]$. Therefore, the conditional expected total loss is

$$
\begin{aligned}
E^{Q}\left[L_{t+T}\times\mathbb{1}\left\{L_{t+T}\geq x\right\}|M=m\right] &= \widetilde{E}^{Q}[L_{t+T}\times\mathbb{1}\left\{L_{t+T}\geq x\right\}exp\{-\theta(m_t)L_{t+T}+\\
&\quad +\psi(\theta(m_t),m_t))exp(-\mu_t^{*'}m_t+((\mu_t^{*'}\mu_t^{*})/2)\}|M=m]
\end{aligned}
$$

where $L_{t+T}=\sum_{i=1}^{N}Y_{i,t}\left(m,T\right)\times LGD_{i,t}$ and the second expectation is still risk-neutral but now under then new probability measure and adjusted by the likelihood ratio. Once again, the latter keeps the identity holding for the two expectations, $E^{\mathbb{Q}}$ and $\widetilde{E}^{\mathbb{Q}}$. Averaging across all the realizations of the common factors, we get the unconditional expected total loss.

A.2 Model Inputs and Simulation Approach

The portfolio approach explained in the previous section requires to know both the marginal default probabilities and the loadings on the global factors for each entity and time.

Under the Poisson distributional assumption, the annualized probability of default is simply $pd_{i,t}\left(T\right)=1-e^{-\lambda_{i,t}^{\mathbb{Q}}T}$, where $\lambda_{i,t}^{\mathbb{Q}}$ is the annualized risk-neutral default intensity. The latter is extracted from the term structure of credit default swap (CDS) spreads by assuming a constant risk-neutral default intensity (Berndt and Obreja (2010)).

Following Andersen, Sidenius, and Basu (2003) we choose the number of factors so that the loadings $B_{i,t}$ in equation 11 explain at least the 95 percent of the variability in the observed time-varying correlation matrix of stock returns. Therefore, the estimated loadings resemble the characteristics of this time-varying correlation.

Once all the inputs are estimated, the simulation approach proceeds as follows: For each time t, we generate 200,000 default scenarios as $Y_{i,t}(m, T) \sim Bernulli\left(pd_{i,t}\left(m, T\right)\right)$; then, we compute the conditional total losses adjusted by the likelihood ratio; finally, we average across all the simulations to get the unconditional expected loss.

B Appendix: Fiscal Space

In this appendix we present how the "fiscal space" is modeled and estimated with macroeconomic data. We abstract from rigorous mathematical proofs as we apply the methodology developed by Ostry et al. (2010) and Ghosh et al. (2013).

B.1 Modeling Fiscal Space

"Fiscal space" is defined as the difference between the theoretical government debt limit and its actual level.[42] To measure the debt limit, we consider an economy with a country borrower and a large number of atomistic lenders. The standard government budget constraint is defined by the following equation:

$$d_{t+1} - d_t = \left(r_t - g\right) d_t - s_{t+1}$$

where d_t is the one-period debt-to-GDP ratio at the end of the period, g is the read GDP growth rate (exogenous and constant) and s_t is the primary balance as a percentage of GDP (*surplus* if $s_t > 0$, *deficit* otherwise) defined as tax collected minus non-servicing debt expenses (total outlays on government purchases and transfers), and r_t is the real interest rate agreed in t and due in $t+1$. Such a budget constraint suggests that, in equilibrium, a government must issue new debt equal to the difference between the interest payments on its existing debt and its primary balance. The behavior of the agents in this economy is formalized by the following three assumptions:

I) The response of the primary balance of a government to lagged debt is captured by the

[42]In appendix we use terms such as "debt load" and "debt level" to refer to debt-to-GDP ratio.

following fiscal reaction function:

$$s_{t+1} = \mu + f(d_t) + \epsilon_{t+1} \tag{13}$$

where μ captures country specific determinants of revenues and outlays other than lagged debt, $f(d_t)$ is a continuous differentiable function that represents the response of the primary balance to lagged debt, and ϵ_{t+1} is an i.i.d. shock with distribution $G(\epsilon)$ whose properties will be specified in the empirical implementation.[43]

II) The model assumes that the government defaults when the one-period-ahead debt is larger that the debt limit, that is, the default rule is represented by the following indicator

$$D_{t+1} = \begin{cases} 1 & if\ d_{t+1} > \bar{d} \\ 0 & otherwise \end{cases}$$

III) In equilibrium, the interest rate that compensates investors for the endogenous default risk of the government is determined by the following arbitrage-free condition:

$$1 + r^* = (1 + r_t)(1 - p_{t+1}) + p_{t+1}\theta(1 + r^*)$$

where r^* is the risk-free interest rate, p_{t+1} is the default probability in the next period at debt maturity and θ is the recovery rate upon default.

Given these three assumptions, Ghosh et al. (2013) shows that a finite debt limit exists and is determined by a sequence of debt and interest rates, such that the government budget constraint is satisfied. Abstracting from a formal mathematical definition of the equilibrium of the economy, we show how the debt limit is determined in a graphical representation.

Figure B.1 gives an idea of the relation between the primary balance, the interest payment schedule and the debt-to-GDP ratio. The primary balance (red line) and the interest rate schedule (black line) determine the equilibria in the economy. At low level of debt, there is no significant

[43]The coefficient μ captures fiscal implications of characteristics such as the currency composition of public debt, seignorage revenue or external deficit, not directly taken into account in the fiscal response function. In an econometric terminology, such features are captured by country specific fixed effect.

fiscal response to variation in debt load (or debt-to-GDP ratio). As debt increases, governments respond by increasing taxes or cutting spending to contain interest payments. However, further adjustments make it more difficult to raise taxes or impose austerity measures, thus, lowering the fiscal responsiveness to debt increases. For debt levels between the two intersections, $d^*$and $\tilde{d}$, the primary balance is enough to meet the interest payments such that the debt load returns dynamically to the stationary equilibrium, d^*. If the primary balance lies above the debt limit $\tilde{d}$, the government is not able to meet interest payments, ending in a spiral of debt load/financing cost unless outside support is obtained or fiscal structural reforms are imposed to get back to a stable path. However, if investors realize that the country is approaching its debt limit (for debt levels above $\hat{d}$), they will charge a premium to the risk-free rate as the probability that the country default is now positive. Therefore, issuing new debt is more expensive and can bring the government closer and closer to the debt limit as new debt is issued. This increasing spiral of interest payments and financing cost leads a debt limit $\bar{d}$ that is lower than the case of an exogenous interest rate schedule $\tilde{d}$. $\bar{d}$ is the debt limit we estimate in the subsequent empirical analysis according to the "fixed point" methodology explained by Ostry et al. (2010) and Ghosh et al. (2013). Finally, the fiscal space is the difference between the debt limit and the actual debt level.

B.2 Estimating the Fiscal Space

Estimating the fiscal space requires the assessment of the fiscal response function, the growth-adjusted interest rate and the debt limit for each country. However, a country specific fiscal response to a wide set of debt ratios is not directly observable, therefore, as in Ostry et al. (2010) and Ghosh et al. (2013), we estimate the historical fiscal response of a panel of 29 economies and assume that cross-country differences are captured by fixed effects. Hence, a fiscal space close to zero suggests that the country should deviate from its historical fiscal response in order to maintain fiscal sustainability.

To further capture cross-country differences, we estimate a different form of equation 13 to include additional variables that significantly affect the primary balance of a country, that is, we estimate

$$s_{t+1} = \mu + f\left(d_t\right) + \gamma \times X_{i,t} + \epsilon_{t+1}$$

where $f(d_t) = \beta_1 \times d_t + \beta_2 \times d_t^2 + \beta_3 \times d_t^3$ and γ is a vector of loadings on countries' characteristics $X_{i,t}$. In particular, we use Debt-to-GDP ratio and its squared and cubic terms as suggested by the empirical relation between primary balances and lagged debt-to-GDP[44], the Output Gap defined as the difference between log real GDP and potential GDP (estimated with the Hodrick-Prescott filter), Expenditure Gap as the difference between actual expenditure-to-GDP ratio and its trend (estimated with the Hodrick-Prescott filter), *Age Dependency ratio*, lagged *Openness* defined as the sum of import-to-GDP and export-to-GDP, *Oil price* for oil-exporting countries only (Norway and United Kingdom) and Fixed Effects. The sample covers the period from 1980 to 2007 since we estimate the historical fiscal response up to one year before the financial crisis hit dramatically. We use this period because we want to assess whether fiscal policies have historically reserved rooms to face extraordinary (negative) shocks such as financial bailouts.

Table B.1 reports the estimation. These variables explain the 65 percent of the variation in the primary balance with the lagged values of debt-to-GDP ratio showing a significant non-linear effect. The sign and significance of the rest of the variables is in line with previous findings (Ostry et al. (2010) and Ghosh et al. (2013)). The output gap has a positive effect on the primary balance since during good economic periods, when the economy's GDP is above its potential, the government collects more taxes and sees a decline in countercyclical variables such as unemployment expenses. The expenditure gap has, instead, a negative effect because it usually rises when the government faces extraordinary expenses such as wars, natural disasters, financial bailouts etc. Age dependency measure by the ratio of old and young non-working people (0-15 and +65 age) over the total working population. As expected, it loads negatively on the primary balance as it is a significant expense for the government. Moreover, globalization and oil-export play a significant role in increasing government's primary balance.

To estimate the interest rate schedule we employ the "fixed point" methodology of Ghosh et al. (2013) and use the real GDP growth rate average across the period 2002 to 2019. The choice of this period is to get a measure that smooths the business cycle as the 2008 has been a critical year for the world economy and to include projections of the growth rate. However, the analysis is robust to different sample periods. Figure B.2 shows the estimated fiscal spaces.

[44] The picture is not reported in this appendix but is available upon request.

