Measuring the Deadly Embrace:

Systemic and Sovereign Risks

Francisco Nadal De Simone§

November 2019

Abstract

This study contributes to the literature by making a first step toward implementing a comprehensive internally coherent measurement of systemic risk in a country. It measures systemic risk and the ensuing conditional contingent liabilities of the sovereign stemming from Luxembourg's Other Systemically Important Institutions (OSIIs), the Global Systemically Important Banks (G-SIBs) to which they belong, the investment funds sponsored by the OSIIs, the household and the non-financial corporate sectors. The estimated systemic contingent claims are included in a stochastic version of the general government balance sheet to gauge their impact on the country's sovereign risk. Results indicate that time-varying conditional implicit guarantees from OSSIs are larger than those from G-SIBs and investment funds, while systemic risk stemming from the household and non-financial corporate sectors is moderate. The robustness of the sovereign is not drastically affected by systemic risk stemming from the rest of the economy. However, illustrating the so-called "deadly embrace", sovereign risk would significantly rise as a result of a historically plausible increase in sovereign assets value volatility combined with an economy-wide shock. Such adverse scenario supports the view that preserving financial stability requires both a resilient financial sector and a sustainable fiscal position.

JEL Classification: C1, E5, F3, G1

Keywords: financial stability; sovereign risk; macro-prudential policy; banking sector; investment funds; default probability; non-linearities; generalized dynamic factor model; dynamic copulas.

Luxembourg School of Finance, University of Luxembourg, and Sacred Heart University, Luxemburg. E-mail: Francisco.nadaldesimone@ext.uni.lu or nadaldesimonef@sacredheart.edu.

1. Introduction

In 2010, the sovereign debt crisis that erupted in Greece, Portugal, and Ireland spread as markets questioned debt sustainability.[1] In April 2010, when some euro area countries were downgraded, markets pushed up Credit Default Swaps (CDS) premia in most advanced countries, including the US and the UK (CGFS, 2011, and Yu, 2017). In turn, higher sovereign risk pushed up banks' cost of funding and changed its composition. In addition, banking sector systemic risk and "too-big-to-fail" global systemic financial institutions amplified the sovereign risk via large implicit contingent liabilities, as in Ireland. While before the onset of the sovereign debt crisis, much of the behavior of sovereign bond yields could be explained by measures of global risk aversion, global factors appeared to give way to more idiosyncratic developments later. Concerns arose about sovereign risk in Italy, Spain and even France with negative repercussions on market perceptions about the viability of the euro area (Broto and Perez-Quiros 2011, Lucas *et al*, 2014). The study of the links between banks and the sovereign has since become one of the most rapidly growing areas of research in financial stability.

Sovereign risk and systemic banking sector risk are intertwined in what has been referred to as "deadly embrace" by Farhi and Tirole (2018) and "diabolic loop" by Brunnermeier *et al* (2016). The links are multiple and run in both directions. First, losses on banks' holdings of government debt weaken their balance sheets, increasing their riskiness and making bank funding more costly and difficult to obtain (Cooper and Nikolov, 2018). Second, higher sovereign risk reduces the value of the collateral banks use to raise wholesale funding and central bank liquidity (Ari, 2016). Third, a weakening of the sovereign's rating also reduces the funding benefits that banks derive from implicit and explicit government guarantees (Leonello, 2018). Fourth, a downgrade of a country by a rating agency generally flows to domestic banks via lower ratings, increasing their wholesale funding costs and potentially impairing their market access (Boccola, 2016). Other risk transmission channels include international spillovers resulting from bank holdings of foreign sovereign debt or simply contagion (Kallestrup *et al*, 2016), and from crowding out effects that raise the cost for banks of issuing securities (Becker and Ivashina, 2018).

Significant financial sector reforms undertaken since 2008 have sought to reduce the links between the sovereign and the financial sector (Alogoskoufis and Langfield, 2018). However, there are still significant areas of disagreement such as how to reform the regulatory treatment of banks' sovereign exposures and how to design a deposit insurance scheme that is credible and offsets its possible moral hazard implications (Allen *et al*, 2015 and 2018). Because of the systemic nature of banks and the sovereign, while weakened,

[1] Throughout the paper, the word "sovereign" is used as a synonym for "general government".

some observers note that the nexus will likely remain, and ongoing policy reforms should acknowledge this limitation (Vergote, 2016, and Dell'Ariccia *et al*, 2018).

Perhaps in part due to the need to have access to granular and supervisory data to perform it, to the best of the authors' knowledge, this is the first study to use a comprehensive internally consistent methodology to empirically estimate a country's systemic risk stemming from the banking and investment fund industries, the household and non-financial corporate sectors, and to integrate the resulting systemic contingent claims into a stochastic version of the country's general government balance sheet. In this integrated framework, systemic risk can originate in both the private and the public sector. The study applies to Luxembourg, a world financial center where 124 out of the 131 registered banks are affiliates of foreign banks; it is the second largest investment fund domicile in the world after the US and its sovereign is one of the 11 countries in the world with AAA rating according to S&P, Moody's and Fitch.

The sources and forms of expected losses stem from the financial sector in the form of systemic risk common across the sector, or "tail risk", and as contagion within the financial sector, from the household and non-financial corporate sectors, and from the general government. The methodology evaluates systemic losses and potential public sector costs from contingent liabilities from the financial sector by explicitly modeling default dependence within the financial sector and capturing the time-varying non-linearities and feedback effects typical of financial markets.[2] In contrast to static network or accounting-driven models, the methodology captures potential losses via "price-mediated" contagion (Cont and Schaanning, 2015), which can expose a financial institution to asset classes that regulation prevents it from holding. This can amplify the institution's exposure to a given risk factor relative to what is apparent from its balance sheet, a fact that lends support to models of imperfect supervision.[3] The methodology also measures banks' exposure through implicit financial support to the investment funds they sponsor.

The main results follow. First, indicators of systemic risk in each of the sectors correlate well with major macro-financial developments in Luxembourg and the euro area. In particular, while persistently low monetary policy rates have helped to reduce the fragility of banks and investment funds, they also seem to have increased interdependence across financial institutions. Second, the implicit government guarantees stemming from Luxembourg's Other Systemically Important Institutions (OSIIs) fell in value after the financial crisis and were hardly affected by the sovereign crisis. The median conditional

[2] Non-linearity refers to the absence of the property of additivity and or proportionality among variables.

[3] Farhi and Tirole (2018) assume that supervision is imperfect because banks may mask exposures to the domestic bond market though derivatives, guarantees or by correlation between the banking book and domestic bonds.

implicit government guarantees stemming from investment funds and European global systemically important banks (G-SIBs) tend to be between 1/2 to 1/3 of those attached to OSIIs. Third, there has been less heterogeneity among G-SIBs than among OSIIs over the sample period. The highest percentile conditional implicit government guarantee among OSIIs was about 1.1bn euro in mid-2008 and lately peaked at around 0.4bn at end-2017. Fourth, while the conditional expected loss profiles among investment funds are broadly like those of OSIIs and G-SIBs, systemic risk stemming from investment funds and G-SIBs is more concentrated than systemic risk stemming directly from OSIIs. Fifth, systemic risk emanating from households and non-financial corporations does not seem to be of immediate concern. Sixth, for the Luxembourg sovereign, distance to distress improved significantly after 2013, reflecting notably the higher general government's primary surplus and the stabilization of sovereign debt. Seventh, the robustness of the Luxembourg sovereign is not drastically affected by systemic risk stemming from the rest of the economy as implicit conditional government guarantees do not deviate significantly from the benchmark following distress in the financial sector or large and plausible shocks to household mortgages or non-financial corporate loans. In contrast, while the sovereign solvency would not be compromised, sovereign risk would be significantly affected by a historically plausible 40% increase in the volatility of sovereign asset values combined with shocks to the OSIIs, G-SIBs, investment funds and the non-financial private sector. This adverse scenario illustrates the importance of a robust fiscal position over the cycle as it triggers wide deviations of Luxembourg sovereign risk from its benchmark in agreement with the doom-loop view of the sovereign-bank nexus.

The next section provides a review of the various strands of literature linked to this study. Section III presents the modeling framework and Section IV discusses the data. Section V presents the results on systemic risk and vulnerability measures. Section VI concludes, draws policy implications and summarizes possible extensions of the methodology.

2. Literature Review

This section presents a *per force* selective review of the literature linking financial stability and sovereign risk. However, most of this literature has referred to the banking sector-sovereign risk nexus. Studies regarding sovereign risk and systemic risk stemming from non-bank financial institutions and non-financial corporate sectors are comparatively scarce. In order to set up the background for the internally coherent integrated framework of systemic risk measurement in a country implemented in this study, the following literature review reflects in detail a holistic view of the financial system as a set of multi-layered segments mutually interacting.

Two strands of literature, one recent and one old, have come together notably after the European sovereign debt crisis. The recent one has been concerned with financial stability and the concept and measurement of systemic risk. Silva *et al* (2017) offer a comprehensive survey. The old one has been concerned with banking and sovereign debt crises and can be captured in Reinhart and Rogoff (2009) study of eight centuries of crises. It seems logical to organize the literature review along the three ingredients of Brunnermeier *et al* "diabolic loop" and their implication for and measurement of systemic risk: the home bias of banks' sovereign debt portfolios, the inability of governments to commit *ex ante* not to bailout domestic banks, and capital flows that result in international investors' incorporation of expected government solvency in the market value of domestic government debt.

The home bias of banks' sovereign portfolios, government guarantees and capital flows

The determinants of the home bias remain controversial. For Korte and Steffen (2014), banks hold above-optimal debt due to the zero-risk weight of government debt holdings. Buch *et al* (2016) find that German banks did not differentiate much between countries based on macroeconomic factors before the financial crisis. Sovereign bond holdings of German banks were larger for weakly capitalized banks, banks active on capital markets and large banks. For the euro area, Altavilla *et al* (2017) find that public, bailed-out and poorly capitalized banks responded to sovereign stress by purchasing domestic public debt more than other banks, especially in coincidence with the largest ECB liquidity injections, consistent with both the "moral suasion" and the "carry trade" hypothesis. Similarly, Drechsler *et al* (2016) show that weakly capitalized banks took out more lender-of-last-resort loans and used riskier collateral than strongly capitalized banks to buy risky assets, including distressed sovereign debt.

Regardless of the cause of the home bias, banks' holdings of sovereign debt make their equity value and solvency dependent on swings in the perceived solvency and market value of their own government's debt. This nexus is present in papers stressing that systemic risk runs from the sovereign to banks, from banks to the sovereign or in both directions.

Systemic risk stemming from expectations of sovereign debt default damages banks' balance sheets (Gennaioli *et al*, 2014) and rises funding costs exacerbating indeterminacy problems (Corsetti *et al*, 2013). Funding constraints reduce resources available to lend and generate a precautionary motive to deleverage (Boccola, 2016), or reduce lending through a credit ratings channel (Almeida *et al*, 2017).

Systemic risk running from banks to the government has been partly explained by the "carry trade" of European banks that raised finance in short-term wholesale markets to invest in peripheral sovereign bonds (Acharya and Steffen, 2013), by government guarantees that induce risk-taking behavior by banks and reduce market discipline (Marques *et al*, 2013), and by a higher proportion of non-performing loans when bailouts cannot be excluded (Brůha and Kočenda, 2018). Capital flows matter as bank risk in stressed countries has not been absorbed by their sovereigns but spilled over to non-stressed euro area sovereigns (Breckenfelder and Schwaab, 2018).

The two previous views of the sovereign-bank nexus are considered as complementary by part of the literature. While banks bailouts alleviate a distortion in the provision of financial services, they impair the sovereign's creditworthiness. Higher sovereign credit risk feeds back on to the financial sector through banks' sovereign bond holdings and implicit and explicit government guarantees. Holding high-yield, risky sovereign bonds may be attractive for surviving banks protected by limited liability (Abad, 2019). Acharya *et al* (2014) find evidence for the two-way feedback between financial and sovereign credit risks from euro area CDS data while Fratzscher and Rieth (2015) find that shocks from the sovereign are more important in explaining bank risk than *vice versa*. Kallestrup *et al* (2016) argue that sovereigns are significantly affected by the foreign exposures of their domestic banks, which optimal capital decisions are influenced by a country's institutions. High-quality institutions, including a transparent government decision-making process and responsible fiscal management, reduce uncertainty and risk taking (Colak *et al*, 2018).

Studies that explicitly quantify systemic risk stemming from the sovereign-bank nexus have used various methodologies. Fisher and Gray (2006) made an early application of Contingent Claims Analysis (CCA) to the measurement of government and banking sector risk in Indonesia. Black *et al* (2016) quantify the two-way interaction between European sovereigns and banks measuring systemic risk as a hypothetical insurance premium to cover distressed losses in the banking system using CDS spreads, equity return correlations, and liabilities of individual banks. Betz *et al* (2016) estimate tail-risk dependencies and time-varying systemic risk contributions for 51 European banking groups and 17 sovereigns. Pagano and Sedunov (2016) use an Adapted Exposure CoVar[4] and the Marginal Expected Shortfall (MES) of Acharya *et al* (2010) and Brownlees and Engle (2012), to show that the aggregate systemic risk exposure of financial institutions is positively related to sovereign debt yields in European countries and shocks to these domestic linkages are stronger and longer lasting than international risk spillovers. Manzo and Picca (2014) decompose systemic risk into a sovereign and banking component using

---

[4] CoVaR was developed by Adrian and Brunnermeier (2008).

a large data set of sovereigns and banks and find that shocks to sovereign systemic risk have a significant and persistent impact on the probability of a collective banking default, while shocks to banking systemic risk have a smaller and more transitory impact on sovereign risk. Vergote (2016) develop time-varying contagion indices of credit risk spillover and feedback between 64 financials and sovereigns in the euro area identifying spillover with bilateral Granger causality regressions. Popescu and Turcu (2017) analyze the eurozone crisis with a systemic sovereign risk measure built on countries' budgetary constraint and the MES estimated through a DCC Garch model during the period 2001−2013. They identify Italy and Greece as the most systemically important countries and measure their contribution to a potential system's default. Xu *et al* (2017) investigate the systemic risk of the European sovereign and banking system during 2008–2013 with a measure of systemic risk reflecting market perceptions, which can be interpreted as an entity’s conditional joint default probability.

Systemic risk among non-bank financial institutions and banks

Systemic risk may result directly from non-bank financial institutions and also from their interaction with banks. Bengtsson (2016) shows that investment funds may pose systemic risk via instability in their funding profile and asset reallocations, and that insufficient risk separation may elude managerial and supervisory oversight and force banks to reduce or interrupt credit intermediation. Kaal and Krause (2016) examine hedge funds’ possible contributions to systemic risk and Lehecka and Ubl (2015) discuss ways in which alternative investment funds may generate or amplify systemic risk stemming from disorderly markets. Aizenman *et al* (2016) use CoVaR and ΔCoVaR to provide evidence of systemic risk contribution in the international mutual fund sector during 2000–2011 by tracking the systemic risk of 10,570 mutual funds investing internationally. Hespeler and Loiacono (2017) propose measures of systemic risk generated through intra-sectorial interdependencies in the hedge fund sector showing significant interdependency between their funds’ individual returns and the moments of the sector’s return distribution. Shaw and Dunne (2017) use the coherent measure of systemic risk MES to capture investment funds’ exposures to pervasive industry-wide tail events.

To measure systemic risk stemming from banks and non-bank financial institutions, Bernal *et al* (2014) extended the original ΔCoVaR approach to include the Kolmogorov–Smirnov test developed by Abadie (2002). They find that between 2004 to 2012, the *other financial services sector* of the euro area contributed relatively the most to systemic risk followed by the banking sector and the insurance sector. Results were the opposite in the United States. Billio *et al* (2012) applied several measures of connectedness based on principal-components analysis and Granger-causality networks to the monthly returns of hedge funds, banks, broker/dealers, and insurance companies. All four sectors became highly interrelated over the past decade, likely increasing systemic risk in the finance and insurance industries through a complex and time-varying network of relationships. Banks played a more important role in transmitting shocks than other financial institutions. Patro *et al* (2013) use daily stock return correlations as a systemic risk indicator among the 22 largest bank holding companies and investment banks from 1988 to 2008. They found an increasing trend in stock return correlation among banks, and no obvious correlation trend among non-financial corporates. Jin and Nadal De Simone (2014a) estimate systemic risk simultaneously in banks and investment funds in Luxembourg with systemic risk measures derived from Merton model and the consistent information multivariate density optimization (CIMDO) methodology of Segoviano (2006) and Radev (2012). Malik and Xu (2017) examine connectedness among US, European and Asian G-SIBs and insurance institutions (GSIIs) from 2007 to 2016. Compared to Asia, G-SIBs and GSIIs headquartered in the US and Europe appear to be main sources of market-based connectedness, likely driven by economic policy uncertainty and US long-term interest rates, while bank profitability and asset quality drive bank-specific return connectedness.

Systemic risk spillovers between the sovereign and the non-financial corporate sector

Gapen *et al* (2008) used CCA to measure corporate default risk and public sector contingent liabilities in 12 emerging market economies. Augustin *et al* (2017) found that the significant reevaluation of sovereign credit risk across Europe after the Greek bailout in 2010 raised corporate credit. Effects were more pronounced for firms that are bank or government dependent suggesting that the nexus occurred through a financial and a fiscal channel. Similarly, Acharya *et al* (2018) found that value impairment in banks' exposures to sovereign debt and the risk-shifting behavior of weakly capitalized banks reduced the probability of firms being granted new syndicated loans significantly. Becker and Ivashina (2018) found that between 2007 and 2013, the share of domestic government debt held by the banking sectors of euro area countries more than doubled, which generated a crowding out of corporate lending in 2010–11 and affected private capital formation negatively. Financial repression was exercised via direct government ownership as well as via government influence through banks' boards of directors.

