

The Impact of Sovereign Shocks

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Abstract

We investigate the interrelationships between macro-systems of governments and financial institutions by studying the dynamic propagation mechanisms of macroeconomic shocks. We propose a novel approach to identify relevant systemic shocks and to classify them into sovereign or banking categories. Our econometric framework quantifies the impact and spillover rates of systemic shocks within and across systems. We find that sovereign shocks have a significant and persistent impact on the probability of a collective banking default, but not vice versa. Finally, we explore sources of systemic fragility, potential mechanisms of shock transmission, and their implications for the real economy.

JEL classification: E44, E50, G21, G28

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1 Introduction

In the wake of the recent “Brexit” vote, with British voters expressing their desire to leave the European Union, financial markets worldwide experienced record losses and many financial institutions have lost up to 30% of their market value within a few days. The consequences of this historical political event are not clear yet, but the British vote highlights once more the relevance of sovereign shocks for the financial system.

In a globally interdependent world, financial crisis have the potential to spread quickly across financial institutions, giving rise to systemic risk – the risk that the capacity of the entire financial system is impaired, with potentially adverse consequences for the real economy.¹ In order to mitigate the spreading of financial distress and its impact on the real economy, governments have announced massive bailout programs worldwide.² The cost of these bailout packages has driven up government indebtedness, making countries more fiscally constrained, and thus adding a sovereign risk component to systemic risk.

In this paper we investigate the potential implications of sovereign credit risk in amplifying adverse shocks to the financial system. Recent developments in the European Debt Crisis make Europe a natural framework to think about governments as a potential source of economic fragility, and to study the interrelation between sovereign and financial risk.

The most recent research on systemic risk has mainly focused on financial institutions, ignoring the potential *systemic* impact of sovereign risk on the financial system and on the real economy.³ The goal of this paper is to fill in this gap by proposing a methodology that captures the time-series and the cross-sectional dimensions of sovereign systemic risk.⁴ Using

¹There is no proper definition of systemic risk, in this paper we adopt the one proposed by [Adrian and Brunnermeier \[2015\]](#).

²In the aftermath of the Lehman default, the US government announced the \$700 billion Troubled Asset Relief Program (TARP), followed by the £500 billion banking recapitalization program in the United Kingdom.

³[Brunnermeier et al. \[2009\]](#), [Adrian and Brunnermeier \[2015\]](#) provide new approaches to define and quantify systemic risk in the financial industry. However, there is a growing literature that focuses on the dynamic interrelation between sovereign and financial credit risk ([Acharya et al. \[2014\]](#), [Gray and Jobst \[2011\]](#), [Billio et al. \[2013\]](#)).

⁴As noted in [Adrian and Brunnermeier \[2015\]](#), [Brockmeijer et al. \[2011\]](#), among others, the time-series and cross-sectional dimensions pertain to the build-up of risk in calm times (volatility paradox), and spillover across the system, respectively.

this methodology, we shed more light on the complex interrelationship between systems of banks and governments and its implications for the real economy. In particular, we investigate the impact of sovereign risk on the probability of a systemic default in the banking system by studying the propagation dynamics of shocks from a system of governments to a system of banks, and viceversa.⁵

In a preliminary analysis, we provide empirical evidence of tail dependence in the distribution of sovereign and financial risk. In particular, we estimate quantile regressions on a panel of credit default swap (CDS) spreads of 163 European financial institutions and 28 European countries. We show that, on average, the financial system is more vulnerable to sovereign downside risk than the sovereign system is to financial (or banking) risk.

This preliminary analysis highlights the importance of sovereign fragility for the financial system. This relation is intuitive if we consider the balance sheet exposure of a bank that holds foreign and domestic sovereign bonds. A drop in the value of foreign bonds can increase the bank's default probability through a decrease in the value of its assets (asset channel). A fall in the value of domestic bonds does not only affect the value of the bank's assets, but also limits the ability of the country to provide implicit guarantees on the bank's debt (liability channel). On top of this, inter-bank exposure (exposure to other financial institutions) amplifies the impact of sovereign shocks, leading to systemic distress.

In the second part of the paper, we investigate the economic mechanisms driving the propagation of shocks across sub-systems of countries and financial institutions. In order to study these mechanisms we face two methodological challenges: i) establishing an economically reasonable measure of sovereign and financial systemic risk, and ii) discerning sovereign and banking shocks in a reliable way.

To address the first challenge, we use a credit-portfolio approach to measure the default risk of macroeconomic systems. Such an approach captures the two dimensions of systemic risk: the time-varying probability of the occurrence of a rare event and the magnitude of the expected loss (time-series dimension), and most importantly, the degree of interconnectedness of entities within the system (cross-sectional dimension). This measure, called the *Distress*

⁵Throughout the paper we use the words "financial" and "banking" interchangeably, to refer to the system of financial institutions.

Insurance Price (DIP), was first introduced by [Huang et al. \[2009\]](#). It is a liability-weighted measure of tails risk that is characterized by marginal default probabilities extracted from credit default swap spreads, and by a copula that captures the cross-sectional dependence among those probabilities.

With respect to the second challenge, we rely on official crisis time-lines and newspaper articles to identify macroeconomic shocks. Based upon the narrative of the events we identify sovereign and banking specific events. This identification schema enables us to identify and label economically and systemically relevant shocks under a rubric of financial, economic and political uncertainty.

Our econometric framework is a structural vector autoregressive (VAR) model where innovations are grouped into “shocks of interest” and “other shocks”.⁶ More specifically, let $u_t = B\epsilon_t$ be the structural shock at time t , with spillover matrix B and innovations ϵ_t , we decompose the structural shock such that

$$u_t = \beta^{sov}\epsilon_t^{sov} + \beta^{bank}\epsilon_t^{bank} + v_t$$

where β^{sov} and β^{bank} capture the impacts of both sovereign (ϵ_t^{sov}) and banking (ϵ_t^{bank}) shocks within and across systems of banks and countries. Examples of these shocks are policy announcements, rating agencies’ actions, and political turmoil. Throughout this paper, a shock is understood to be sovereign (banking) if and only if the content of news articles primarily refers to countries (banks). That is, sovereign and banking shocks *directly* impact sovereign and banking systems, respectively.

Recent research has proposed several *statistical* approaches to identify shocks and to study spillover across systems.⁷ While such approaches are useful to understand the dynamics of contagion, they have little *economic* interpretation, and thus are not very informative about the economic mechanism driving contagion. In this paper, we rectify this shortcoming by overtly mixing statistical information with the narratives of macroeconomic events. More

⁶This empirical framework is similar to that of [Romer and Romer \[1989\]](#), [Mendoza and Ostry \[2008\]](#), [Mertens and Ravn \[2010\]](#).

⁷[Kalotychou et al. \[2014\]](#) define sovereign credit events as the 99th percentile of the distribution of changes in CDS spreads. Other approaches consist in measuring (monetary) surprises as changes in future contract prices around the policy action ([Bernanke and Kuttner \[2005\]](#), among others)

specifically, we present a methodology that exploits the narrative of the events to identify economic, financial, and political shocks, and uses statistics to capture shocks that are *systemically* relevant.⁸ With such an approach we offer a better understanding of the economic channels that contribute to spillover across the sovereign and the financial sectors.

Using a comprehensive data set of fundamental and credit data, we measure sovereign and banking systemic risk (DIPs) of a pool of 28 European countries and 163 European financial institutions, over the daily period from August 2007 to May 2015. We show that sovereign risk and banking risk are time varying, highly correlated, and have similar magnitudes. This finding highlights how the two systems share similar risk profiles although they play two different roles in the economy. We also find that sovereign shocks have an average within-system impact of approximately 7 bps, that, compared to a sample average DIP of 64 bps, amounts to a 10 percent daily variation. More importantly, the spillover rate of sovereign shocks onto the banking system is about 75 percent, twice as big as the spillover rate of banking shocks onto sovereign risk, that is, 36 percent. This result is in line with the preliminary quantile analysis described above, and it is the primary empirical contribution of the paper. This observation suggests that monitoring banking risk *and* sovereign risk does provide a more complete picture of the sources of systemic risk.

To further explore the nature of sovereign risk, we investigate the role of sovereign fragility, proxied by fiscal constraints, in the dynamic propagation of shocks. We assess systemic risk for portfolios of countries sorted on their level of fiscal flexibility, measured as the country’s “fiscal space”—the difference between a theoretical government debt limit and its actual debt load. We show that highly fiscally constrained countries are more heavily impacted by sovereign and banking shocks than countries with more fiscal flexibility. The rationale is that a government with low fiscal space cannot use conventional fiscal tools (issuing new debt and/or increasing taxes) to support extraordinary expenses, such a bank bailout.⁹

Finally, we study the channels of contagion behind the propagation of sovereign shocks to the banking system. We hypothesize the existence of two channels, on the asset and on

⁸A similar approach has been proposed by [Collin-Dufresne et al. \[2010\]](#).

⁹Because fiscal space is model-driven and could be questionable, we show that our results are robust using the country’s debt-to-GDP ratio as a measure of fiscal flexibility.

the liability side of the balance sheet. The latter refers to the inability of fiscally constrained governments to provide implicit guarantees on the liabilities of their *domestic* financial institutions. The asset channel affects both *domestic* and *foreign* financial institutions that hold sovereign debt, because more volatile assets due to sovereign risk affect the probability of default of the financial institutions.¹⁰

In an attempt to disentangle these two channels, we create two categories of financial institutions that are exposed to fragile economies, splitting them into domestic and foreign categories. The underlying logic is that foreign institutions are only affected through the asset channel, whereas local institutions are affected from both the liability and the asset side. We find that, although the spillover of sovereign shocks is significant for both groups, it is stronger for domestic institutions. This result provides empirical evidence that that exposure to fiscally fragile economies affects financial institutions through both the asset and the liability side. This finding constitutes an important contribution to the literature as it sheds light on the economic sources of spillover across the sovereign and the banking system.

In the last part of the paper we investigate the implications of systemic risk for the real economy. Inspired by the work of Bloom [2009] on the impact of uncertainty shocks, we explore the influence of sovereign and banking systemic risk on the real economy. We find that, above some commonly used macroeconomic controls, industrial production and employment drop significantly following a banking shock, with the former declining by two percent ten months after the shock impact. Conversely, sovereign systemic risk does not significantly and directly influence the real economy. This empirical evidence has important policy implications because it suggests that an intervention on sovereign risk may mitigate banking risk and, in turn, stabilize the real economy.

Literature Review and Contribution. Our research question builds on several strands of literature. It is related to recent works that focus on sovereign risk and, in particular, on the importance of interactions between financial institutions and governments.

¹⁰This is in line with the theoretical mechanisms highlighted by Merton [1974].

There is a growing literature on the implications of sovereign risk in the financial sector. [Billio et al. \[2013\]](#) propose the network analysis to measure linkages between financial institutions and countries through correlation between credit spreads. They find the risks of the banking and insurance systems have become increasingly interconnected with sovereign risk. [Gennaioli et al. \[2014\]](#) propose a theoretical model in which sovereign defaults are costly because they damage the balance sheets of domestic banks, and find empirical evidence in support of their theoretical predictions. [Bolton and Jeanne \[2011\]](#) introduce a similar model to analyze the role of banks in transmitting the effects of sovereign defaults across financially integrated economies. In line with this literature, we propose an empirical framework to study and quantify the impact of macroeconomic shocks *within* and *across* macroeconomic systems. Therefore, our work provides further empirical evidence on the still largely unexplored contagion mechanism among and from distressed macroeconomic systems. [Acharya et al. \[2014\]](#) provides a model and empirical support for the notion of a loop between sovereign and bank credit risk. However, their empirical analysis on the risk-transfer between governments and banks following a bailout does not take into account potential shock spillover on other economies and financial systems. Instead, in this paper we provide an empirical approach that looks at shock spillover *within* and *across* macroeconomic systems of governments and financial institutions.

There is a vast literature on sovereign risk that has primarily focused on emerging markets ([Zhang \[2003\]](#), [Longstaff et al. \[2011\]](#), [Pan and Singleton \[2008\]](#), [Remolona et al. \[2007\]](#)), and then on developed economies from the beginning of the European debt crisis ([Sgherri and Zoli \[2009\]](#), [Ang and Longstaff \[2013\]](#), [Arce et al. \[2013\]](#), [Black et al. \[2013\]](#), [Manzo \[2013\]](#), [Engle et al. \[2014\]](#), among others).¹¹ Our paper focuses on Europe as it provides a natural framework to think about governments as a potential source of economic fragility. However, our approach can be readily applied to other regions.

This paper also relates to the recent literature on the measurement of systemic risk and the information it conveys about the macroeconomic cycle. Two main approaches have been proposed to measure systemic risk: a structural method that uses contingent claims analysis *à la* [Merton \[1974\]](#), where the equity is a call option on the bank's assets (see [Lehar \[2005\]](#),

¹¹[Manzo and Veronesi \[2016\]](#) provides an empirical analysis on credit risk in both emerging and advanced economies.

Gray et al. [2008], Gray and Jobst [2011], among others), and a reduced-form approach that exploits the information content of the tail distribution of asset returns. We borrow the DIP measure from Huang et al. [2009] and we show how it can be used to investigate the interaction between macroeconomics systems and their sub-systems.

With contagion at the heart of systemic risk, recent papers have proposed several measures to capture spillover and externalities across financial institutions.¹² Brunnermeier et al. [2009], Adrian and Brunnermeier [2015] 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.¹³ Brownlee and Engle [2010], Acharya et al. [2012] introduce the SRISK index, which measures the expected capital shortage of a financial institution conditional on a significant market decline. These measures use realized equity returns and thus measure systemic risk under the physical probability measure. The DIP is different from these studies, its risk-neutrality serves as a crucial aspect of measuring systemic risk for policymakers, because it corrects for the risk aversion of the market. Indeed, systemic risk is not only priced into the market 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.

Our paper also builds on the literature regarding macroeconomic shocks. Statistical and narrative approaches are often used to test the impact of shocks on markets. When using the statistical approach researchers let the data talk, that is, shocks can be represented by large variations such as changes above the 99th percentile of CDS spreads (Kalotychou et al. [2014]), or deviations of variables from expected values such as monetary shocks. Conversely, the narrative approach allows the researcher to study certain types of shocks

¹²Contagion is meant to be a particular strong propagation of failures from one institution, market or system to another (De Bandt and Hartmann [2000])

¹³Other 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 et al. [2012] propose the Dynamic Conditional Correlation model (Engle [2002]) to capture the time-varying nature of the degree of contagion. Adams et al. [2012], Wong et al. [2011], Gauthier et al. [2012] also use CoVaR to estimate systemic risk of banking systems. Finally, in an IMF report Chan-Lau et al. [2009] present the Co-Risk measure that assesses the risk of financial institutions with quintile regressions.

collected from central bank reports or newspapers. This approach was first pioneered by [Friedman and Schwartz \[1982\]](#), [Romer and Romer \[1989\]](#) and then applied in several works (The impact of sovereign shocks is found systemically relevant for the risk of a collective default of banks. In the last part of the paper we investigate systemic risk implications for the real economy. [Romer and Romer \[1997, 2007\]](#), [Mertens and Ravn \[2010, 2011\]](#)). We propose a combination of the two approaches to collect shocks from newspapers as we are interested in pinning down sovereign and banking specific shocks, and then use data analysis to test the shocks sign.

