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Georgios Moratis, Plutarchos Sakellaris

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MEASURING THE SYSTEMIC IMPORTANCE OF BANKS

Georgios Moratis[1] Plutarchos Sakellaris[2]

Abstract

We provide a new metric for the systemic importance of banks based on the intensity of spillovers of daily CDS movements. We denote this a bank's Individual Systemic Risk (ISR). Our novel empirical tool uses Bayesian VAR to address the dimensionality problem in large networks of banks and maps for every pair of banks in the system the shocks that they exchange. We apply this tool to all banks that issue publicly traded CDS contracts among the world's biggest 150 and identify which of these may trigger instability in the global financial system. Our methodology provides measures that are relatively stable across time, contain persistent information, have strong explanatory power for standard variables of systemic risk, and provided early warning signals in the case study of Deutsche Bank in mid-2016. Using our measure, ISR, we demonstrate which bank- and country-specific characteristics are related to bank systemic importance. We find higher systemic importance for banks that are relatively larger, less profitable, have G-SIB status, and are headquartered in economies with fiscally strong sovereigns. We also show that there is a negative relationship between concentration in the domestic banking sector and the systemic importance of a bank. We examine the relationship of ISR to alternative systemic risk metrics.

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[1] Athens University of Economics and Business, 76, Patission Str., GR10434 Athens-Greece. Email: gmoratis@aueb.gr.

[2] Corresponding Author. Athens University of Economics and Business, 76, Patission Str., GR10434 Athens-Greece. Email: plutarch@aueb.gr.

1. Introduction

"During the recent financial crisis that started in 2007, the failure or impairment of a number of large, global financial institutions sent shocks through the financial system which, in turn, harmed the real economy." (BIS, 2011)

Which banks are important to the stability of the global financial system? What characteristics are associated with systemically important banks? In response to the financial crisis that started in 2007, policy makers asked these questions and designated global systemically important banks (G-SIBs), which they subjected to additional regulatory measures. The goal has been to safeguard financial stability by limiting negative externalities and moral hazard behavior. Ideally, regulators need measures of bank systemic importance that are timely and capture valid economic mechanisms that cause financial instability. These measures should provide the picture of systemic risk at a given point in time (cross-section dimension), as well as monitor how a given bank's risk evolves over time (time series dimension).

Our paper answers the opening questions and provides a novel empirical tool to measure the systemic importance of individual banks. We follow Allen and Gale (2000), who explain that the interbank network determines the extent of contagion in the system and, thus, has a first-order impact on system-wide risk. We define a bank's systemic importance, equivalently its interconnectedness, by the intensity of spillovers of daily bank CDS movements. We call this metric, Individual Systemic Risk (ISR). This is the sum of CDS shocks the bank sends to and receives from banks in the global network. A key advantage of our measure over existing alternative ones is that it provides estimates of bilateral interconnectedness for all pairs of banks in the system. Our measurement of total systemic risk of a bank is based on two pillars: its exposure to the overall systemic risk (vulnerabilities) and its impact on systemic risk (externalities). In our approach, total systemic risk is the sum of both parts.

Our methodology has several other virtues. It is directly derived from market information on the degree of spillovers among banks. It is easily implementable and may be updated even daily. It may be applied to a network of banks at the global, regional, or national level. We employ Bayesian VAR to confront the high dimensionality problem of estimating relationships in large networks. Our methodology identifies separately the degree of externalities originating in a bank from its vulnerability to the rest of the system.[3]

Responding to the first opening question, we provide a global systemic importance score for all banks in our sample. Our sample contains all banks that issued publicly traded CDS contracts among the world's biggest 150 banks, for the period January 2008 to June 2017. Throughout the examined period, European banks were the main source of global systemic risk with strong interconnections to U.S. banks. Global systemic risk peaked in the period around the middle of 2010 and beginning of 2011. This was a period of increased interconnections among banks, as systemic and idiosyncratic shocks were propagated more intensely via the network.

We conduct several tests of validity of the new systemic importance metric. First, we check and indeed confirm that banks with higher systemic importance scores display a higher degree of interconnectedness with the global financial system. This accords with theoretical conjectures (see Basel Committee on Banking Supervision (2013)) as well as prior empirical evidence (see Bostandzic and Weiss (2018), and Drehmann and Tarashev (2013)).