For the purpose of our analysis, it is worth noticing that the most indebted countries such as Greece, Italy, Portugal, Ireland and Cyprus have no fiscal space, suggesting that these governments cannot avoid default unless they impose structural fiscal reforms or ask for outside financial support. For the countries in the high risk and significant risk zones, the analysis suggests that they need to deviate from the historical fiscal path to gain space for fiscal maneuver to be able to absorb potential extraordinary shocks to their primary balance. As shown in the paper, we sort our sample of 24 European economies on their fiscal space and sort European banks according to their large/medium/small exposure to countries with lowest fiscal space. We interpret fiscal space as the ability of a country in sustaining extraordinary expenses in the form of financial bailouts. From a market or investor perspective, this ability can be seen as credibility of the country in bailing out its own banking system without the need of outside support. Therefore, a less credible country or group of countries can have systematically consequences for the stability of an entire system such as the European Union and the European banking system.

C Systemic Risk in the U.S. Economy

In this appendix we implement our methodology to study systemic risk in the U.S. economy. We measure banking systemic risk from a portfolio of liabilities of 19 U.S. banks and use the credit default swap spread on the U.S. economy as a measure of sovereign systemic risk. Although the U.S. credit spread can move as a result of flight-to-quality, it still remains a valuable proxy for sovereign systemic risk as the federal government is ultimately in charge of bailing out banks and single states.

Figure C.1 plots the U.S. banking systemic risk and the credit default swap spreads over the period from 2004 to 2013. Differently from Europe, U.S. sovereign risk exhibits a weak comovement with banking risk and has a much smaller magnitude.

In this work we do not provide an empirical explanation for this behavior, because we are interested in highlighting that (i) our methodology can be extended geographically, and that (ii) sources of risk in economic networks differ. Therefore, looking only at one risk component could lead to an underestimation of risk in the system.

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Table 1: The Sovereign System: Summary Statistics

The table reports summary statistics for 24 European countries over three sub-samples: the pre-crisis period (2001 to 2006), the financial crisis (2007 to 2009), and the European debt crisis (2010 to 2013). *Mean* and *Std Dev* refer to the average and the standard deviation of the 5-year credit default swap spreads in basis points. *Slope* is the average of the 10-year and 1-year CDS spreads. *Liab* is the average central government debt expressed in billions of euros, and *Stock* is the average local stock market index in index points.

	Pre-Crisis (2001-2006)					*Financial Crisis (2007-2009)*					*Debt Crisis (2010-2013)*				
	Mean	*Std Dev*	*Slope*	*Liab (bn)*	*Stock*	*Mean*	*Std Dev*	*Slope*	*Liab (bn)*	*Stock*	*Mean*	*Std Dev*	*Slope*	*Liab (bn)*	*Stock*
Austria	3.9	1.6	4.2	147.2	2089.8	47.0	58.5	16.9	168.9	3372.5	89.6	51.5	68.0	210.7	2391.3
Belgium	4.4	1.6	5.0	275.2	2805.9	33.5	34.3	18.4	290.4	3223.1	146.9	81.5	80.4	354.1	2480.6
Germany	4.5	2.6	5.0	1355.6	4588.9	17.8	19.5	11.3	1603.3	6229.4	52.4	24.2	56.4	2016	6935.2
Finland	3.5	1.2	3.5	62.4	7165.3	19.0	20.7	13.9	64.0	8409.3	40.9	19.5	38.1	89.3	6332.6
France	4.1	2.0	4.6	969.2	4160.4	20.7	21.5	13.0	1226.5	4470.5	106.2	51.7	87.6	1660.9	3648.6
Greece	13.2	3.5	14.6	166.5	2746.4	85.2	82.2	32.9	242.2	3490.6	2357.2	3216.6	-1661.3	322.4	1144.1
Ireland	3.6	1.3	4.7	42.2	5783	85.1	95.6	20.3	56.8	5446.8	426.2	255.6	-21.9	151.6	3210.5
Italy	9.3	2.1	11.6	1399.8	31287.6	58.4	52.9	28.7	1621.1	29966.1	278.5	126.8	97.3	1876.6	17983.7
Nether	2.8	1.2	2.3	243.1	408.6	26.1	31.6	14.1	287.3	395.7	62.5	27.7	55.4	384.3	336.0
Portugal	7.4	2.0	8.7	83.1	7740.9	44.5	36.4	23.9	116.9	9659.8	614.5	356.5	-81.8	172.6	6431.9
Spain	4.6	1.9	5.2	383.2	8813.5	48.4	41.5	25.5	403.4	12227	298.6	113.6	88.7	703.6	9065.1
Sweden	3.6	1.6	3.8	143.1	764.6	33.8	40.0	19.8	131.6	955.8	36.7	16.4	37.5	146	1086.9
UK	1.6	0.2	-	665.0	4965.5	38.6	42.7	26.6	835.4	5445	62.3	18.3	58.2	1412	5826.8
Czech Rep	18.2	11.3	17.2	22.3	828.9	69.8	74.7	26.7	38.0	1367.5	94.0	30.6	72.5	59.5	1052.9
Denmark	3.2	0.8	3.4	87.9	293	29.9	37.5	19.7	70.1	386.8	57.9	37.9	50.2	103.5	455.4
Bulgaria	179.7	159.0	163.0	8.6	-	205.3	180.2	47.1	5.3	582.4	228.8	89.4	121.0	6.1	295.1
Cyprus	17.1	10.2	12.7	7.7	1886.1	52.4	50.3	25.4	9.0	2964.4	739.8	465.6	-188.5	12.1	589.4
Malta	10.7	5.5	10.5	2.9	3064.4	51.0	45.6	26.3	3.4	4011.5	246.3	93.0	40.6	4.4	3326.2
Slovenia	15.5	10.4	12.5	6.7	901	49.3	52.3	23.6	8.1	1603.3	225.2	134.3	110.4	15.5	703.5
Slovakia	46.6	50.8	32.4	12.4	2531.7	58.9	57.9	26.4	16.5	6041.9	131.0	72.5	90.9	29.0	7084.0
Estonia	7.5	2.3	6.6	0.4	365.7	206.5	200.8	19.6	0.6	587.5	99.4	29.6	70.2	1.1	668.2
Latvia	8.2	3.6	7.6	1.3	345.7	359.3	322.2	-4.0	2.7	477.8	247.5	102.5	95.4	8.1	395.3
Lithuania	31.3	32.4	17.7	3.4	223.4	242.2	233.6	10.0	4.7	373.8	218.5	73.7	107.2	10.8	359.6
Poland	35.3	18.5	33.4	91.2	1802.5	99.4	97.0	38.3	141.3	2696.9	148.1	59.6	112.2	192.6	2445.5

Table 2: The Banking System: Summary Statistics

The table reports summary statistics for 41 European banks over three sub-samples: the pre-crisis period (2001 to 2006), the financial crisis (2007 to 2009), and the European debt crisis (2010 to 2013). *Mean* and *Std Dev* refer to the average and the standard deviation of the 5-year credit default swap spreads in basis points. *Slope* is the average of the 10-year and 1-year CDS spreads. *Lev* is the average leverage ratio expressed in percentage, and *Stock* is the average bank-specific stock price.