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. \[2013\]](#), [Ostry et al. \[2010\]](#) to study debt sustainability in advanced economies.¹⁴ To the best of our knowledge, we are the first to use the concept of fiscal space to better identify the fragility of a system of governments and how shocks impact those countries.

Finally, this paper also links to the literature that studies the real impact of banking crisis ([Rajan and Zingales \[2001\]](#), [Dell’Ariccia et al. \[2008\]](#), among others). In particular, we introduce our DIP measures in the empirical framework of [Bloom \[2009\]](#) to study the impact of systemic risk on the real economy.¹⁵

In summary, recent works have mainly focused on the risk of contagion across financial institutions *within* the same system. To the best of our knowledge, our paper is the first in proposing a tool to measure sovereign systemic risk, in providing empirical evidence on the complex interrelation between macro systems of banks and governments by studying systemically relevant sovereign and financial shocks, and in studying sources of fragility and contagion.

Structure of the paper. The paper is organized as follows: In Section 2 we present preliminary empirical results on the propagation of shocks between sovereign and financial

¹⁴The concept of fiscal space is mainly related to the research on the primary balance of governments in advanced and emerging economies ([Bohn \[1998\]](#), [Mendoza and Ostry \[2008\]](#)).

¹⁵[Kelly and Jiang \[2014\]](#) also introduce a tail risk measure in the VAR specification of [Bloom \[2009\]](#) and provide evidence of a large impact on the real economy.

risk, and present the data; in Section 3 we estimate the distress insurance prices and discuss the economic relevance of systemic risk in Europe; in Section 4 we set up the empirical framework and the methodology to identify shocks, and show the empirical results in Section 5; finally, Section 7 concludes the paper.

2 The Distribution of Sovereign and Financial Risk Spillover

To measure tail risk dependencies between institution i and j , we employ quantile regressions of the form:¹⁶

$$\Delta CDS_t^i = \alpha_q + \mathbf{X}_t' \gamma_q + \beta_q^{i \leftarrow j} \Delta CDS_t^j + \epsilon_t^i \quad (1)$$

where ΔCDS_t^j and ΔCDS_t^i are changes in credit default swap spreads of entities $i, j \in \{\text{sov, fin}\}$. \mathbf{X}_t contains a set of macro variables, such as changes in VIX, changes in term slope (10y minus 3m Treasury securities), changes in the U.S. credit spread (10y-Baa yield minus 3m-Tbill rate), return on the U.S. real estate market, and S&P500 returns. q is the percentile of the distribution we want to analyze.

Because we are interested in the impact of sovereign and financial systemic shocks, we set q to 98 per cent (or top 2 percentile), meaning that we focus on variations in credit risk in the tail of the distribution. Therefore, $\beta_q^{i \leftarrow j}$ quantifies the impact of j 's extreme negative shocks on entity i 's risk distribution, after controlling for global market variations.¹⁷

2.1 Data

Our data set consists of 28 European countries and 163 European financial institutions. For each country and bank, we collect credit default swap (CDS) spreads from the Markit

¹⁶There is an increasing interest in applying quintile regressions in finance, recently. Examples are Chan-Lau et al. [2009], Hautsch et al. [2014], Adrian and Brunnermeier [2015] Chan-Lau et al. [2009], Hautsch et al. [2014], Adrian and Brunnermeier [2015], among others. We refer the reader to the aforementioned works for a formal and more detailed presentation of quantile regressions.

¹⁷This approach has also the advantage of measuring a CDS-implied network, where each institution represents a node, and $\beta_q^{i \leftarrow j}$ measures the size and the direction of each node's edge (or link). A similar approach to measure links in a network is proposed by Billio et al. [2012, 2013], Adrian and Brunnermeier [2015], Hautsch et al. [2014].

database.¹⁸ Government public debt is collected from Eurostat and the IMF, and book data of financial institutions from Compustat International, supplemented by Datastream and Bloomberg. The sample covers the daily period from July 2007 to May 2015.

A CDS is an agreement between two parties: The buyer and the seller. The buyer pays a periodic premium, usually quarterly or semiannually, to hedge the underlying security, loan or 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) 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. Credit default swap spreads have been used extensively in recent literature as they provide a better measure of default risk as opposed to bond yields. Indeed, CDS are constant maturity contracts and available only at specific maturities. Being standardized contracts, they are not affected by call premiums, such as callable bonds, or liquidity risk. Moreover, they are collateralized so that the default risk of the buyer and seller of these contracts is negligible.

Table 1 reports summary statistics for the 5-year sovereign CDS spreads and debt-to-GDP ratios over the financial crisis 2007/09 and the European debt crisis 2010/2015. During the financial crisis Eastern European countries have recorded high spreads of about 200 bps on average. 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. The European debt crisis period

¹⁸For each entity, identified by the Markit Redcode, we create the longest possible time series of data by using the Markit Redcode succession table. In case of mergers we create a long time series for the larger company, that is going to be more systemically important. The smaller company drops out of the sample after the merge. In case of acquisitions we create a long time series for the acquiring company.

shows a reverted scenario where Western developed economies experienced high spikes in spreads. This scenario was mostly driven by the increasing indebtedness of countries such as Portugal, Italy, Ireland, Greece and Spain, the so-called PIIGS, as shown by their debt-to-GDP ratios across the two periods. Term structure slopes are negative on average for Greece, Cyprus, Ireland and Portugal, signaling that the probability of defaulting in one year was very high for these countries.

The European financial sector has also recorded high spreads during the two sub-periods as shown in Table 2. Greek, Irish and Portuguese banks have the highest spreads, on average, and inverted term structures. These simple descriptive statistics point to the main research question of this paper that i) the default risk of financial institutions is somehow correlated with that of their local governments, and that ii) such a link also exists across the two macro systems as highlighted by high spreads throughout Europe.

2.2 Sovereign Versus Financial Tail Risk

We estimate equation 1 for each country on each financial institution and viceversa, using weekly data, sampled on each Friday. Given that we are estimating non-linear relationships conditional on the top 2 percentile of the distribution, we require each time series to have at least 260 weeks (5 years) of observations.¹⁹

Figure 1 plots the Kernel densities of the impact coefficients $\beta_q^{i \leftarrow j}$. The notation $Y|X$ identifies the distribution of Y 's impact *given* that X is in distress, that is, in the top 2 percentile of the distribution. In other words, the solid black line (Sov|Fin) plots the impact distribution of financial distress shocks on the sovereign sector, whereas the solid gray line (Fin|Sov) plots the impact distribution of sovereign distress shocks on the financial sector.²⁰ The dashed lines represent the means of the distributions.

The impact distribution of sovereign risk presents a fatter tail than that of financial risk with more mass around large spillover rates ranging from 1.5 to 3.5. Moreover, the average sovereign spillover is 1.53 times as larger as that of financial risk ($\bar{\beta}_q^{fin \leftarrow sov} / \bar{\beta}_q^{sov \leftarrow fin} =$

¹⁹In the practical implementation we use the Python function QuantReg with robust covariance, Epanechnikov kernel, Hall-Sheather bandwidth, and with 1000 max iterations and 1e-06 tolerance.

²⁰We consider only the impacts that are statistically different from 0 at the 5% confidence level.

1.53), and they are significantly different. These results suggest that a distressed sovereign system may have systemic implications for financial institutions, and may lead to disastrous consequences for the real economy.

3 Quantifying Systemic Risk

The preliminary analysis in the previous section has highlighted that sovereign spillovers matter for the financial system. To better quantify the impact and persistence of these shocks and study the transmission channels, in this section we introduce a methodology that enables us to gauge the systemic risk of sub-regions. The advantage of splitting a large system of countries or financial institutions into small parts is that we can explore sources of shocks and contagion channels.²¹

We introduce a measure of systemic risk, first proposed by [Huang et al. \[2009\]](#), that summarizes in one number the size, the probability of default, and the degree of interconnectedness of an institution as part of a larger system. This measure is the *distress insurance price* (DIP) and is an expected tail loss similar to a senior tranche of a collateralized debt obligation.²² Its construction draws on the following simple reasoning: Assume a hypothetical investor holds a portfolio of liabilities of N entities. The DIP, then, represents 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.²³

Specifically, let x be such a threshold and $L_t = \sum_{i=1}^N L_{i,t} w_{i,t}$ 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

²¹The argument will be clearer in section 5.1.

²²As CDOs, DIP 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. A detailed overview on CDOs is provided by [Longstaff and Rajan \[2008\]](#) and [Bhansali et al. \[2008\]](#).

²³To 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. Eurostat reports that the GDP of the European Union (25 countries) in 2011 amounted to about 12.1 trillion.

weights $w_{i,t} = Debt_{i,t} / \sum_i Debt_{i,t}$. Then, the T -year DIP at time t is:

$$\mathbf{DIP}_t(T) = E^{\mathbb{Q}}[L_{t+T} \times \mathbb{1}\{L_{t+T} \geq x\}] \quad (2)$$

where \mathbb{Q} indicates that the expectation is taken under the risk-neutral probability measure. Using a risk neutral measure has the advantage of adjusting 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, being an expected loss, the DIP can also be thought of as a capital buffer, that is, as the amount of capital that is needed to bailout the institutions. This is one of the main advantages of using a liability-based measure as, differently from equity-based measures ([Acharya et al. \[2010\]](#), [Adrian and Brunnermeier \[2015\]](#), [Brownlee and Engle \[2010\]](#) among others), have a direct implications for bailouts. [Appendix A](#) provides a technical description of the DIP and how it is estimated.

In summary, the DIP offers several benefits to address our research question: i) for the reason explained above, it is a liability-based risk-neutral measure, as opposed to a stock-based physical measure; ii) being similar to a (super) senior CDO tranche, it is a valuable proxy for the “economic catastrophe risk”, which refers to the risk of those institutions (or bonds) that default only under harsh economic conditions ([Coval et al. \[2009\]](#), [Berndt and Obreja \[2010\]](#)); iii) as an expected tail loss, it belongs to the family of coherent risk measures and its sub-additivity property enable us to investigate systemic risk of sub-macroeconomic regions; iv) it provides a greater flexibility in studying portfolios of defaultable institutions than the traded tranches on the CDX index that groups 125 companies; moreover, to the best of our best knowledge, there are no traded tranches on sovereign CDX indices, thus, making it impossible to study sovereign catastrophic risk.

3.1 Sovereign and Banking Systemic Risk in Europe

[Figure 2](#) plots the sovereign and the banking DIPs for the 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 influence 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.

The Summer of 2007 is particularly important for the European banking sector. Spillover 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. 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 200 basis points in the Summer/Fall of 2011. A sequence of political and economic events throughout Europe contributed to rising risk. Particularly important for systemic implications were political shocks in Greece, Italy, and Spain that destabilized the European Union as a whole.²⁴ A significant event was the announcement of the possibility of using European Stability Mechanism funds to rescue banks. This announcement at the end of June 2013 brought back sovereign and banking systemic risk to pre-crisis levels.

In summary, this preliminary graphical analysis of distress risk reveals that there is a significant interaction between risks in the two systems, and that systemic risk is time-varying and spikes in periods of high financial and political uncertainty. In an effort to shed more light on the interaction between sovereign and banking risk, in the next section we introduce an empirical tool to investigate economically relevant shocks that impact the probability of a systemic default.

²⁴Significant events were the resignation of the Italian and Greek Prime Ministers and the possibility of national referendums on Euro-exit

4 Empirical Framework

To investigate the impact of sovereign and banking shocks and their across-system spillover rates, we now introduce a structural vector autoregressive (VAR) model that enables us to distinguish exceptional shocks from ordinary shocks. We then show how these shocks are identified and what they actually capture.

4.1 The Structural VAR and the Narrative Approach

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

$$y_t = \Phi_y(L)y_t + \Phi_x x_t + u_t,$$

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 u_t is a vector of i.i.d. innovations. In a more compact form, this model can be written as

$$y_t = \Phi z_t + u_t, \tag{3}$$

where $z_t = [y_{t-1}^\top, \dots, y_{t-J}^\top, x_t^\top]$ is a $p \times 1$ vector of both lagged endogenous and exogenous variables with $p = 2J + m$ and $\Phi = [\Phi_{y,1}, \dots, \Phi_{y,J}, \Phi_x]$ as a $2 \times p$ matrix of coefficients.²⁵

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

$$u_t = \mathbf{B}\varepsilon_t, \tag{4}$$

where ε_t is an i.i.d. vector of shocks with zero mean. The matrix B , therefore, reflects the within-system impact (the main diagonal) and the across-system rates of transmission (off-diagonal elements).

The relation between sovereign and banking systemic risk is complex, as economies and financial sectors are highly interconnected. Therefore, classical statistical approaches such

²⁵In the empirical implementation, we choose $p = 3$ as indicated by the Akaike Information Criterion.

as Cholesky ordering are not directly applicable unless economic theory guides this ordering. To the best of our knowledge, this complex nature of shock transmission is still largely unexplored empirically, thus, the challenge we face in this paper is to find a way to overcome this identification problem.²⁶

We use the *narrative approach*, first introduced by [Romer and Romer \[1989\]](#), that allows us to split structural shocks into “shocks of interest” and “ordinary shocks”. To address our research question, we further categorize our shocks of interest into two groups, sovereign and banking. These ones are called “exceptional” systemic shocks and reflect, to some extent, observable events, as opposed to ordinary ones that capture only the residuals. Specifically, we partition the matrix B into three $n \times 1$ vectors such that $\mathbf{B} = [\beta^{sov}, \beta^{bank}, \tilde{\beta}]$ 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 variables will be valid instruments if they satisfy the following conditions:

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

$$\begin{aligned} E[\mathbb{1}_{bank} \epsilon^{sov}] &= 0 \\ E[\mathbb{1}_{sov} \epsilon^{bank}] &= 0 \end{aligned} \tag{6}$$

where (5) assures that the instruments are reliable. Additionally, (6) assures that the

²⁶Recent research has proposed new tool to study contagion. [Billio et al. \[2013\]](#) introduce the network analysis to measure linkages between financial institutions and countries through correlation between credit spreads. [Gennaioli et al. \[2014\]](#) test the link between sovereign default and banks' holding of public bonds in a regression framework. [Eichengreen et al. \[2012\]](#) study common factors influencing international bank credit spreads, using principal component analysis.

sovereign shock indicator is not an instrument for banking shocks and vice versa.²⁷

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

$$u_t = \beta^{sov} \underbrace{\mathbb{1}_{sov} \xi_{sov}}_{\epsilon^{sov}} + \beta^{bank} \underbrace{\mathbb{1}_{bank} \xi_{bank}}_{\epsilon^{bank}} + v_t \quad (7)$$

where $\beta^{sov} = [\beta^{sov \leftarrow sov}, \beta^{bank \leftarrow sov}]'$ and $\beta^{bank} = [\beta^{sov \leftarrow bank}, \beta^{bank \leftarrow bank}]'$ with $\beta^{Y \leftarrow X}$ being the impact of the X shock onto systemic risk of Y , and ξ measuring the average size of the exceptional event within networks to be estimated. Given that ϕ in (5) is not directly observable, we normalize the loading matrix such that sovereign (banking) shocks have a one-to-one impact on sovereign (banking) risk. Finally, the impact (or spillover) matrix becomes

$$\mathbf{B} = \begin{bmatrix} 1, & B^{sov \leftarrow bank} \\ B^{bank \leftarrow sov}, & 1 \end{bmatrix} \quad (8)$$

where $B^{sov \leftarrow bank} = \beta^{sov \leftarrow bank} / \xi_{bank}$ and $B^{bank \leftarrow sov} = \beta^{bank \leftarrow sov} / \xi_{sov}$ measure the spillover rates, that is, $B^{sov \leftarrow bank}$ quantifies how much of the average banking shock ξ_{bank} is propagated to the sovereign system, and viceversa.