Second, we test and confirm that banks' measured relative ranking of systemic importance is stable across neighboring, but not only adjacent, time periods. This criterion reflects the requirement that the novel measure of systemic importance contain mostly persistent information. Otherwise, the signals would include a lot of transitory information that would not be as useful. To perform this test, we generate separate cross-sections of risk measures at overlapping estimation periods through a rolling window from January 2009 to June 2017.

Third, we provide evidence that an aggregated index constructed from individual bank systemic risk scores has strong explanatory power for a set of

[3] A key reason for the lack of empirical work on global bank connectedness is the high dimensionality of bank networks. There are many important banks globally, which renders unrestricted vector autoregressive (VAR) and related analyses intractable.

variables that capture market-wide risk, namely iTraxx, VIX, EONIA and CISS.[4] We also show that these standard risk variables have low explanatory power for the novel aggregated index. The aggregated systemic risk index that we use is constructed from daily CDS spreads of the top-5 ranked banks. The ranking is estimated at each one of 56 rolling-window periods between January 2009 and June 2017. In complementary evidence, we show than an analogous index constructed from daily CDS spreads of the bottom-5 ranked banks has low explanatory power for standard measures of global systemic risk. Finally, we investigate the relationship between the top-5 and bottom-5 indices through a Granger causality test. As expected, the results suggest that a shock that is experienced by the banks in the top of the systemic importance list is finally transmitted to the rest of the system, while the opposite path does not exist.

We use a case study to demonstrate the validity of our novel individual bank systemic importance metric. In June 2016, the IMF stated that Deutsche Bank appeared to be the most important net contributor to global systemic risk (IMF, 2016), making the bank the biggest potential risk to the wider financial system. We estimate Deutsche Bank's score to have peaked in July 2016 at a level more than double what it had attained a year earlier. This coincides with market perceptions and IMF analysis that Deutsche Bank was a source of global financial instability. Global systemic risk, measured by the sum of all bank scores in our sample, did not move much in the run-up to Deutsche Bank's crisis but did jump 23% the period following the peak of the crisis: September 2016. Subsequently, it came back down. So, in this event, the substantial increase in Deutsche Bank's measured systemic risk was an early warning for the rise in global systemic risk that ensued.

Our second opening question was: What characteristics are associated with bank systemic importance? We perform a dynamic panel analysis of the relationship among bank systemic risk scores and various bank-specific and country-specific characteristics. We examine separately the degree of externalities originating in a bank from its vulnerability to the rest of the system. Externalities are captured by the degree to which a shock experienced by a bank

[4] These variables are defined in section 4 below.

is propagated to other banks in the global banking system. Vulnerability is captured by the shocks it receives from each bank in the global system. Bank-related characteristics that are significantly related to systemic importance are Return on Equity, Total Assets and G-SIB status. Size does have a significant positive relationship with systemic importance, other things equal. Even controlling for size, being classified as G-SIB is highly related to a bank's estimated systemic importance. G-SIBs have vulnerability score 0.23 standard deviations higher than average and externality score 0.19 standard deviations higher than average, controlling for other relevant characteristics. Thus, our metric indicates that G-SIB classification provides important information for bank systemic risk.

Regarding country-specific characteristics, the sovereign's fiscal strength has a significant positive relationship with domestic bank systemic importance. This finding provides support for the view that implicit or explicit bailout guarantees generate global systemic risk. Another important issue that has occupied researchers has been the relationship between banking market concentration and financial stability. A series of conflicting results have created a puzzle (see Ijtsma et al., 2017) for a review of results and a proposed resolution). We find that there is a negative relationship between concentration in the domestic banking sector and the systemic importance of a bank, supporting the concentration-stability view. This result holds whether looking at externalities or vulnerabilities. Banks in national systems whose concentration is one standard deviation above average are estimated to have vulnerabilities (or externalities) 0.02 (0.02) standard deviations below average, *ceteris paribus*. These numbers indicate a weak relationship, however.