Quantifying systemic financial and sovereign risks

The literature review suggests that a coherent and comprehensive assessment of a country's systemic risk must consider all sectors of an open economy. Interactions and spillovers may occur between the home sovereign and its financial system, between the home and the foreign countries' financial systems, between the domestic and the foreign sovereigns and between the domestic sovereign and the foreign financial system (Pagano and Sedunov, 2016). Interactions and spillovers between the home country sovereign and its financial system stemming from the household and corporate sectors should also be considered. Finally, measurement of systemic risk requires methodologies that capture all its forms, i.e. as a common shock, as contagion and as underlying vulnerabilities that may unravel in a disorderly manner and affect the real economy (ECB, 2009).

As argued by Hansen (2012, p. 27), "We should not underestimate the difficulty of measuring systemic risk in a meaningful way." It seems important to mention that measures of systemic risk used in the reviewed literature do not model banks' default dependence explicitly and often fail to capture the time-varying non-linearities and feedback effects typical of financial markets. Some of the measures are not even coherent measures of risk as they fail to comply with one or more of the axioms a coherent risk measure should respect (Roccioletti, 2016), e.g. CoVaR violates the sub-additivity axiom.

Volatility measures have almost no explanatory power for specific events (Acharya *et al*, 2017). Variations of Value at Risk, while used to measure risk of an individual institution in isolation (Adrian and Brunnermeier, 2016), are not suited to measure systemic risk, which requires capturing all three forms of systemic risk and implies taking into account feedback effects and non-linearities. CoVaR and ΔCoVaR can capture the risk of the banking industry, for instance, but they have the drawback of only measuring the system's loss conditional on individual institutions. Therefore, they can only identify systemically important institutions and cannot model the system's joint or multivariate distribution (Baur, 2013). In addition, like the VaR measure, CoVaR is likely to behave very differently in crises and normal periods.

Three other measures used in the literature on systemic risk are the distress insurance premium (DIP) (Huang *et al*, 2010), MES (Brownlees and Engle, 2012), and SRISK (Brownlees and Engle, 2016). While in contrast to MES, the other two measures take the size of a financial institution explicitly into account, SRISK computes only the expected capital shortfall of a bank. Yet, MES is not a good indicator for predicting risk before a crisis (Idier *et al*, 2014). An additional important drawback of MES and DIP is that they are calculated using equity returns and CDS data, respectively. As the experience of the run-up to the crisis shows, however, booming stock markets coincided with low volatility and low risk premia pointing at markets' poor performance in pricing risk over time.

Gray and Jobst (2011) proposed the Systemic CCA framework to measure systemic risk in the financial sector. The methodology can be applied to individual financial institutions and estimate a multivariate generalized extreme value distribution with a time-varying and non-linear dependence structure. It can quantify all forms of systemic risk and provide a conditional and non-linear measure of systemic contingent liabilities. It has been used by the IMF in the Stress Testing module of its Financial Sector Assessment Program for the United States (2010) and Germany (2010), for example. This paper's methodology, the CIMDO, is closely linked to the Systemic CCA. It is based on a multivariate copula, allowing for the non-parametric estimation of both individual and joint default risk, and it captures the non-linearities and feedback effects typical of financial markets. Cortes *et* al (2018) applied CIMDO to the US largest banks and insurance companies, and to the pension, mutual fund, and hedge fund sectors, but not to the rest of the economy.

3. The Integrated Modeling Framework

This study uses the integrated modeling framework developed by Jin and Nadal De Simone to measure systemic credit risk that results from the interaction among banks and investment funds (2014a), from domestic banks and their European mother companies (2014b) and from investment funds (2014c).[5] While the core methodology is the same, the sources of systemic risk are extended to cover the remaining sectors of the economy: households, the non-financial corporate sector and the sovereign. Pension funds and insurance companies could not be included due lack of data. To the best of the authors' knowledge, this is the first empirical application of the extended framework to build interlinked stochastic balance sheets of all the sectors of a country. Appendix I contains a schematic depiction of the estimation procedure and the sectoral balance sheets used in this study. The main features of the framework are briefly discussed below.

3.1 Merton Credit Risk based on Book Value

Since only balance sheet data are available for Luxembourg banks and investment funds, the Merton model cannot be applied directly. Therefore, probabilities of distress (PDs) were calculated using balance sheets. Souto *et al.* (2009) and Blavy and Souto (2009) show that book-based and market-based Merton credit risk measures are highly correlated.[6]

Asset volatility based on book value σ_B is calculated by a rolling window as follows:[7]

$$\sigma_B = \sqrt{\sum_{t=1}^{N} (\ln(V_t^B / V_{t-1}^B))^2} \ ,$$

[5] Given the objective of this study, the Generalized Dynamic Factor Model module of the framework is not implemented.
[6] Gray and Jones (2006) present an early application of this idea. See also Adrian *et al*, 2013.
[7] Following usual practice, quarterly volatility is annualized.

where V_t^B denotes the book value of total assets in quarter *t* and *N* is the width of a rolling window set at four consecutive quarters.[8] The book-value risk neutral PD of the Merton model can be directly estimated by:

$$\pi_B = \Phi(-\frac{\ln(V^B / X) + (r - \frac{1}{2}\sigma_B^2)(T-t)}{\sigma_B \sqrt{T-t}}),$$

where $\Phi()$ is the cumulative density function of the standard normal distribution, *X* is the stock of debt, r is the risk-free interest rate, and *T,* following usual practice, is assumed to be one year. The implied book-value risk neutral distance-to-distress (DD) is simply the number of standard deviations that the firm is away from default:

$$DD_B = \frac{\ln(V^B / X) + (r - \frac{1}{2}\sigma_B^2)(T-t)}{\sigma_B \sqrt{T-t}}.$$

In contrast to banks, assets on the government balance sheet are measured less precisely.[9] However, total sovereign assets can be estimated using book values of sovereign equity by simultaneously solving the optimal hedge equation and the call option equation:

$$\sigma_E = (\frac{V^B}{V^E})\frac{\partial V^E}{\partial V^B}\sigma_B,$$

$$V^E = V^B N(d_1) - Xe^{-r(T-t)}\Phi(d_2).$$

where: $d_1 = \frac{\ln(\frac{V^B}{X}) + (r + \frac{1}{2}\sigma_B^2)(T-t)}{\sigma_B\sqrt{T-t}}$ and $d_2 = d_1 - \sigma_B\sqrt{T-t}$. Sovereign equity volatility is calculated using a four-quarter rolling window as before: $\sigma_E = \sqrt{\sum_{t=1}^{N}(\ln(V_t^E / V_{t-1}^E))^2}$ where V_t^E denotes the book value of sovereign equity at time *t*.[10] The implied book-value risk

---

[8] For tractability purposes, book-value assets are assumed to follow a geometric Brownian motion. The mean of quarterly asset returns in a large sample is assumed to be zero to avoid the noise brought by the sample means to the volatility process (Jin and Nadal De Simone, 2011).

[9] For example, while foreign reserves, financial assets and the net present value of the general government primary surplus are either observable or can be approximated with relative ease, the value of government buildings, land and other government assets can be difficult to estimate.

[10] Section 3.3 explains how the stochastic sovereign balance sheet is constructed.

neutral sovereign DD tracks the full profile of sovereign systemic risk instead of the risk-neutral sovereign PDs, which are usually close to zero.

3.2 The CIMDO Approach

Given its central importance in this study, the CIMDO-approach developed by Segoviano (2006) is briefly presented in this section.[11] The CIMDO approach minimizes the cross-entropy objective function that links the *prior* and *posterior* distributions under a set of constraints on the posterior. As the general dependence measures calculated via the CIMDO are tightly related to the prior distribution of the correlation structure (Gorea and Radev, 2014), to avoid understating PDs dependence, a simple rolling window approach is used for estimating the prior correlation input to the CIMDO. A Newton-type method guarantees that the estimated correlation matrix of asset returns is symmetric and positive semi-definite (Qi and Sun, 2006).

Assume two financial institutions X and Y, with logarithmic returns represented by random variables x and y, the following function can be minimized:

$$
\begin{aligned}
L(p,q) = & \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} p(x,y)\ln\left[\frac{p(x,y)}{q(x,y)}\right]dxdy \\
& + \lambda_1\left[\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} p(x,y)dxdy - 1\right] \\
& + \lambda_2\left[\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} p(x,y)I_{[x_d^x,\infty)}dxdy - PD_t^x\right] \\
& + \lambda_3\left[\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} p(x,y)I_{[x_d^y,\infty)}dxdy - PD_t^y\right],
\end{aligned}
$$

where PD_t^x and PD_t^y are probabilities of distress for these two financial entities, and $p(x;y)$, $q(x;y) \in \Re^2$ are the posterior and the prior distributions, with λ_1, λ_2, and λ_3 being the Lagrange multipliers of the additivity constraint and the two consistency constraints (i.e. that probabilities are non-negative). For each obligor, the region of distress PD_t is described by the part of the distribution over its distress threshold x_d^x or x_d^y. The optimal solution for the posterior density is of the form:

$$p^*(x,y) = q(x,y)\, exp\{-[1 + \lambda_1 + (\lambda_2 I_{[x_d^x,\infty)}) + (\lambda_3 I_{[x_d^y,\infty)})]\}.$$

[11] Jin and Nadal De Simone (2014b) provide a thorough discussion.

The posterior joint density will diverge from its prior whenever one or both random variables take values above the specified cutoff values, e.g., in times of distress when more mass shifts toward the tails of the distribution. To calibrate the thresholds, an average distress threshold is assumed for each financial institution using the inverse standard Normal distribution of its average PDs (Segoviano and Goodhart, 2009).

The CIMDO density is a convenient way of capturing the dependence structure among the marginal PDs. From the CIMDO density it is possible to extract the copula function that describes the dependence structure.[12] Given that by construction the CIMDO copula puts a greater emphasis on the distress region of the joint distribution, it provides a robust and consistent method to estimate distress dependence among financial institutions. Among its several advantages and importantly for the objective of this study, the CIMDO describes linear or non-linear dependencies among variables which are invariant under increasing and continuous transformations of the marginal distributions and the dependence structure while characterized over the entire domain of the multivariate density, appears to be especially robust in the tail of the density, which is the relevant part for any operationally useful discussion of systemic risk.

The output of this methodology is a set of systemic credit risk measures originally proposed for banks by Segoviano and Goodhart (2009) and by Radev (2012). The measures are consistent with the three forms that systemic risk can take according to the ECB (2009): common distress, contagion and the growth of vulnerabilities over time that unravel in a disorderly manner. The first form of systemic risk is measured by the Banking Fragility (BF) measure and the Banking Stability Index (BSI). The BF measure is defined as the probability that at least two financial institutions get distressed and the BSI is defined as the *expected number* of financial institutions that will become distressed conditional on *any one* financial institution having become distressed as a result of a common shock. The second form of systemic risk, contagion, is measured by the Distress Dependence Matrix (DDM), which displays pair-wise probabilities of distress of financial institutions, and the PAO measure, which is defined as the probability that at least one more financial institution will default following the default of a *given* institution. The third form of systemic risk is proxied by the average of the columns/rows of the DDM.

Assuming for simplicity a banking system made of three banks whose asset value processes are characterized by the random variables x, y, and z, the BF measure

[12] The converse of Sklar's theorem implies that it is possible to couple together any marginal distribution, of any family with any copula function, and a valid joint density will be defined. The corollary of Sklar's theorem is that it is possible to extract the implied copula and marginal distributions from any joint distribution (Nelsen, 1999). This alleviates the bias associated with the unavoidable fact that PDs are generated regressors.

represents the general vulnerability of the sector to systemic events (the *systemic distress potential*) and is calculated as follows:

$$BF = P\left(X \geq \chi_d^x, Y \geq \chi_d^y\right) + P(X \geq \chi_d^x, Z \geq \chi_d^z) + P\left(Y \geq \chi_d^y, Z \geq \chi_d^z\right) + P\left(X \geq \chi_d^x + Y \geq \chi_d^y, Z \geq \chi_d^z\right).$$

The BF measure describes the part of the posterior distribution where distress occurs because at least two among X, Y and Z go over their respective distress-thresholds x_d^x, x_d^y or x_d^z.

The BSI measures the case in which a bank becomes distressed following a common shock and takes the floor value of 1 when the linkages across financial institutions are minimal. The measure can be written as follows:

$$BSI = \frac{P(X \geq \chi_d^x) + P\left(Y \geq \chi_d^y\right) + \; P(Z \geq \chi_d^z)}{1 - P\left(X < \chi_d^x, Y < \chi_d^y, Z < \chi_d^z\right)}.$$

As the *expected number* of financial institutions that will become distressed conditional on any one financial institution having become distressed rises above 1, systemic interdependence increases.

PAO measures the likelihood that an idiosyncratic shock to a bank is propagated to the rest of the financial sector and ends up affecting the real economy. Assuming a financial system of four financial institutions for illustrative purposes (i.e. X, Y, R, and Z), and that financial institution Z becomes distressed, simplifying notation, the measure is calculated as follows:

$$PAO = P(X/Z) + P(R/Z) + P(Y/Z) - [P(X \cap R/Z) + P(X \cap Y/Z) + P(R \cap Y/Z)] + \; P(X \cap R \cap Y \,/\, Z).$$

Finally, pair-wise conditional probabilities of distress of financial institutions are calculated, for instance, as the PD of institution X conditional on institution Y becoming distressed:

$$DDM = \frac{P\left(X \geq \chi_d^x \,/\, Y \geq \chi_d^y\right)}{P\left(Y > \chi_d^y\right)}.$$

While conditional probabilities do not imply causation, sets of pairwise conditional probabilities estimated over time can provide important insights into interconnectedness and the likelihood of contagion between the entities in the system.

3.3 Stochastic Balance Sheets of the Non-financial Private Sector and the Sovereign

The CCA balance sheets for households, non-financial corporations and the government are constructed following Gray and Malone (2008) and Gray and Jobst (2011). In line with the literature, the sovereign comprises the general government and the monetary authority. The three sectoral stochastic balance sheets contain both observed and unobserved items.

The sovereign balance sheet raises several conceptual issues. The first one regards the liability side of the monetary authority. Given that Luxembourg belongs to the euro area, the currency-in-circulation component of the monetary base has to be calibrated. This study uses Luxembourg's "capital allocation key" (as adjusted through time), which is public information available from the Luxembourg central bank balance sheet.

A second issue regards "other public assets" on the government balance sheet. Sovereign assets can be broken down into three key components: reserves, "net fiscal assets" and "other public assets", from which implicit and explicit contingent liabilities from the financial sector are subtracted. The value of reserves can be observed, and contingent liabilities are estimated from the financial sector. "Net fiscal assets" are proxied by a five-year moving average of the present value of the general government primary fiscal surplus, where the projected primary surplus is taken from the Luxembourg Stability Program submitted to the European Commission with the discount rate set at the average interest rate on general government debt. "Other public assets" are obtained by subtracting the above items from the total implied sovereign assets. Total implied sovereign assets are obtained by applying the book-value Merton model to sovereign equity and using short-term debt plus 50% of long term debt as threshold.[13]

Finally, the balance sheets of households and non-financial corporations are built using national account and the flow-of-funds statistics published by Eurostat. Some unobserved items must be estimated. To preserve the internal coherence of the integrated framework proposed in Section III, following Gray and Malone (2008), this study uses the aggregate production function of the Luxembourg economy to link household and corporate assets (see Appendix II). The after-tax present value of labor income is calibrated using the Luxembourg central bank output projections. The value of households' stock of residential property is taken from national accounts. The present value of after-tax capital income of the non-financial corporate sector is also calibrated using the production function of the economy and the central bank's output projections.

[13] See Gray and Jobst (2011) application of the approach to Sweden, a country that like Luxembourg only issues domestic-currency denominated debt.

4. Data

This study considers seven OSIIs in Luxembourg and the 4 investment funds sponsored by the OSIIs for which data are available over the sample period 2008Q4-2018Q4. They represented 376% and 37% of 2018 GDP, respectively. All the Luxembourg OSIIs are unlisted, so quarterly book value data is drawn from reporting data provided to the supervisory authority.[14] Investment funds balance sheet data are also drawn from reporting data provided to supervisors. For banks and investment funds, short-term debt includes deposits up to one-year maturity, short term funding, and repos, while long-term debt includes time deposits over one-year maturity and other long-term funding.

The Basel Committee on Banking Supervision (BCBS) has considered the "step-in" risk that a bank may provide financial support to an entity beyond or in absence of any contractual obligations (BCBS, 2015). As a primary indicator of step-in risk, the BCBS proposes the sponsorship concept.[15] Investment funds selected in this study are based on their sponsorship by the OSIIs.

The OSIIs belong to 5 G-SIBs that managed assets representing 17% of euro area GDP at end-2018. Bloomberg provides data on short-term borrowing (BS047) and long-term debt (BS051) at annual, semi-annual, and quarterly frequencies. To make the data consistent, four filtering rules are used (Appendix III). Market data for the G-SIBs include banks' stock prices and the number of outstanding shares, and book value data from Bloomberg.

For households, non-financial corporations and the government sector, the financial part of the sectoral balance sheets is constructed using flow of funds data published by Eurostat. The non-financial part is constructed calibrating the present value of after-tax salary income for households and the present value of after-tax profits for non-financial corporations as explained above. The balance sheet of the monetary authority and the general government budget are used for constructing the sovereign balance sheet.