	Pre Crisis (2001-2006)					*Fin Crisis (2007-2009)*					*Debt Crisi (2010-2013)*				
	Mean	*Std Dev*	*Slope*	*Lev (%)*	*Stock*	*Mean*	*Std Dev*	*Slope*	*Lev (%)*	*Stock*	*Mean*	*Std Dev*	*Slope*	*Lev (%)*	*Stock*
UniCredit	16.9	5.0	17.3	94.3	24.7	76.1	50.6	22.2	94.3	22.2	288.5	136.8	95.0	93.0	7.3
BNP Paribas	12.2	6.1	12.7	96.3	52.9	49.5	28.5	19.4	96.7	60.4	151.0	64.8	93.6	95.6	44.2
Erste Bk	15.4	2.9	17.1	95.6	28.4	126.5	101.6	21.0	94.0	37.3	187.0	66.2	81.1	92.3	24.8
Raiffeisen	15.1	3.3	17.1	92.5	61.2	139.6	118.3	21.6	91.7	66.9	183.6	46.0	82.9	91.9	29.2
Dexia	11.8	4.0	13.6	97.2	14.5	161.4	127.5	10.3	97.8	11.3	462.2	220.5	58.2	98.9	1.4
KBC Bk	12.6	4.0	13.8	95.0	51.9	119.6	97.0	9.6	95.2	60.6	216.6	93.9	95.8	94.1	26.0
Danske Bk	11.5	4.6	12.4	96.6	19.8	72.7	56.9	22.7	96.9	19.3	154.8	78.5	80.2	96.4	14.3
Cr Agricole	10.1	2.7	12.6	96.4	20.1	65.5	37.9	23.8	96.8	17.4	184.5	68.5	104.5	97.0	7.9
Soc Gen	12.1	4.7	13.5	97.1	68.1	66.6	39.3	23.0	96.6	69.9	193.1	84.8	102.9	95.6	32.3
Natixis	7.8	0.1	11.3	96.8	7.4	134.0	101.5	14.7	96.7	6.2	182.5	46.8	81.9	95.9	3.2
Alpha Bk	24.5	4.7	27.9	93.2	4.3	188.4	181.5	-2.1	93.0	5.4	1332.9	616.0	-707.8	93.5	1.0
EFG Ergasias	21.4	4.1	23.7	91.8	128.8	170.6	143.8	15.8	93.2	155.4	1365.0	680.9	-611.3	95.6	22.6
Natl Bk Greece	22.2	3.2	25.0	94.2	215.9	149.6	127.6	3.1	90.8	294.3	1290.5	598.6	-728.0	95.8	45.5
Piraeus Bk	-	-	-	92.0	44.2	196.3	164.0	7.1	93.6	77.0	1324.6	606.1	-658.2	96.9	8.9
IKB Deutsche	17.1	5.3	17.2	96.4	19.0	412.6	378.1	-165.8	96.4	8.7	386.8	46.5	69.9	97.3	0.6
Commerzbank AG	32.1	30.7	26.3	97.4	114.2	67.7	37.1	23.2	97.3	108.4	173.6	65.5	99.5	96.2	20.0
Deutsche Bk	16.5	4.5	17.6	96.4	61.1	74.5	42.4	24.2	98.1	57.8	128.5	41.4	90.2	97.4	34.9
Gov & Co Bk Irlnd	10.8	3.3	11.9	95.8	7.4	171.6	151.0	21.2	103.6	4.7	687.4	408.4	-188.1	95.0	0.3
Bca MPS	18.1	5.6	20.2	95.1	13.6	64.5	37.9	22.4	93.9	12.3	409.2	205.0	53.7	96.4	3.0
BPM	22.8	9.4	22.9	92.8	1.7	64.1	38.5	19.8	91.9	2.1	367.1	203.7	79.6	92.2	0.6
UBI	-	-	-	93.0	15.5	75.8	41.4	28.6	89.7	14.0	283.6	131.1	82.2	91.3	4.7
Intesa	16.5	6.6	19.1	99.4	3.3	56.3	38.9	19.0	91.5	3.7	262.3	130.0	95.0	92.0	1.7
Barclays Bk	10.3	2.9	12.3	96.4	7.2	89.5	62.1	23.7	97.4	5.2	149.3	43.6	95.8	95.9	2.9
HSBC	11.8	4.2	13.0	94.1	11.1	60.7	39.6	20.4	94.7	8.9	98.4	26.9	76.7	93.7	7.4
Lloyds Bk	9.5	3.1	11.7	96.7	4.0	81.5	60.9	20.7	96.9	2.2	207.2	67.9	104.4	95.3	0.6
Royal Bk Scotland	9.6	2.4	11.7	95.4	70.0	97.3	64.5	22.2	95.5	34.9	216.9	68.0	112.6	94.7	4.0
Standard Chartered	18.4	10.5	19.4	93.4	12.3	90.5	75.8	19.0	94.0	16.1	115.5	31.6	85.9	93.0	18.5
ING Groep	11.2	4.6	12.9	96.7	19.2	68.2	45.2	22.8	107.4	14.9	142.3	47.5	86.5	95.9	7.0
F Van Lanschot	-	-	-	94.1	47.6	156.9	95.0	8.7	92.6	55.9	188.9	17.1	59.6	91.7	23.6
Dnb Nor Bk	11.5	1.8	13.5	94.0	6.1	64.3	47.4	21.7	95.2	7.4	84.3	28.7	52.1	94.6	9.7
Bco Bilbao	12.8	4.7	14.0	93.4	12.3	68.5	40.2	24.2	94.7	12.7	271.8	89.6	106.1	93.3	7.6
Bco de Sabadell	12.0	1.3	16.2	91.1	3.4	153.8	103.2	20.1	93.8	4.5	456.5	188.9	69.8	94.0	2.1
Bco Pop Espanol	11.0	3.1	13.0	92.4	25.3	139.3	94.7	20.6	93.7	25.7	454.7	186.9	68.7	93.6	8.2
Bco Santander	-	-	-	92.7	8.8	84.6	31.0	27.4	94.2	10.7	255.6	87.7	105.9	93.5	7.0
Bankinter	17.1	3.2	19.8	95.4	4.5	143.3	97.6	28.8	96.2	5.8	416.1	186.9	90.9	94.9	2.9
Nordea Bk	10.6	2.2	13.2	95.2	5.3	60.9	42.4	20.2	95.8	7.4	96.7	35.9	68.8	95.9	7.6
Skandinaviska	14.6	5.1	14.6	96.5	6.6	91.0	67.7	22.7	96.5	7.3	120.4	42.0	69.8	95.6	5.9
Svenska Handelsbanken	12.4	4.5	13.0	95.8	16.9	56.8	39.4	19.2	96.4	17.8	80.8	28.8	55.6	96.1	25.2
Swedbank	9.0	0.3	12.5	95.8	13.3	120.7	98.4	22.9	95.7	12.1	124.6	40.5	73.6	94.8	12.4
Cr Suisse Gp	-	-	-	96.6	34.7	114.3	46.4	22.1	95.6	36.2	116.7	34.5	82.0	95.6	24.1
UBS	10.2	3.7	11.4	96.9	27.4	101.1	79.5	22.3	97.7	21.0	124.6	41.6	82.9	96.0	11.7

Table 3: Shock Identification

The table reports how shocks are identified across the daily period 2006-2013. A shock is a relevant news article reported by several sources such as newspapers, rating agencies and policymakers' websites. A shock generator, Panel A, is an institution that has the power to mitigate or exacerbate financial risk through announcements or actions. The shock recipient, Panel B, is the system that is *directly* affected by the shock: Either the sovereign and/or banking systems. The definition of the generator serves only as a guidance in identifying shocks as we are only interested in the recipients. The square brackets contain the direction of the shock. Other shock generators, such as social unrest or political instability, are directly included among the recipients. Sovereign (banking) shocks cover approximately 3 (2.6) percent of the daily sample period from 2007 to 2014. A detailed description of all the shocks and their directions are reported in the online Appendix.

<table>
<tr><th colspan="3">Panel A: Shock Generators</th></tr>
<tr><th>European Central Bank</th><th>European Union</th><th>Rating Agency</th></tr>
<tr><td>• Monetary Policy
- Expansion [+1]
- Contraction/stable [-1]
• Unconventional monetary policy tools [+1]
• Policy announcements [+1]
• Plan's approval [+1]</td><td>• Policy Announcement [+1]
• Plan's approval [+1]
• Agreements [+1]
• Disagreement [-1]
• Lack of commitment [-1]</td><td>• Downgrade [-1]
• Upgrade [+1]</td></tr>
</table>

<table>
<tr><th colspan="2">Panel B: Shock Recipient</th></tr>
<tr><th>Banking System</th><th>Sovereign System</th></tr>
<tr><td>• Bankruptcy [-1]
• Bailout or nationalization [+1]
• Recapitalization [-1]
• Rating Agency's action
• Fed/ECB's action</td><td>• Announcements and approvals or austerity plans [+1]
• Social unrest [-1]
• Bank bailout [-1]
• Forecast/Actual disagreement [-1]
• Political instability [-1]
• Asking for help [-1]
• Rating Agency's action
• ECB
• EU/IMF</td></tr>
</table>

Table 4: The Impact of Sovereign and Banking Shocks

The table reports the estimated size of sovereign (ξ_{sov},) and banking exceptional shocks (ξ_{bank}) and spillover rates ($B^{Y \leftarrow X}$) where the superscript refers to the X-shock onto the system Y. Confidence intervals are estimated with the block-bootstrap technique using 1,000 simulations and 5-day blocks to account for the autocorrelation of residuals. The results are in basis points and cover the daily period July 3, 2006 to November 29, 2013.

	Coefficient	*t-Stat*	*Confidence Intervals*		*pval*
ξ_{sov}	-11.87	-12.14	-13.86	-9.96	0
ξ_{bank}	-13.43	-13.10	-15.48	-11.43	0
Rate of Transmission					
$B^{sov \leftarrow bank}$	0.32	5.56	0.21	0.44	0
$B^{bank \leftarrow sov}$	0.88	13.01	0.74	1.01	0

Table 5: The Impact of Sovereign and Banking Shocks: Robustness Check

The table reports the estimated size of sovereign (ξ_{sov},) and banking exceptional shocks (ξ_{bank}) and spillover rates ($B^{Y \leftarrow X}$) where the superscript refers to the X-shock onto the system Y. Confidence intervals are estimated with the block-bootstrap technique using 1,000 simulations and 5-day blocks to account for the autocorrelation of residuals. The results are in basis points and cover the daily period September 2009 to November 29, 2013.

	Coefficient	*t-Stat*	*Confidence Intervals*		*pval*
ξ_{sov}	-11.79	-12.02	-13.80	-9.95	0
ξ_{bank}	-13.41	-10.91	-15.83	-10.99	0
Rate of Transmission					
$B^{sov \leftarrow bank}$	0.54	7.04	0.40	0.70	0
$B^{bank \leftarrow sov}$	0.88	13.47	0.74	1.01	0

Table 6: Risk Premia and Default Risk: Parameter Estimation

The table reports the estimation parameters of the modified Longstaff and Rajan (2008) pricing model for CDO tranches, estimated with a Quasi-Maximum Likelihood approach. Numerical standard errors are in parenthesis. The sample covers the daily period from July 2006 to November 2013 for the 1-, 3-, 5-, 7- and 10-year maturities of sovereign and banking SIPs.

	Sovereign Systemic Risk	*Banking Systemic Risk*
$\sigma_{\lambda_t^{\mathbb{Q}}}$	0.27	0.15
	(0.004)	(0.0023)
$\beta^{\mathbb{Q}}$	0.88	0.79
	(0.0006)	(0.0075)
α	0.42	0.30
	(0.0081)	(0.0056)
$\beta^{\mathbb{P}}$	0.091	0.0006
	(0.0133)	(0.0032)
$\sigma\,(1)$	0.0079	0.0241
	(0.000056)	(0.000056)
$\sigma\,(3)$	0.0011	0.0048
	(0.000023)	(0.000089)
$\sigma\,(7)$	0.0008	0.0006
	(0.000073)	(0.000034)
$\sigma\,(10)$	0.0013	0.0059
	(0.000025)	(0.000074)
δ	2.92	5.26
	-	-

Table 7: Systemic Shocks: Distress Risk Premium versus Default Risk

The table reports the estimated size of sovereign (ξ_{sov}) and banking (ξ_{bank}) exceptional shocks and spillover rates for the distress risk premia (Panel A) and default-related components (Panel B). $B^{Y \leftarrow X}$ measures the X-shock onto the variable Y. Confidence intervals are estimated with the block-bootstrap technique using 1,000 simulations and 5-day blocks to account for the autocorrelation of residuals. The results are in basis points and cover the daily period July 3, 2006 to November 29, 2013.