Our methodology is based on two pillars. First, we use market information incorporated in CDS spreads as a reduced-form measure of the linkages among banks.[5] CDS spreads incorporate credit risk information faster than bond spreads.[6] Second, we use Bayesian VAR to confront the high dimensionality of

[5] These linkages may arise from correlated exposures, counterparty relationships or other structural channels. Our approach follows the suggestion in Flannery (1998), for using market information in the regulatory and supervisory process.

[6] Relevant studies (ECB, 2004; Norden and Weber, 2004; Blanco et al., 2005; Zhu, 2006; Baba and Inada, 2007) have shown that the CDS market leads the bond market, implying that innovations in the CDS market may spill over to bond spreads and not the opposite.

bank networks. Past work on this topic had to limit attention to a subset of global banks because of the dimensionality problem.[7] The closest to our approach is Alter and Beyer (2013), which builds upon the framework of Diebold and Yilmaz (2009, 2012).

We compare and contrast our systemic risk ranking measure, ISR, with three widely used market-based systemic risk metrics that are based on daily frequency publicly available data. These are the Long Run Marginal Expected Shortfall (LRMES) of Acharya et al. (2012), the Systemic Risk (SRISK) measure of Brownlees and Engle (2017), and the Delta Conditional Value-at-Risk (ΔCoVaR) of Adrian and Brunnermeier (2016). From the three metrics, the LRMES appears to produce the most similar systemic rankings and measures to ISR. A key conceptual difference of our methodology from the above three is that it quantifies pairwise directional connectedness. Put simply, this means that our methodology provides a complete picture of the links between any two banks in the systemic network in terms of shocks that they send and receive. This disaggregated description of the banking system is not possible with the other three methodologies.

The remainder of this document is structured as follows. Section 2 presents some of the relevant literature. Section 3 provides our definition of systemic risk. Section 4 presents our novel methodology and the data, while section 5 presents the main empirical results. Section 6 investigates the characteristics related to systemic importance, section 7 compares our metric to other prominent systemic risk measures and section 8 provides conclusions. An Internet Appendix contains additional results.

2. Relevant literature

Our paper is closely related to several literature strands. The first strand deals with bank interconnectedness. Allen and Gale (2000) explain that the interbank network determines the extent of contagion in the financial system and,

[7] There are two exceptions that address the dimensionality problem using LASSO methods applied to stock return data: Demirer et al. (2017) for the global bank system and Basu et al. (2017) for the U.S. financial system.

thus, has a first-order impact on system-wide risk. Forbes (2012) defines "interconnectedness" as linkages among financial institutions or correlations across market prices of financial institutions during all states of the world. Our paper is an empirical attempt to measure bank interconnectedness based on the intensity of spillovers of daily CDS movements.

Second, several studies produce alternative systemic risk measures and rankings for financial institutions. There are several useful surveys on systemic risk: among others De Bandt and Hartmann (2002), De Bandt et al. (2012), Bisias et al. (2012), Glasserman and Young (2015), Betz et. al. (2016), Benoit et al. (2017), Kreis and Leisen (2018), and Roukny et al. (2018). Here, we concentrate on just a few of the relevant studies and refer the reader to the surveys for completeness. One grouping of methodologies employs price-based systemic risk rankings such as banks' VaR (Adams, Fuss, and Gropp, 2014; White, Kim, and Manganelli, 2015), ΔCoVaR (Adrian and Brunnermeier, 2016; Castro and Ferrari, 2014) and MES (Acharya, Pedersen, Philippon, and Richardson, 2017). These measure the VaR or MES of financial institutions conditional on the entire set of institutions performing poorly.[8]

Other metrics incorporate book values as well. These include SRISK (Acharya, Engle, and Richardson, 2012; Brownlees and Engle, 2017), leverage ratio (Fostel and Geanakoplos, 2008; IMF, 2009; Geanakoplos and Pedersen, 2014), and CAPM beta times market capitalization (Benoit, Colliard, Hurlin, and Perignon, 2017). Finally, the distressed insurance premium (DIP) by Huang et al. (2012) measures the insurance premium required to cover distressed losses in the banking system.

These closely related approaches have a common disadvantage, which is that they do not provide information on pairwise directional interconnectedness. In other words, they do not describe the transmission of shocks between any two banks in the global system. In response to this shortcoming, some papers (see Billio et al, 2012) use Granger causality as a tool to uncover directionality.