5. Vulnerability and Systemic Risk Exposures

Book value data are used for OSIIs and for investment funds, while market data are used for G-SIBS. For the government, both market data and the sovereign balance sheet are

[14] See footnote 8.

[15] The definition of sponsor includes not only more or less explicit financial support, but also decision making and operations. The BCBS proposes these three elements as part of the list of indicators that banks will have to consider in assessing step-in risk.

used. PDs and DD reported below are always risk-neutral in the framework of Merton model.

This first subsection below presents a set of vulnerability indicators for the seven OSIIs in Luxembourg, the five G-SIBs to which the OSIIs belong, and the four investment funds sponsored by the seven Luxembourg OSIIs. Systemic risk measures are also presented for the OSIIs, along with the PD and the associated expected loss (EL) of an unconditional distress scenario. Subsection 2 discusses the conditional EL and the conditional implicit government guarantee stemming directly from distress of the OSIIs. Subsection 3 focuses on distress transmitted from the G-SIBs to their affiliated Luxembourg OSIIs. Subsection 4 turns to distress among investment funds transmitted to their sponsor OSIIs. Subsection 5 considers distress in the household sector and the non-financial corporate sector transmitted to their creditor OSIIs. Finally, subsection 6 discusses the impact of implicit government guarantees on standard measures of sovereign risk.

5.1 Vulnerability Indicators for Luxembourg's Financial Sector

Figure 1a presents the simple mean, median and inter-quintile ranges of the PDs and DD of the seven OSIIs and the corresponding EL. Together, the OSIIs represented about 30% of total assets in the banking sector as of end-2018 (almost 3.8 times the country's GDP).[16] The charts suggest a great deal of heterogeneity across OSIIs as illustrated by the disparity between the mean and the media distribution of EL. The median EL peaked at around 650 million euro after Lehman's collapse and was virtually unaffected during the sovereign crisis. It fell to low values thereafter especially following the spike in 2014 due to the uncertainty linked to the Asset Quality Review and the launch of the EU Single Supervisory Mechanism. In contrast, the 80th percentile of EL had moved between 1¼bn and 2¼bn euro in 2009.

Figure 1b presents the PDs and the DD of the five G-SIBs to which the seven OSIIs belong and the corresponding EL. As in Figure 1a, the median EL was larger after Lehman's collapse than during the sovereign crisis, although it declined more rapidly than for the Luxembourg's OSIIs, partly reflecting the most parsimonious nature of balance sheet data used for estimating OSIIs EL. Similarly, the 80th percentile of EL was relatively limited after the sovereign crisis, compared to over 2.5bn euro at the height of the financial crisis. In contrast to their Luxembourg affiliates, the distribution of EL across G-SIBs is more homogeneous as suggested by the relative closer median and mean distribution profiles. It is noteworthy that markets seem to factor-in banks' idiosyncratic factors more during

[16] For reference, Deutsche Bank, one of the 13 German OSIIs reported to the ESRB, held total assets equal to about 40% of Germany's nominal GDP at end-2018.

stressful times than during tranquil times given that EL heterogeneity rises around periods such as the aftermath of Lehman's collapse and the sovereign crisis in the euro area.

Given that the book-value risk-neutral PDs of investment funds can be very close to zero, "synthetic" PDs are estimated by rescaling Merton's DD so that the lowest possible level of π_B (i.e. book-value risk neutral PD) is 10^{e-8}. Figure 1c focuses on the set of investment funds sponsored by the seven OSIIs and reports synthetic PDs, DD and synthetic EL.[17] While the median and mean of investment funds synthetic PDs correlate well with the PDs of their sponsoring OSIIs, for some investment funds the correlation was higher during the sovereign crisis. This suggests that step-in risk was material at least during these stressful times for some investment funds and their sponsor banks. More analysis is clearly needed on this matter. However, the median EL was negligible in economic terms.

Figure 2 reports the 4-quarter rolling correlations of the log of asset returns among OSIIs, G-SIBs, and investment funds. Three features stand out. First, correlations among OSIIs' asset returns can be negative while those among G-SIBs' asset returns are usually positive possibly due to the fact that stock prices used for G-SIBs capture joint market fundamentals faster than OSIIs' balance sheet data. Second, the distributions are quite symmetric. Third, among G-SIBs and between the OSIIs and the G-SIBs, asset return correlations increased in the second half of 2014 (among OSIIs they started rising earlier in the year) and lasted until end-2015. This result illustrates the rise in correlation across asset classes referred to in the November 2015 ECB Financial Stability Review. As suggested by the ECB, the narrowing gap of the distribution may be linked to an increase in systemic risk. This interpretation is also consistent with the increase in OSIIs Banking Stability Index (i.e. a measure of interdependence) and in OSIIs Banking Fragility (Figure 3). Similar results were reported in Jin and Nadal De Simone, 2014b and 2014c, in the banking sector and in the investment fund sector, respectively. Especially the rise of both measures in 2016 suggests that "search for yield" may have driven up correlations across asset classes as indicated by the ECB, despite the significant deleveraging going on at the time by the banking sector. Against a macroeconomic background of persistently low interest rates, several observers have reported significant risk-taking in the euro area (e.g. Kabundi and Nadal De Simone, 2018, Jin and Nadal De Simone, 2018, and Gibson *et al*, 2018).

Figure 3 also reports the unconditional PDs and the corresponding EL of what is referred to as "all scenarii" in the text. This is the probability that OSIIs becomes distressed including one, two, three, up to the seven OSIIs. From Merton model, the corresponding

[17] Granular enough data for investment funds is only available from 2008Q4.

EL can be expressed as the product of the risk-neutral PD and the implied risk-neutral loss-given-default (LGD) in all scenarii. The resulting unconditional systemic risk measure PDs peaked in the first half of 2009, when the financial crisis aggravated with high government deficits, rapidly increasing public debt-to-GDP ratios and rising contingent liabilities linked to government guarantees provided to banks. As it is to be expected, Luxembourg OSIIs reflected developments affecting their mother companies. Against this background, at an extraordinary meeting on 9/10 May 2010, the European Council agreed a comprehensive package of measures to preserve financial stability in Europe and established the European Financial Stabilization Mechanism. Also, in May, the ECB Governing Council decided to intervene in the secondary markets for public and private debt securities through its Securities Markets Program. These measures led to a significant drop in market volatility reflected in the unconditional PDs (ECB December 2010 Financial Stability Review).

The unconditional PDs peaked again during 2012, when many large euro area banking groups posted significant losses reflecting high loan-loss provisioning. Several banks saw their return on equity falling below their cost of equity, indicating the need for further balance sheet adjustment (ECB November 2013 and 2014 Financial Stability Review). Banks continued the much needed de-risking even as they struggled to raise profits. The increase in unconditional PDs in the second half of 2016 stemmed from banks' lower stock prices as a result of profitability concerns and markets' volatility following the Brexit vote. This was reversed when in 2017 euro area growth prospects supported banks' expected profits.

Table 1 reports the measure of pair-wise contagion DDM, which is computed as the EL of each financial institution in the row conditional on distress on the financial institution in the column. It is computed for OSIIs, the G-SIBs to which they belong, and the investment funds sponsored by the OSIIs. The increase in OSIIs' fragility shown in Figure 3 in 2014-2015 is also clear in the DDM. The average EL of OSIIs increased to 4bn at end-2015 from 0.3bn at end-June 2014.

5.2 Systemic Risk and Conditional Contingent Liabilities Emanating from OSIIs

Figure 4 reports the conditional measure of systemic risk in the form of contagion, PAO, and its corresponding EL for the OSIIs. There is a great deal of heterogeneity in systemic risk across the OSIIs, largely as a result of large differences in their respective PDs. The drivers of such disparity are partly OSIIs' different business models and leverage ratios.

Regulatory changes promoted by the Financial Stability Board and the European Commission (e.g. the Total Loss Absorbing Capacity, bail-in, capital surcharges, the

Single Resolution Authority and the Single Resolution Fund) seek to prevent bailing out financial institutions with tax payer money. Despite that these and other macroprudential measures will likely reduce excessive *ex ante* risk-taking and the direct *ex post* fiscal cost of bank resolution, simply limiting government backstops and safety nets could worsen an eventual banking crisis and increase its indirect fiscal and economic costs (Dell'Ariccia *et al*, 2018).[18] Figure 4 reports the conditional implicit government guarantees that result from the EL illustrating thereby how much could be at stake.

As stated above, EL is the product of the risk-neutral PD and the implied risk-neutral LGD. The conditional implicit government guarantee is calculated as follows: the LGD of the OSII assumed to have distressed is added to the conditional EL of at least one other OSII, weighted either by the share of the Luxembourg government in the OSII's equity, or by the OSII's asset share in the total assets of the banking group to which it belongs.

Figure 4 illustrates three significant points. First, OSIIs' differences mentioned above are reflected on the distribution of conditional implicit government guarantees with a time-varying mean that often, notably during stressful times, diverges significantly from the median suggesting markets' increased regard to idiosyncratic factors. Second, conditional implicit government guarantees have fallen since the height of the financial crisis. Finally, and importantly, the volatility of the government guarantees was largely driven by the fall in PDs volatility against higher correlation among OSIIs in the second half of the sample.

5.3 Systemic Risk and Contingent Liabilities Emanating from G-SIBs Cross-border Contagion

The PAO measure is also used to evaluate the cross-border systemic risk emanating from the G-SIBs to which the OSIIs belong.[19] For a country where foreign banks represented more than 95% of the total number of banks at end-2018, this source of systemic risk is significant. Figure 5 reports the PAO and the associated EL. PAO assumes that one G-SIB defaults and measures the conditional PD of at least one OSII. In contrast to the OSIIs' PAO in Figure 4, the PAO for OSIIs stemming from G-SIBs in Figure 5 displays less heterogeneity. Cross-border contagion is more homogeneous than contagion among OSIIs. However, markets seemed to distinguish among G-SIBs at the height of the sovereign crisis, with some remaining closer to the top of the panel, indicating thereby a

[18] When banks and the sovereign are fragile and the credibility and feasibility of government guarantees are determined endogenously, guarantees link banks' and sovereign stability, even in the absence of banks' holdings of sovereign bonds (Leonello, 2018). In addition, depending on the specific characteristics of the economy and the nature of banking crises, an increase in the size of guarantees can be beneficial for the bank-sovereign nexus as it enhances financial stability without undermining sovereign solvency.

[19] This is what the ECB calls "the banking channel of sovereign risk" (Financial Stability Review, December 2011).

larger systemic risk via cross-border contagion. The ECB Financial Stability Review (December 2011, pp. 82-84) used CDS-derived expected shortfall measures to assess systemic risk and found that prior to 2010, sovereign CDS and bank CDS were sensitive to tail events in other CDS in the same sectors, respectively, but transmission channels among sovereign CDS became more heterogeneous after 2010. That means that after 2010, a tail event in an Italian bank, for example, affected French sovereign CDS about twice as much as German sovereign CDS. This seems to be well captured by the PAO measure during the period 2010-2012, and even more conspicuously by the rise in the PAO dispersion in the run up to the Asset Quality Review and the launch of the EU Single Supervisory Mechanism, a period that coincided with a weak, fragile and uneven macroeconomic recovery.

Differences in conditional implicit government guarantee across G-SIBs and across time are revealing. The top percentile conditional implicit government guarantee was about 0.55bn euro in 2008Q1 and rose to about 0.58bn euro in the aftermath of the sovereign debt crisis and the run up to the Asset Quality Review and the launch of the EU Single Supervisory Mechanism. It peaked at around 0.25bn at 2016Q1 as a result of market concerns with the low profitability and legacy issues of some G-SIBs. According to the DDM in Table 1, three out of the five G-SIBs experienced an increase in its significance (sum across rows) and five out of the seven OSIIs became more vulnerable (sum across columns) at end-2014 relative to end-2013. Increased vulnerabilities stemmed mostly from the rise in G-SIBs' PDs.

These results support the need to consider the different forms of systemic risk, including their components. While banks may reduce leverage and fragility, for example, a persistent rise in asset correlations may be harbinger of future possible financial instability.

5.4 Systemic Risk and Contingent Liabilities Emanating from Investment Funds

This section discusses the conditional implicit government guarantees that would result from distress in investment funds sponsored by the OSIIs (i.e. sponsorship proxies the BCBS's concept of "step-in" risk). During the sample period, the investment funds sponsored by Luxembourg OSIIs represented about 0.50% of the total assets managed by the Luxembourg investment fund industry at end-2018.[20] While seemingly small, this percentage amounted to 37% of the country's annual GDP.

[20] The choice of the investment funds sponsored by Luxembourg OSIIs makes sense from a political economy viewpoint. It is not reasonable to expect that the Luxembourg sovereign becomes responsible for the contingent liabilities that non-OSII sponsors may face as it is likely that, in case of need, they will be rescued by their European mother companies.

In Figure 6, synthetic PAO and synthetic PAO EL profiles are broadly similar to those of OSIIs and G-SIBs. However, there is overall less heterogeneity than in the case of distress stemming directly from OSIIs (Figure 4). The years 2015-2016, following bouts of market turbulence, illustrate potential systemic risk stemming from liquidity mismatches and yield-search behavior by investment funds (Jin and Nadal De Simone, 2018). According to several issues of the ECB Financial Stability Review (2015 and 2016), bond fund flows seem to follow past returns, increasing when returns are higher and *vice versa*, which suggests procyclicality in investment patterns and may amplify repricing in global fixed income markets and rise systemic risk. This behavior explains why growth in the investment fund sector, which had been growing over several years, stalled during the second half of 2015 amid a decline in asset prices and a partial reversal of net flows.

Over the sample period, the median of public guarantees associated with investment funds tend to be 1/2 to 1/3 of those emanating directly from OSIIs. However, the investment funds considered in this study represent a much smaller share of total assets than do the OSIIs. The panel of “synthetic” conditional implicit government guarantees reveals the potential cost of contagion risk. Table 1 indicates that investment funds EL increased in all cases at end-2015 relative to end-2014, and more than for G-SIBs. It clearly fell since then.

5.5 Systemic Risk Emanating from the Household and Non-financial Corporate Sectors

Figure 7 reports the DD for both the non-financial corporate and the household sectors. According to the DDs, credit was quite volatile in the non-financial corporate sector. This reflects the volatility in the financing needs of international holding companies located in Luxembourg and the DD is highly correlated with the economy’s output cycle. DD has remained well above the low level reached at the onset of the global financial crisis, but this should be evaluated in the context of the high volatile financial component of the sector’s stochastic balance sheet. The household sector DD is less volatile than the corporate sector’s and has a lower correlation with the economy’s business cycle. It has been supported in recent years by rising prices in the housing market given that house ownership is the most important asset in households’ balance sheet. Overall, DD profiles do not suggest that risk emanating from non-financial corporations and households may be of immediate concern. However, this will be explored further below with other systemic risk measures.

5.6 Systemic Risk and Sovereign Risk

5.6.1 Selected Statistics

This section brings together the financial sector, G-SIBs, the non-financial corporate and the household sectors, and discusses general supplementary indicators of systemic risk and sovereign risk.

Given the lack of CDS for the Luxembourg sovereign and the low liquidity of its debt, the Luxembourg sovereign DD is calculated using the framework proposed by Houweling and Vorst (2005). For a given default intensity process, the valuation of a CDS is well known. Following market practice, a simple annualized unconditional risk-neutral default intensity model is specified, and the closed-form expressions for CDS spreads are inverted to solve for the corresponding values of the constant annual intensity using a standard nonlinear optimization technique. German sovereign senior CDS with maturities of 1, 2, 3, 4, 5, 7, and 10 years are considered. Luxembourg CDS are constructed from German sovereign CDS through the following steps: first, credit spreads from German sovereign CDS are derived; second, credit spreads are adjusted proportionally using the ratios between Luxembourg and German government bond yields. Consistent with the Merton model, the implied Luxembourg sovereign DD is the inverse of the standard normal cumulative distribution of the 1Y PD derived from the CDS.

Figure 8a compares the Luxembourg sovereign DD implied from German sovereign CDS to that of Germany's. Given that Luxembourg and Germany share the same sovereign rating according to all international rating agencies, it is thus not surprising that their DDs are similar. Moreover, applying the Merton model to the sovereign balance sheet broadly confirms the DD profile (Figure 8b).[21] The noticeable improvement in the DD after 2011 reflects a combination of factors. These factors include the vanishing effect of the 2009 and 2010 primary deficits in the five-year moving average of the present value of the general government primary balance, buoyant tax revenues, and the stabilization of general government debt to GDP. The reversal in 2015 and part of 2016 is partly due to the lower present value of the primary surplus projected after 2018.

[21] Gray and Jobst (2011) suggest to use the sovereign default barrier from the sovereign balance sheet and the full-term structure of the sovereign credit curve (e.g. the sovereign CDS spreads at maturity of 1, 3, 5, 7, and 10 years) to estimate implied total sovereign assets and asset volatility using the Merton model. They applied it to Sweden. However, combining Gray and Jobst's method with the implied Luxembourg CDS that results from following Houweling and Vorst produces an estimate of Luxembourg implied total sovereign assets that is too low when compared with the observable components of sovereign assets. Because of the limited volume, maturity and liquidity of Luxembourg government bonds, Gray and Jobst method to derive Luxembourg credit spreads may not compute the term structure of the sovereign credit curve appropriately.

To ease comparison, Figure 8c displays the unconditional implicit government guarantees stemming from Luxembourg's OSIIs and Figure 8d reports the average conditional implicit government guarantees from the OSIIs, the G-SIBs and the investment funds shown already in Figures 4-6. As mentioned above, the de-leveraging process, the bad-loans provisions and the write-offs undertaken by major G-SIBs amidst a morose economic environment in the run-up to the Single Supervisory Mechanism are reflected in the three sectors during 2014, and especially for G-SIBs during 2015. Although the overall reduction in systemic risk in the banking sector since 2009Q2 is obvious, notably for government guarantees stemming directly from the OSIIs, these remain broadly higher than those stemming indirectly from G-SIBs and investment funds.