Panel A: Distress Risk Premium					
	Coefficient	*t-Stat*	*Confidence Intervals*		*pval*
ξ_{sov}	-4.02	-11.60	-4.70	-3.35	0
$B^{sov \leftarrow bank}$	0.36	5.71	0.25	0.50	0
$B^{bank \leftarrow sov}$	0.73	11.86	0.60	0.84	0
ξ_{bank}	-4.21	-10.48	-5.22	-3.59	0
Panel B: Default Risk					
	Coefficient	*t-Stat*	*Confidence Intervals*		*pval*
ξ_{sov}	-7.83	-10.66	-9.37	-6.47	0
$B^{sov \leftarrow bank}$	0.31	5.61	0.20	0.42	0
$B^{bank \leftarrow sov}$	0.96	12.96	0.81	1.10	0
ξ_{bank}	-9.19	-11.93	-10.73	-7.67	0

Table 8: Fiscal Fragility

The table reports estimates of the VAR(3) for two sets of portfolios sorted on government's fiscal space (Panel A) and indebtedness as a percentage of GDP (Panel B). ξ_{sov_i}/ξ_{sov} is the relative impact of sovereign shocks onto the group of country i, relative to the aggregate shock. $B^{Y_i \leftarrow X}$ is the spillover rate of banking shocks onto the portfolio i. The portfolio with the lowest fiscal space is comprised of Greece, Italy, Ireland, Portugal and Cyprus with zero fiscal space and Belgium, Spain and United Kingdom with a fiscal space of 14, 29, and 35 percent of GDP. The portfolio of highly indebted countries contains Belgium (89%), France (73%), Greece(171%), Ireland (117%), Italy (121%), Portugal (123%), Spain (74%) and Cyprus (139%). The medium portfolio contains Austria (66%), Germany (50%), Finland (48%), Netherlands (64%), United Kingdom (72%), Malta (67%), Slovenia (52%) and Poland (53%). The portfolio of low indebted countries contains Sweden (31%), Czech Rep (44%), Slovakia (51%), Estonia (6%), Latvia (37%) and Lithuania (35%). 95-percent confidence intervals are computed with a 5-day block bootstrapping (1,000 simulations) to account for a potential dependency in the residuals. The results cover the daily period July 3, 2006 to November 29, 2013.

Panel A: Countries sorted on GOVERNMENT FISCAL SPACE															
	High Fiscal Space										Low Fiscal Space				
	Coeff	*t-Stat*	*Confidence Intervals*		*pvalue*	*Coeff*	*t-Stat*	*Confidence Intervals*		*pvalue*	*Coeff*	*t-Stat*	*Confidence Intervals*		*pvalue*
ξ_{sov_i}/ξ_{sov}	0.75	6.10	0.53	1.00	0	0.70	6.95	0.52	0.92	0	1.95	8.00	1.53	2.49	0
$B^{sov_i \leftarrow bank}$	0.43	5.94	0.30	0.59	0	0.29	5.08	0.19	0.41	0	0.62	5.47	0.43	0.87	0
Panel B: Countries sorted on GOVERNMENT DEBT-TO-GDP RATIO															
	Low Indebtedness										High Indebtedness				
	Coeff	*t-Stat*	*Confidence Intervals*		*pvalue*	*Coeff*	*t-Stat*	*Confidence Intervals*		*pvalue*	*Coeff*	*t-Stat*	*Confidence Intervals*		*pvalue*
ξ_{sov_i}/ξ_{sov_i}	0.62	5.82	0.43	0.85	0	0.64	8.27	0.50	0.80	0	3.00	8.07	2.36	3.80	0
$B^{sov_i \leftarrow bank}$	0.31	5.10	0.20	0.45	0	0.26	4.95	0.17	0.37	0	0.75	4.49	0.46	1.11	0

Table 9: Contagion Risk: Banks

The table reports estimates of the VAR(3) for two sets of portfolios sorted on banks' exposure to the governments with the lowest fiscal space (Panel A) and with the highest indebtedness (Panel B). In Panel C banks are split into foreign and domestic. Domestic banks are those of highly indebted countries exposed to them. Foreign banks are only exposed to these highly indebted countries. ξ_{bank_i}/ξ_{bank} is the relative impact of banking shocks onto the group of banks i, relative to the aggregate shock. $B^{Y_i \leftarrow X}$ is spillover rate of sovereign shocks onto the portfolio i. Banks mostly exposed to highly indebted countries are the ones of the most indebted countries. The portfolio of banks less exposed to these governments contains banks from the United Kingdom, Belgium, Switzerland, Germany, France, the Netherlands, Sweden and Norway. 95-percent confidence intervals are computed with a 5-day block bootstrapping (1,000 simulations) to account for a potential dependency in the residuals of the model. The results are in basis points and cover the daily period July 3, 2006 to November 29, 2013.

Panel A: Banks sorted on the Lowest-Fiscal Space-Exposure over Total Sovereign Exposure																
	Low Exposure											High Exposure				
	Coeff	*t-Stat*	*Confidence Intervals*		*pvalue*	*Coeff*	*t-Stat*	*Confidence Intervals*		*pvalue*	*Coeff*	*t-Stat*	*Confidence Intervals*		*pvalue*
$B^{bank_i \leftarrow sov}$	0.71	6.60	0.55	0.94	0	1.10	6.44	0.79	1.47	0	1.55	6.10	1.09	2.10	0
ξ_{bank_i}/ξ_{bank}	0.84	8.46	0.67	1.05	0	1.20	8.90	0.92	1.49	0	1.24	7.90	0.98	1.59	0

Panel B: Banks sorted on Exposure to Highly Indebted Countries over Total Sovereign Exposure															
	Low Exposure										High Exposure				
	Coeff	*t-Stat*	*Confidence Intervals*		*pvalue*	*Coeff*	*t-Stat*	*Confidence Intervals*		*pvalue*	*Coeff*	*t-Stat*	*Confidence Intervals*		*pvalue*
$B^{bank_i \leftarrow sov}$	0.74	6.02	0.53	1.00	0	1.20	6.75	0.88	1.56	0	1.82	7.00	1.35	2.38	0
ξ_{bank_i}/ξ_{bank}	1.01	7.87	0.78	1.29	0	1.17	9.11	0.95	1.45	0	1.43	9.08	1.16	1.78	0

Panel C: Foreign vs Local Banks Exposed to Local Governments											
	Foreign Banks: Asset-Side Effect						Domestic Banks: Asset+Liab Effect				
	Coeff	*t-Stat*	*Confidence Intervals*		*pvalue*		*Coeff*	*t-Stat*	*Confidence Intervals*		*pvalue*
$B^{bank_i \leftarrow sov}$	0.91	6.68	0.67	1.20	0		1.53	6.36	1.10	2.10	0
ξ_{bank_i}/ξ_{bank}	1.00	8.46	0.79	1.25	0		1.23	8.79	0.98	1.53	0

Table B.1: Panel Estimation: Fiscal Response Function

The table reports the (unbalanced) panel estimation of 29 economies such as Australia, Austria, Belgium, Canada, Cyprus, Czech Republic, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Israel, Italy, Japan, Latvia, Malta, the Netherlands, New Zealand, Norway, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, the United Kingdom and the United States. The sample covers the period from 1980 to 2007 and include lagged values of the *Debt-to-GDP ratio* and its squared and cubic terms to capture non-linearity effects; *Output Gap* as the difference between log real GDP and potential GDP (estimated with the Hodrick-Prescott filter); *Expenditure Gap* as the difference between actual expenditure-to-GDP ratio and its trend (estimated with the Hodrick-Prescott filter); *Age Dependency ratio*; lagged *Openness* defined as the sum of import-to-GDP and export-to-GDP; *Oil price* for oil-exporting countries only (Norway and United Kingdom); and Fixed Effects. The dependent variable is the primary balance defined as tax revenue minus non-debt servicing expenses scaled by GDP. Levels of significance: ***1%, **5% and *10%. Sources: IMF World Economic Outlook, World Bank Database and authors' computation.

	Coeff	*t-stat*	*p-value*
$Debt/GDP_{t-1}$	-0.02	-0.79	0.43
$(Debt/GDP_{t-1})^2$	0.13**	2.56	0.01
$(Debt/GDP_{t-1})^3$	-0.06***	-3.4	0.0000
$Output\,Gap_t$	0.03*	1.72	0.086
$Expenditure\,Gap_t$	-0.89***	-15.1	0.0000
$Age\,Dependency_t$	-0.17***	-3.4	0.0006
$Openness_{t-1}$	0.03***	3.45	0.0006
$Dummy \times \ln Oil\,Price_t$	0.03***	4.69	0.0000
$Cons$	0.08***	2.97	0.003
Fixed Effect	YES		
$adj - R^2$	0.654		
F-stat	28.18		
p-value	0		
df	481 , 36		

Figure 1: Risk of Contagion Across Sovereign and Banking Systems

The Figure plots the one-year rolling window correlation (in percentage) between daily changes in the credit default swap spreads of a country and daily changes in the average credit default swap spreads of its banking system. Spain, the United Kingdom and Germany are the only countries reported here but similar paths have been observed in other European countries such as Ireland and Italy. The correlation between the US government and its local banks' credit risk is included for comparing differences across macro regions. The sample covers the daily period from the end of 2007 to November 2013.

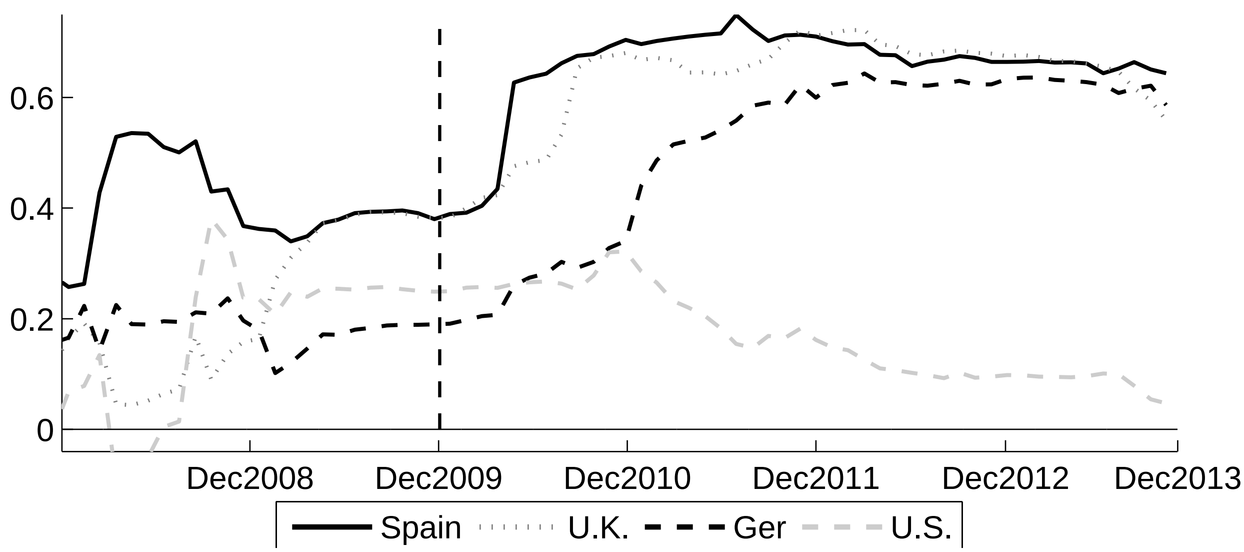

Figure 2: Contagion Risk Within the Sovereign and the Banking Systems

The Figure plots the average one-year rolling window pairwise correlations of bank stock returns (black line) and country stock market indices returns (gray line). Correlation is used as a proxy for contagion risk within the sovereign and banking systems. The sample covers the daily period from January 2001 to November 2013 and spans three periods: the pre-crisis period, the 2007/09 financial crisis and the European debt crisis of 2010/13.