[8] However, according to Zhang et al. (2015), some of these measures of systemic risk have inconsistent performance across financial crises that present different characteristics. They reach the same conclusion for several conventional proxies employed by regulators to identify the most global systemically important financial institutions. In addition, Danielsson et. al., 2016, analyze the MES and CoVaR measures, and express doubts about their ability to identify the most systemically risky banks.

However, Granger causality is unable to consider contemporaneous movements, control for exogenous variables, quantify intensity of effects, or consider multi-dimensional networks. All these important aspects are enabled by our methodology and measures.

A third group of relevant papers deals with the estimation of high-dimensional VAR models. The high-dimensionality problem had forced research on global bank connectedness to limit analysis to small samples of banks. This is not appropriate when considering bank importance for the global system. A relevant methodology has been recently suggested by Demirer, Diebold, Liu and Yilmaz (2017), who use LASSO methods to shrink, select and estimate the high-dimensional network linking the publicly traded subset of global banks. In a similar vein, Basu et al. (2017) use LASSO-penalized Vector Autoregressive model to estimate a model that leverages a system-wide approach to identify systemically important financial institutions in the U.S, while Covi et al. (2020) develop a Contagion Mapping (CoMap) methodology to study contagion potential of an exogenous default shock via counterparty credit and funding risks.

Our distinct approach is to use Bayesian VAR and prior shrinkage in order to resolve the dimensionality problem. The LASSO-based methodologies pick up only strong relationships and drop the rest, whereas our framework provides estimates of all bilateral relationships. There are two more differences between our approach and that of Basu et al. (2017) and Demirer et al. (2017). First, the measures of connectedness used differ. Basu et al. (2017) rely on Granger causality, and Demirer et al. (2017) rely on Generalized Forecast Error Variance Decomposition (GFEVD). We rely on Generalized Impulse Response Functions (GIRF), closely related to the approach developed by Alter and Beyer (2013), which in turn is based on the framework of Diebold and Yilmaz (2009, 2012).

Second, these papers study interconnectedness through stock returns, whereas we do so through CDS spreads that are arguably more closely driven by credit risk (see Bratis et al., 2020). CDS spreads are sensitive to changes in market perceptions of the probability of default (see e.g., Creal et al., 2014) Several papers provide evidence for the existence of a systemic risk component that drives CDS spreads across all industries (see e.g. Longstaff and Rajan, 2008). Rodríguez-Moreno and Peña (2013) examine the variance of CDS spreads of a sample of

European and US banks and find that 90% of that is explained by one common factor.

Longstaff et al. (2003), investigated the lead-lag relationships among changes in CDS spreads, changes in bond spreads, and stock returns. They concluded that information flows first into the CDS and the stock markets, and then into the bond market. Furthermore, innovations in the CDS market may spill over to bond spreads and not the opposite (Norden and Weber, 2004; Blanco et al., 2005; Zhu, 2006; Baba and Inada, 2007). Rodríguez-Moreno & Peña (2013) compare different measures that are based on CDS, interbank interest rate spreads, structural credit risk models and Co-risk measures (such as ΔCoVaR,) and show that the better performing measures of systemic risk are based on simple indicators obtained from credit derivatives and interbank markets and the least reliable indicators are the Co-risk measures that incorporate data from the stock market.

3. Definition of systemic importance

Systemic risk may originate in an endogenous build-up of financial imbalances possibly associated with a booming financial cycle; large aggregate shocks hitting the economy or the financial system; or contagion effects across markets, intermediaries or infrastructures. Our study focuses on contagion among banks and measures the systemic importance of a bank by the amount of spillovers it receives from and sends to the rest of the banking system. According to Allen et al. (2012) and Allen and Carletti (2013), contagion refers to the risk that the failure of one financial institution leads to the default of others through a domino effect in the interbank market, the payment system, or through asset prices. We adopt the "pure contagion" definition by controlling for external common systemic risk factors, and allow for a bank to become itself a source of systemic risk following an idiosyncratic shock.