4.2 Identifying Shocks

In order to identify the instruments $\mathbb{1}_{sov}$ and $\mathbb{1}_{bank}$, we employ a methodology similar to the one proposed by Collin-Dufresne et al. [2010].²⁸ It proceeds as follows:

Step 1. Collect news articles that are economically relevant for the researcher, using the crisis timeline provided by several sources such as the Financial Times, the Wall Street Journal, BBC, Reuters, Bloomberg, rating agency websites, the ECB, Brugel, the Saint Louis Fed, and Stratfor.

²⁷All 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.

²⁸Collin-Dufresne et al. [2010] define credit events as months in which credit spreads widen significantly. Then, to avoid spurious results, they select only those large variations that are associated to an event reported by the financial press. Such procedure allows them to get only “relevant” credit events. Our approach takes the same rationale.

Step 2. Read news articles to understand if the content refers to countries or financials. In the next section we will provide more details about our choice.

Step 3. Use changes in systemic risk measures (DIPs) to compute the shock size as $\Delta DIP_t^i \times \mathbf{1}_t$ with $i = sov, bank$ and where $\mathbf{1}_t$ is a dummy that takes value of 1 if at time t there is an event, and zero otherwise. Keep only those sovereign (banking) shocks that cause at least a 5 bps change in the sovereign (banking) DIP.²⁹

Step 4. Build $\mathbb{1}_{sov}$ and $\mathbb{1}_{bank}$ by setting the sign so that positive (negative) shocks will decrease (increase) systemic risk.

The final set includes 60 sovereign and 77 banking shocks, covering about the 3.5 percent of the days in the sample period.

A major critique to the narrative approach is the ability of the researcher to identify shocks, and in our case also to disentangle them into sovereign and banking categories. To avoid this issue, several statistical approaches have been proposed in literature.³⁰ We believe that such approaches are very important in understanding the dynamics of contagion, but they offer little economic intuition about the sources of contagion, and, therefore are not well suited to investigate such a complex and unexplored topic. Conversely, our methodology that fuses the narrative approach with the statistical approach is more flexible, and enables us to identify, label and categorize economic, financial and political shocks that are relevant for systemic risk. We believe that our choice is better suited to provide primary empirical evidence on the complex and still unexplored relation between two large macroeconomic systems.

Figure 3 plots the shock distribution. In Panel A we aggregate shocks by year and plot negative and positive shocks as a percentage of the total number. Sovereign shocks are more concentrated over the period 2010 to 2012 that coincides with the beginning of the European debt crisis. This period was characterized by a sequence of events such as government changes, requests for financial assistance by countries and the Greek default, that posed serious threats to the stability of the European Union. Banking shocks saw the

²⁹For shocks after the year 2013 we lowered such a threshold to 2 bps as changes in systemic risk are significantly lower. Varying the 5 bps threshold does not affect our result significantly.

³⁰See [Hinich \[1996\]](#), [Hinich and Serletis \[2007\]](#), [Wild et al. \[2010\]](#), [Coronado and Gatica \[2011\]](#), [Kalotychou et al. \[2014\]](#)

highest peak in 2008, when a series of banking defaults from the U.S. financial sector raised concerns about the ability of the European financial system to absorb losses.

Panel B provides a view of the shocks from a different perspective. It plots the shock size distribution conditional on shock days (excluding days without shocks). The shock size ranges from a minimum of 2 bps to a maximum of 28 bps per day. If compared to the average size of changes in DIPs, we realize that the impact size ranges from 11 to 63 percent per day. The large range of variation enables us to conclude that, with our methodology, we have selected shocks that are systemically relevant. In the following section we provide a closer look at those shocks.

4.3 Macroeconomic Shocks: A Closer Look

Our shocks can be categorized into: i) policy-related events by central banks, the European Commission, or individual countries; ii) actions or announcements by rating agencies, the IMF, or other supranational agencies; iii) social unrest; and iv) extraordinary events such as bankruptcy or war.

Distinguishing between sovereign and banking shocks is the main challenge of this work. We are aware that it is not an easy task but we think it is important to investigate the complex relation that exists between macro systems of governments and financial institutions. Once we collect relevant events from crisis-related time lines (*Step 1*), we read news articles on that specific day, reported by several newspaper agencies.³¹ We then classify a shock as sovereign if the news refers *directly* to countries, or as banking if the news refers *directly* to financial institutions. With this approach we obtain two independent time series of shocks to be included in the VAR specification.

Table 3 reports some examples of banking and sovereign shocks. On May 5, 2010 a violent protest erupted in Athens against austerity measures. This is an example of a social unrest shock that is sovereign specific. On August 8, 2011 the ECB stepped in to buy Italian and Spanish bonds. We label this as a sovereign shock, as the ECB was *clearly* targeting

³¹Once the relevant event has been identified, we use Google News to search for news on that specific day. If the distinction between sovereign and banking does not come up easily, we ignore the event. If, instead, the event happens during the weekend or on a holiday, we move it to the next trading day.

the skyrocketing credit spreads of these two countries. One critique could be related to the fact that helping countries is not part of the ECB’s mandate, thus, our shock identification method may be biased. However, in January 2015 an adviser to Europe’s highest appeals court declared it legal for the ECB to buy unlimited quantities of eurozone sovereign bonds to stabilize the European economy during a crisis. We are certainly aware that such a bond-buying program also benefits banks, but our empirical framework does not rule out its (contemporaneous) impact on banks, as it is captured by spillover rates. Examples of banking shocks are the announcement by the ECB of additional liquidity measures on September 15, 2011 and the downgrade by Moody’s of a pool of 37 Italian banks on February 10, 2012. Therefore, some of the banking shocks are announcements aimed at restoring liquidity in the financial system.

5 Empirical Results

In the empirical application, we estimate a bivariate VAR of order three where the endogenous variables are daily changes in the sovereign and banking DIPs. The lagged variables control for information that is already included in the market and that might have implications on the significance of our shocks. Using first difference has a clear economic interpretation: a reduction of the spread 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 \$100,000.³²

Table 4 reports the coefficients in basis points estimated over the period from July 2007 to May 2015 and bootstrapped confidence intervals. 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 7.72 (7.03) basis points a day, on average. Interestingly, the transmission rate of sovereign shocks to banking risk is 76 percent, twice as large as that of banking shocks to sovereign risk ($B^{bank \leftarrow sov} / B^{sov \leftarrow bank} \approx 2.1$). To look at these magnitudes from a different perspective, we see that ξ_{sov} and ξ_{bank} account for almost the 11 percent of their sample averages of changes in sovereign and banking DIPs. These results suggest that shocks to sovereign risk have important implications for the stability of the system, especially for banking risk.

³²From the investor perspective, significant changes in default derivatives, such as credit default swaps or CDO spreads, may be very costly as they have to provide margins in case of large movements.

The aggregate relative impact (sovereign minus financials) measured using our narrative analysis is very similar to the one found in section 2.2. The estimated impact is 0.40 versus 0.34, with a ratio of 2.1 versus 1.53, respectively. The similarity of the results from the two methodologies supports our shock identification. However, our approach allows us to disentangle sovereign and financial specific shocks in an economically sensible way.

To further analyze these shock spillover rates, we measure their persistence by estimating cumulative impulse response functions (IRFs), reported in Figure 4. Banking shocks significantly impact sovereign risk but are transitory. They die off three days after impact as shown by cumulative (5th and 95th) confidence intervals (in red) crossing the zero line. Instead, sovereign shocks persistently affect banking risk with a spillover rate that ranges from 60 to 120 percent a week after the impact.

These aggregate results provide empirical evidence that most of the relevant shocks that lead to significant variations in systemic risk are directly related to sovereign risk, and significantly affect the probability of a collective default of the financial sector.

Aware of structural difference across countries and banks, in the next section we study systemic risk of sub-systems to provide empirical evidence of the sources of fragility and contagion in the European sovereign and financial systems.

5.1 Fiscal Fragility and Contagion Risk

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.

We test whether government 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 channels through which sovereign shocks propagate to the financial 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 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 sizable 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 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.³³ 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 return 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 and government implicit guarantees channels.

5.1.1 Fiscal Fragility and Its Systemically Importance

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 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

³³The fiscal space embeds four dimensions: The debt load, the real GDP growth rate, tax revenues and non-debt interest expenses.

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 the online Appendix we show how fiscal space is estimated for our sample of European countries.³⁴ 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. 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 distress insurance price of portfolio i of countries and the aggregate banking DIP as endogenous variables. This implies that the two main vectors of the transmission matrix in (8) can be written as $[\xi_{sov_i}, B^{bank \leftarrow sov}]'$ and $[B^{sov_i \leftarrow bank}, \xi_{bank}]'$. 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). This ratio is meaningful because portfolios are built by summing single DIPs (expected tail losses), therefore, aggregate shock's impacts are a sum of the disaggregated ones.³⁵

Table 5, Panel A (Panel B), reports the estimation of shock impacts on countries sorted on their debt-to-GDP (fiscal space) together with t-statistics, and 5th and 95th bootstrapped confidence intervals.³⁶ Sovereign shocks are sorted in an increasing order across the two portfolios and are strongly significant. The coefficient ξ_{sov_i}/ξ_{sov} equal to 0.74 and 0.60 for

³⁴Fiscal 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.

³⁵By construction of the DIP, portfolios obtained by summing single-entity expected tail losses do take into account the interconnections of the entire system, as the factor model is estimated across the entire sample.

³⁶We only report estimates of the two extreme portfolios as we are interested in capturing cross-sectional heterogeneity in shock impacts.

debt-to-GDP and fiscal space sorting, respectively, indicates that the 74 and the 60 percent of the aggregate sovereign shock ($= -7.72$) impact (sub-) systemic risk of countries with a high indebtedness and no room for fiscal maneuver. In addition to this, banking shocks significantly impact the default risk of these countries with a spillover rate lower than that of sovereign shocks. Moreover, non-overlapping confidence intervals for the riskiest portfolios implies that sovereign shocks are statistically different than banking shocks, whereas non-overlapping intervals across portfolios indicates that our measures of fiscal fragility capture well the heterogeneity in shock impacts.

In summary, this set of results is in line with our hypothesis that highly fiscally constrained governments increase fragility in the system, as they are largely affected by sovereign shocks.

5.1.2 Bank Exposure as a Contagion Channel

We now investigate potential channels of shock propagation across the two macro systems. Sovereign shocks can impact financial institutions through their liabilities and/or their assets: governments provide implicit guarantees to banks (liability effect) and banks hold sovereign debt (asset channel). As for countries, we use the portfolio sorting approach and form three sub-systems of banks sorted by their exposure to countries with a high indebtedness and the lowest-fiscal-space. 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. Therefore, for the purpose of this empirical analysis, we select a sub-sample of 59 European banks for which sovereign exposure is available.

Similar to the previous section, we estimate a bivariate VAR(3) where we include each portfolio of banks and the aggregate sovereign DIP as endogenous variables. The two main vectors of the transmission matrix in (8) can be written as $[\xi_{sov}, B^{bank_i \leftarrow sov}]'$ and $[B^{sov \leftarrow bank}, \xi_{bank_i}]'$. 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 . As before, ξ_{bank_i} is reported as a percentage of the size of the aggregate sovereign shock, ξ_{bank} (Table 4).

Table 6, panel A and B, reports the estimated shock impacts for the two sets of portfolios.

Interestingly, the spillover of sovereign shocks to banks with the highest exposure to fragile countries occurs at a rate that is as large as that found with a similarly sized banking shock (ξ_{bank_i}/ξ_{bank}). Within each portfolio, confidence intervals do not overlap, meaning that bank exposure captures heterogeneity in shock impacts. Moreover, overlapping confidence intervals of the impact of sovereign shocks and banking shocks within the two portfolios does not allow for a clear separation between the two. Therefore, systemic banking risk can be heavily affected by one or a combination of the two sources of shocks.

In an attempt to disentangle the liability from the asset effect, we split the highest-exposed banks into domestic and foreign groupings.³⁷ Foreign banks are only exposed to the most indebted countries through the asset side, whereas domestic banks are *also* exposed through the liability side. Table 7 reports the estimated impacts. Local banks are affected the most by both sovereign and banking shocks as those banks are subject to both effects, whereas a smaller but significant percentage of the aggregate shocks propagate to foreign banks. In summary, these results suggest exposure to the weakest economies drives contagion risk in the banking system, from sovereign to banking risk.

5.2 Systemic Risk and the Real Economy

In this section we explore the link between sovereign systemic risk and the real economy. So far we have shown that sovereign shocks are systemically relevant for banking risk. Another interesting question is whether sovereign shocks also have an impact on the real activity. We test the real impact using the approach developed by Bloom [2009] that is useful to test uncertainty shocks. In this section shocks are meant to be innovations of an estimated VAR and do not have to be confused with our narrative shocks we dealt with in the previous sections.

We estimate an extended version of the monthly VAR proposed by Bloom [2009]. We use variables in the following order: European stock market volatility (V2X), banking and sovereign DIPs, Euribor, industrial production, CPI index and unemployment.³⁸ All the

³⁷For 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.

³⁸Industrial production, CPI index and unemployment are collected from Eurostat and are aggregated statistics. V2X and Euribor are obtained from Bloomberg.

variables are monthly log-levels as we are interested in measuring the impact and persistence of shocks.

Figure 8 report impulse response function of volatility, banking and sovereign shocks onto the industrial production (top row) and unemployment (bottom row). The top left graph shows how industrial production drops by 2 percent 10 months after the impact of a banking shock, then rebounding after almost 2 years. Conversely, industrial production does not react significantly to sovereign shocks as confidence bounds cross the zero line. Moreover, unemployment peaks significantly almost 20 months after a banking shock.

Our analysis shows that sovereign shocks have an *indirect* impact on the real economy, through banking risk. These findings highlight the importance of financial institutions for the real activity, and thus, (indirectly) of sovereign risk. Even if a deeper analysis is needed to test the real impact, these findings lay the ground for future research.