Figures 8e and 8f illustrate the impact on conditional implicit government guarantees from shocks to household mortgages and to loans to non-financial corporations, respectively. The shocks assume that OSIIs have to write off 10% of their outstanding mortgage loans to households, and 10% of their outstanding loans to non-financial corporations. These shocks, very significant by historical standards, only produce a minor deviation from the (no shock) benchmark, which is mostly due to the high risk-weighted capital of OSIIs.

5.6.2 Systemic Risk Shocks and Sovereign Risk

In contrast to the implicit assumption underlying results discussed so far, other things may not be equal. Therefore, this section shows the outcome of an exercise that relaxes such assumption in a partial equilibrium setup.

Figure 9 shows the impact of various shocks on the government stochastic balance sheet via the contingent implicit government guarantees stemming from each of the five sectors. The figures report both the average conditional DD of the Luxembourg sovereign after the shocks and the (no shock) benchmark DD. Clearly, systemic risk from Luxembourg OSIIs has a relatively small effect on sovereign DD given the strong fiscal position. This result holds despite feedback effects and nonlinearities typical of financial markets captured by the multivariate CIMDO approach.

However, this partial equilibrium exercise does not account for the likely increase in the volatility of sovereign assets following these shocks. As an *ad* hoc attempt to capture this feedback channel, Figure 9 combines the shocks with an assumed increase in sovereign assets' volatility by 40%. This magnitude is consistent with the maximum implied sovereign asset volatility recorded over 2009-2011. Only when conditional implicit government guarantees are combined with such a large increase in implied sovereign asset volatility does the negative impact of the shocks on sovereign risk become visible.

The main implication of this exercise is that even in the extreme, but plausible scenario combining shocks with a 40% rise in implied sovereign assets volatility, the solvency of the Luxembourg sovereign remains robust. However, the severity of the shock also illustrates the fundamental importance of a sound fiscal position for financial stability given that the sovereign's DD falls about 25 standard deviations.[22]

Table 2 summarizes the transmission of systemic risk from the five sectors via each of the OSIIs as well as their impact on EL, conditional implicit government guarantees and the sovereign's DD (assuming a 40% rise in sovereign assets volatility). This table is based on the conditional PAO estimates displayed in the graphs above but adds the EL of the institution or sector assumed to be in distress. Two points warrant mentioning. First, contributions to EL and to the conditional implicit government guarantees vary significantly over time suggesting the need to monitor systemic risk regularly. Second, the volatility of Luxembourg implied sovereign assets has a much stronger effect on sovereign risk than systemic risk stemming from the OSIIs, G-SIBs, investment funds or the non-financial private sector, a result consistent with Fratzscher and Rieth's (2015) and Manzo and Picca's (2016). In addition, results vindicate recurrent calls for banks to hold larger capital buffers and effective supervision in order to reduce the risk of financial sector-induced sovereign distress. Similarly, the findings support expectations that larger fiscal buffers and better management of public debt will improve countries' debt sustainability and reduce the risk of sovereign-related bank distress.

6. Conclusions, Policy Implications and Possible Extensions

To the best of the authors' knowledge, this is the first study to use an integrated and internally consistent framework to measure systemic risk and vulnerabilities from the financial and the real sectors as well as their interaction with a country's sovereign risk. In this study, systemic risk can arise directly from the Luxembourg OSIIs, or indirectly from the G-SIBs they belong to, from the investment funds that the OSIIs sponsor, or from the non-financial private sector (via the OSIIs' lending). While the impact on sovereign risk and vulnerability of conditional implicit government guarantees is found to be relatively contained, in agreement with a rapidly growing literature, the study highlights the crucial role of fiscal sustainability in preserving financial stability (e.g. Cortes *et al*, 2018, and Vergote, 2018).

[22] Feedback effects from the simulated increase in government asset volatility on the private sector systemic risk via, for instance, a rise in the cost of funding and a fall in the market value of sovereign debt is not considered in this paper.

The framework used in this study is an important tool for regulators, supervisors and macroprudential authorities to monitor systemic risk at a national level accounting for the non-linearities and feedback effects that characterize financial markets. The estimated coherent systemic risk measures constitute a first line of monitoring that can flag policymakers the need to deepen their analysis of vulnerabilities. It can also help in the calibration of macro-prudential instruments. In particular, the framework can help determining banks' additional loss absorbing capacity that reflects their direct and indirect contribution to systemic risk. Given that the framework can also generate robust out-of-sample forecasts of systemic risk measures (Jin and Nadal De Simone, 2012), it can provide value added to other areas where non-linearities and feedback effects matter, such as in systemic macro-financial stress testing exercises.

Another possible application of the framework is to simulate the effects of changes in economic conditions and government policies on vulnerability indicators and on sovereign credit risk measures. For example, it is straightforward to study how changes in sovereign debt composition or the primary surplus affect sovereign credit spreads, other risk indicators and the financial sector funding costs. Within the private sector, technological shocks or demographic changes affect the present value of total assets of the non-financial corporate and household sectors. Those changes interact with the sovereign balance sheet and different indicators of funding costs, and systemic financial and sovereign risk and can be captured easily within the framework. In addition, given the observed positive time-varying correlation between systemic risk exposure of financial institutions and sovereign debt yields in European countries (Pagano and Sedunov, 2016), the framework may be a useful component in models of sovereign debt yields in order to avoid potentially important mis-specification errors.

However, as stated above, despite its comprehensive nature, this study is a first step toward a full-fledged simultaneous estimation of a country's systemic risk. A full-fledged estimation of EL and contingent liabilities in general equilibrium would require incorporating the feedback effects among the non-financial private sector and the financial sector as well as the feedback effects of changes in the sovereign fiscal position on the private sector systemic risk. This important extension implies a more complex form of dependency and a higher degree of technical difficulty, and it constitutes the subject of a future study.

References

Abad, J., 2019, “Breaking the Feedback Loop: Macroprudential Regulation of Banks' Sovereign Exposures”, Working Paper.

Abadie, A., 2002, “Bootstrap Tests for Distributional Treatment Effects in Instrumental Variable Models”, *Journal of American Statistical Association* 97, pp. 284–292.

Acharya, V. V., L. H. Pedersen, T. Philippon and M. Richardson, 2012, “Measuring Systemic Risk”, *Federal Reserve Bank of Cleveland* Working Paper.

Acharya, V. V and S. Steffen, 2013, “The “Greatest” Carry Trade Ever? Understanding Eurozone Bank Risks”, *NBER* No. 19039.

Acharya, V., I. Dreschler, and P. Schnabl, 2014, “A Pyrrhic Victory: Bank Bail-outs and Sovereign and Sovereign Credit Risk”, Journal of Finance, 69(6):2689-2739.

Acharya, V., L. Pedersen, T. Philippon, and M. Richardson, 2017, “Measuring Systemic Risk”, *The Review of Financial Studies* 30, pp. 2-47.

Acharya, V. V., T. Eisert, C. Eufinger and C. Hirsch, 2018, “The Real Effects of the Sovereign Debt Crisis in Europe: Evidence from Syndicated Loans”, *The Review of Financial Studies* 31, pp. 2855-2896.

Adrian, T. and M. K. Brunnermeier, 2008. “CoVaR,” Staff Reports 348, *Federal Reserve Bank of New York.*

Adrian, T., E. Moench, and H. S. Shin, 2013, “Leverage Asset Pricing”, Staff Report No. 625, *Federal Reserve Bank of New York*.

Aizenman, J., Y. Jinjarak and H. Zheng, 2016, “Measuring Systemic Risk Contribution of International Mutual Funds”, Working Paper Series No. 594, *Asian Development Bank Institute*.

Allen, F., El Carletti, I. Goldstein and A. Leonello, 2015, “Moral Hazard and Government Guarantees in the Banking Industry”, *Journal of Financial Regulation*, 1, pp. 30-50.

Allen, F., El Carletti, I. Goldstein and A. Leonello, 2018, “Government Guarantees and Financial Stability”, *Journal of Economic Theory* 177, pp. 518-557.

Alogoskoufis, S. and S. Langfield, 2018, “Regulating the Doom Loop”, Working Paper Series No. 74, *European Systemic Risk Board*.

Altavilla, C., M. Pagano and S. Simonelli, 2017, “Bank Exposures and Sovereign Stress Transmission”, *Review of Finance*, pp. 2103-2139.

Ari, A., 2016, “Sovereign Risk and Bank Risk-taking”, Working Paper Series No. 1894, *European Central Bank.*

Augustin, P., H. Boustanifar, J. Breckenfelder and J. Schnitzler, 2018, “Sovereign to Corporate Risk Spillovers”, *Journal of Money, Credit and Banking* 50, pp. 857-891.

Basel Committee on Banking Supervision, 2015, “Consultative Document - Identification and Measurement of Step-in Risk”, *Bank for International Settlements*, December.

Baur, D. G., 2013, “The Degree and Structure of Dependence – A Quantile Regression Approach”, *Journal of Banking & Finance*, 37, pp. 786-798.

Becker, B. and V. Ivashina, 2018, “Financial Repression in the European Debt Crisis”, Review of Finance, pp. 83-115.

Bengtsson, E., 2016, “Investment Funds, Shadow Banking and Systemic Risk”, *Journal of Financial Regulation and Compliance* 24, pp. 60-73.

Bernal, O., J-I Gnabo and G. Guilmin, 2014, “Assessing the Contribution of Banks, Insurance and other Financial Services to Systemic Risk”, *Journal of Banking and Finance* 47, pp. 270-287.

Betz, F., N. Hautsch, T. A. Peltonen, and M. Schienle, 2016, “Systemic Risk Spillovers in the European Banking and Sovereign Network”, *Journal of Financial Stability* 25, pp 206-224.

Billio, M., M. Getmansky, A. W. Lo, and L. Pelizon, 2012, ”Econometric Measures of Systemic Risk in the Finance and Insurance Sectors”, *Journal of Financial Economics 104, pp. 535-559.*

Blavy, R., and M. Souto, 2009, “Estimating Default Frequencies and Macrofinancial Linkages in the Mexican Banking Sector”, IMF Working Paper, WP/09/109, *International Monetary Fund*.

Boccola, L., 2016, “The Pass-Through of Sovereign Risk”, *The Journal of Political Economy* 14, pp. 879-926.

Breckenfelder, J. and B. Schwaab, 2018, “Bank to Sovereign Risk Spillovers Across Borders: Evidence from the ECBs Comprehensive Assessment”, Working Paper Series No. 2193, *European Central Bank.*

Broto, C. and G. Perez-Quiros, 2011, “How can we Interpret Sovereign CDS Spreads over Time? A Dynamic Factor Approach”, *Economic Bulletin*, Banco de España, 2011.

Brownlees, C. T. and R. Engle, 2012, “Volatility, Correlation and Tails for Systemic Risk Measurement”, NYU-VLAB Working Paper.

Brownlees, C. and R. F. Engle, 2016, “SRISK: A Conditional Capital Shortfall Measure of Systemic Risk”, *The Review of Financial Studies* 30, pp. 48-79.

Brůha, J. and E. Kočenda, 2018, “Financial Stability in Europe: Banking and Sovereign Risk”, *Journal of Financial Stability* 36, pp. 305-321.

Brunnermeier, M. K., L. Garicano, P. R. Lane, M. Pagano, R. Reis, T. Santos, D. Thesmar, S. van Nieuwerburgh and D. Vayanos, 2016, “The Sovereign-Bank Diabolic Loop and ESBies”, *American Economic Review: Papers & Proceedings* 106, pp. 508-512.

Buch, C., M. Koetter and J Ohls, 2016, “Banks and Sovereign Risk: a Granular View”, *Journal of Financial Stability* 25, pp. 1-15.

Colak, G., A. Gungoraydinoglu and O. Oztekin, 2018, “Global Leverage Adjustments, Uncertainty, and Country Institutional Strength”, *Journal of Financial Intermediation*, 35A, pp. 41-56.

Committee on the Global Financial System, 2011, “The Impact of Sovereign Credit Risk on Bank Funding Conditions”, *Bank for International Settlements*.

Cont, R. and E. Schaanning, 2015, “Systemic Risk and Macro Stress Testing: A Threshold Model for Fire Sales and Price-mediated Contagion”, Working Paper.

Cooper, R. and K. Nikolov, 2018, “Government Debt and Banking Fragility: the Spreading of Strategic Uncertainty”, *International Economic Review* 59, pp. 1905-1925.

Corsetti, G., K. Kuester, A. Meier and G. Müller, 2013, “Sovereign Risk, Fiscal Policy and Macroeconomic Stability”, *The Economic Journal* 123, pp. F99-F132.

Cortes, F., P. Lindner, S. Malik and M. A. Segoviano, 2018, “A Comprehensive Multi-Sector Tool for Analysis of Systemic Risk and Interconnectedness (SyRIN)”, WP/18/14 *International Monetary Fund* Working Paper.

Dell’Ariccia, G., C. Ferreira, N. Jenkinson, L. Laeven, A. Martin, C. Minoiu and A. Popov, 2018, “Managing the Sovereign-Bank Nexus”, Working Paper Series No. 2177, *European Central Bank*.

Drechsler, I., T. Drechsler, D. Marques-Ibanez and P. Schnabl, 2016, “Who Borrows from the Lender of Last Resort?”, *The Journal of Finance* LXXI, pp. 1933-1974.

European Central Bank, “The Concept of Systemic Risk”, *Financial Stability Review,* pp. 134-142, December 2009.

European Central Bank, *Financial Stability Review*, December 2010 and 2011

European Central Bank, *Financial Stability Review*, November 2013-2018.

Farhi, E. and J. Tirole, 2018, “Deadly Embrace: Sovereign and Financial Balance Sheets Doom Loops”, *Review of Economic Studies* 85, pp. 1781-1823.

Fisher, M. and D. Gray, 2006, “Measuring Sovereign and Banking Sector Risk in Indonesia: An Application of the Contingent Claims Approach”, IMF Country Report No. 06/318, *International Monetary Fund*.

Fratzscher, M. and M. Rieth, 2015, “Monetary Policy, Bank Bailouts and the Sovereign-bank Risk Nexus in the Euro Area”, DIW Discussion Papers, No. 1448, *Deutsches Institut für Wirtschaftsforschung (DIW)*.

Gapen, M., D. F. Gray, C. H. Lim, and Y. Xiao, 2004, “The Contingent Claims Approach to Corporate Vulnerability Analysis: Estimating Default Risk and Economy-wide Risk Transfer”, IMF Working Paper WP/04/121, *International Monetary Fund*.

Gennaioli, N. A. Martin and S. Rossi, 2014, “Sovereign Default, Domestic Banks, and Financial Institutions”, *Journal of Finance*, 69(2):819-866.

Gibson, H. D., S. G. Hall and G. S. Tavlas, 2018, “Measuring Systemic Vulnerability in European Banking Systems”, *Journal of Financial Stability* 36, pp. 279-292.

Gorea, D. and D. Radev, 2014, “Tail Risk and Sovereign Debt”, *International Review of Economics and Finance, 30, pp. 78-100*

Gray, D. F. and S. W. Malone, 2008, *Macrofinancial Risk Analysis*, John Wiley & Sons, Ltd.

Gray, D. and A. Jobst, 2011, “Modelling Systemic Financial Sector and Sovereign Risk”, *Sveriges Riksbank Review,* pp. 68-106.

Hansen, L. P., 2012, “Challenges in Identifying and Measuring Systemic Risk, Working Paper 18505, *National Bureau of Economic Research*, pp. 15-30.

Hespeler, F. and G. Loiacono, 2017, “Monitoring Systemic Risk in the Hedge Fund Sector”, *Quantitative Finance*, 17, pp. 1859-1883.

Houweling, P., and T. Vorst (2005), “Pricing Default Swaps: Empirical Evidence”, *Journal of International Money and Finance*, 24, pp. 1220–1225.

Huang, X., Zhou, H. and H. Zhu, 2010, “Assessing the Systemic Risk of a Heterogeneous Portfolio of Banks during the Recent Financial Crisis,” BIS Working Paper 296.

Idier, J. G. Lamé, J-S. Méssonier, 2014, “How Useful is the Marginal Expected Shortfall for the Measurement of Systemic Exposure?: A Practical Assessment”, *Journal of Banking and Finance* 7, p. 134-146.

International Monetary Fund, 2010, “Financial Sector Assessment Program: United States of America. Stress Testing Technical Note”, IMF Country Report No. 10/244, *International Monetary Fund*.

International Monetary Fund, 2010, “Financial Sector Assessment Program: Germany. Stress Testing Technical Note”, IMF Country Report No.11/371, *International Monetary Fund*.

Jin, X. and F. Nadal De Simone, 2011, “Market- and Book-based Models of Probability of Default for Developing Macroprudential Policy Tools”, Working Paper No. 65, *Banque centrale du Luxembourg*.

Jin, X. and F. Nadal De Simone, 2012, “An Early-warning and Dynamic Forecasting Framework of Default Probabilities for the Macroprudential Policy Arsenal?“, Working Paper No. 75, *Central Bank of Luxembourg*.

Jin, X. and F. Nadal De Simone, 2014a, “Tracking Changes in the Intensity of Financial Sector’s Systemic Risk”, Working Paper No. 102, *Banque centrale du Luxembourg*.