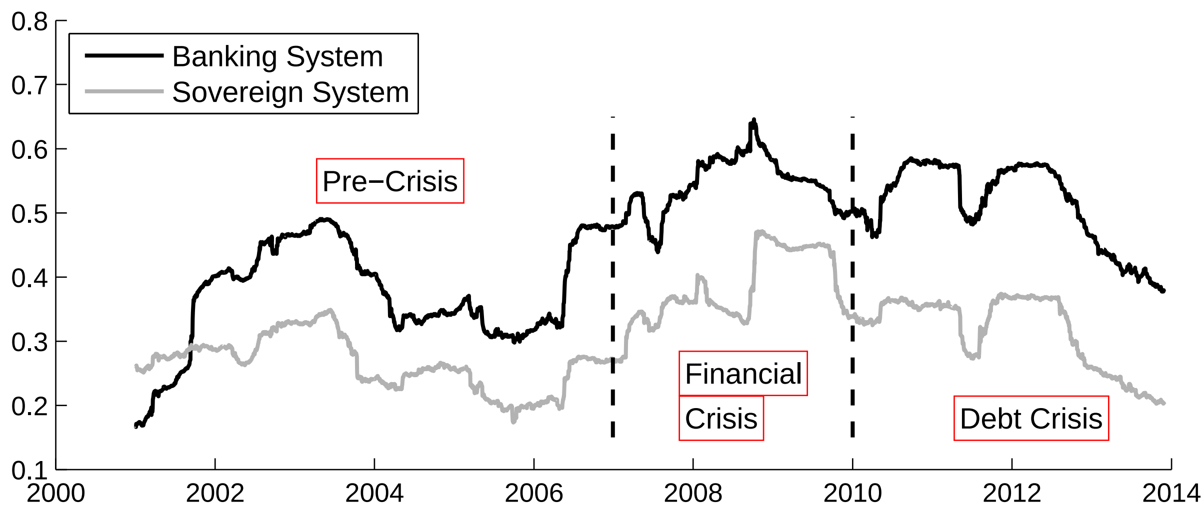

Figure 3: Systemic Insurance Price and the Traded Senior Tranche

The Figure compares the actual (gray line) and the replicated (black line) senior tranche (22-100) on the iTraxx Europe CDX in basis points. The replicated line refers to the one measured with our methodology (SIP). The iTraxx Europe is an equally-weighted CDS basket index on 125 European companies from different sectors. The available sample spans the period from September 2011 to November 2012 and is collected from a J.P. Morgan proprietary database.

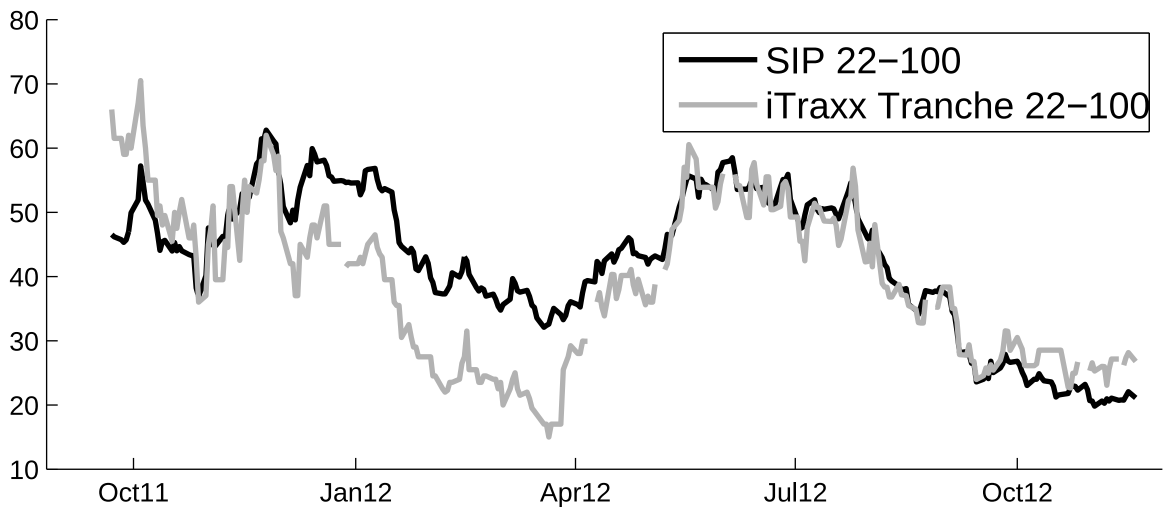

Figure 4: Systemic Risk in Europe

The Figure plots the systemic insurance prices (SIPs) for both the banking (black line) and the sovereign (dotted gray line) systems in basis points. SIP measures the risk-neutral expected loss on the total liabilities of the respective system, given that the loss is greater than 10 percent. The sample covers the daily period from January 2004 to November 2013 and spans three periods: The pre-crisis period, the financial crisis of 2007/09, and the European debt crisis of 2010/13. The dashed vertical lines identify some of the main shocks that have an impact on sovereign and banking risk.

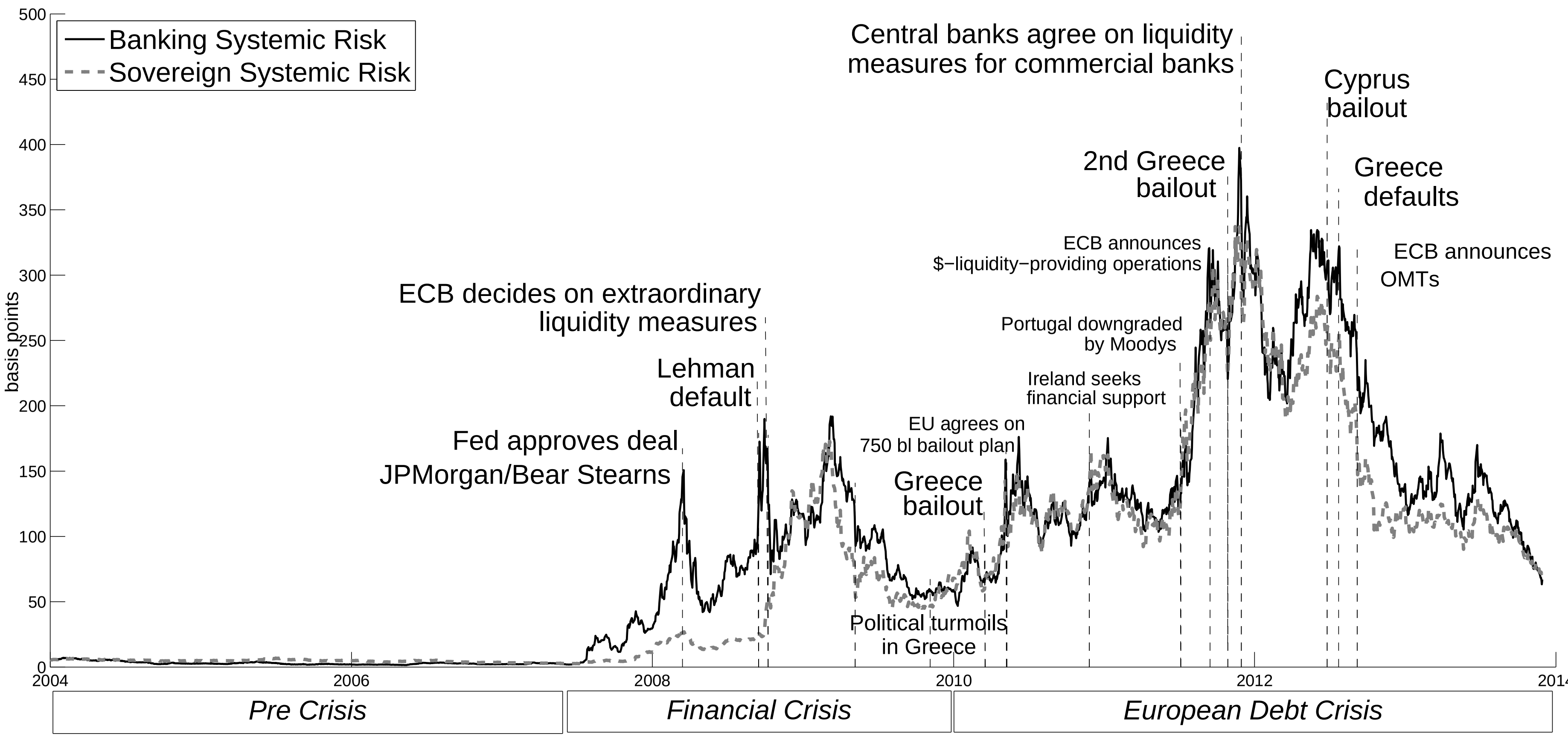

Figure 5: Shock Impact and Their Persistence

The figure plots the impulse response functions (IRFs) of banking (sovereign) shocks onto sovereign (banking) systemic risk in the top two panels. The bottom graphs plot the cumulative IRFs. Dashed red lines are 95 percent confidence intervals estimated with a 5-day block bootstrapping method with 1000 simulations. The response is estimated over a period of 9 days after the shock impact.