6 Discussion

The financial system is more vulnerable to sovereign risk than the sovereign system is to financial (or banking) risk. Our main empirical result emphasizes the importance of governments' policies in the stability of the domestic and the global financial systems. Intuitively, deposit insurance, government bond-holdings or other institutional features may cause a strong dependence of banking credit risk on sovereign risk. This dependence is formalized in the theoretical framework developed by [Gennaioli et al. \[2014\]](#). In this model, sovereign credit risk is a component of bank credit risk because banks hold government bonds. Because of this channel, sovereign defaults may impair banks' assets and their ability to lend to the private sector, leading to a real economic effect. The theoretical link between sovereign fragility and the real economy is supported by our empirical evidence of the significant impact of banking systemic risk on the real economy, as a consequence of a sovereign shock.

[Gray and Jobst \[2011\]](#), instead, provide an alternative theoretical specification that builds on the contingent claim analysis of [Merton \[1974\]](#). In this model, sovereign credit risk is a component of bank credit risk to the extent that governments provide implicit and explicit contingent guarantees in the form of a put option. More specifically, the sovereign asset

value can be represented as the sum of reserves (R), primary balance (PB), guarantees (αPut_{Bank}), and other items. The bank credit risk will be a function of $(1 - \alpha) Put_{Bank}$, that is, it increases if the government loses credibility (lower α), or if the value of banks' holdings of sovereign debt decreases. Our empirical evidence supports these two theoretical channels, exploiting the cross-sectional heterogeneity in sovereign indebtedness and banks' holdings of sovereign debt. The only difference is that we deal with macro-systems of financial institutions and governments as opposed to the one-county-one-bank model most of these theoretical frameworks built on. We leave the generalization of such a theoretical framework on a multi-county-multi-bank level for future research.

Although our result may not seem surprising, given the established theoretical links between a government and its domestic banking system, the shock dynamics existing between systems of governments and financial institutions has not yet been fully explored empirically. Our empirical contribution also embraces the two-way feedback effect—in the spirit of [Acharya et al. \[2014\]](#), by *quantifying* the shock spillovers and their direction. Yet, our work has also a normative goal, that is, it provides an empirical setting for policymakers to study and monitor risk dynamics across governments and sectors as well as for portfolio managers to quantify, for example, international and sector diversification.

To provide an answer to our research question we use a particular shock identification whose first step is to select *relevant* news articles. Although the relevance of a news article may be the result of a discretionary choice, we validate our selection using a measure of aggregate systemic risk. This approach gives rise to an identification that combines the narrative with the statistics of the events so to identify systemically relevant news. It is the narrative of the events that gives an *economic* meaning to our shocks, while the statistics helps reducing the influence of discretionary choices.

Alternatively, we could rely on news analytics that has found applications among researchers, and among fund managers. News analytics aims to extract quantitative or qualitative data from news stories in order to extrapolate the sentiment of the news. However, although this approach seems to be highly systematic, it is not free of discretionary influence. Indeed, it is based on algorithms that need inputs such as dictionaries to extrapolate the psychology behind an article, the choice between document-level or phrase-level sentiment

as well as the selection of input-words.³⁹ These inputs are at the discretion of the researcher and, thus, not free of identification concerns.

Finally, our results are based on a risk-neutral measure, the distress insurance premium (DIP), that bundles together the market risk aversion (or credit risk premium) and the default risk. An interesting empirical exercise would be to separate these two components in order to understand which of them drives the co-movement across various market prices. In the credit risk space, disentangling the two components is very difficult as one cannot observe, from price only, the true or physical dynamics driving default rates, as they are rare by definition (e.g. [Pan and Singleton \[2008\]](#), [Longstaff et al. \[2011\]](#)). Some papers attempt to disentangle the two by combining prices with physical default probabilities provided by third-part providers, such as Moody's (e.g. [Remolona et al. \[2007\]](#)). However, these alternative approaches are not free of critiques, as default events are very rare, especially when dealing with countries. Moreover, quantifying the spillover rates using risk-neutral prices may still provide helpful insights for policymakers or investors as the overall impact on the risk of a system still remains the sum of the two components.

7 Conclusions

Understanding the complex interaction between systems of governments and financial institutions is of crucial importance for policymakers. We provide evidence that monitoring banks alone does not offer a complete picture of the sources of systemic shocks. Fiscally fragile governments make the financial system more vulnerable to shocks as their primary balance is not enough to support extraordinary expenses related, for example, to banking bailouts.

We also introduce a methodology to identify economically relevant shocks and investigate their impact. 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 financial system. However, the approach we use in this paper can be extended geographically to other macro

³⁹Recent research ([Wilson et al. \[2005, 2009\]](#)) reports that, in an experimental setting, sentiment or text-based analysis have an accuracy of about 80 percent.

systems and/or across sectors, in order to help policymakers identify sources of systemically relevant shocks.

Our empirical results can serve as a guide for future macroeconomic models that aim at formalizing the propagation of shocks across economic networks.

We are aware that more empirical research is needed to better understand the propagation mechanism of shocks within and across systems. However, our results suggest that 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, see for example [Lorenzoni and Werning \[2013\]](#)), (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 distress 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 [2](#) embeds the small probability of large losses. To estimate a the probability of the occurrence of a rare event, we follow [Glasserman and Li \[2005\]](#) and [Grundke \[2009\]](#) and employ a Bayesian technique: the Importance Sampling (IS). The IS approach twists the probability measure from which the loss paths are generated, such that “important” events become more likely. In other words, the twisting helps producing rare events even in a Normal-distributed world. For a complete presentation of the risk 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 as it consists in piecing together information of the single entities, or subsystems, to give rise to a single or larger system. In our case, an entity is represented by 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,
- $L = ELGD_1 Y_1 + \dots + ELGD_N Y_N$: 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 marginal 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. \[2005\]](#), [Acharya et al. \[2007\]](#)) 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 historical computation.

Structural models a la [Merton \[1974\]](#), [Vasicek \[1987\]](#) assume that a firm i defaults on its obligations the *first time* the asset return, $R_{i,t} = \Delta \ln A_{i,t}$, with asset value A , 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. The dependence among marginal default probabilities (or market interconnections) is captured by a Normal copula that is specified through a factor model, as in [Vasicek \[1987\]](#). Specifically, we specify a f -factor model for asset return as follows: , where the latter depends on f -global factors M_t and entity-specific idiosyncratic components $Z_{i,t}$, that is,

$$R_{i,t} = B_{i,t}M_t + \sqrt{1 - B_{i,t}B_{i,t}^T} \cdot Z_{i,t} \quad (9)$$

where M_t is a set of f factors and $Z_{i,t}$ is the firm idiosyncratic component, $B_{i,t} = [\beta_{i,1,t}, \dots, \beta_{i,F,t}]$ 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 9 into the default indicator, the conditional default probability, conditional on the realization of the global factors, $M_t = m_t$, is given by

$$PD_{i,t}(m_t, T) = Pr(Y_{i,t}(T) = 1 | M_t = m_t)$$

⁴⁰Some studies simulate the loss given default from either a beta or triangular distribution ([Tarashev and Zhu \[2008\]](#), [Huang et al. \[2009\]](#)). 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.

$$\begin{aligned}
&= \Pr(R_{i,t} < a_{i,t}(T) | M_t = m_t) \\
&= \Pr\left(B_i M_t + \sqrt{1 - B_i B_i^T} \cdot Z_{i,t} < a_{i,t}(T) | M_t = m_t\right) \\
&= \Phi\left(\frac{a_{i,t}(T) - B_i m_t}{\sqrt{1 - B_i B_i^T}}\right)
\end{aligned} \tag{10}$$

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 firm i , $PD_{i,t}(T)$, is increased by a parameter θ , such that the twisted probability is now equal to

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

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 $PD_{i,t}(\theta, T) = PD_{i,t}(T)$. 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

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

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

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

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

$$E^{\mathbb{Q}}[L_{t+T} \times \mathbb{1}\{L_{t+T} \geq x\} | M = m] = \tilde{E}^{\mathbb{Q}}[L_{t+T} \times \mathbb{1}\{L_{t+T} \geq x\} \exp\{-\theta(m_t)L_{t+T} + \psi(\theta(m_t), m_t)\} \exp(-\mu_t^* m_t + ((\mu_t^*)^2 / 2)) | M = m]$$

where $L_{t+T} = \sum_{i=1}^N Y_{i,t}(m, T) \times LGD_{i,t}$ and the second expectation is still risk-neutral but now under the 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 $\tilde{E}^{\mathbb{Q}}$. Averaging across all the realizations of the common factors, we get the unconditional expected total loss.

A.2 Model Inputs and Simulation Approach

The main inputs of this portfolio approach are the marginal default probabilities and the loadings on the global factors for each institution and time.

Under the Poisson distributional assumption, the annualized probability of default is simply $pd_{i,t}(T) = 1 - e^{-\lambda_{i,t}^{\mathbb{Q}} T}$, 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 et al. [2003] we choose the number of factors so that the loadings $B_{i,t}$ in equation 9 explain at least the 95 percent of the variability in the observed time-varying CDS-implied default correlation matrix. According to Tarashev and Zhu [2006], such a correlation can be computed as $\rho_{i,j} = \text{corr}(R_{i,t}, R_{j,t}) = \text{corr}(\Delta a_{i,t}(T), \Delta a_{j,t}(T))$ where Δ denotes first differences. 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 $Y_{i,t}(m, T) \sim \text{Bernoulli}(pd_{i,t}(m, T))$; 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.

References

- Viral Acharya, Lasse Heje Pedersen, Thomas Philippon, and Matthew P Richardson. Measuring systemic risk. *CEPR Discussion Paper*, 2010.
- Viral Acharya, Robert Engle, and Matthew Richardson. Capital shortfall: A new approach to ranking and regulating systemic risks. *The American Economic Review*, 102(3):59–64, 2012.
- Viral Acharya, Itamar Drechsler, and Philipp Schnabl. A pyrrhic victory? bank bailouts and sovereign credit risk. *The Journal of Finance*, 69(6):2689–2739, 2014.
- Viral V Acharya, Sreedhar T Bharath, and Anand Srinivasan. Does industry-wide distress affect defaulted firms? evidence from creditor recoveries. *Journal of Financial Economics*, 85(3):787–821, 2007.
- Zeno Adams, Roland Füss, and Reint Gropp. Spillover effects among financial institutions: A state-dependent sensitivity value-at-risk approach. *Journal of Financial and Quantitative Analysis*, pages 1–48, 2012.
- Tobias Adrian and Markus K Brunnermeier. Covar. Technical report, American Economic Review (Forthcoming), 2015.
- Edward I Altman, Brooks Brady, Andrea Resti, and Andrea Sironi. The link between default and recovery rates: Theory, empirical evidence, and implications*. *The Journal of Business*, 78(6):2203–2228, 2005.
- Leif Andersen, Jakob Sidenius, and Susanta Basu. All your hedges in one basket. *London Risk Magazine Limited*, 16(11):67–72, 2003.
- Andrew Ang and Francis A Longstaff. Systemic sovereign credit risk: Lessons from the us and europe. *Journal of Monetary Economics*, 60(5):493–510, 2013.
- Óscar Arce, Sergio Mayordomo, and Juan Ignacio Peña. Credit-risk valuation in the sovereign cds and bonds markets: Evidence from the euro area crisis. *Journal of International Money and Finance*, 35:124–145, 2013.

- Ben S Bernanke and Kenneth N Kuttner. What explains the stock market's reaction to federal reserve policy? *The Journal of Finance*, 60(3):1221–1257, 2005.
- Antje Berndt and Iulian Obreja. Decomposing european cds returns*. *Review of Finance*, 14(2):189–233, 2010.
- Vineer Bhansali, Robert Gingrich, and Francis A Longstaff. Systemic credit risk: What is the market telling us? *Financial Analysts Journal*, pages 16–24, 2008.
- Monica Billio, Mila Getmansky, Andrew W Lo, and Lioriana Pelizzon. Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics*, 104(3):535–559, 2012.
- Monica Billio, Mila Getmansky, Dale Gray, Andrew Lo, Robert C Merton, and Lioriana Pelizzon. Sovereign, bank and insurance credit spreads: Connectedness and system networks. *Sloan School of Management Working Paper, Massachusetts Institute of Technology (forthcoming)*, 2013.
- Lamont Black, Ricardo Correa, Xin Huang, and Hao Zhou. *The systemic risk of European banks during the financial and sovereign debt crises*. Federal Reserve Board, 2013.
- Nicholas Bloom. The impact of uncertainty shocks. *econometrica*, 77(3):623–685, 2009.
- Henning Bohn. The behavior of us public debt and deficits. *Quarterly journal of economics*, pages 949–963, 1998.
- Patrick Bolton and Olivier Jeanne. Sovereign default risk and bank fragility in financially integrated economies. *IMF Economic Review*, 59(2):162–194, 2011.
- Jan Brockmeijer, M Moretti, J Osinski, N Blancher, J Gobat, N Jassaud, CH Lim, E Loukoianova, S Mitra, E Nier, et al. Macro prudential policy: An organizing framework. *IMF, March*, 14, 2011.
- Christian T Brownlee and Robert Engle. Volatility, correlation and systematic risk measurement. *Department of Finance, Stern School of Business, New York University, available at <http://vlab.stern.nyu.edu/analysis/RISK>*, 2010.

- Markus Konrad Brunnermeier, Andrew Crockett, Charles AE Goodhart, Avinash Persaud, and Hyun Song Shin. The fundamental principles of financial regulation. *Geneva Report on the World Economy*, 2009.
- Jorge A Chan-Lau, Marco Espinosa, Kay Giesecke, and Juan A Solé. Assessing the systemic implications of financial linkages. *IMF global financial stability report*, 2, 2009.
- Pierre Collin-Dufresne, Robert S Goldstein, and Jean Helwege. Is credit event risk priced? modeling contagion via the updating of beliefs. Technical report, National Bureau of Economic Research, 2010.
- Semei Coronado and Leonardo Gatica. Identification of non linear dependence episodes in the mexican peso. *Cuadernos de Economia*, 30(55):91–104, 2011.
- Joshua D Coval, Jakub W Jurek, and Erik Stafford. Economic catastrophe bonds. *The American Economic Review*, pages 628–666, 2009.
- Olivier De Bandt and Philipp Hartmann. Systemic risk: A survey. Technical report, CEPR Discussion Papers, 2000.
- Giovanni Dell’Ariccia, Enrica Detragiache, and Raghuram Rajan. The real effect of banking crises. *Journal of Financial Intermediation*, 17(1):89–112, 2008.
- Barry Eichengreen, Ashoka Mody, Milan Nedeljkovic, and Lucio Sarno. How the subprime crisis went global: evidence from bank credit default swap spreads. *Journal of International Money and Finance*, 31(5):1299–1318, 2012.
- Robert Engle. Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics*, 20(3):339–350, 2002.
- Robert Engle, Eric Jondeau, and Michael Rockinger. Systemic risk in europe*. *Review of Finance*, page rfu012, 2014.
- Milton Friedman and Anna J Schwartz. The role of money. In *Monetary Trends in the United States and United Kingdom: Their Relation to Income, Prices, and Interest Rates, 1867-1975*, pages 621–632. University of Chicago Press, 1982.