Jin, X. and F. Nadal De Simone, 2014b, “Banking Systemic Vulnerabilities: A Tail-risk Dynamic CIMDO Approach”, *Journal of Financial Stability*, vol. 14, 2014, pp. 81-101.

Jin, X. and F. Nadal De Simone, 2014c, “Investment Funds Vulnerabilities: A Tail-risk Dynamic CIMDO Approach”, Working Paper No. 95, *Banque centrale du Luxembourg.*
Jin, X. and F. Nadal De Simone, 2018, “(Systemic) Risk-taking in the Euro Area Investment Fund Industry”, Working Paper.
Kaal, W. A. and T. A. Krause, 2016, “Hedge Funds and Systemic Risk”, Working Paper.
Kabundi, A. and F. Nadal De Simone, 2018, “Monetary Policy and Systemic Risk-taking in the Euro Area Banking Sector”, *Economic Modelling*, forthcoming.
Kallestrup, R., D. Lando and A. Murgoci, 2016, *Journal of Empirical Finance* 38, pp. 374-393.
Korte, J. and S. Steffen, 2015, “Zero Risk contagion – Banks’ Sovereign Exposure and Sovereign Risk Spillovers”, SSRN.
Lehecka, G. and E. Ubl, 2015, “Analyzing the Systemic Risks of Alternative Investment Funds on AIFMD Reporting: A Primer”, Financial Stability Report 30, *Oesterreichische Nationalbank* pp. 62-70.
Leonello, A., 2018, “Government Guarantees and the Two-way Feedback Between Banking and Sovereign Debt Crises”, *Journal of Financial Economics* 130, 592-619.
Lucas, A., B. Schwaab and X. Zhang, 2014, “Conditional Euro Area Sovereign Default Risk”, Journal of Business & Economic Statistics, 32(2):271-284.
Malik, S. and T. T. Xu, 2017, “Interconnectedness of Global Systemically-important Banks and Insurers”, WP/17/210, *International Monetary Fund*.
Manzo, G. and A. Picca, 2014, “The sovereign Nature of Systemic Risk”, monograph.
Marques, L. B., R. Correa, and H. Spinoza, “International Evidence on Government Support and Risk Taking in the Banking Sector”, 2013, IMF Working Paper WP/13/94, *International Monetary Fund*.
Merton, R., 1974, “On the Pricing of Corporate Debt: The Risk Structure of Interest Rates”, *Journal of Finance* 29, pp. 449-470.
Nelsen, R., 1999, "An Introduction to Copulas", Lecture Notes in Statistics 139, Springer.
Pagano, M. S. and J. Sedunov, 2016, “A Comprehensive Approach to Measuring the Relation Between Systemic Risk Exposure and Sovereign Debt”, *Journal of Financial Stability* 23, pp. 62-78.
Patro, D. K., M. Qi and X. Sun, 2013, “A Simple Indicator of Systemic Risk”, *Journal of Financial Stability* 9, pp. 105-116.
Popescu, A. and C. Turcu, 2017, “Sovereign Debt and Systemic Risk in the Eurozone – A Macroeconomic Perspective”, *Economic Modelling* 67, pp. 275-284.
Qi, H. and D. Sun, 2006, “A Quadratically Convergent Newton Method for Computing the Nearest Correlation Matrix”, SIAM Journal on Matrix Analysis and Applications, 28(2):360-385.
Radev, D., 2012, “Assessing Systemic Fragility – A Probabilistic Perspective”, Working Paper, GSEFM Frankfurt-Mainz-Darmstadt and Johannes Gutenberg University Mainz, 2012.
Reinhart, C. and K. Rogoff, 2009, “This Time is Different – Eight Centuries of Financial Folly”, *Princeton University Press*.
Roccioletti, S., 2016, Backtesting Value at Risk and Expected Shortfall, Chapter 2, Sp*ringer.*
Segoviano, M., 2006, “Consistent Information Multivariate Density Optimization Methodology”, FMG Discussion Papers #557.
Segoviano, M. and C. Goodhart, 2009, “Banking Stability Measures”, IMF Working Paper WP/09/04*, International Monetary Fund*.

Shaw, F. and P. G. Dunne, 2017, “Investment Fund Risk: the Tale in the Tails”, Research Technical Paper 01/RT/17, *Central Bank of Ireland*.

Silva, W., H. Kimura and V. A. Sobreiro, 2017, “An Analysis of the Literature on Systemic Risk: A Survey” *Journal of Financial Stability*, 28, pp. 91-114.

Souto, M., Tabak, B., and F. Vazquez, 2009, “Linking Financial and Macroeconomic Factors to Credit Risk Indicators of Brazilian Banks”, *Banco Central do Brasil*, Working Paper No. 189.

Vergote, O., 2016, “Credit Risk Spillovers between Financials and Sovereigns in the Euro Area during 2007-2015”, Working Paper Series No. 1898, *European Central Bank*.

Xu, S., C. Forbes and I. Hwang, 2017, “Systemic Risk in the European Sovereign and Banking System”, *Quantitative Finance* 17, pp. 633-656.

Yu, S., 2017, “Sovereign and Bank Interdependencies-Evidence from the CDS Market”, *Research in International Business and Finance*, 39, pp. 68-84.