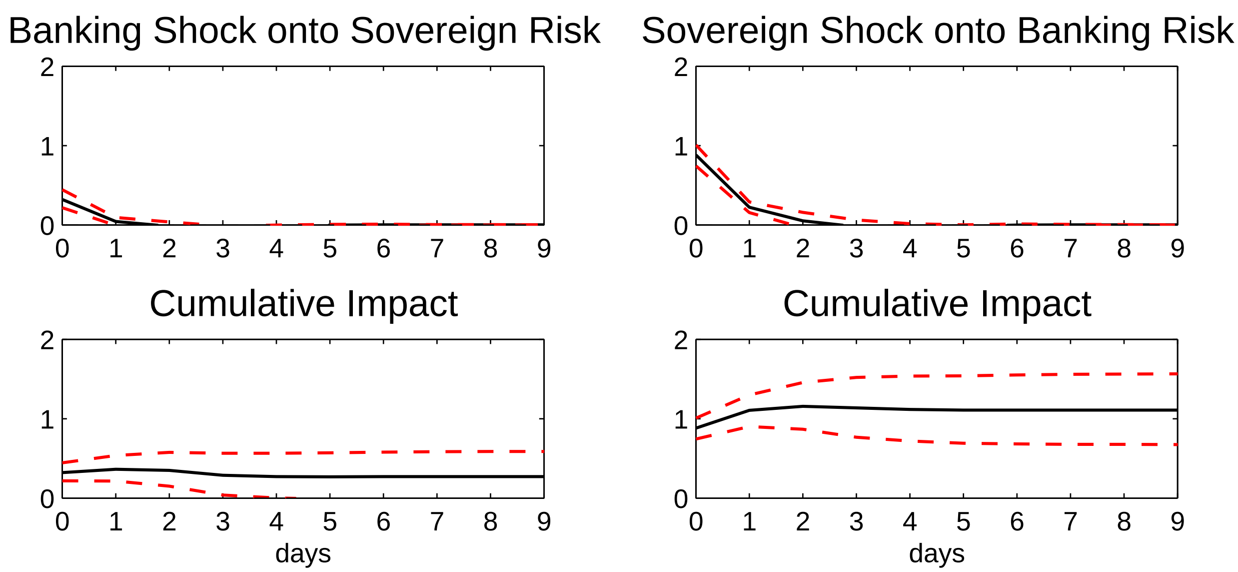

Figure 6: Distress Risk Versus Default Risk

The figure plots the 5-year default-related component (gray lines) and the "observed" systemic insurance price (black lines). The gap between the two lines is the distress risk premium for both sovereign (top graph) and banking (bottom graph) risk. Distress risk premium ($SIP^{\mathbb{Q}} - SIP^{\mathbb{P}}$) measures the compensation investors ask to be exposed to unpredictable variations in the probability of default. $SIP^{\mathbb{P}}$ measures the default-related component (or default risk). Both default risk and its associated premium are extracted by estimating the Longstaff and Rajan (2008) pricing model for CDO tranches. The sample covers the period from the 2007 to 2013.

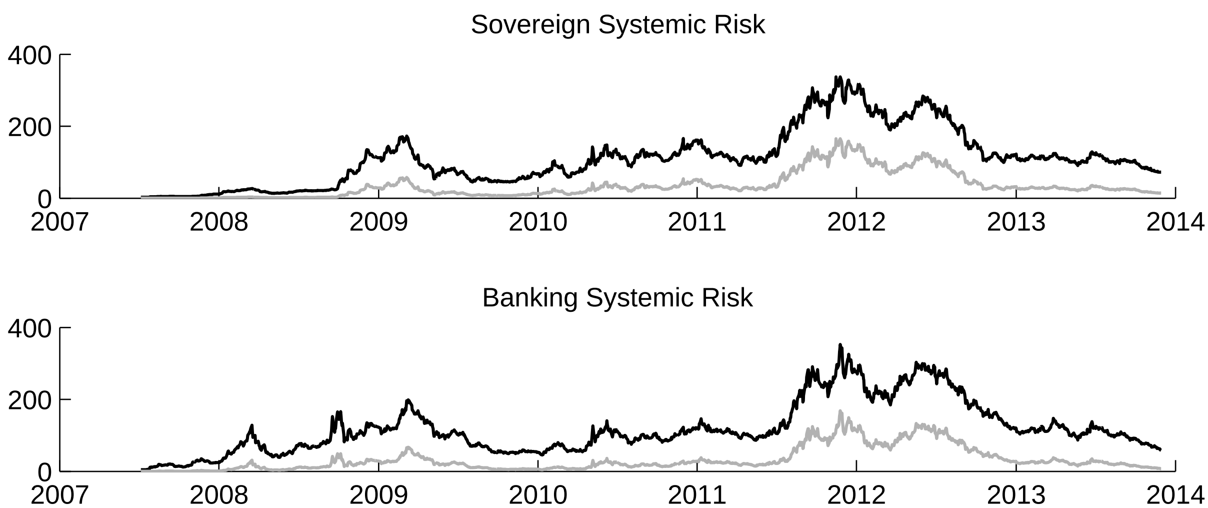

Figure 7: Distress Risk Premium: Shock Persistence

The figure plots the Impulse Response Functions (IRFs) of banking (sovereign) shocks onto sovereign (banking) distress risk premium in the top two panels. The bottom graphs plot the cumulative IRFs. Distress risk premium ($SIP^{\mathbb{Q}} - SIP^{\mathbb{P}}$) measures investors' compensation to be exposed to default risk. Dashed red lines are 95 percent confidence intervals constructed with a 5-day block bootstrapping method with 1,000 simulations. The response is estimated over a period of 9 days from the shock impact.

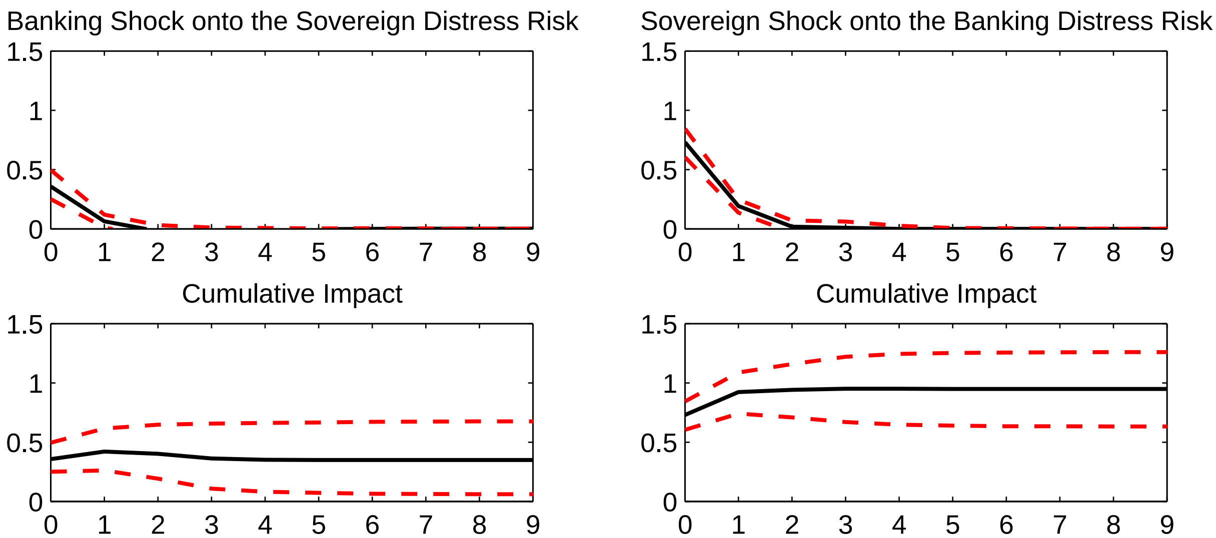

Figure 8: Default Risk: Shock Persistence

The figure plots the Impulse Response Functions (IRFs) of banking (sovereign) shocks onto the sovereign (banking) default risk in the top two panels. The bottom graphs plot the cumulative IRFs. Default risk ($SIP^{\mathbb{P}}$) is a measure of the physical default probability, that is, the price net of the risk premium. Dashed red lines are 95 percent confidence intervals from a 5-day block bootstrapping method with 1,000 simulations. The response is estimated over a period of 9 days from the shock impact.

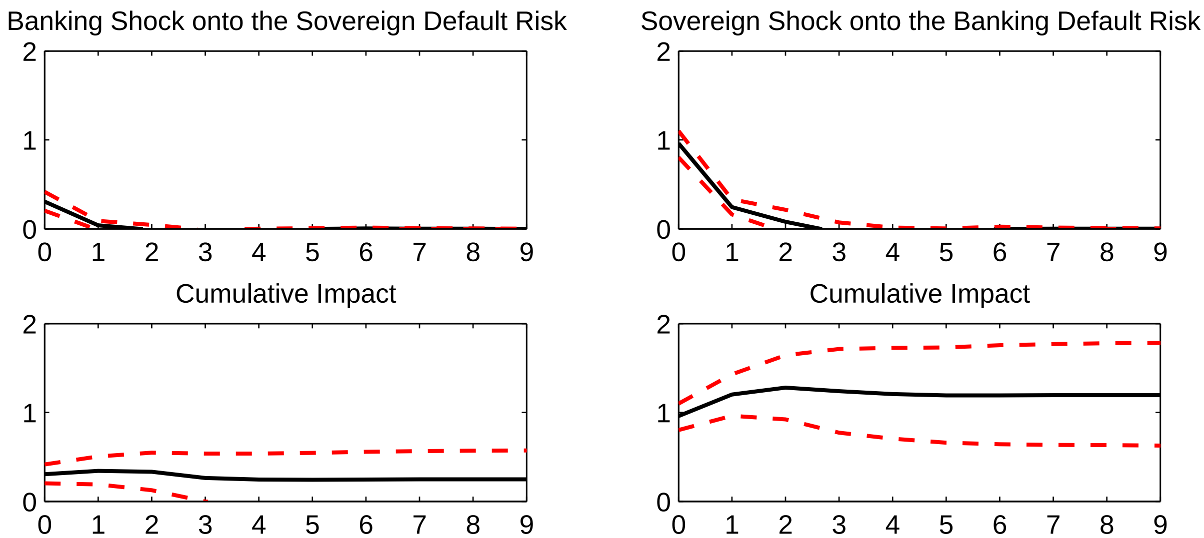

Figure 9: Systemic Insurance Price of Governments Sorted on Fiscal Space

The Figure plots the systemic insurance price for portfolios of countries sorted on the fiscal space in basis points. Fiscal space is estimated with an historical fiscal response function over the period from 1980 to 2007 and compared with the 2015-projected debt-to-GDP ratio. The portfolio with the lowest fiscal space (black line) is comprised of Greece, Italy, Ireland, Portugal and Cyprus with zero fiscal space and Belgium, Spain and United Kingdom with a fiscal space of 14, 29, and 35 percent of GDP. The portfolio with the highest fiscal space is represented by the dotted gray line. Appendix B provides a specific composition of these portfolios.