- Céline Gauthier, Alfred Lehar, and Moez Souissi. Macprudential capital requirements and systemic risk. *Journal of Financial Intermediation*, 21(4):594–618, 2012.
- Nicola Gennaioli, Alberto Martin, and Stefano Rossi. Sovereign default, domestic banks, and financial institutions. *The Journal of Finance*, 69(2):819–866, 2014.
- Atish R Ghosh, Jun I Kim, Enrique G Mendoza, Jonathan D Ostry, and Mahvash S Qureshi. Fiscal fatigue, fiscal space and debt sustainability in advanced economies. *The Economic Journal*, 123(566):F4–F30, 2013.
- Paul Glasserman and Jingyi Li. Importance sampling for portfolio credit risk. *Management science*, 51(11):1643–1656, 2005.
- D Gray, R Merton, and Zvi Bodie. A contingent claims analysis of the subprime credit crisis of 2007-2008. In *CREDIT 2008 Conference on Liquidity and Credit Risk, Venice*, pages 22–23, 2008.
- Dale F Gray and Andreas A Jobst. modelling systemic financial sector and sovereign risk. *sveriges riksbank economic review*, page 2, 2011.
- Peter Grundke. Importance sampling for integrated market and credit portfolio models. *European Journal of Operational Research*, 194(1):206–226, 2009.
- Nikolaus Hautsch, Julia Schaumburg, and Melanie Schienle. Financial network systemic risk contributions. *Review of Finance*, page rfu010, 2014.
- Peter Heller. Back to basics-fiscal space: What it is and how to get it. *Finance and Development-English Edition*, 42(2):32–33, 2005.
- Melvin J Hinich. Testing for dependence in the input to a linear time series model. *Journal of Nonparametric Statistics*, 6(2-3):205–221, 1996.
- Melvin J Hinich and Apostolos Serletis. Episodic nonlinear event detection in the canadian exchange rate. *Journal of the American Statistical Association*, 102(477):68–74, 2007.
- Xin Huang, Hao Zhou, and Haibin Zhu. A framework for assessing the systemic risk of major financial institutions. *Journal of Banking & Finance*, 33(11):2036–2049, 2009.

- Elena Kalotychou, Eli M Remolona, and Eliza Wu. What makes systemic risk systemic? contagion and spillovers in the international sovereign debt market. 2014.
- Bryan Kelly and Hao Jiang. Tail risk and asset prices. *Review of Financial Studies*, page hhu039, 2014.
- Mark Kritzman, Yuanzhen Li, Sebastien Page, and Roberto Rigobon. Principal components as a measure of systemic risk. *The Journal of Portfolio Management*, 37(4):112–126, 2011.
- Alfred Lehar. Measuring systemic risk: A risk management approach. *Journal of Banking & Finance*, 29(10):2577–2603, 2005.
- Francis A Longstaff and Arvind Rajan. An empirical analysis of the pricing of collateralized debt obligations. *The Journal of Finance*, 63(2):529–563, 2008.
- Francis A. Longstaff, Jun Pan, Lasse H. Pedersen, and Kenneth J. Singleton. How sovereign is sovereign credit risk? *The American Economic Review*, 3:75–103, 2011.
- Guido Lorenzoni and Ivan Werning. Slow moving debt crises. Technical report, National Bureau of Economic Research, 2013.
- Gerardo Manzo. Political uncertainty, credit risk premium and default risk. *Credit Risk Premium and Default Risk (August 31, 2013)*, 2013.
- Gerardo Manzo and Pietro Veronesi. Sovereign credit risk. *Handbook of Fixed-Income Securities*, pages 561–586, 2016.
- Enrique G Mendoza and Jonathan D Ostry. International evidence on fiscal solvency: Is fiscal policy responsible? *Journal of Monetary Economics*, 55(6):1081–1093, 2008.
- Karel Mertens and Morten O Ravn. Measuring the impact of fiscal policy in the face of anticipation: A structural var approach*. *The Economic Journal*, 120(544):393–413, 2010.
- Karel Mertens and Morten O Ravn. Understanding the aggregate effects of anticipated and unanticipated tax policy shocks. *Review of Economic Dynamics*, 14(1):27–54, 2011.
- Robert C Merton. On the pricing of corporate debt: The risk structure of interest rates*. *The Journal of Finance*, 29(2):449–470, 1974.

- Investors Service Moody's. Corporate default and recovery rates, 1920-2010. *Moody's Global Corporate Finance*, 2011.
- Jonathan David Ostry, Atish R Ghosh, Jun I Kim, and Mahvash S Qureshi. *Fiscal space*. International Monetary Fund, Research Department, 2010.
- Jun Pan and Kenneth J Singleton. Default and recovery implicit in the term structure of sovereign cds spreads. *The Journal of Finance*, 63(5):2345–2384, 2008.
- Raghuram G Rajan and Luigi Zingales. Financial systems, industrial structure, and growth. *Oxford review of economic Policy*, 17(4):467–482, 2001.
- Eli M Remolona, Michela Scatigna, and Eliza Wu. The dynamic pricing of sovereign risk in emerging markets: fundamentals and risk aversion. 2007.
- Christina D Romer and David H Romer. Does monetary policy matter? a new test in the spirit of friedman and schwartz. In *NBER Macroeconomics Annual 1989, Volume 4*, pages 121–184. MIT Press, 1989.
- Christina D Romer and David H Romer. Identification and the narrative approach: A reply to leeper. *Journal of Monetary Economics*, 40(3):659–665, 1997.
- Christina D Romer and David H Romer. The macroeconomic effects of tax changes: estimates based on a new measure of fiscal shocks. Technical report, National Bureau of Economic Research, 2007.
- Silvia Sgherri and Edda Zoli. Euro area sovereign risk during the crisis. *IMF Working Papers*, pages 1–23, 2009.
- Nikola Tarashev and Haibin Zhu. Specification and calibration errors in measures of portfolio credit risk: The case of the asrf model. *International Journal of Central Banking*, 4(2): 129–173, 2008.
- Nikola A Tarashev and Haibin Zhu. The pricing of portfolio credit risk. 2006.
- Oldrich Vasicek. Probability of loss on loan portfolio. *KMV Corporation*, 12(6), 1987.

- Phillip Wild, John Foster, and Melvin J Hinich. Identifying nonlinear serial dependence in volatile, high-frequency time series and its implications for volatility modeling. *Macroeconomic Dynamics*, 14(S1):88–110, 2010.
- Theresa Wilson, Janyce Wiebe, and Paul Hoffmann. Recognizing contextual polarity in phrase-level sentiment analysis. In *Proceedings of the conference on human language technology and empirical methods in natural language processing*, pages 347–354. Association for Computational Linguistics, 2005.
- Theresa Wilson, Janyce Wiebe, and Paul Hoffmann. Recognizing contextual polarity: An exploration of features for phrase-level sentiment analysis. *Computational linguistics*, 35(3):399–433, 2009.
- Eric Wong, Tom Fong, Ka-fai Li, and Henry Choi. Loan-to-value ratio as a macro-prudential tool: Hong kong’s experience and cross-country evidence. Technical report, Hong Kong Monetary Authority, 2011.
- Frank X Zhang. *What Did the Credit Market Expect of Argentina Default?: Evidence from Default Swap Data*, volume 3. Division of Research & Statistics and Monetary Affairs, Federal Reserve Board, 2003.

Table 1: The Sovereign System: Summary Statistics

The table reports summary statistics of 5-year credit default swap (CDS) spreads for 28 European countries over the financial crisis 2007/09, and the European debt crisis 2010/15. *Mean*, *Std Dev* and *Median* are the average mean, standard deviation, and median across the two sub-periods. *Min* and *Max* are the minimum and maximum values. *Slope* is the average of the 10-year minus 1-year CDS spreads. CDS data are expressed in basis points. *Debt/GDP* is the average debt-to-GDP ratio in percentage points.

Country	Financial Crisis 2007/09							European Debt Crisis 2010/15						
	<i>Debt/GDP</i>	<i>Mean</i>	<i>Std Dev</i>	<i>Min</i>	<i>Median</i>	<i>Max</i>	<i>Slope</i>	<i>Debt/GDP</i>	<i>Mean</i>	<i>Std Dev</i>	<i>Min</i>	<i>Median</i>	<i>Max</i>	<i>Slope</i>
Czech Rep	28.18	79.36	72.45	5.34	59.86	336.14	29.32	40.41	74.53	29.18	39.51	69.02	180.21	65.72
Germany	64.82	20.31	19.12	1.30	11.27	88.68	11.63	77.24	26.96	16.05	7.90	23.40	80.53	31.51
France	65.88	23.82	21.01	1.58	15.50	94.94	12.58	86.14	60.60	33.88	21.02	48.70	198.68	56.07
Greece	104.60	97.38	78.09	4.50	61.78	283.64	35.69	150.89	1711.93	2472.08	84.20	842.90	23571.95	-1249.43
Belgium	89.74	38.22	32.92	1.88	29.61	149.31	19.90	102.08	88.27	66.41	21.24	54.31	339.34	53.25
Denmark	30.58	34.19	37.09	1.15	18.43	140.67	18.78	44.11	41.87	34.90	12.20	25.18	148.51	40.92
Netherlands	47.97	29.84	31.19	1.39	13.93	123.56	13.34	62.74	35.80	21.51	8.17	29.67	129.95	34.58
Norway	50.30	16.50	14.36	1.34	8.58	61.08	12.18	34.92	17.59	8.33	8.36	14.61	49.95	18.79
Spain	37.74	55.63	38.13	3.30	48.72	162.76	28.42	73.25	194.78	102.07	43.96	185.58	504.15	72.13
Sweden	38.62	38.76	39.39	1.26	16.18	152.84	19.40	38.19	24.85	15.16	9.29	18.14	74.69	28.28
Austria	66.72	53.93	57.90	1.47	17.08	259.44	18.11	81.56	51.56	36.99	12.10	40.14	176.27	43.20
Bulgaria	16.22	233.87	168.09	13.17	185.51	662.90	50.52	17.22	189.61	80.06	82.74	179.19	405.83	112.86
Croatia	35.92	187.39	140.00	14.36	149.58	570.36	48.72	60.39	302.99	83.95	168.60	272.42	561.24	158.31
Cyprus	51.63	59.92	48.52	5.25	40.68	195.00	27.76	73.93	633.64	407.82	86.75	479.29	1601.16	-119.21
Estonia	4.16	237.06	189.81	6.00	186.42	711.96	21.49	8.01	82.00	27.83	49.67	74.71	180.52	64.64
Finland	34.32	21.93	20.41	1.08	13.09	90.87	13.46	49.83	28.32	17.87	8.66	20.96	80.26	29.27
Hungary	68.11	211.11	152.95	18.25	188.33	610.87	49.58	79.04	310.74	98.22	162.76	283.99	584.98	94.35
Ireland	31.38	97.78	92.68	2.08	57.65	368.20	20.08	101.26	291.91	251.85	32.76	152.23	1193.98	-8.48
Italy	101.30	66.24	50.17	5.58	50.56	191.10	30.41	119.98	197.39	106.77	68.46	160.95	501.52	86.41
Latvia	12.77	412.20	296.19	10.62	334.39	1114.56	-6.31	40.95	194.33	103.69	67.14	180.09	540.03	94.96
Lithuania	15.64	278.42	219.98	6.51	236.77	819.56	9.06	36.47	173.52	75.61	65.85	177.67	352.05	101.55
Malta	62.96	58.25	45.11	4.50	40.00	177.50	28.20	68.32	236.43	81.38	91.33	208.62	466.10	53.61
Poland	45.74	112.38	93.10	7.87	87.78	401.82	41.19	53.36	115.63	56.84	46.35	100.02	304.82	98.57
Portugal	69.88	50.59	33.24	4.14	44.58	152.06	26.15	110.39	460.21	338.00	81.06	346.41	1554.03	-20.40
Slovenia	22.92	56.30	50.89	3.44	42.82	241.46	25.85	50.77	186.33	109.31	45.56	140.32	470.56	115.43
Romania	12.82	264.59	191.99	17.04	221.69	740.35	54.20	32.94	231.89	90.00	96.37	207.47	448.34	132.42
Slovak Rep	29.34	66.69	55.55	5.35	56.36	256.74	28.25	45.82	101.85	63.84	38.07	78.33	296.54	85.97
UK	46.65	44.22	41.45	1.15	29.49	159.72	25.43	79.99	50.96	23.33	18.60	52.93	103.56	53.98

Table 2: The Banking System: Summary Statistics

The table reports summary statistics of 5-year credit default swap (CDS) spreads of 163 European financial institutions over the financial crisis 2007/09, and the European debt crisis 2010/15. Bank CDSs are aggregated by countries using an equally-weighted average. *Mean*, *Std Dev* and *Median* are the average mean, standard deviation, and median across the two sub-periods. *Min* and *Max* are the minimum and maximum values. *Slope* is the average of the 10-year minus 1-year CDS spreads. CDS data are expressed in basis points. *Leverage* is the average leverage ratio computed as total liabilities over total assets.

<i>Country</i>	Financial Crisis 2007/09										European Debt Crisis 2010/15									
	<i>Leverage</i>	<i>Mean</i>	<i>Std Dev</i>	<i>Min</i>	<i>Median</i>	<i>Max</i>	<i>Slope</i>	<i>Leverage</i>	<i>Mean</i>	<i>Std Dev</i>	<i>Min</i>	<i>Median</i>	<i>Max</i>	<i>Slope</i>						
Austria	.95	148.70	74.16	10.42	141.14	229.79	25.71	.94	200.74	66.30	71.94	187.00	204.64	67.35						
Belgium	.93	105.68	63.04	7.18	96.09	350.82	16.86	.90	147.61	72.23	48.42	132.21	330.84	80.45						
Denmark	.96	152.68	73.93	5.05	127.82	11.00	74.40	.95	149.08	63.55	55.72	138.92	332.99	136.91						
Finland	.85	86.17	46.93	6.91	106.88	114.42	33.24	.82	130.75	43.36	63.38	115.23	130.03	44.87						
France	.89	164.74	102.12	6.00	143.11	30.50	28.63	.89	198.56	88.42	30.50	174.78	137.91	119.81						
Germany	.97	109.31	47.31	7.69	103.87	43.70	20.65	.96	135.10	41.23	17.16	130.38	39.88	64.69						
Greece	.92	198.69	147.69	14.21	152.94	564.17	3.40	.95	1140.77	618.39	268.09	964.86	2790.54	-489.56						
Hungary	.89	311.85	250.97	43.20	212.50	746.70	133.00	.86	340.54	112.06	160.59	370.32	548.60	43.68						
Ireland	.96	282.96	192.58	11.75	277.63	582.09	-62.38	.95	759.93	508.64	87.88	551.29	769.70	-380.00						
Italy	.92	94.00	50.35	6.89	84.15	28.58	14.52	.93	227.41	96.75	49.08	201.56	125.54	71.78						
Netherlands	.85	187.04	132.66	4.94	156.43	190.52	-1.30	.89	156.27	41.03	37.77	155.85	66.01	81.71						
Norway	.96	63.01	35.14	8.08	56.19	99.55	30.46	.93	201.56	121.14	43.18	263.07	204.14	52.65						
Portugal	.94	94.01	36.40	9.83	97.44	177.29	29.49	.94	453.67	254.92	63.37	381.96	100.00	-9.34						
Spain	.92	172.89	86.63	11.63	166.70	161.00	10.55	.94	360.16	163.10	62.07	327.53	150.03	63.47						
Sweden	.93	142.98	100.71	5.54	111.52	157.53	21.11	.91	117.50	34.97	35.51	112.43	169.71	68.26						
UK	.92	214.06	136.81	6.00	178.52	145.38	6.34	.87	154.18	47.95	35.84	150.57	168.38	86.61						

Table 3: Shock Identification: Few Examples

The table reports few examples of sovereign and banking shocks. A shock is a relevant news article reported by several sources such as newspapers, rating agencies and policymakers' websites. A shock can be generated by policymakers through announcements that have the power to mitigate or exacerbate financial risk. A shock can also be a social unrest or announcements of rating agencies. A shock is classified as sovereign or banking if it has a *direct* impact on the sovereign or banking system, respectively. Sovereign and banking shocks cover approximately the 5.5 percent of the daily sample period from 2007 to 2015. A detailed description of all the shocks and their directions are reported in the online Appendix.