Figure 1a: Luxembourg OSIIs

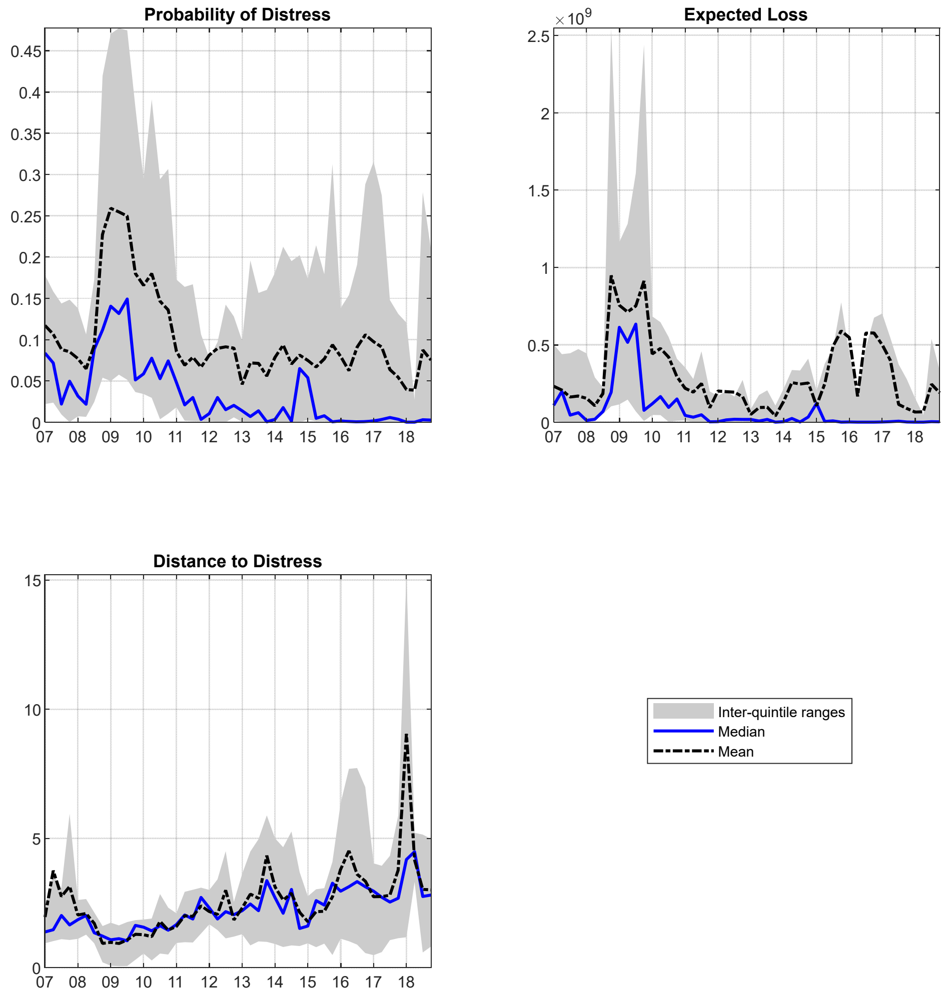


Figure 1b: G-SIBs

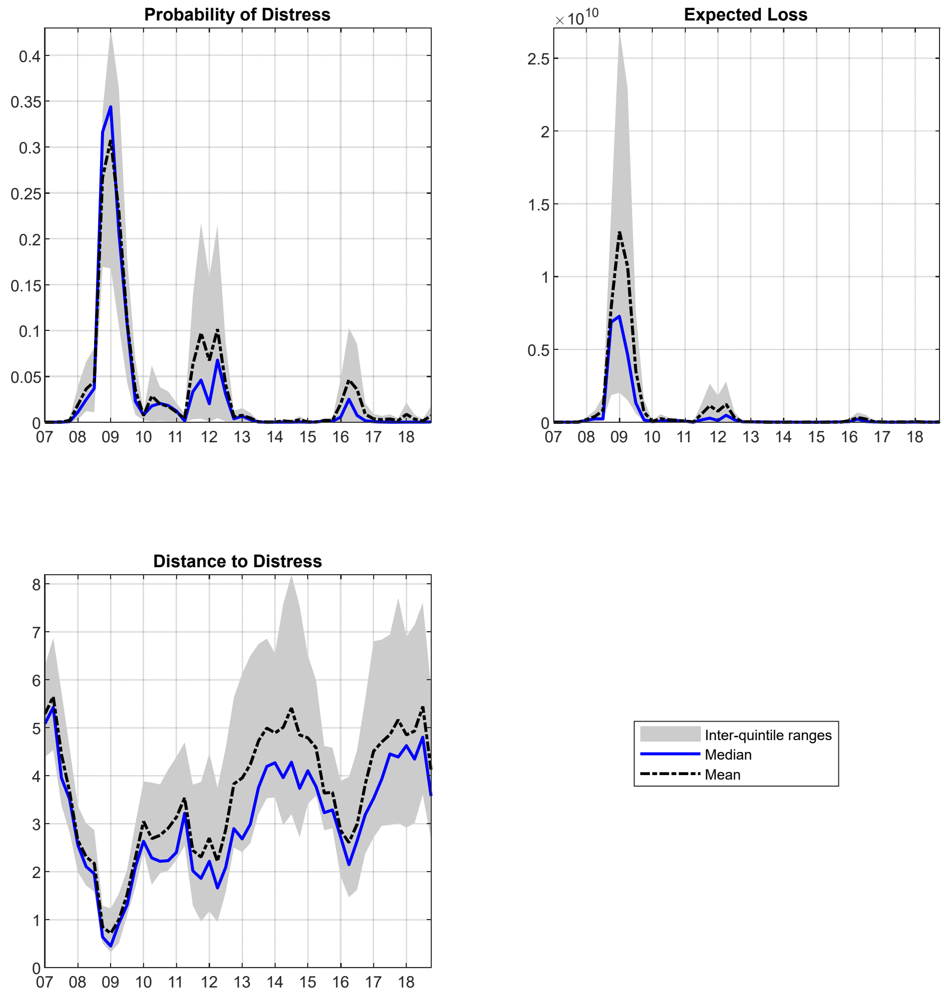


Figure 1c: Investment Funds

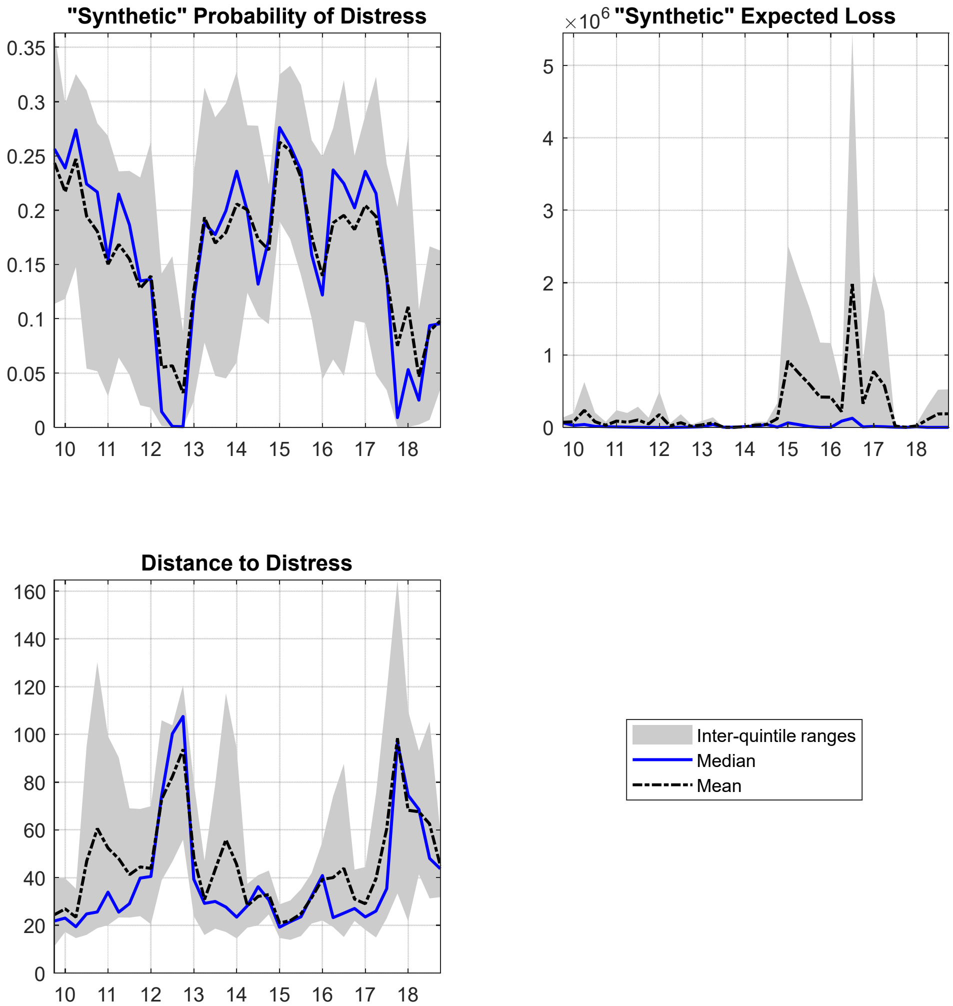


Figure 2: Asset Return Correlations among OSIIs, G-SIBs and Investment Funds

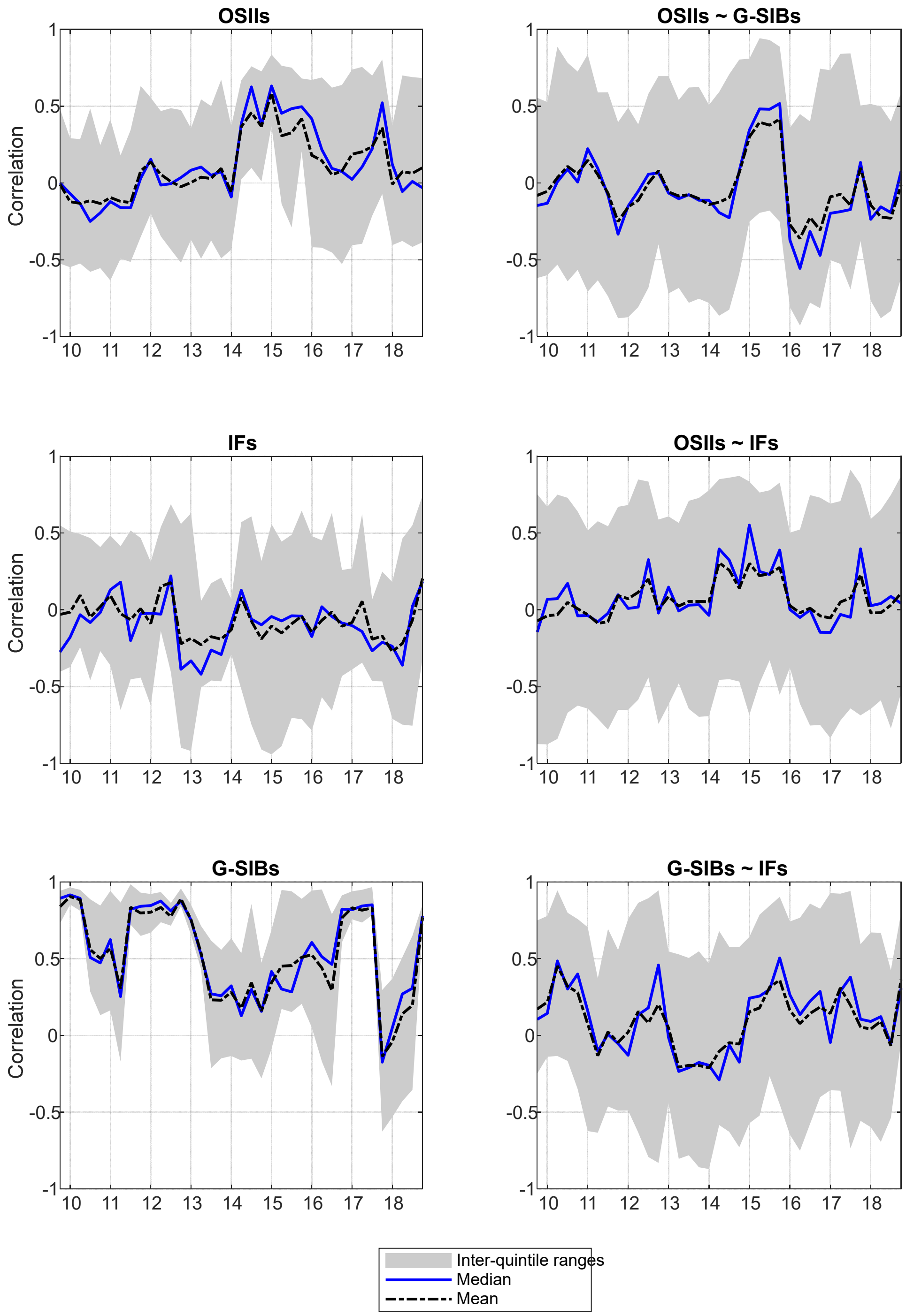
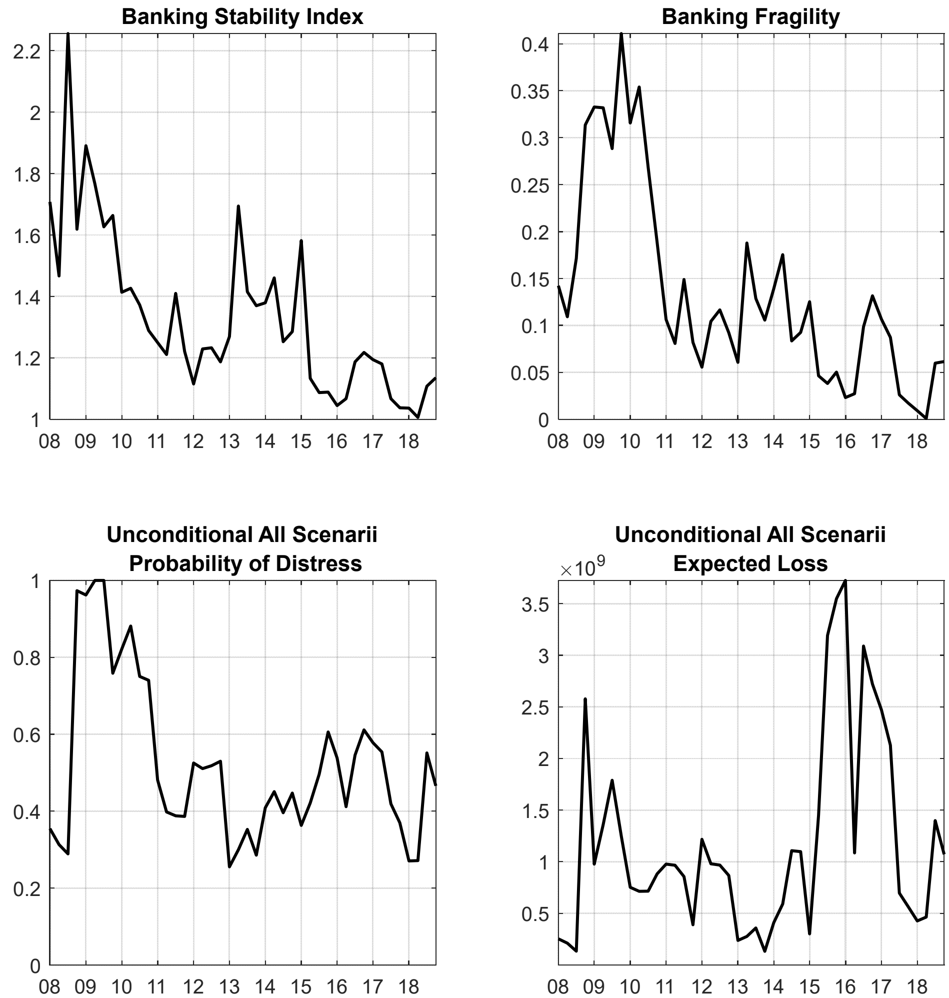
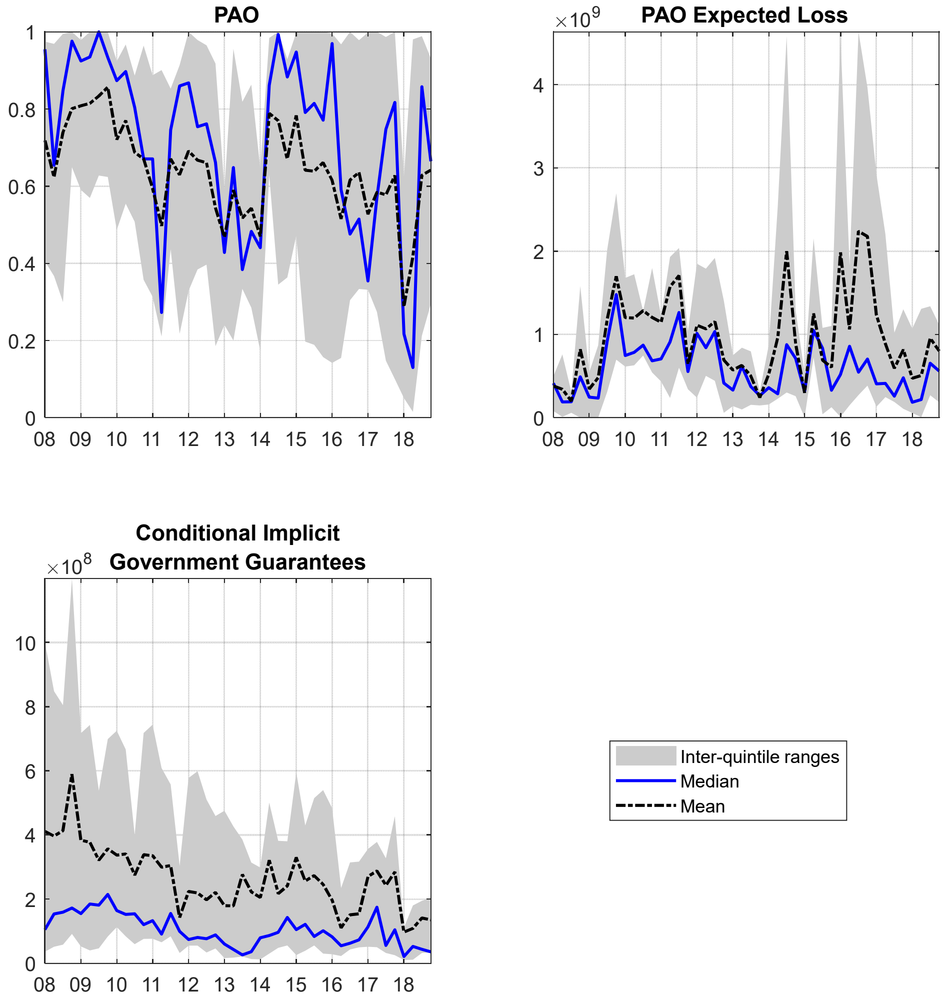


Figure 3: Systemic Risk Measures for OSIIs



Note: All scenarii PDs and Els result from summing the default of one, two, three, up to the seven OSIIs.

Figure 4: PAO, PAO Expected Loss, and Conditional Implicit Government Guarantees for OSIIs



Note: conditional implicit government guarantees are computed by adding the loss-given-default of the OSII assumed to have defaulted to the conditional ELs of at least one other OSII, weighted either by the share of the Luxembourg government in the OSII's equity, or by the OSII's share in the total assets of the banking group to which it belongs.

Figure 5: PAO, PAO Expected Loss, and Conditional Implicit Government Guarantees for OSIIs stemming from G-SIBs

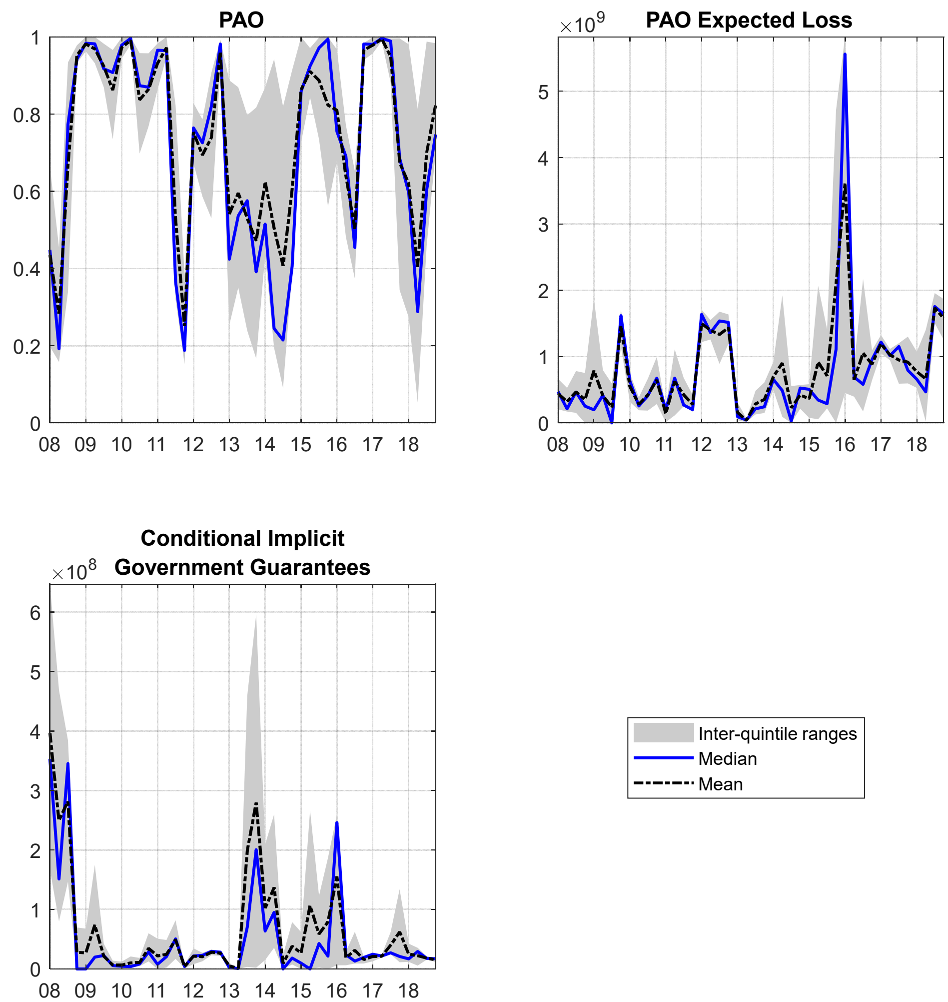


Figure 6: PAO, PAO Expected Loss, and Conditional Implicit Government Guarantees for OSIIs stemming from Investment Funds