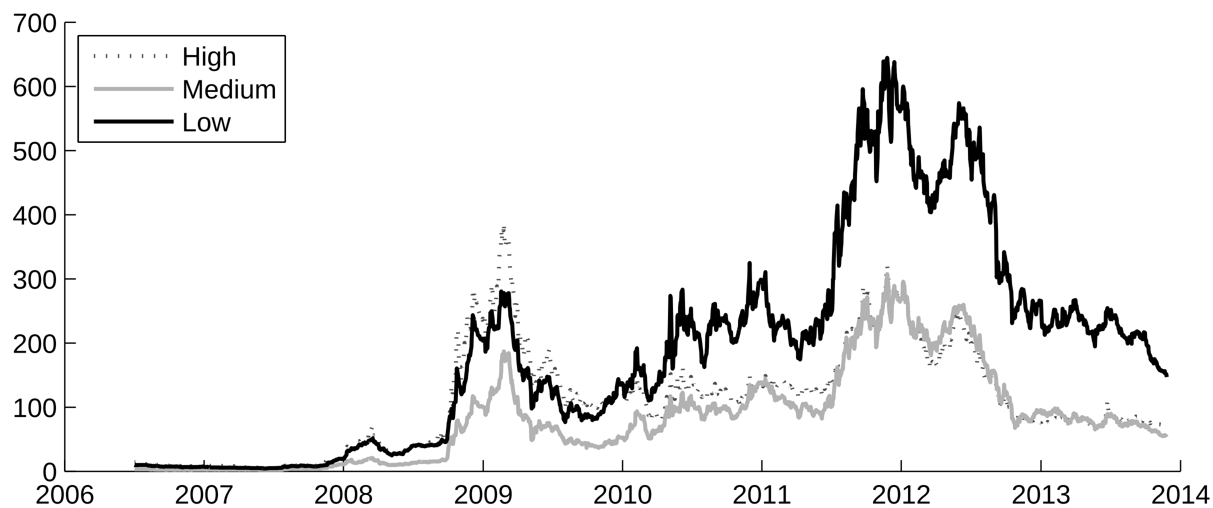

Figure 10: Systemic Insurance Price of Governments Sorted on Debt-to-GDP ratio

The Figure plots the systemic risk for portfolios of countries sorted on public debt-to-GDP in basis points. The sorting is dynamic as it is performed every year from 2006 to 2013 with a very little portfolio-turnover. On average, the portfolio of highly indebted countries (black line) contains Belgium (89%), France (73%), Greece(171%), Ireland (117%), Italy (121%), Portugal (123%), Spain (74%) and Cyprus (139%). The medium portfolio (gray line) contains Austria (66%), Germany (50%), Finland (48%), Netherlands (64%), United Kingdom (72%), Malta (67%), Slovenia (52%) and Poland (53%). The portfolio of low indebted countries (dotted gray line) contains Sweden (31%), Czech Rep (44%), Slovakia (51%), Estonia (6%), Latvia (37%) and Lithuania (35%).

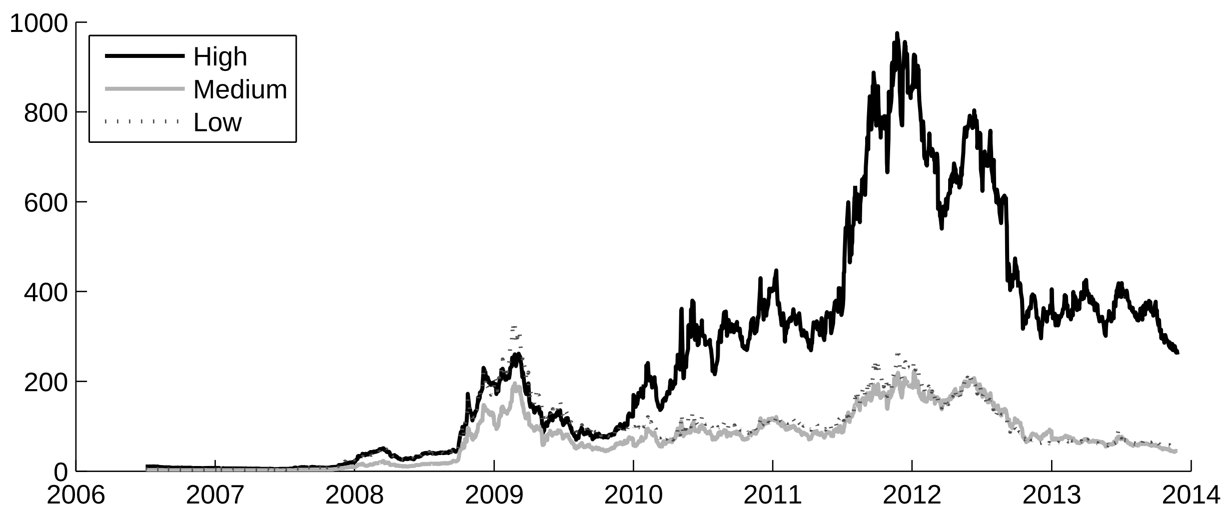

Figure 11: Systemic Insurance Price of Banks Sorted on Exposure to Low-Fiscal Space Governments

The figure plots the systemic risk for portfolios of banks sorted on their exposure to the countries with the lowest fiscal space over the total sovereign exposure as reported by BIS stress-tests reports. The portfolio with the highest (the lowest) exposure to the lowest-fiscal-space countries is represented by the black (dotted gray) line. The fiscal space is estimated with an historical fiscal response function over the period from 1980 to 2007 and compared with the 2015-projected debt-to-GDP ratio. The lowest fiscal space governments are Greece, Italy, Ireland, Portugal and Cyprus with zero fiscal space and Belgium, Spain and United Kingdom with a fiscal space of 14, 29, and 35 percent of GDP.

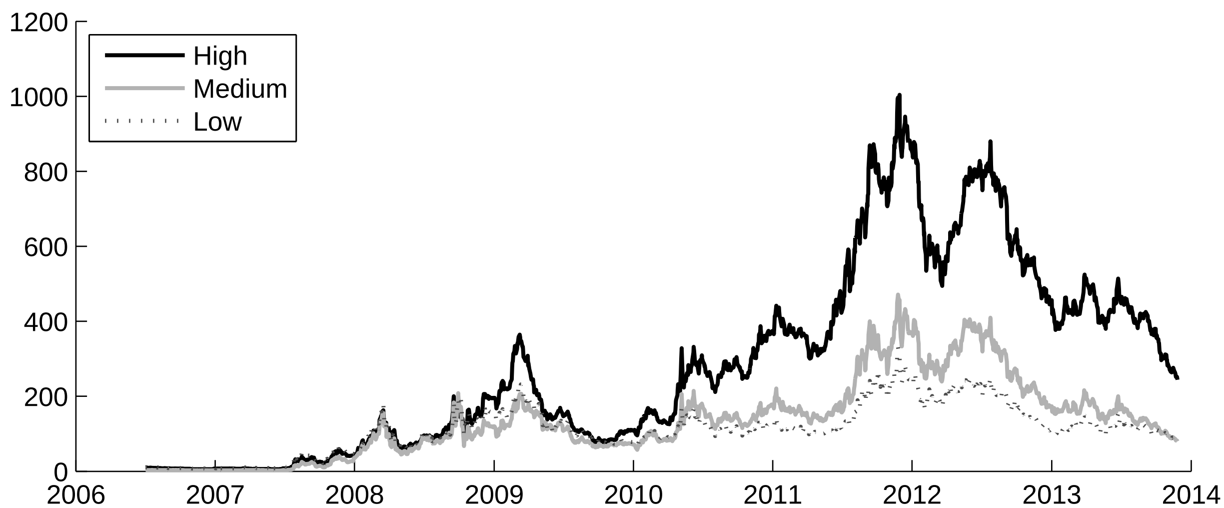

Figure 12: Systemic Insurance Price of Banks Sorted on Exposure to High-Debt-to-GDP ratio Governments

The figure plots the systemic insurance price for portfolios of banks sorted on their exposure to the most indebted countries over the total sovereign exposure as reported by BIS stress-tests reports. The portfolio with the highest (the lowest) exposure to the most indebted countries is represented by the black (dotted gray) line. The sorting is static as the sovereign exposure is available only for the year 2010. Banks mostly exposed to highly indebted countries (black line) are the ones of the most indebted countries. The medium portfolio (gray line) contains banks from France, Belgium, Germany, United Kingdom, Spain, Austria and the Netherlands. The portfolio of banks less exposed to these governments (dotted gray line) contains banks from United Kingdom, Belgium, Switzerland, Germany, France, the Netherlands, Sweden and Norway.