SOVEREIGN SHOCKS	BANKING SHOCKS
<u>Apr 22, 2010</u> : Eurostat says Greece's 2009 budget higher than reported. Papandreou asks for activation of EU aid	<u>Oct 8, 2008</u> : ECB decides on extraordinary liquidity measures for banks
<u>May 5, 2010</u> : Violent protest erupt in Athens against austerity measures	<u>Sept 15, 2011</u> : ECB announces additional US dollar liquidity-providing operations
<u>Aug 8, 2011</u> : ECB steps in to buy Italian and Spanish bonds	<u>Oct 6, 2011</u> : ECB announces second covered bond purchase program
<u>Sept 6, 2012</u> : ECB announces OMT to buy government bonds if a country asks for financial assistance	<u>Feb 10, 2012</u> : Moody's downgrades 37 Italian banks

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 . We estimate a daily VAR that includes changes in banking and sovereign systemic risk measures (DIPs), and exogenous sovereign and banking shocks, over the period August 2007 to May 2015. Confidence intervals are the 5th and the 95th percentiles and are bootstrapped using 1,000 simulations.

Within-System Average Shock Impact				
	<i>Coefficient</i>	<i>t-Stat</i>	<i>Confidence Intervals</i>	
ξ_{sov}	-7.72	-10.62	-9.23	-6.30
ξ_{bank}	-7.03	-13.60	-8.06	-6.02
Across-System Average Spillover Rate				
	<i>Coefficient</i>	<i>t-Stat</i>	<i>Confidence Intervals</i>	
$B^{sov \leftarrow bank}$	0.36	4.90	0.22	0.51
$B^{bank \leftarrow sov}$	0.76	13.61	0.64	0.87

Table 5: Fiscal Fragility

The table reports the estimated spillover impacts of banking and sovereign shocks. The spillover shock is the $B^{Y \leftarrow X}$ coefficient (X -shock onto the system Y) in equation 8 and is reported as a percentage of the aggregate average shock impacts in Table 4. ξ_{sovi_i}/ξ_{sov} represent how much of the aggregate sovereign shock impact is transmitted to that specific sub-group of countries. We estimate a daily bivariate VAR that includes changes in systemic risk measures (DIPs) of banks and sub-groups of countries sorted on their debt-to-GDP ratios (Panel A) and fiscal space (Panel B), and exogenous sovereign and banking shocks, over the period August 2007 to May 2015. Confidence intervals are the 5th and the 95th percentiles and are bootstrapped using 1,000 simulations.

Panel A: Countries Sorted on Debt-to-GDP ratio									
Low Indebtedness					High Indebtedness				
	<i>Coefficient</i>	<i>t-Stat</i>	<i>Confidence Intervals</i>		<i>Coefficient</i>	<i>t-Stat</i>	<i>Confidence Intervals</i>		
ξ_{sovi_i}/ξ_{sov}	0.008	6.64	0.006	0.01	ξ_{sovi_i}/ξ_{sov}	0.74	7.46	0.57	0.96
$B^{sovi_i \leftarrow bank}$	0.003	4.67	0.002	0.005	$B^{sovi_i \leftarrow bank}$	0.27	4.30	0.16	0.41
Panel B: Countries sorted on Fiscal Space									
High Fiscal Space					Low Fiscal Space				
	<i>Coefficient</i>	<i>t-Stat</i>	<i>Confidence Intervals</i>		<i>Coefficient</i>	<i>t-Stat</i>	<i>Confidence Intervals</i>		
ξ_{sovi_i}/ξ_{sov}	0.02	7.04	0.020	0.03	ξ_{sovi_i}/ξ_{sov}	0.60	7.34	0.46	0.78
$B^{sovi_i \leftarrow bank}$	0.008	4.25	0.005	0.01	$B^{sovi_i \leftarrow bank}$	0.22	4.5	0.13	0.33

Table 6: Contagion Risk: Financial Institutions

The table reports the estimated spillover rate impacts of banking and sovereign shocks. The spillover shock is the $B^{Y \leftarrow X}$ coefficient (X -shock onto the system Y) in equation 8 and is reported as a percentage of the aggregate average shock impacts in Table 4. $\xi_{bank_i} / \xi_{bank}$ represent how much of the aggregate banking shock impact is transmitted to that specific sub-group of banks. We estimate a daily bivariate VAR that includes changes in systemic risk measures (DIPs) of countries and sub-groups of banks sorted on their exposure to countries with a high debt-to-GDP ratio (Panel A) and low fiscal space (Panel B), and exogenous sovereign and banking shocks, over the period August 2007 to May 2015. Confidence intervals are the 5th and the 95th percentiles and are bootstrapped using 1,000 simulations.

Panel A: Banks Sorted on Exposure to High Debt-to-GDP Countries Over Total Sovereign Exposure								
Low Exposure			High Exposure					
	<i>Coefficient</i>	<i>t-Stat</i>	<i>Confidence Intervals</i>		<i>Confidence Intervals</i>			
$B^{bank_i \leftarrow sov}$	0.13	6.01	0.09	$B^{bank_i \leftarrow sov}$	0.28	6.80	0.20	0.36
$\xi_{bank_i} / \xi_{bank}$	0.14	9.30	0.11	$\xi_{bank_i} / \xi_{bank}$	0.29	9.96	0.24	0.35
Panel B: Banks Sorted on Exposure to Low Fiscal Space Countries Over Total Sovereign Exposure								
Low Exposure			High Exposure					
	<i>Coefficient</i>	<i>t-Stat</i>	<i>Confidence Intervals</i>		<i>Confidence Intervals</i>			
$B^{bank_i \leftarrow sov}$	0.14	6.22	0.10	$B^{bank_i \leftarrow sov}$	0.30	6.53	0.22	0.41
$\xi_{bank_i} / \xi_{bank}$	0.15	9.71	0.13	$\xi_{bank_i} / \xi_{bank}$	0.30	9.68	0.25	0.37

Table 7: Contagion Risk: Banks

The table reports the estimated spillover impacts of banking and sovereign shocks. The spillover shock is the $B^{Y \leftarrow X}$ coefficient (X -shock onto the system Y) in equation 8 and is reported as a percentage of the aggregate average shock impacts in Table 4. $\xi_{bank_i} / \xi_{bank}$ represent how much of the aggregate banking shock impact is transmitted to that specific sub-group of banks. We estimate a daily bivariate VAR that includes changes in systemic risk measures (DIPs) of countries and sub-groups of banks split into local and foreign banks exposed to countries with a high debt-to-GDP ratio (Panel A) and low fiscal space (Panel B), and exogenous sovereign and banking shocks, over the period August 2007 to May 2015. Confidence intervals are the 5th and the 95th percentiles and are bootstrapped using 1,000 simulations.

Panel A: Local versus Foreign Banks Exposed to High Debt-to-GDP Countries						
Local Banks			Foreign Banks			
	<i>Coefficient</i>	<i>t-Stat</i>	<i>Confidence Intervals</i>	<i>Coefficient</i>	<i>t-Stat</i>	<i>Confidence Intervals</i>
$B^{bank_i \leftarrow sov}$	0.25	6.62	0.18	0.03	6.10	0.02
$\xi_{bank_i} / \xi_{bank}$	0.26	10.07	0.22	0.05	7.70	0.04
Panel A: Local versus Foreign Banks Exposed to Low Fiscal Space Countries						
Local Banks			Foreign Banks			
	<i>Coefficient</i>	<i>t-Stat</i>	<i>Confidence Intervals</i>	<i>Coefficient</i>	<i>t-Stat</i>	<i>Confidence Intervals</i>
$B^{bank_i \leftarrow sov}$	0.24	6.76	0.18	0.04	5.96	0.03
$\xi_{bank_i} / \xi_{bank}$	0.25	10.01	0.21	0.07	8.05	0.05

Figure 1: Sovereign and Financial Spillover Distributions

The figure plots the distributions (Kernel densities) of the impacts ($\beta_q^{i \leftarrow j}$) of sovereign tail risk on financial tail risk, and viceversa. The impact is measured by quintile regressions of the form

$$\Delta CDS_t^i = \alpha_q + \mathbf{X}_t' \gamma_q + \beta_q^{i \leftarrow j} \Delta CDS_t^j + \epsilon_t^i$$

where ΔCDS_t^j and ΔCDS_t^i are the changes in credit default swap spreads of entity $i, j \in \{\text{sovereign, financials}\}$. \mathbf{X}_t contains a set of N macro factors (changes in VIX, term slope (10y minus 3m Treasury yields), U.S. credit spread (Baa minus 3m-Tbill yields), and return on real estate index (ticker: MXUS0RE) and SP500), and $q = 98\%$ is the percentile of the distribution. $Y|X$ is the distribution of Y given that X is in distress. The densities include only statistically significant $\beta_q^{i \leftarrow j}$ at the 5 per cent and they are trimmed at 1 per cent. *Mean Diff* reports the distributional test of the difference in means (vertical dotted lines), and “*” indicate significance at the 1 per cent level. The sample covers the weekly (Friday) period from August 2007 to May 2015. The table reports summary statistics of the two distributions.

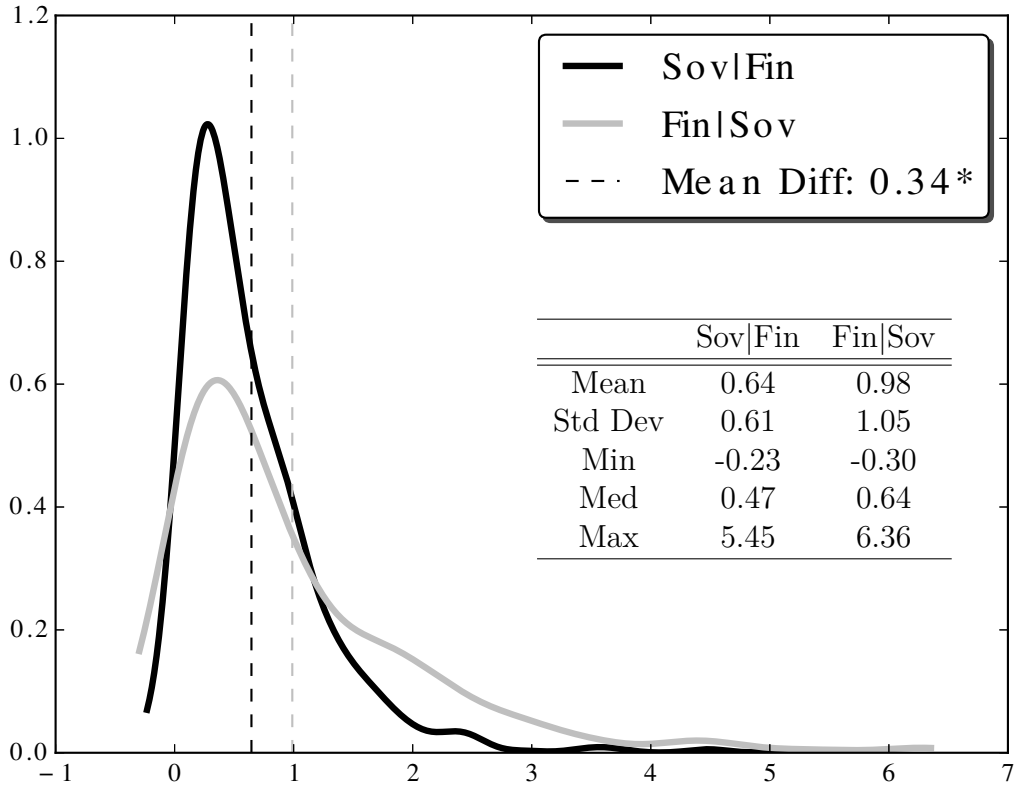


Figure 2: Systemic Risk in Europe

The figure plots the distress insurance prices (DIPs) for the banking (gray line) and the sovereign (black line) systems in basis points. The DIP measures the risk-neutral expected tail loss on the total liabilities of the macro region, given that the loss is greater than 10 percent. The sample covers the daily period from August 2007 to May 2015 and spans two periods: the financial crisis of 2007/09, and the European debt crisis of 2010/15. The dashed vertical lines identify some of the main shocks that have an impact on sovereign and banking risk.