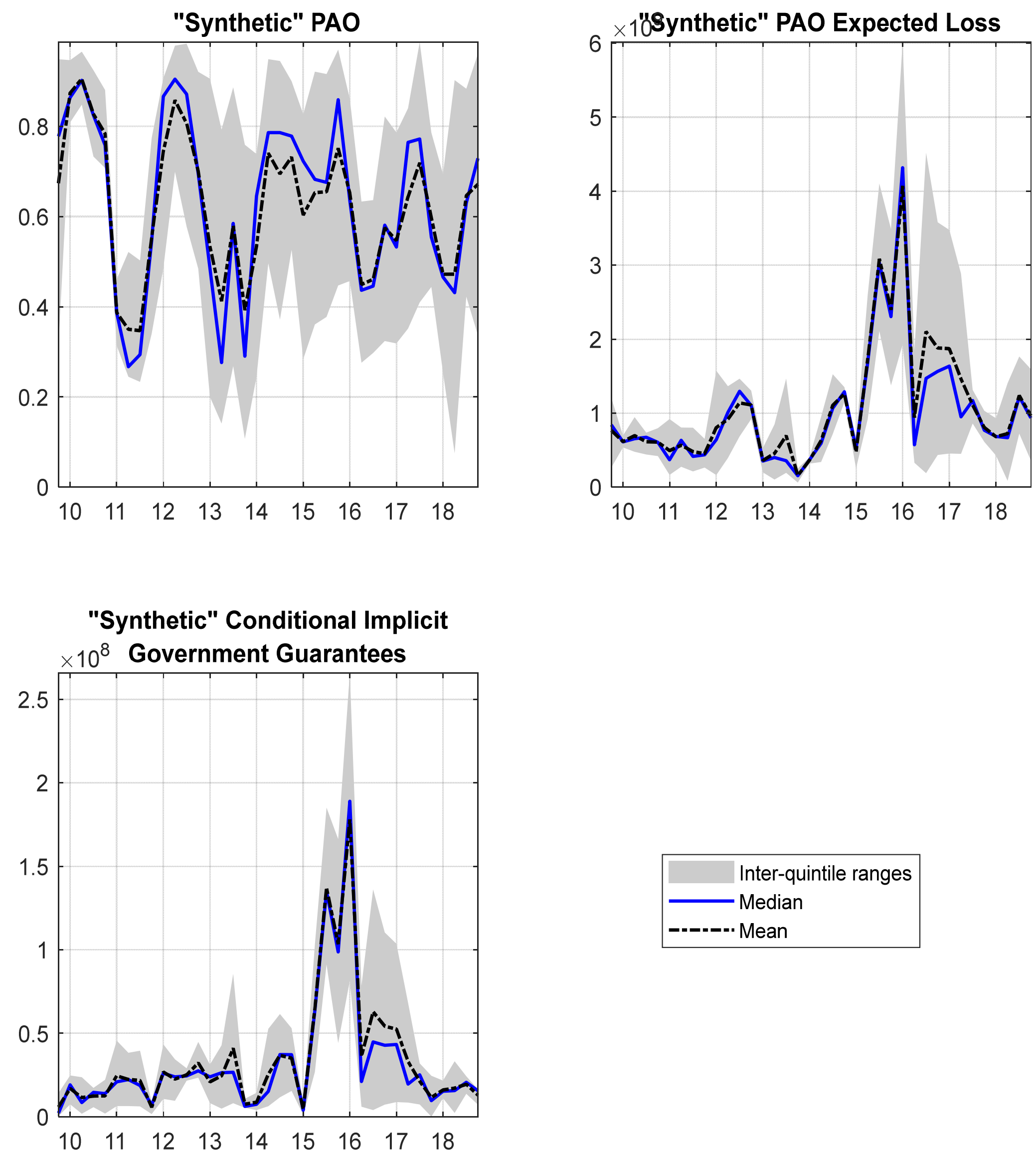


Figure 7: Risk Measures for the Non-financial Corporate and Household Sectors

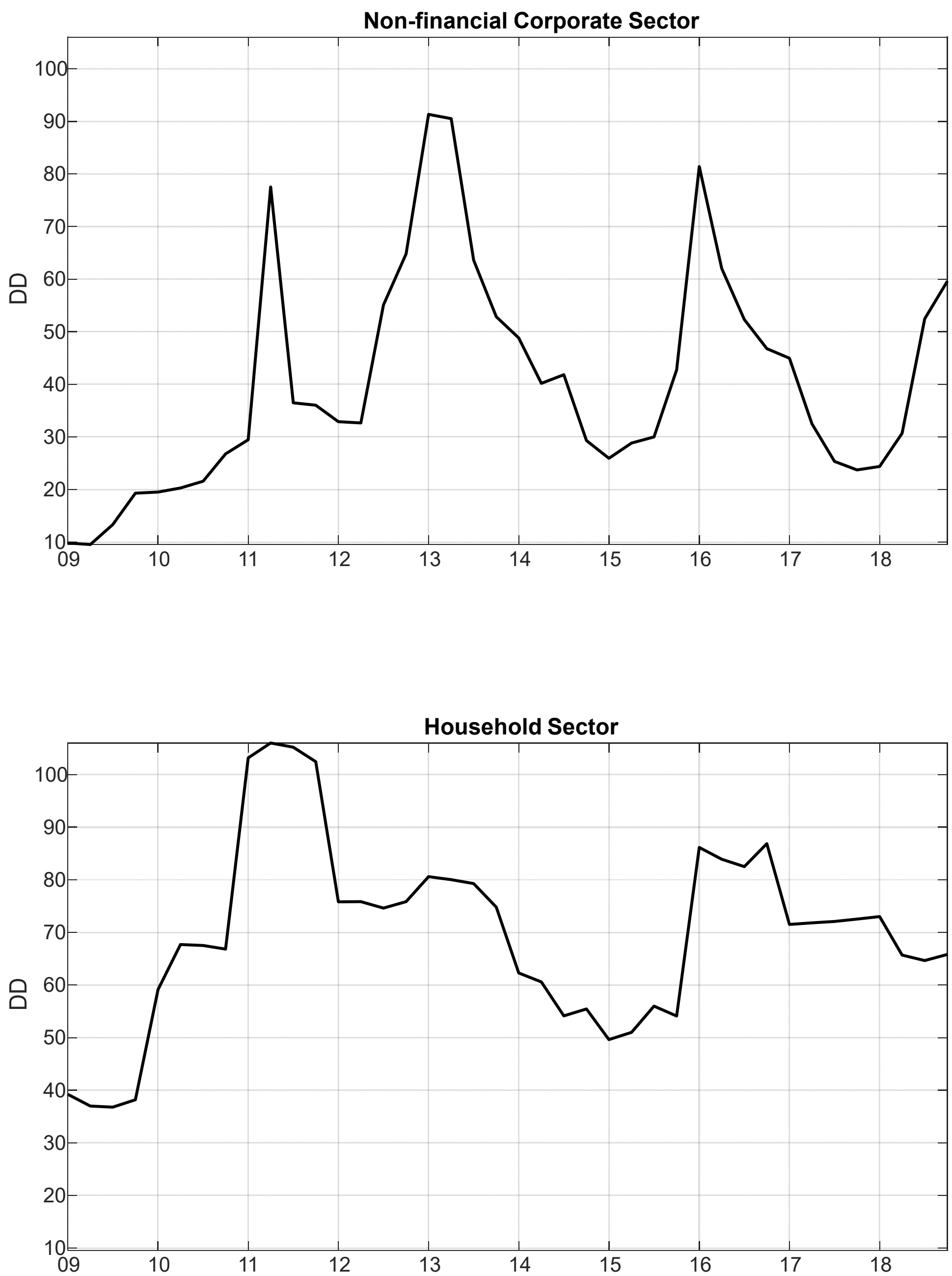


Figure 8: Sovereign-Risk Measures for Luxembourg

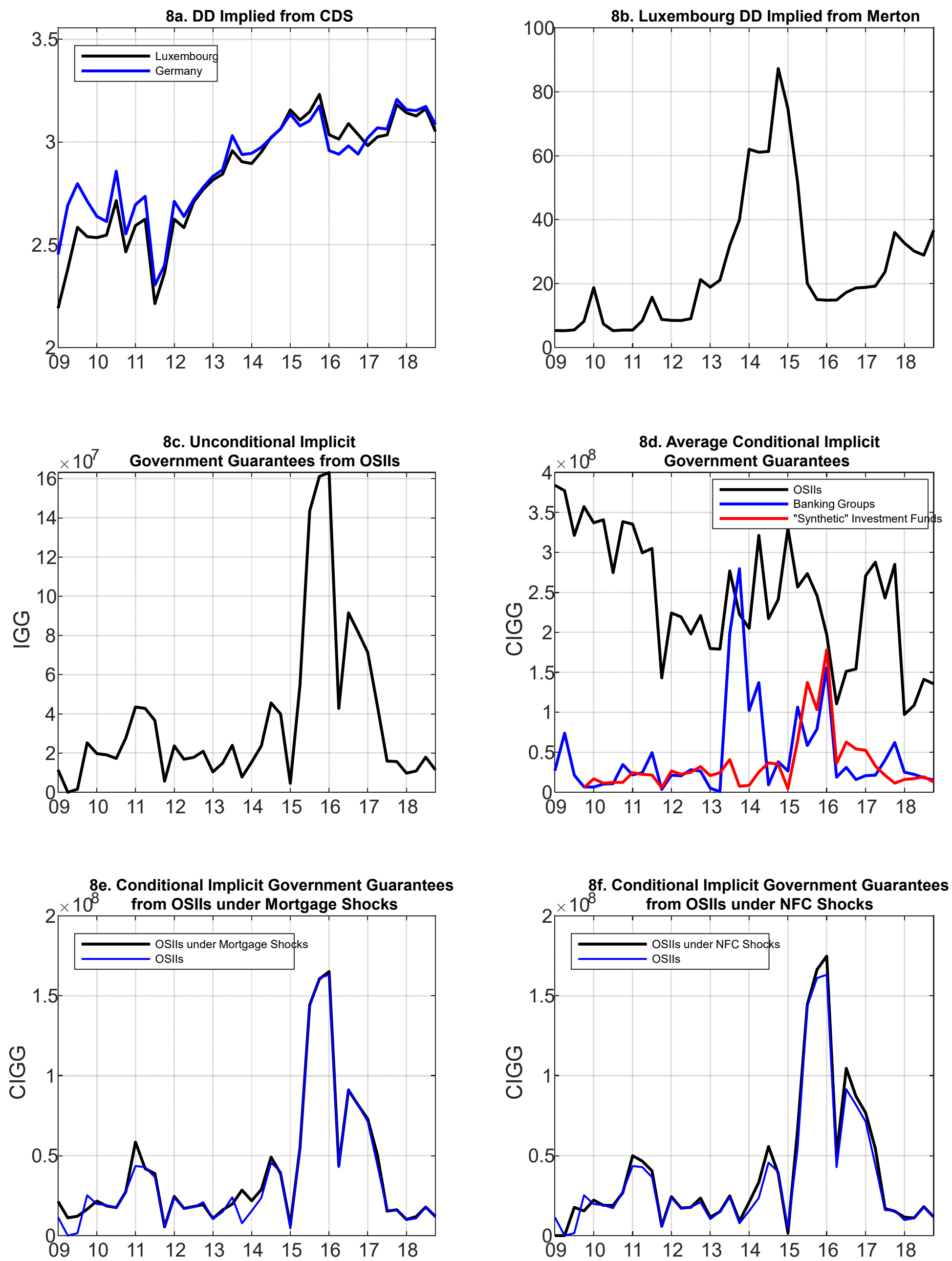


Figure 9: Luxembourg Sovereign Risk Conditional DD under Conditional Implicit Government Guarantees shocks (assuming 40% higher Sovereign Asset Value Volatility)

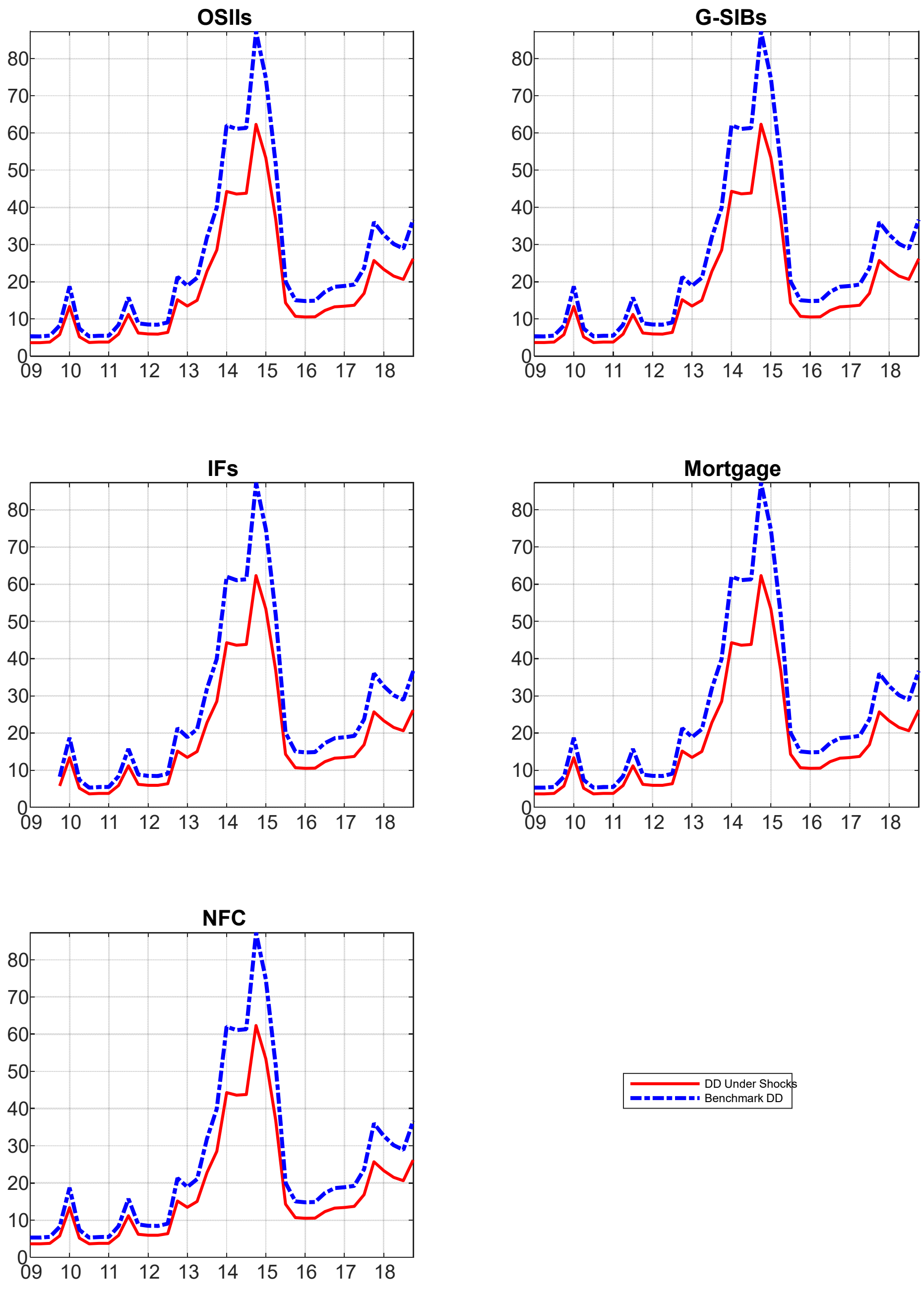


Table 1: The Expected Losses (in Billion) of DDM between OSIIs and Banking Groups and Investment Funds

	OSIIs								Banking Groups						Investment Funds				
OSIIs	OSII_A	OSII_B	OSII_C	OSII_D	OSII_E	OSII_F	OSII_G	Average	G-SIB_A	G-SIB_B	G-SIB_C	G-SIB_D	G-SIB_E	Average	IF_A	IF_B	IF_C	IF_D	Average
31-Dec-2010																			
OSII_A	0.97	0.00	0.00	0.00	0.00	0.00	0.04	0.14	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.03	0.00	0.01
OSII_B	0.00	7.12	5.63	0.04	1.74	1.68	0.63	2.40	0.98	0.29	0.91	3.91	0.90	1.40	0.75	0.57	0.66	0.02	0.50
OSII_C	0.00	0.14	1.58	0.05	0.12	0.02	0.01	0.27	0.03	0.00	0.03	1.11	0.67	0.37	0.02	0.04	0.06	0.00	0.03
OSII_D	0.00	0.00	0.01	0.79	0.00	0.00	0.01	0.11	0.08	0.04	0.02	0.02	0.47	0.12	0.15	0.00	0.01	0.02	0.04
OSII_E	0.00	0.20	0.57	0.15	2.02	0.39	0.00	0.47	0.21	0.59	0.72	0.54	0.09	0.43	0.00	0.51	0.03	0.42	0.24
OSII_F	0.00	0.32	0.13	0.04	0.65	0.70	0.00	0.26	0.26	0.54	0.58	0.10	0.00	0.30	0.01	0.54	0.00	0.33	0.22
OSII_G	1.02	0.15	0.10	0.57	0.00	0.00	1.03	0.41	0.25	0.04	0.01	0.16	0.67	0.23	0.86	0.02	0.65	0.23	0.44
Average	0.28	1.13	1.15	0.23	0.65	0.40	0.24	0.58	0.26	0.22	0.32	0.84	0.40	0.41	0.26	0.24	0.21	0.15	0.21
31-Dec-2011																			
OSII_A	0.38	0.00	0.00	0.00	0.00	0.01	0.00	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
OSII_B	0.01	1.33	0.00	0.07	0.00	0.05	0.01	0.21	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.06	0.04	0.03
OSII_C	0.00	0.00	0.83	0.00	0.01	0.01	0.00	0.12	0.01	0.02	0.01	0.00	0.00	0.01	0.11	0.00	0.00	0.00	0.03
OSII_D	0.00	1.72	0.00	2.19	0.33	0.04	0.41	0.67	0.00	0.00	0.03	0.00	0.00	0.01	0.00	0.00	0.07	0.53	0.15
OSII_E	0.00	0.00	0.07	0.02	0.87	0.00	0.02	0.14	0.01	0.01	0.01	0.03	0.04	0.02	0.16	0.04	0.00	0.01	0.05
OSII_F	0.02	0.00	0.00	0.00	0.00	0.10	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.01
OSII_G	0.00	0.81	1.17	1.12	1.24	0.39	1.26	0.86	0.23	0.39	0.57	0.20	0.06	0.29	0.84	0.46	0.25	1.02	0.64
Average	0.06	0.55	0.30	0.49	0.35	0.09	0.24	0.30	0.04	0.06	0.09	0.03	0.01	0.05	0.16	0.08	0.06	0.23	0.13
31-Dec-2012																			
OSII_A	0.73	0.01	0.03	0.00	0.00	0.01	0.00	0.11	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00
OSII_B	2.17	3.24	0.42	0.33	0.05	0.21	0.12	0.93	0.03	0.00	0.00	0.03	0.01	0.02	0.00	0.88	0.06	0.35	0.32
OSII_C	0.36	0.02	1.17	0.00	0.00	0.01	0.02	0.23	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.02	0.01
OSII_D	0.00	0.01	0.00	1.07	0.02	0.00	0.01	0.16	0.13	0.05	0.03	0.09	0.14	0.09	0.01	0.01	0.02	0.05	0.02
OSII_E	0.00	0.00	0.00	0.05	0.86	0.00	0.00	0.13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.17	0.00	0.08	0.06
OSII_F	0.20	0.04	0.03	0.00	0.00	0.38	0.06	0.10	0.02	0.08	0.05	0.04	0.13	0.06	0.08	0.00	0.12	0.00	0.05
OSII_G	2.01	0.52	1.78	1.09	0.00	1.37	2.02	1.26	1.95	1.82	1.83	2.01	1.90	1.90	1.72	0.00	1.85	0.66	1.06
Average	0.78	0.55	0.49	0.36	0.13	0.28	0.32	0.42	0.31	0.28	0.27	0.31	0.31	0.30	0.26	0.15	0.29	0.16	0.22
31-Dec-2013																			
OSII_A	1.03	0.00	0.00	0.00	0.24	0.00	0.00	0.18	0.00	0.20	0.77	0.00	0.40	0.27	0.00	0.00	0.01	0.01	0.00
OSII_B	0.00	0.64	0.00	0.00	0.00	0.00	0.00	0.09	0.01	0.01	0.00	0.01	0.00	0.01	0.06	0.00	0.00	0.00	0.02
OSII_C	0.00	0.00	0.62	0.01	0.00	0.00	0.00	0.09	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00
OSII_D	0.00	0.00	0.00	0.31	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00
OSII_E	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
OSII_F	0.00	0.51	0.09	0.52	0.04	0.66	0.29	0.30	0.01	0.03	0.04	0.35	0.01	0.09	0.38	0.07	0.03	0.03	0.13
OSII_G	0.00	0.52	0.38	0.76	0.04	0.53	0.76	0.43	0.00	0.00	0.00	0.58	0.00	0.12	0.67	0.35	0.06	0.08	0.29
Average	0.15	0.24	0.16	0.23	0.05	0.17	0.15	0.16	0.00	0.03	0.12	0.13	0.06	0.07	0.16	0.06	0.01	0.02	0.06
31-Dec-2014																			
OSII_A	0.85	0.01	0.30	0.04	0.06	0.00	0.04	0.19	0.10	0.00	0.00	0.00	0.23	0.07	0.00	0.01	0.02	0.00	0.01
OSII_B	7.01	6.55	3.38	2.40	1.35	1.04	5.54	3.90	5.08	0.21	0.05	0.11	6.15	2.32	0.25	1.70	2.24	1.70	1.48
OSII_C	0.00	0.00	0.46	0.00	0.00	0.00	0.00	0.07	0.25	0.00	0.00	0.00	0.01	0.05	0.00	0.00	0.00	0.00	0.00
OSII_D	1.64	0.21	1.37	1.59	0.34	0.00	0.56	0.82	0.20	0.58	0.63	0.00	0.12	0.30	0.00	0.40	0.37	0.00	0.19
OSII_E	0.00	0.00	0.00	0.00	0.33	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
OSII_F	0.07	0.24	0.07	0.00	0.96	1.38	0.20	0.42	0.31	0.00	0.00	0.54	0.99	0.37	1.28	0.00	0.50	0.95	0.68
OSII_G	0.52	0.14	0.34	0.17	0.05	0.02	0.51	0.25	0.52	0.03	0.01	0.01	0.49	0.21	0.02	0.04	0.10	0.04	0.05
Average	1.44	1.02	0.85	0.60	0.44	0.35	0.98	0.81	0.92	0.12	0.10	0.09	1.14	0.48	0.22	0.31	0.46	0.39	0.34
31-Dec-15																			
OSII_A	0.66	0.00	0.56	0.19	0.37	0.00	0.00	0.25	0.05	0.35	0.04	0.00	0.00	0.09	0.00	0.00	0.00	0.01	0.00
OSII_B	7.76	10.70	10.00	2.67	9.78	0.08	1.54	6.08	8.97	6.34	2.69	0.00	0.00	3.60	4.98	2.97	6.82	2.28	4.26
OSII_C	0.33	0.00	0.63	0.03	0.51	0.00	0.00	0.21	0.11	0.38	0.08	0.00	0.00	0.11	0.01	0.00	0.07	0.00	0.02
OSII_D	0.21	0.00	0.06	0.37	0.02	0.01	0.00	0.10	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
OSII_E	0.11	0.00	0.27	0.00	0.31	0.00	0.00	0.10	0.06	0.19	0.04	0.00	0.00	0.06	0.01	0.00	0.04	0.00	0.01
OSII_F	0.00	0.00	0.00	0.02	0.00	0.25	0.00	0.04	0.02	0.07	0.00	0.01	0.04	0.03	0.01	0.00	0.01	0.00	0.01
OSII_G	0.82	0.19	1.24	0.84	1.32	1.04	1.46	0.99	0.41	1.43	1.44	1.44	0.56	1.05	1.39	0.00	0.83	1.08	0.82
Average	1.41	1.56	1.82	0.59	1.76	0.20	0.43	1.11	1.37	1.25	0.61	0.21	0.09	0.71	0.91	0.43	1.11	0.48	0.73
31-Dec-16																			
OSII_A	0.18	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
OSII_B	8.38	9.56	0.00	1.85	0.00	2.21	3.60	3.66	4.06	0.49	1.86	2.17	0.00	1.72	2.39	6.21	0.77	0.00	2.34
OSII_C	0.00	0.00	0.21	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
OSII_D	0.00	0.00	0.01	0.81	0.01	0.00	0.00	0.12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00
OSII_E	0.00	0.00	0.10	0.01	0.51	0.00	0.00	0.09	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
OSII_F	0.09	0.04	0.78	0.75	0.40	0.78	0.03	0.41	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.04	0.19	0.06
OSII_G	0.00	0.35	0.00	0.08	0.00	0.14	1.25	0.26	1.20	1.22	1.23	1.16	1.27	1.22	0.14	0.47	1.02	0.09	0.43
Average	1.24	1.42	0.16	0.50	0.13	0.45	0.70	0.66	0.75	0.25	0.44	0.48	0.18	0.42	0.37	0.95	0.26	0.04	0.41
31-Dec-17																			
OSII_A	1.26	0.04	0.70	0.14	0.43	0.06	0.00	0.38	0.00	0.02	0.21	0.00	0.17	0.08	0.07	0.00	0.00	0.12	0.05
OSII_B	4.59	2.88	0.28	1.60	0.90	0.03	0.10	1.48	0.00	0.55	0.87	0.41	2.89	0.95	0.69	1.07	0.00	0.56	0.58
OSII_C	0.00	0.00	0.58	0.00	0.00	0.00	0.00	0.08	0.00	0.01	0.08	0.00	0.00	0.02	0.01	0.00	0.00	0.01	0.01
OSII_D	0.00	0.00	0.00	0.34	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.01
OSII_E	0.02	0.00	0.04	0.01	0.06	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
OSII_F	0.05	0.00	0.13	0.03	0.08	0.32	0.00	0.09	0.02	0.00	0.01	0.00	0.00	0.01	0.06	0.00	0.02	0.02	0.02
OSII_G	0.00	0.08	0.20	0.75	0.56	0.48	1.07	0.45	0.72	0.00	0.00	1.03	0.58	0.47	0.08	0.16	0.91	0.46	0.40
Average	0.85	0.43	0.27	0.41	0.29	0.13	0.17	0.36	0.11	0.08	0.17	0.21	0.52	0.22	0.13	0.18	0.13	0.17	0.15
31-Dec-18																			
OSII_A	0.59	0.00	0.00	0.00	0.00	0.00	0.00	0.08	0.00	0.00	0.04	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
OSII_B	0.00	1.09	0.02	0.45	0.02	0.00	0.06	0.24	0.07	0.15	0.07	0.03	0.05	0.07	0.15	0.16	0.52	0.01	0.21
OSII_C	0.00	0.00	0.46	0.00	0.19	0.00	0.00	0.09	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
OSII_D	0.00	0.05	0.23	1.11	0.17	0.00	0.01	0.22	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.04	0.00	0.02
OSII_E	0.00	0.00	0.17	0.00	0.17	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
OSII_F	3.06	0.01	0.45	0.00	0.30	3.44	0.86	1.16	2.19	2.01	1.97	3.04	3.28	2.50	1.63	0.00	0.10	1.90	0.91
OSII_G	0.09	0.67	1.25	0.76	1.15	0.21	1.28	0.77	0.24	0.30	0.12	0.57	1.01	0.45	0.79	0.19	1.11	0.08	0.54
Average	0.53	0.26	0.37	0.33	0.28	0.52	0.32	0.37	0.36	0.35	0.31	0.52	0.62	0.43	0.37	0.05	0.25	0.28	0.24