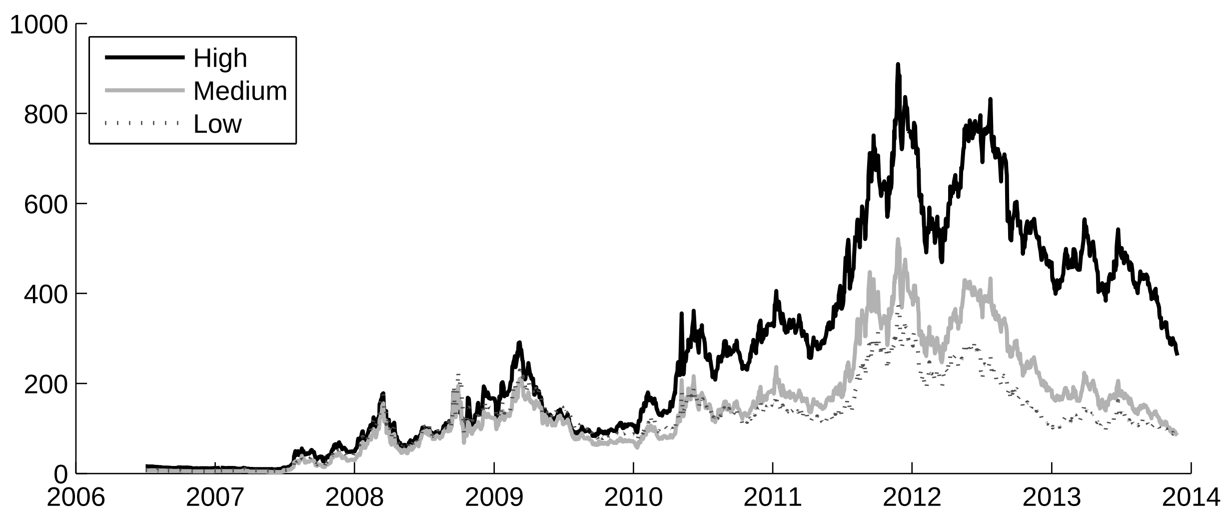

Figure B.1: Fiscal Space and Debt Limit

The figure plots the fiscal response function (red line) of the government and its growth-adjusted interest rate schedule (black line). There are two stationary equilibria: The first in d^* is the result of the first intersection between the fiscal response and the growth-adjusted interest rate. This level is the long-run debt level to which the economy conditionally converges; the second equilibrium is in $\tilde{d}$ where the primary balance intersects the deterministic interest rate schedule $(r-g)d$ where r, g and d are the exogenous risk-free rate, the economy growth rate and the debt-to-GDP ratio, respectively. If debt were to exceed this limit, then it would never return to the long-run equilibrium as the primary balance is never sufficient to cover the interest payment and the debt ratio would increase unboundedly. However, if the market realizes that the government is approaching its debt limit, the debt limit is at a lower level than $\tilde{d}$, as investors will charge a premium ($r(def) = r + premium$) for debt loads greater than $\hat{d}$, because they face a positive probability of default of the government. In the latter case, the debt limit is reached in $\bar{d}$, a level lower than the deterministic debt limit $\tilde{d}$ as a negative shock to the primary balance makes it less likely that the balance would be sufficient to meet interest payments, thus increasing the probability of default and the premium. In the stochastic case, negative (positive) shocks to the primary balance will cause downward (upward) shifts in the red curve.

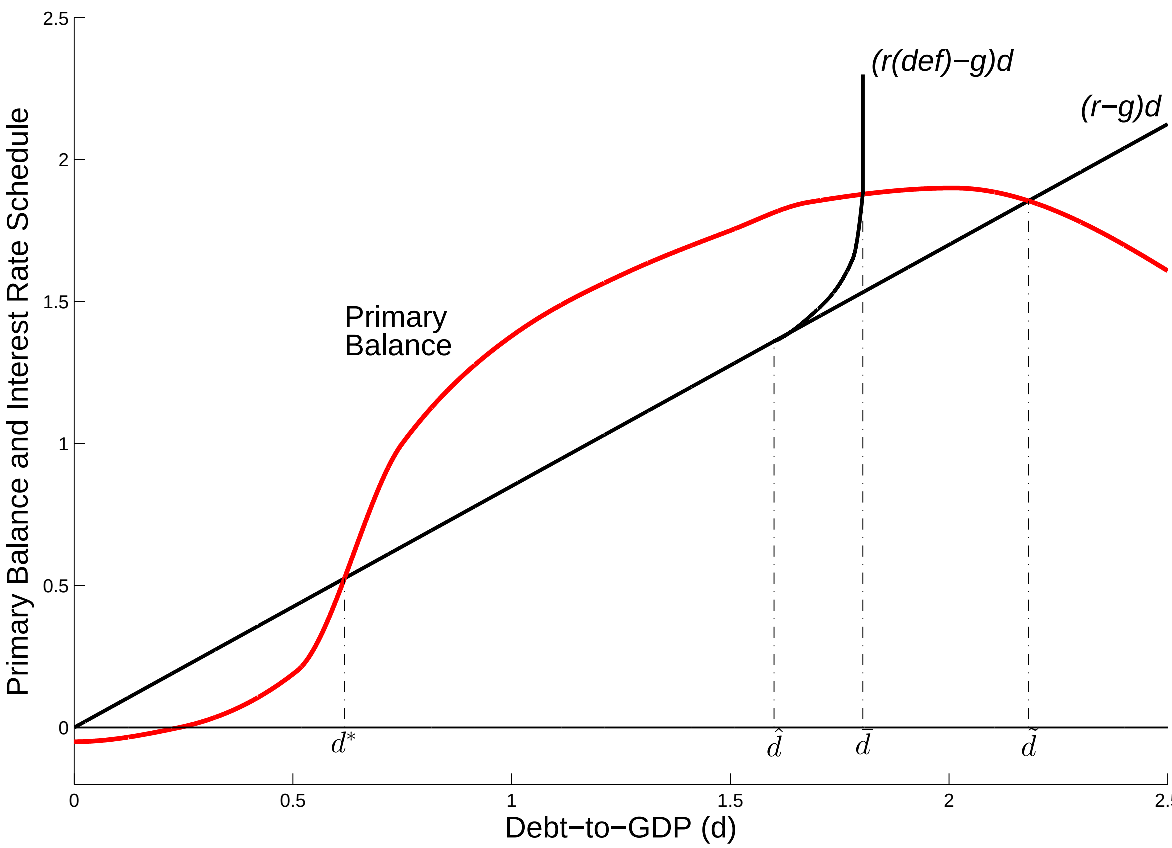

Figure B.2: Estimated Fiscal Space by Country

The figure plots the estimated fiscal space for 29 economies. The fiscal space is the difference between the 2015-projected debt-to-GDP ratio and the actual debt limit and is estimated with a historical fiscal response function over the period from 1980 to 2007. The debt limit is the point beyond which the sovereign default cannot be avoided, unless the government imposes structural fiscal reforms or asks for outside assistance. "No Space" suggests that the government has no room to spend without threatening macroeconomic stability. Vertical lines separate four zones of riskiness: From the high or grave risk to the safest zone with a fiscal space grater than 110 percentage points. The fiscal space is shown in percentage points of GDP.

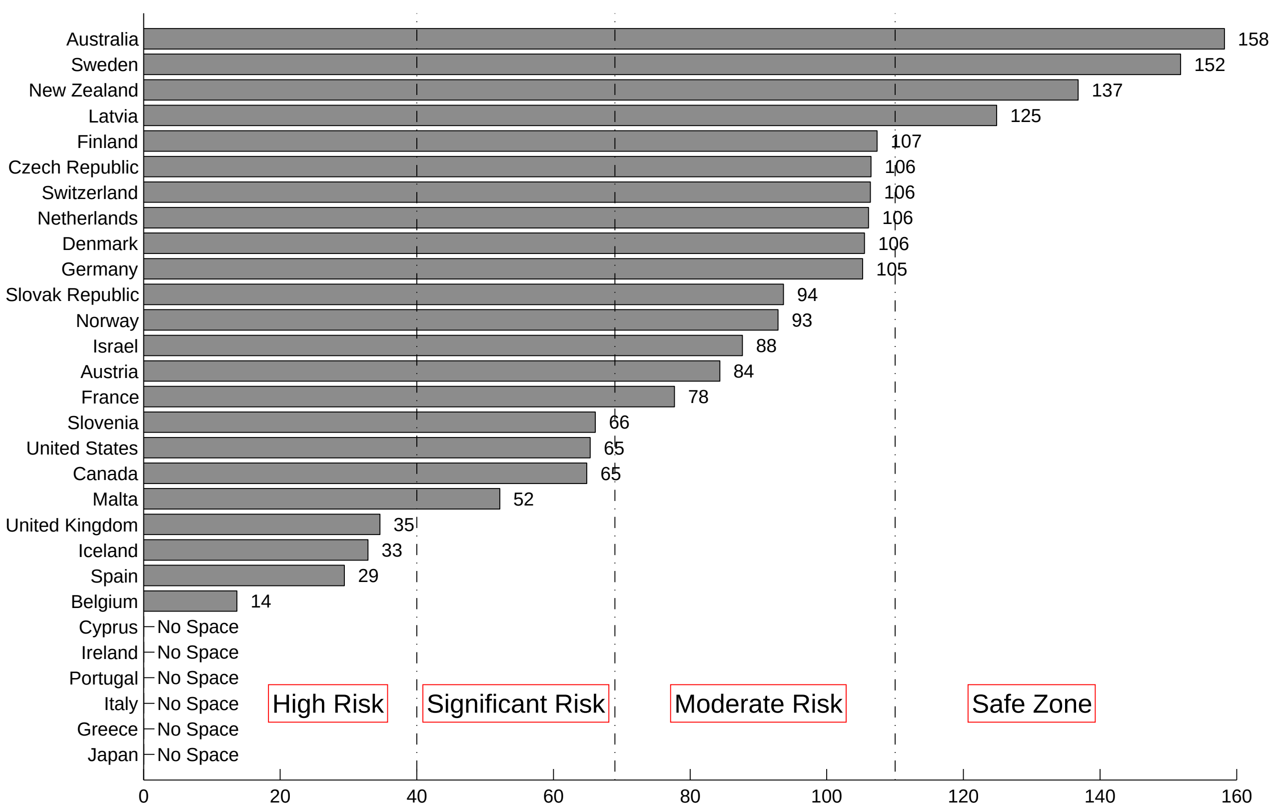

Figure C.1: Systemic Risk in the U.S. Economy

The Figure plots the systemic insurance price (SIP) for the U.S. banking (black line) system and the credit default swap spread on the U.S. government (gray line) in basis points. SIP measures the risk-neutral expected loss on the total liabilities of the respective system, given that the loss is greater than 10 percent. The sample covers the daily period from January 2004 to November 2013 and spans three periods: The pre-crisis period, the financial crisis of 2007/09, and the European debt crisis of 2010/13.