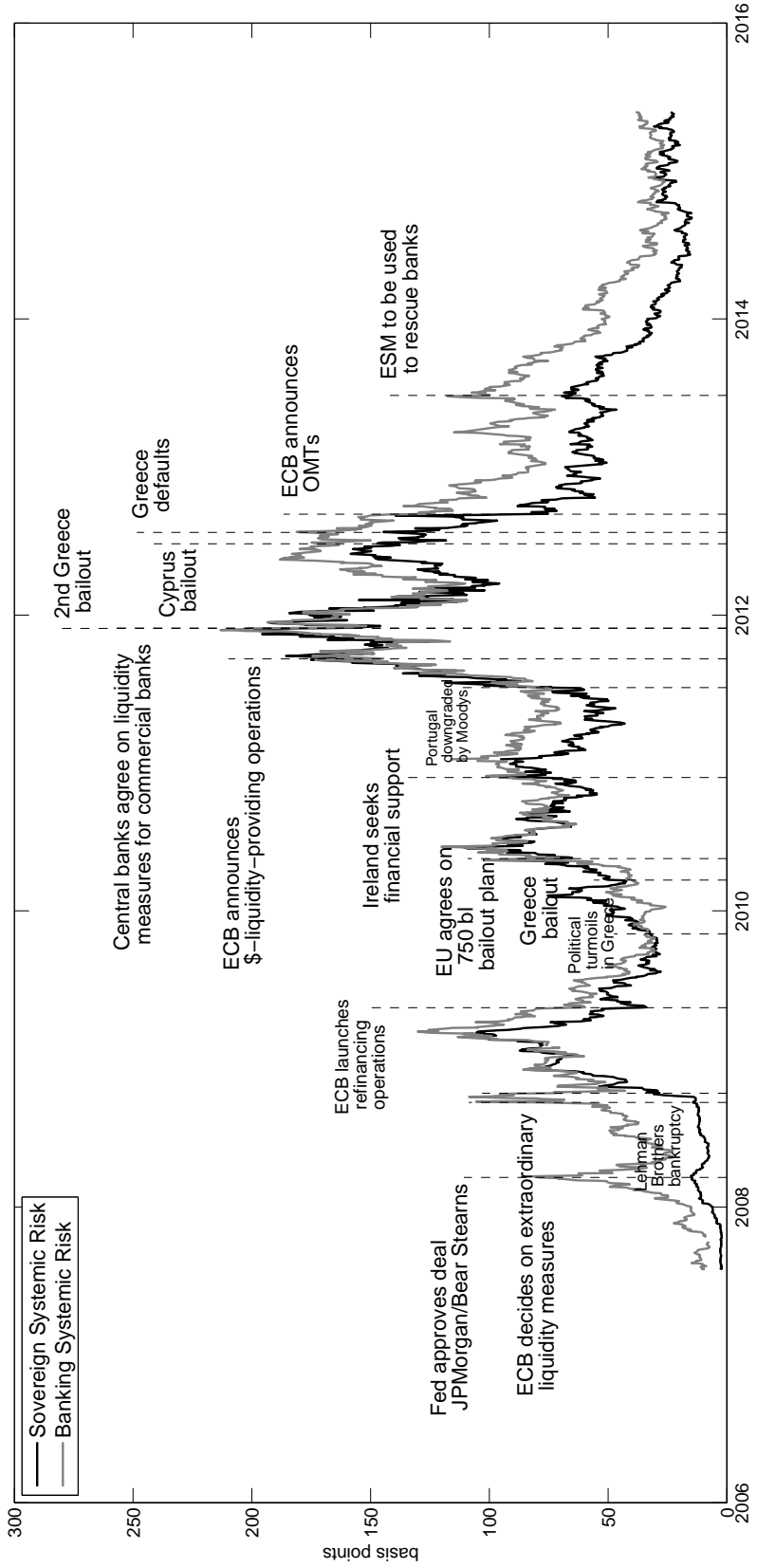
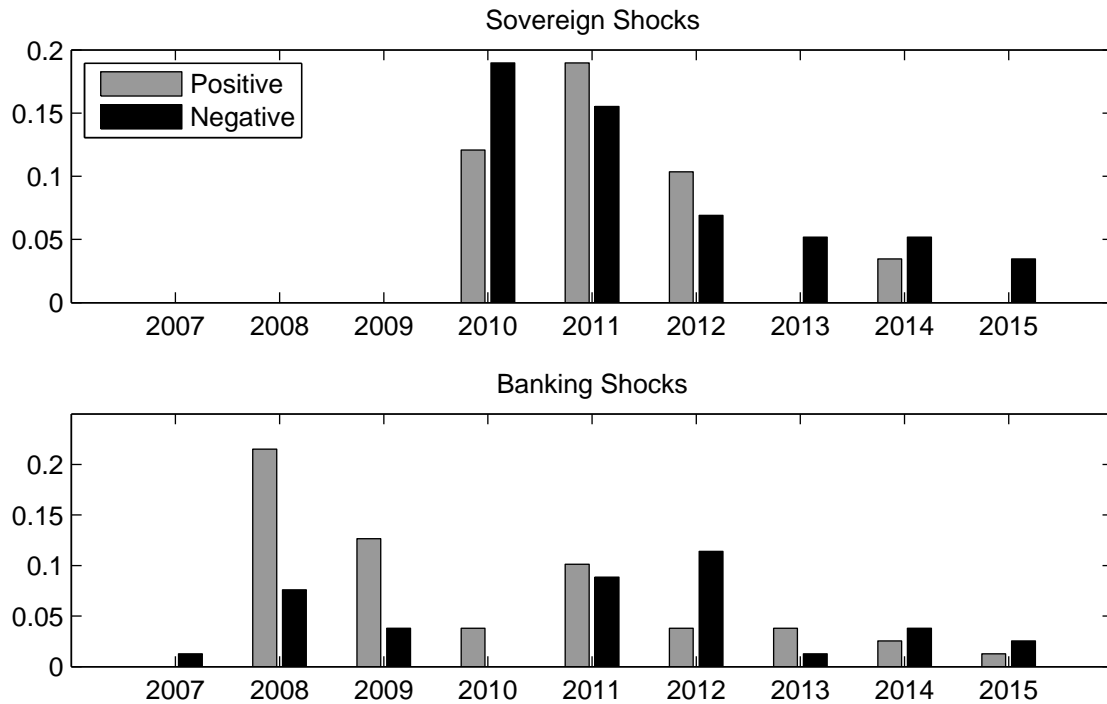


Figure 3: Shock Distribution

The figure plots the distribution of sovereign and banking shocks. Panel A plots the percentage of positive and negative shocks over time, aggregated by year, for sovereign (top graph) and banking (bottom graph) shocks. Panel B plots the shock size distribution conditional on shock days (excluding days without shocks), where the shock indicator is multiplied by the variation in DIPs on that day, that is, $size = \Delta DIP^i \times \mathbb{1}_i$ where $i = sov, bank$. The size is reported in negative numbers as the indicator associates -1 to positive shocks and $+1$ to negative shocks.

(a) Shock Distribution: Time



(b) Shocks Distribution: Size

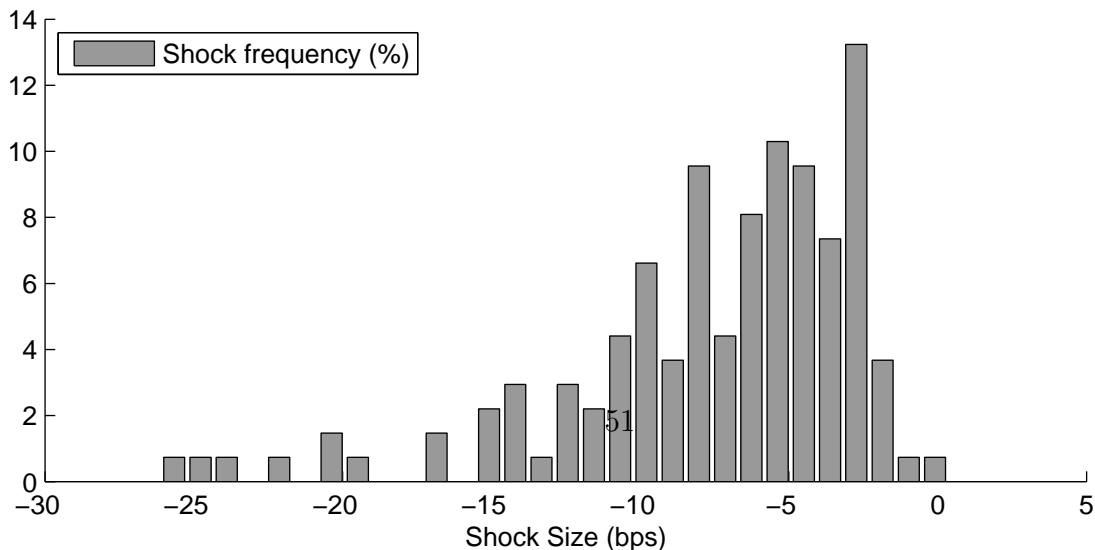


Figure 4: Aggregate Shock Impact and Persistence

The figure plots the estimated spillover impacts of banking (left graph) and sovereign (right graph) shocks. We plot cumulative impulse response functions for unit-size spillover shocks. The spillover shock is the $B^{Y \leftarrow X}$ coefficient (X -shock onto the system Y) in equation 8. We estimate a daily bivariate VAR that includes changes in banking and sovereign systemic risk measures (DIPs), and exogenous sovereign and banking shocks, over the period August 2007 to May 2015. Dashed lines are the 5th and the 95th bootstrapped percentiles.

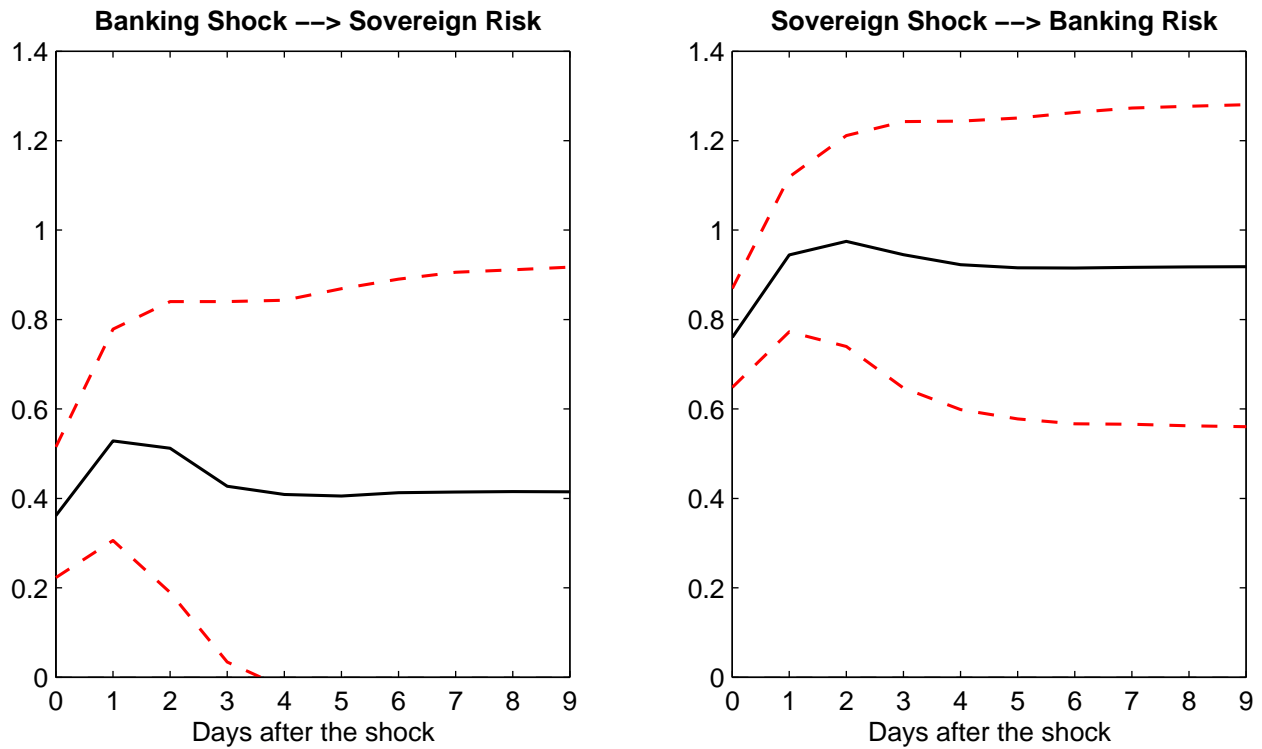
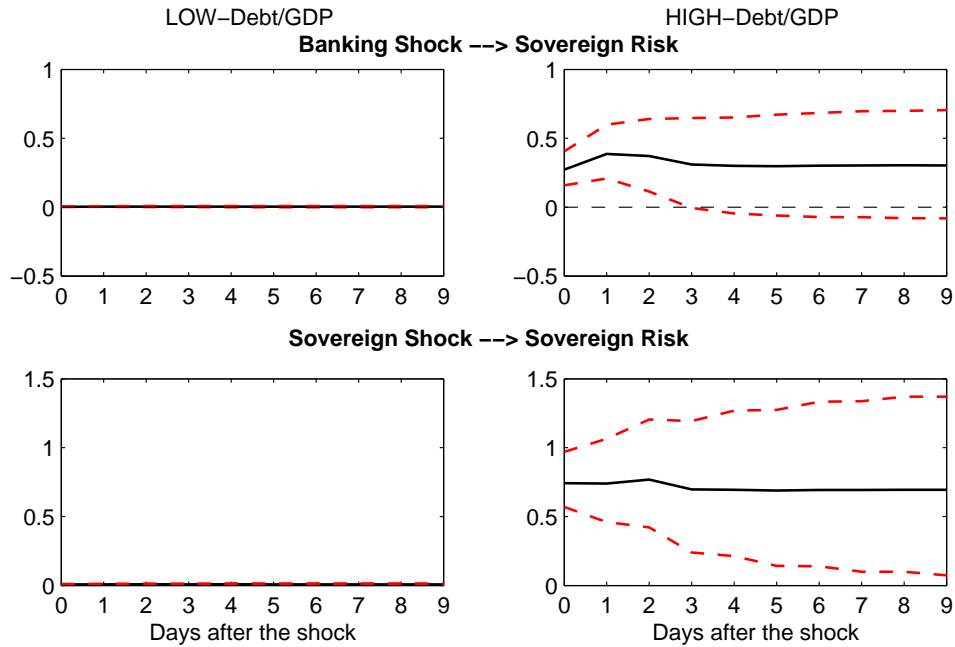


Figure 5: Shock Impact and Persistence: Fiscally Fragile Countries

Within each panel, the figure plots the estimated spillover impacts of banking (top row) and sovereign (bottom row) shocks. We plot cumulative impulse response functions for unit-size spillover shocks. The spillover shock is the $B^{Y \leftarrow X}$ coefficient (X -shock onto the system Y) in equation 8 and is reported as a percentage of the aggregate average shock impacts in Table 4. We estimate a daily bivariate VAR that includes changes in systemic risk measures (DIPs) of banks and sub-groups of countries sorted on their debt-to-GDP ratio (Figure 5a) and fiscal space (Figure 5b), and exogenous sovereign and banking shocks, over the period August 2007 to May 2015. Dashed lines are the 5th and the 95th bootstrapped percentiles.