The following example illustrates how we measure the systemic importance of banks (see Figure 1). Assume that the global system comprises three banks. Focusing on bank A as the source of shocks, Figure 1 presents the direct impact of an idiosyncratic shock on bank A to bank B and to bank C, separately. Bank A sends a shock to B, equivalent to 10% of its idiosyncratic shock and a shock to C equivalent to 17% of its idiosyncratic shock. In total, bank A generates externalities equal to 27% of its idiosyncratic shock. Next, we focus on shocks received by bank A when the other banks in the system experience idiosyncratic shocks of equal magnitude. Bank A receives a shock from bank B equivalent to 21% of its idiosyncratic shock and from bank C equivalent to 5%, respectively. Thus, the total vulnerabilities of bank A amount to 26% of an equal idiosyncratic shock to the other banks in the system (bank B and C). If we sum the shocks that bank A sends to and receives from the system as a result of an equal shock hitting every bank in the system, we obtain a measure of the degree of connectedness for bank A. This is a valid measure of bank A's systemic importance. This procedure is repeated in order to calculate the systemic importance of bank B and bank C.

[Figure 1 here]

[Table 1 here]

Table 1 provides an alternative representation of connections in the system. Shocks emanate from row banks to column banks. Each row shows the contagion effects of an equal-sized impulse to the relevant bank in the first column. In the last column, we aggregate the total externality effects of each row bank. The columns provide the picture of vulnerability of each bank to shocks in different banks. The second to last row is a measure of total vulnerability of a bank to all other banks in the system. It contains the answer to the question: "If all other banks in the system experienced simultaneously an idiosyncratic shock of 100 basis points, what would be the impact on bank X?" In the bottom row, we aggregate the total externality effect and the total vulnerability effect of each bank. In other words, we lump together shocks sent and received by an individual bank as a measure of total individual bank connectedness.

In calculating a bank's systemic importance, we assign equal weights to shocks it sends as to shocks it receives, being agnostic as to whether one source of systemic instability is more dangerous than the other. There are two aspects of financial contagion due to a bank's participation in a banking system that are of relevance to regulators: externalities emanating from a bank's failure and individual bank vulnerability to financial contagion. Both components are important for regulators, but their importance may not be equal. If they are of equal importance, then the regulator would consider the sum of these two. However, the clear decomposition in Table 1, as well as in our econometric method, allows the regulator to assign different weights in order to capture the appropriate measure of systemic importance.

4. Data and methodology

In this section, we describe the data used in the Vector Autoregressive model (4.1) and the econometric methodology we use to estimate interconnections among banks (4.2).

4.1 Data

In this sub-section we present the endogenous and exogenous variables for the Bayesian VAR used to estimate the map of interconnectedness in large networks of banks. These estimates lead to the ISR metric for each bank consisting of its *externalities* (shocks it sends) and its *vulnerabilities* (shocks it receives). We also present here the endogenous variables for further analysis of bank ISR that we pursue in subsection 5.4, more specifically a Vector Autoregression Model and a Granger causality test.

Endogenous Variables for the Bayesian VAR

The CDS spreads of the banks in the sample constitute the endogenous variables We study 70 banks from 19 developed and 7 emerging economies. Our selection procedure is as follows. We started with the list of the world's top 150 banks, in terms of total assets in Q4:2016. Using bank names, we matched 70 banks to CDS prices from Thomson-Reuters Datastream and Bloomberg. These are the banks that have publicly traded CDS contracts. CDS spreads cover the period from January 2008 to June 2017 and are at daily frequency. We use CDS spreads for USD denominated contracts.

The sample contains all banks that are designated as *"global systemically important banks"* ("G-SIB's") by the Basel Committee on Banking Supervision, except for three Chinese banks (Agricultural Bank of China, Bank of China, and Industrial and Commercial Bank of China) and one French bank (Group BPCE). The sample of the 70 banks is presented in the internet appendix (see Table I.1), along with information on the total assets and each bank's home-country. We note that 40 out of the 70 banks (52%) in the sample are from Europe while 28 of them (34%) are headquartered in Eurozone countries. Regional characteristics are presented in the internet appendix as well (see Table I.2).