Note: These matrices present the expected loss of each of the OSIIs in the row, conditonal on each of the financial institutions in the columes become distressed.

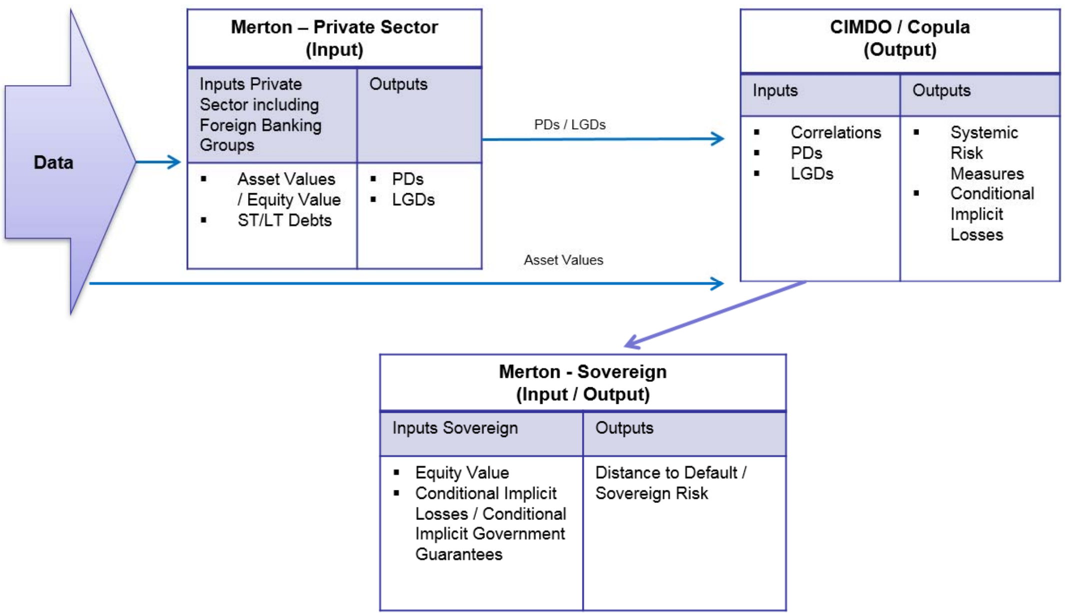
Table 2: The Systemic Risk Transmitting Channels from Financial Sector, Non-financial Corporate Sector and & Household Sector

		OSIIs								Banking Groups						Investment Funds					NFC & Household	
Systemic Risk Transmitting through OSIIs	Date	OSII_A	OSII_B	OSII_C	OSII_D	OSII_E	OSII_F	OSII_G	Average	G-SIB_A	G-SIB_B	G-SIB_C	G-SIB_D	G-SIB_E	Average	IF_A	IF_B	IF_C	IF_D	Average	Non-financial Corporate Sector	Household Sector
Expected Loss in Billion (include the assumed distressed OSIIs)	31-Dec-2010	2.064	7.595	4.923	1.469	2.567	2.328	1.672	3.231	0.676	0.182	0.391	0.723	1.269	0.648	0.807	0.434	0.776	0.415	0.608	0.848	0.858
	31-Dec-2011	0.399	1.885	1.860	3.268	1.910	0.478	1.681	1.640	0.201	0.349	0.502	0.185	0.155	0.278	0.497	0.376	0.217	0.721	0.453	0.389	0.386
	31-Dec-2012	0.734	3.653	2.699	2.347	0.927	1.771	2.190	2.046	1.647	1.356	1.516	1.629	1.032	1.436	1.343	0.993	1.216	0.891	1.111	0.918	0.841
	31-Dec-2013	1.029	0.801	0.880	0.475	0.299	1.188	1.052	0.818	0.081	0.221	0.823	0.246	0.398	0.354	0.241	0.259	0.058	0.070	0.157	0.137	0.149
	31-Dec-2014	0.851	6.837	1.169	2.033	1.445	2.190	3.369	2.556	0.000	0.536	0.611	0.528	0.431	0.421	1.232	1.346	1.114	1.354	1.261	1.055	0.998
	31-Dec-2015	0.657	10.888	0.768	1.390	0.636	1.310	2.969	2.660	8.066	0.000	1.108	1.360	0.007	2.108	1.261	2.966	3.712	1.643	2.395	3.644	3.467
	31-Dec-2016	7.607	9.933	0.825	1.516	0.898	2.922	4.829	4.076	0.873	1.217	0.977	0.957	0.410	0.887	2.224	4.161	0.907	0.233	1.881	2.886	2.720
	31-Dec-2017	4.556	2.990	0.689	1.421	0.598	0.796	1.177	1.747	0.668	0.524	0.794	0.972	1.631	0.918	0.586	1.103	0.866	0.672	0.806	0.654	0.584
	31-Dec-2018	3.475	1.714	0.461	1.507	0.730	3.651	2.203	1.963	1.869	1.633	1.645	1.867	0.871	1.577	1.107	0.186	0.764	1.803	0.965	1.076	1.066
Conditional Implicit Government Guarantees in Billion	31-Dec-2010	0.990	0.354	0.688	0.055	0.120	0.079	0.084	0.339	0.028	0.009	0.016	0.040	0.080	0.035	0.021	0.006	0.022	0.000	0.012	0.027	0.027
	31-Dec-2011	0.380	0.078	0.295	0.099	0.102	0.013	0.035	0.143	0.004	0.004	0.008	0.002	0.000	0.004	0.009	0.005	0.000	0.009	0.006	0.006	0.005
	31-Dec-2012	0.742	0.145	0.428	0.067	0.089	0.029	0.048	0.221	0.028	0.025	0.029	0.030	0.019	0.026	0.026	0.051	0.022	0.029	0.032	0.024	0.019
	31-Dec-2013	1.029	0.036	0.215	0.013	0.235	0.013	0.016	0.223	0.000	0.200	0.768	0.004	0.425	0.280	0.005	0.005	0.012	0.007	0.007	0.009	0.028
	31-Dec-2014	0.855	0.328	0.194	0.057	0.064	0.048	0.143	0.241	0.032	0.012	0.018	0.003	0.125	0.038	0.007	0.059	0.039	0.036	0.035	0.039	0.039
	31-Dec-2015	0.690	0.523	0.293	0.058	0.031	0.025	0.102	0.246	0.348	0.000	0.022	0.026	0.000	0.079	0.040	0.144	0.176	0.054	0.103	0.166	0.160
	31-Dec-2016	0.413	0.307	0.073	0.029	0.052	0.070	0.136	0.154	0.019	0.023	0.018	0.019	0.000	0.016	0.069	0.128	0.017	0.003	0.054	0.087	0.082
	31-Dec-2017	1.309	0.105	0.364	0.020	0.124	0.048	0.026	0.285	0.014	0.008	0.106	0.021	0.162	0.062	0.000	0.027	0.019	0.000	0.011	0.015	0.016
	31-Dec-2018	0.613	0.036	0.159	0.043	0.031	0.034	0.034	0.136	0.017	0.016	0.019	0.017	0.007	0.015	0.016	0.004	0.015	0.017	0.013	0.012	0.012
Change of Sovereign Risk DD (assuming 40% higher sovereign asset value volatility)	31-Dec-2010	-1.726	-1.713	-1.720	-1.707	-1.708	-1.707	-1.707	-1.713	-1.706	-1.706	-1.706	-1.706	-1.707	-1.706	-1.706	-1.706	-1.706	-1.706	-1.706	-1.706	-1.706
	31-Dec-2011	-2.635	-2.630	-2.634	-2.630	-2.630	-2.629	-2.629	-2.631	-2.629	-2.629	-2.629	-2.629	-2.629	-2.629	-2.629	-2.629	-2.629	-2.629	-2.629	-2.629	-2.629
	31-Dec-2012	-6.160	-6.131	-6.144	-6.127	-6.128	-6.125	-6.126	-6.135	-6.125	-6.125	-6.125	-6.125	-6.125	-6.125	-6.125	-6.126	-6.125	-6.125	-6.125	-6.125	-6.125
	31-Dec-2013	-11.535	-11.440	-11.457	-11.437	-11.459	-11.437	-11.438	-11.458	-11.436	-11.455	-11.510	-11.437	-11.477	-11.463	-11.437	-11.437	-11.437	-11.437	-11.437	-11.437	-11.439
	31-Dec-2014	-25.117	-25.003	-24.973	-24.944	-24.945	-24.942	-24.963	-24.984	-24.939	-24.934	-24.936	-24.932	-24.959	-24.940	-24.933	-24.944	-24.940	-24.939	-24.940	-24.940	-24.940
	31-Dec-2015	-4.368	-4.364	-4.358	-4.352	-4.352	-4.351	-4.353	-4.357	-4.359	-4.351	-4.351	-4.351	-4.351	-4.353	-4.352	-4.354	-4.355	-4.352	-4.355	-4.355	-4.355
	31-Dec-2016	-5.382	-5.379	-5.374	-5.373	-5.374	-5.374	-5.376	-5.376	-5.373	-5.373	-5.373	-5.373	-5.373	-5.373	-5.374	-5.375	-5.373	-5.373	-5.375	-5.375	-5.374
	31-Dec-2017	-10.368	-10.321	-10.331	-10.318	-10.322	-10.319	-10.318	-10.328	-10.317	-10.317	-10.321	-10.318	-10.323	-10.319	-10.317	-10.318	-10.317	-10.317	-10.317	-10.317	-10.317
	31-Dec-2018	-10.530	-10.507	-10.512	-10.508	-10.507	-10.507	-10.507	-10.511	-10.507	-10.507	-10.507	-10.507	-10.506	-10.507	-10.507	-10.506	-10.507	-10.507	-10.506	-10.506	-10.506

Note: These matrices present the expected loss, the conditional implicit government guarantees, and the change of sovereign risk DD through OSIIs in the row conditonal on shocks from the financial sector, the non-financial corporate sector, and household Sector.

Appendix I: The Integrated Framework and Stylized Sectoral Balance Sheets

The graph depicts in a schematic manner the estimation methodology. See Jin and Nadal De Simone (2014b) for a detailed discussion.



The sectoral balance sheets and the interconnections among them considered in this study are as follows.

Corporate Non-financial Sector		Household Sector	
Assets	Liabilities	Assets	Liabilities
Corporate Real Assets	Debt	Real Estate and Durables	Debt
Financial Assets		Financial Assets	
PV of After-tax Capital Income	Net Worth	PV of After-tax Labor Income	Net Worth

Financial Sector		Sovereign Sector	
Assets	Liabilities	Assets	Liabilities
Financial Assets	Debt	Foreign Reserves	Foreign Currency Debt
Real Assets		Net Fiscal Assets	Base Money
PV of After-tax Income		Other Public Assets	
Plus Implicit Guarantees	Net Worth	*Less Implicit Guarantees*	Net Worth

The approach to estimate systemic risk includes all sectors of the economy (the financial sector includes 95% of total assets as data on insurance and pension funds is available at annual frequency and does not cover the whole sample period). Systemic risk in its three forms (ECB, 2009) can result from the banking and investment fund industries, the household and non-financial corporate sectors as well as from the sovereign. Systemic losses stem from systemic risk that is common across the financial sector, or tail risk; from contagion within the financial sector; from a build-up of financial sector vulnerabilities over time (including those stemming from the housing market or from the non-financial corporate sector). Once the systemic losses that result from systemic risk are estimated capturing time-varying non-linearities and feedback effects, the resulting sovereign contingent liabilities are included in the balance sheet of the country's sovereign and its credit risk is estimated. In contrast to static or accounting-driven models, the approach captures potential losses via "price-mediated" contagion (Cont and Schaanning, 2015), which can expose a financial institution to asset classes that regulation prevents it from holding. This can amplify the institution's exposure to a given risk factor relative to what is apparent from its balance sheet. The approach also measures banks' exposure through implicit financial support for the investment funds they sponsor. Section 3.3 and Appendix II describe how the present value of after-tax capital income and labor income are simultaneously calibrated as well as how the country's sovereign balance sheet items are constructed.

Appendix II: Calibration of After-tax Capital Income and Labor Income

Let us assume a Cobb-Douglas production function with constant returns to scale and a constant elasticity of substitution between physical capital and labor equal to one:

$$Y(K,L) = A(t)K^{1-\alpha}L^{\alpha},$$

where Y is output, A is total factor productivity, K is physical capital, and L is labor. The share of physical capital in production is $(1-\alpha)$ and the share of labor in production is α. Profit maximization implies that the total remuneration of physical capital equals $\pi = (1-\alpha)PY$ and the total remuneration of labor is $wL = \alpha PY$, where w is the real wage and P is the price of output Y.

The part of the non-financial corporate sector balance sheet not accounted for by other asset holdings is equal to the present value of the after-tax physical capital income over a given time horizon T:

$$A_C = E_t \sum_{i=t}^{T} (1+r)^{-(i-t)} (1-\tau_C)\pi_i,$$

where A_C is the after-tax physical capital income, r the interest rate and τ_C is the marginal tax rate on income from physical capital. Similarly, the part of the household balance sheet not represented by physical and financial asset holdings is equal to the present value of after-tax labor income:

$$A_L = E_t \sum_{i=t}^{T} (1+r)^{-(i-t)} (1-\tau_L) w_i L_i,$$

where A_L is the after-tax labor income and τ_L is the marginal tax rate on wage income. After simple algebra, it results:

$$A_L = \frac{\alpha(1-\tau_L)}{(1-\alpha)(1-\tau_C)} A_C,$$

which allows to produce an internally consistent calibration of the household and non-financial corporate sectors' other asset holdings. As stated in the text, the financial components of balance sheets of the two sectors are obtained from public flow of funds statistics and the household's stock of residential property is taken from national accounts.

Appendix III: Filtering Rules to Achieve Banking Groups Data Consistency

The short-term debt (BS047) and the long-term debt (BS051) from Bloomberg can have annual, semi-annual, and quarterly frequencies, and are not consistent. Therefore, to make the data consistent, four filtering rules are applied as follows:

I. Take any zero as missing data.

II. If the annual data exist and are not equal to the semi-annual/quarterly data, then let semi-annual/quarterly data be equal to the annual data. (Take annual data as trusted).

III. If the annual data do not exist, and both the semi-annual/quarterly data and the annual data exist at the previous and the next fiscal years, but semi-annual/quarterly data are very different from the corresponding annual data at the same previous and next fiscal years, then treat the semi-annual/quarterly as missing data (to avoid unreliable semi-annual/quarterly data).

IV. If the annual data do not exist, and annual data exist at both the previous and the next fiscal years, but they are very different from the semi-annual/quarterly data, then treat the semi-annual/quarterly data as missing data (to avoid unreliable and too choppy semi-annual /quarterly data between the previous and the next fiscal years).