(a) Countries Sorted on Debt-to-GDP Ratios



(b) Countries Sorted on Fiscal Space

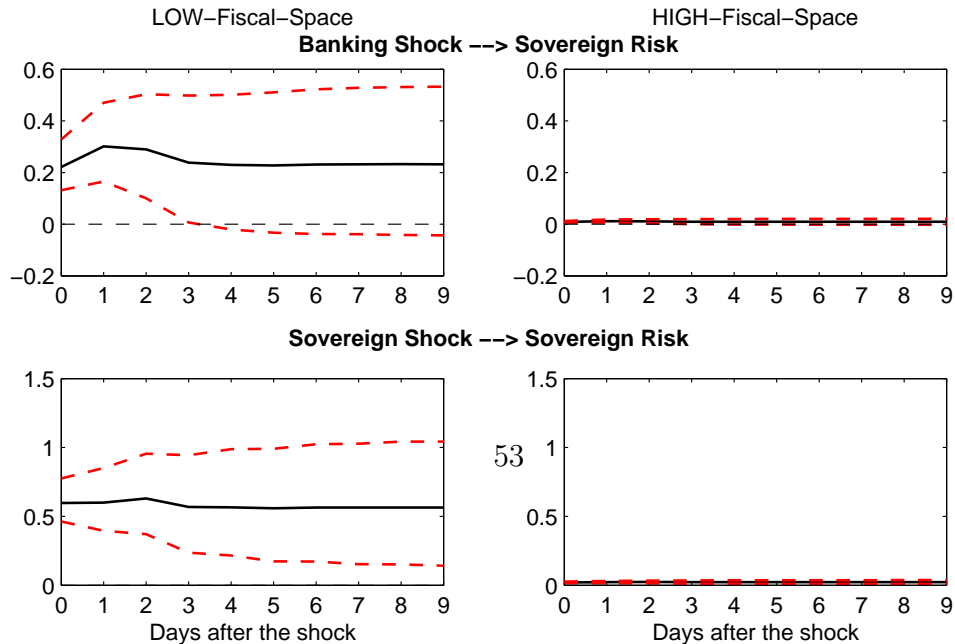
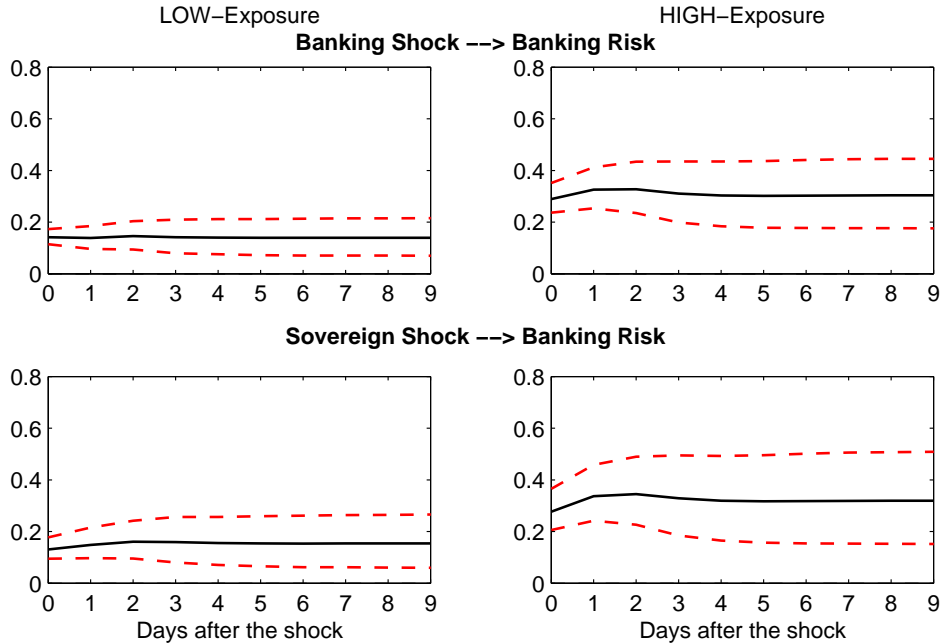


Figure 6: Shock Impact and Persistence: Banking Exposure to Sovereign

Within each panel, the figure plots the estimated spillover impacts of banking (top row) and sovereign (bottom row) shocks. We plot cumulative impulse response functions for unit-size spillover shocks. The spillover shock is the $B^{Y \leftarrow X}$ coefficient (X -shock onto the system Y) in equation 8 and is reported as a percentage of the aggregate average shock impacts in Table 4. We estimate a daily bivariate VAR that includes changes in systemic risk measures (DIPs) of countries and sub-groups of banks sorted on their exposure to countries with a high debt-to-GDP ratio (Figure 6a) and low fiscal space (Figure 6b), and exogenous sovereign and banking shocks, over the period August 2007 to May 2015. Dashed lines are the 5th and the 95th bootstrapped percentiles.

(a) Banks Sorted on Their Exposure to High Debt-to-GDP Countries



(b) Banks Sorted on Their Exposure to Low-Fiscal-Space Countries

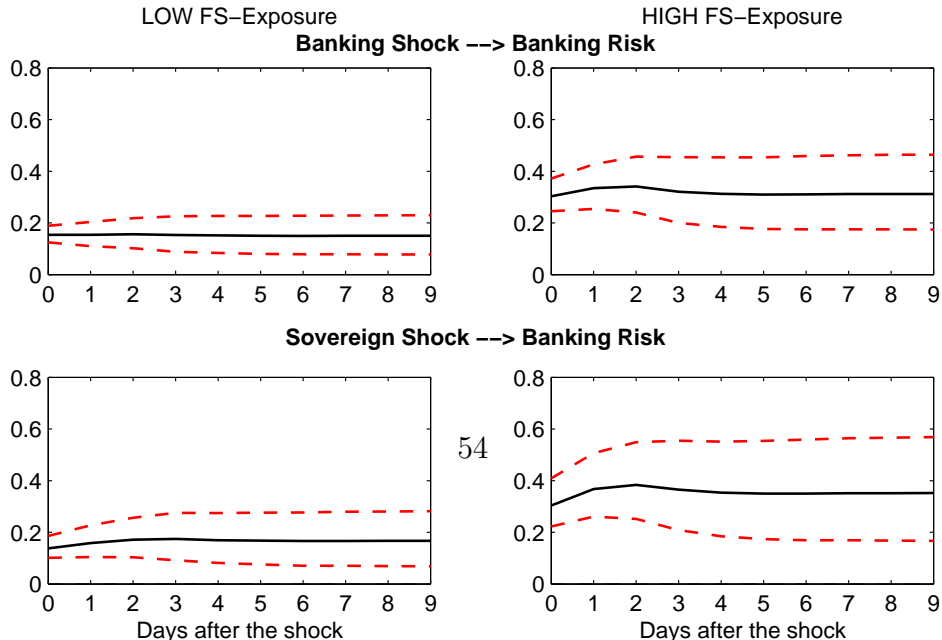
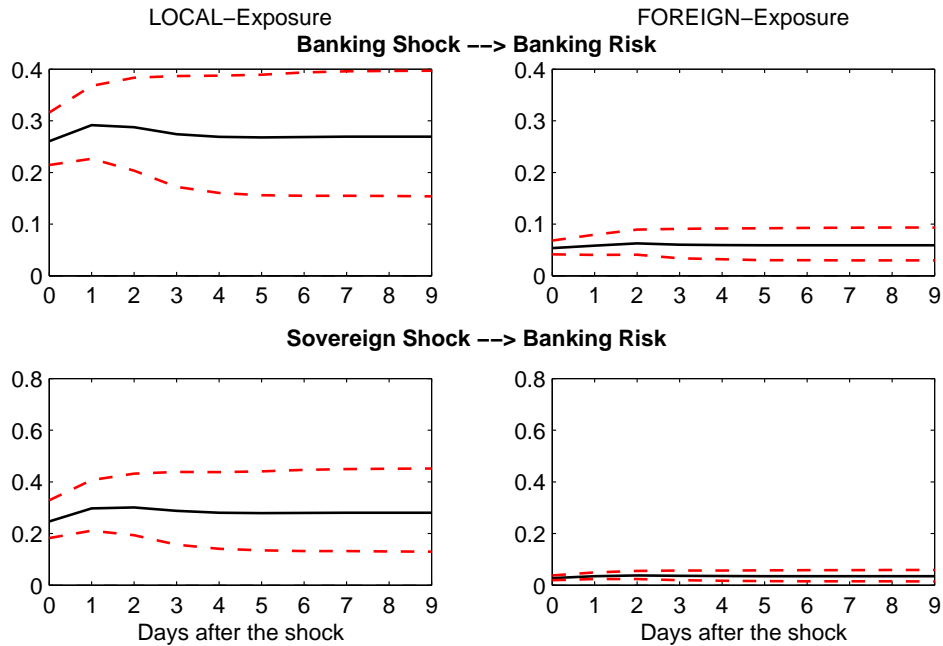


Figure 7: Shock Impact and Persistence: Local vs Foreign Banking Exposure

Within each panel, the figure plots the estimated spillover impacts of banking (top row) and sovereign (bottom row) shocks. We plot cumulative impulse response functions for unit-size spillover shocks. The spillover shock is the $B^{Y \leftarrow X}$ coefficient (X -shock onto the system Y) in equation 8 and is reported as a percentage of the aggregate average shock impacts in Table 4. We estimate a daily bivariate VAR that includes changes in systemic risk measures (DIPs) of countries and sub-groups of banks split into local and foreign banks exposed to countries with a high debt-to-GDP ratio (Figure 7a) and low fiscal space (Figure 7b), and exogenous sovereign and banking shocks, over the period August 2007 to May 2015. Dashed lines are the 5th and the 95th bootstrapped percentiles.

(a) Local vs Foreign Banks Exposed to High Debt-to-GDP Countries



(b) Local vs Foreign Banks Exposed to Low-Fiscal-Space Countries

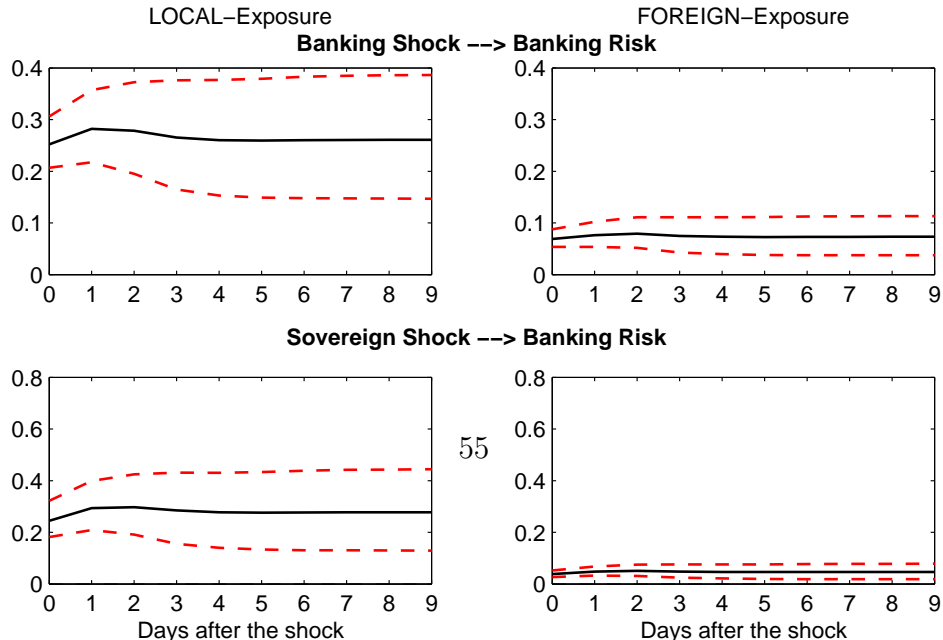
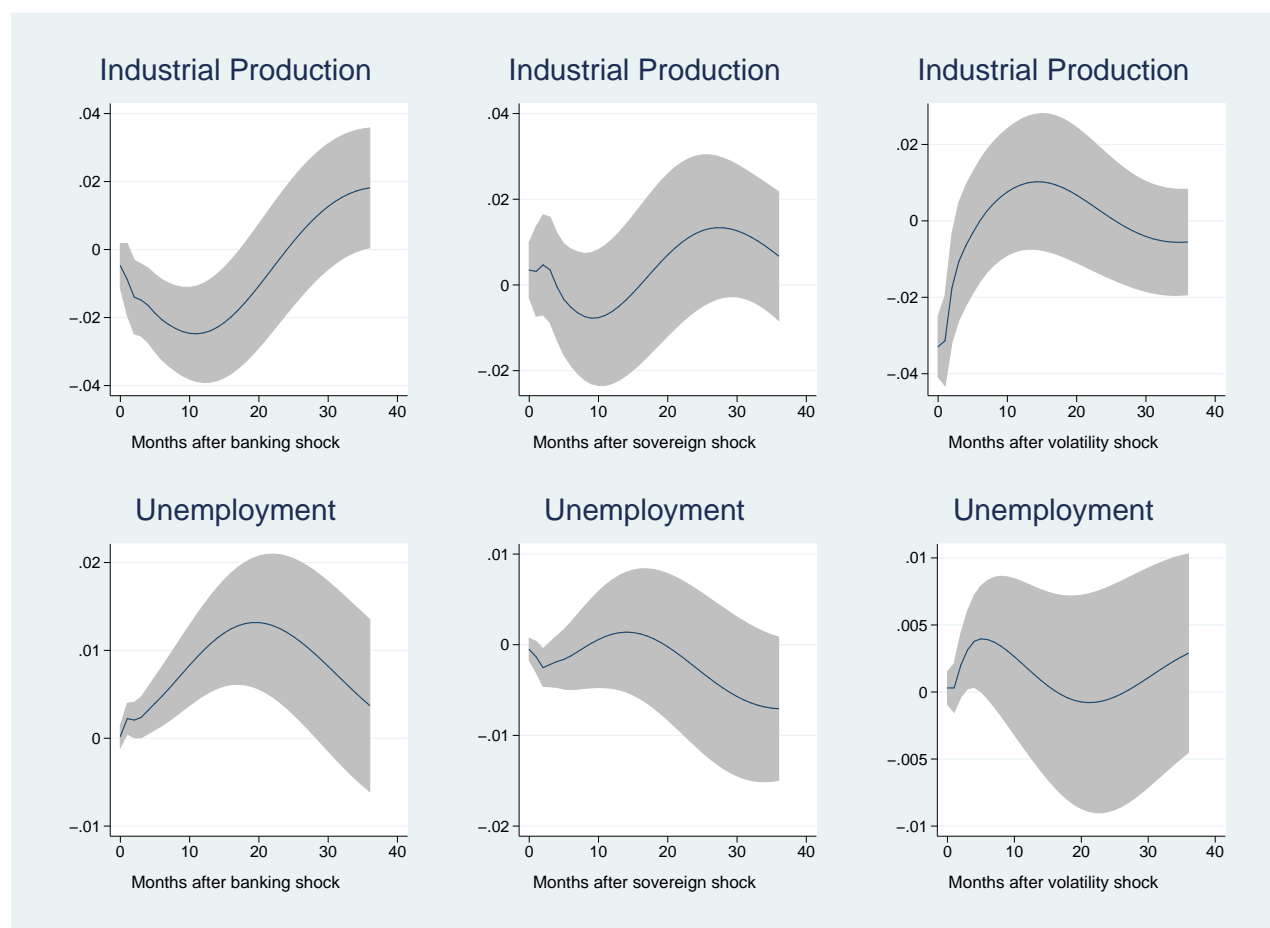


Figure 8: Systemic Risk and the Real Economy

The figure plots the impacts of uncertainty shocks on industrial production (top row) and unemployment (bottom row). Graph columns report impulse response functions for a one-standard deviation shock to banking risk, sovereign risk and volatility, respectively. For both industrial production and unemployment we estimate a monthly VAR that includes log values of European stock market volatility (V2X), banking systemic risk, sovereign systemic risk, 3-month Euribor, industrial production, inflation and unemployment over the period August 2007 to May 2015. Grey area captures the 5th and 95th percentiles.



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