Exogenous Variables for the Bayesian VAR

The variables whose role is to capture market conditions are the exogenous ones. We adopt the definition of systemic risk that describes a situation of cross-market correlation when the effect of common shocks has been controlled for. Longstaff et al. (2011), for instance, argue that credit risk appears related to global rather than country-specific factors, while Aizenman et al. (2013) establish the importance of international economic factors in the pricing of credit risk. The variables we employ in order to capture global financial risk conditions have been widely used in related studies as control variables (see, among others, De Santis, 2012, 2014; Aizenman et al., 2013; Ang and Longstaff, 2013). These are: the CDX, which is the family of CDS indices covering North America, the VIX volatility index, which captures the global capital markets' "fear" condition, and the global liquidity conditions, captured by the US 3-month treasury bills. The global systemic factor is assumed to affect the endogenous variables contemporaneously. Table 2 contains the variable definitions and Table 3 provides descriptive statistics.

Along with VIX, three more variables are used in subsection 5.4 where we examine the explanatory power of our metric over a set of variables that capture global financial market conditions. The first variable is iTraxx, which represents the 125 most liquid European entities with investment grade credit ratings as published by Markit. The second one is the composite indicator of systemic stress by ECB (CISS) (see ECB, 2012), and the third one is the Euro Overnight Index average (Eonia).

[Tables 2, 3 here]

4.2 Econometric Methodology

We estimate a VARX(p,s) model with two lags (p=2) for the endogenous variables and contemporaneous exogenous variables (s=0).

$$Y_t = a_0 + A_1 Y_{t-1} + A_2 Y_{t-2} + B_1 X_t + u_t \tag{1}$$

The vector of endogenous variables (Y) consists of log differences of daily CDS spreads for the 70 banks. By including the exogenous variables, we account for common factors that affect simultaneously all bank CDS spreads (Bekaert et al., 2005). These variables capture global default risk conditions and were described in section 4.1.

4.2.1 Bayesian VAR

The classical approach of estimating the VAR model may lead to 'overfitting' due to the large number of variables. Researchers working in the relevant literature typically use prior shrinkage on the parameters to overcome such over-parametrization concerns. Most flexible Bayesian priors that result in shrinkage of high-dimensional parameter spaces rely on computationally intensive Markov Chain Monte Carlo (MCMC) methods and their application may be prohibitive or even infeasible. The only exception is the traditional "Minnesota prior", an empirical-Bayes prior which is due to Littermann (1979) and co-authors (see, e.g. Doan, Litterman, and Sims, 1984) and still dominates many applications of VAR models in economics.

The "Minnesota prior" is based on the natural conjugate prior, an idea that has recently been exploited by Banbura, Giannone and Reichlin (2010) and Giannone, Lenza and Primiceri (2015), among others. While this prior allows for an analytical formula for the posterior, there is a cost in terms of flexibility in that *a priori* all VAR equations are treated in the same manner. Koop and Korobilis (2010) provide a discussion of this aspect of the natural conjugate prior. For computational simplicity we restrict the model to use conjugate prior (whose posterior has the same distributional family as the prior distribution). This restriction allows for analytical calculation of the Bayesian VAR, rather than simulation-based estimation (*e.g.* the MCMC method). It is also worth noting that the choice of priors does not imply the need for different Bayesian techniques of estimation. Disagreement over the priors may be addressed by post-estimation sensitivity analysis evaluating the robustness of posterior quantities of interest to different prior specifications.

We estimate the coefficients of a VARX for 70 banks using the log differences of each bank's CDS. As we explained above, a key concern of users of Bayesian statistics, and criticism by critics, is the dependence of the posterior distribution on one's prior and for this reason we employ hyperparameters for the prior.

The Bayesian VARX(p,s) model can be written as:

$$y_t = a_0 + \sum_{j=1}^{p} A_j y_{t-j} + \sum_{i=0}^{s} \Theta_i^* x_{t-i} + \varepsilon_t \tag{2}$$

where y_t for $t = 1,...,T$ is an $M \times 1$ vector of log-difference CDS, ε_t is an $M \times 1$ vector of errors, α_0 is an $M \times 1$ vector of intercepts, A_j is an $M \times M$ matrix of coefficients, and x_t is a vector of the exogenous variables. In our data, M refers to the number of banks in our sample. We assume ε_t to be *i.i.d.* $N(0, \Sigma)$. The prior means for the exogenous coefficients are set to zero.

4.2.2. The externalities/vulnerabilities matrix

Our novel tool for measuring banks' systemic importance is based on a medium-size Bayesian vector autoregressive model with exogenous variables (Bayesian VARX) that accounts for common global and regional trends, and can include bank-specific characteristics. Then, like the framework described by Diebold and Yilmaz (2009, 2012) and the one described by Alter and Beyer (2013), we construct the spillover matrix in order to capture any potential spillovers among banks. This methodology relies either on Generalized Forecast Error Variance Decomposition (GFEVD) or on Generalized Impulse Response Functions (GIRF), obtained as shown in Pesaran and Shin (1998). We have decided to base our analysis on Generalized Impulse Response Functions and calculate those as functions of residuals together with the interdependent coefficients. According to Alter and Beyer (2013), it is of little importance which methodology one selects, since both produce qualitatively similar results.

[Table 4 here]

In Table 4, each row variable is an origin of unexpected shock. Column variables are the respondents that receive the contagion effects. We can examine the implications of our estimates for the aggregate level of systemic risk in the banking system. We define Individual Systemic risk (ISR) as the sum of the shocks that each entity sends to the system and receives from the system, excluding any own shocks:

$$ISR_i = \sum_{i,j\neq i}^{N} IR_{y_i \to y_j} + \sum_{i,j\neq i}^{N} IR_{y_j \to y_i} \quad (3)$$

We define Total Systemic risk (TSR) as the sum of the off-diagonal entries in the interconnections matrix. In other words, it is the sum of all the externalities measured in the network:

$$TSR = \sum_{j\neq i} \sum_{i,j=1}^{N} IR_{y_i \to y_j} \quad (4)$$

where IR stands for the Impulse Response of bank ***i*** to bank ***j***. Equivalently, TSR could have been defined in terms of the sum of all vulnerabilities measured in the network.

TSR may be also expressed as an index by dividing TSR by the total number of banks in the sample. The transformation of total systemic risk into an index makes the overall risk measure independent of the number of banks in the sample, making comparison between different samples more precise. The potential contagion effects from and to each bank are aggregated on each line and column and represent measures of externalities (To Others) and vulnerability (From Others). The main diagonal values represent the effect of a variable's shock on itself, and they are excluded from any calculations. The possible contagion effects answer the question *"How would bank B's CDS evolve in the following period if bank A's CDS was hit by one-unit shock?"* We use accumulated Impulse Response functions over an H-step horizon (H days). The framework is flexible enough to accommodate different horizons.

5. Empirical Results

5.1 Bank – level results

- ***Systemic risk demographics***

We estimate the systemic risk matrix as described in section 4.2.2 for the period 1st January 2009 to 31st June 2017. Table A.1 (in Appendix) provides estimates of banks' individual systemic risk (*ISR*) along with relevant metrics that will be discussed next.

The bank that creates the most systemic risk over the whole period is BNP Paribas, which is headquartered in Europe and is designated as G-SIB. BNP Paribas is ranked 4th in terms of size in our sample. The ISR_{BNP} equals 1.925 and is further decomposed into a 0.867 externality score and a 1.058 vulnerability score. The externality score indicates that a one-unit shock to BNP's CDS spread will move the CDS's of all other 69 banks in the global system by the sum of 0.867 units cumulatively over a 10-day horizon.[9] The vulnerability score shows that a simultaneous one-unit shock to all other banks in the system will affect BNP by 1.058 over a 10-day horizon.

According to our metric, most of the GSIBs are categorized as systemically important. Specifically, 83% of the banks in the upper quartile of systemic importance are G-SIBs.[10] However, there are also some G-SIBs that are not systemically important, according to our metric. This means that there is important heterogeneity in the systemic behavior among G-SIBs. Certain papers argue that during crises large banks behave differently than small or medium-sized banks[11] (see e.g. Laeven et al., 2014; Demsetz and Strahan, 1997). The heterogeneity that we have measured in the systemic importance of G-SIBs indicates that even within the group of large banks there is different behavior during crises.

- ***Bank systemic importance and relative interconnectedness***

The Basel Committee on Banking Supervision (2013) conjectures that a bank's contribution to systemic risk is positively related to the degree of its interconnectedness with the global financial system. Some empirical research

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[9] It is remarkable that sensitivity analysis reveals that over 90% of shocks are transmitted within 1-day horizon after the shock occurs. Note that 1-day horizon TSR is 39.14, the incremental contribution of a 3-days horizon to TSR is 4.64. Increasing the horizon to 6 days contributes almost nothing further to TSR.

[10] G-SIBs are denoted with an asterisk.

[11] Laeven et al. (2014) attribute this difference to some common characteristics shared by large banks that are associated with higher levels of risk, namely increased portion of market-based activities, reduced capital adequacy, less stable funding and higher organizational complexity. Demsetz and Strahan (1997) find that large bank holding companies have a diversification advantage, as evidenced by lower idiosyncratic risk. This literature is partially applicable to systemic risk as it does not identify a threshold of bank size above which systemic importance kicks in and the different behaviors among large banks.

confirms this. Bostandzic and Weiss (2018), using the measure of interconnectedness proposed by Billio et al. (2012), find that it is positively related to a bank's exposure and its contribution to systemic risk. Drehmann and Tarashev (2013) also find that interconnectedness is a key driver of systemic importance in their sample of 20 large global banks.

It is important to check whether our measure of bank systemic importance (ISR) is consistent with these findings. The question we ask is the following. Do banks displaying high ISR have a larger network of highly connected banks? If so, the more systemically important banks, according to our metric, are more interconnected with the global network and are more prone to generate financial crises.

We construct a novel measure of a bank's interconnectedness as follows. For each rolling window over the period January 2009 to June 2017 we calculate the average impulse that a bank sends to its peers.[12] Then we set a threshold of one standard deviation above the average impulse and we count how many peer banks fall into this tail. We denote this the *systemic network* of a bank. This is the group of peer banks that are most affected by shocks in the originating bank. The higher the number of banks that fall into this region, the more strongly interconnected to the global system is the originating bank in question. For our ISR metric to be plausible, a bank that is measured to have high ISR should tend to have a relatively large systemic network. We rank banks in each rolling window by the size of their systemic network and calculate the Spearman rank correlation between banks' systemic network size and ISR for each rolling window. The average rank correlation over the 56 rolling windows is 54%. Thus, more interconnected banks, as measured by the size of their systemic network, tend to be of higher systemic importance, according to the ISR metric.

- ***Investigating the stability of the ranking***

[12] Rolling window analysis refers to a 70-days window and 35-days step. The period of estimation for the impulse responses (and thus the ISRs) is the 70 days of the window and not the whole sample period of 1 January 2008 to 31 June 2017. For all analyses based on rolling window estimates the horizon used to measure bank externalities and vulnerabilities is 1-day. As mentioned before, extending this to a 10-day horizon does not change the results. The length of the window must be sufficiently large to support the size of the sample. The results presented have been evaluated using a 70-day window, reflecting all the information of the specific period. Results are qualitatively similar when using slightly larger windows. We choose a 35-day step, in order to get a suitable frequency for the metric. Depending on the purpose of the analysis, the methodology could be applied with a step as short as one day.

An important issue is how stable the ISR metric is over time. For a measure of systemic importance to be useful it must include mostly persistent information. We judge stability of ISR by whether the systemic ranking of banks that it implies does not change much from one period to the next. Again, we employ a rolling window analysis over the period January 2009 to June 2017. We calculate the cross-sectional rank correlation of the ISRs across every pair of consecutive periods, through rolling window analysis. The correlations range from 0.6 to 1 with an overall average of 0.85.[13] [14]

5.2 Aggregate level of systemic risk

We now examine the implications of our proposed metric for the aggregate level of systemic risk in the banking system. We have defined above *Total Systemic risk (TSR)* as the total sum of the off-diagonal entries in the interconnections matrix. In other words, it is the sum of all the *externalities* measured in the network.

Figure 2 presents the fluctuation of TSR over the 56 rolling windows from Jan. 2009 to Jun. 2017 along with some major financial systemic events. The figure uncovers periods mostly associated with the developments in the European banking and sovereign debt markets that shocked some European Union member countries until mid-2012. The Greek crisis in early 2010, the Portugal's bailout program and then the inclusion of Italy and Spain to the countries with stressed banking systems pushed total systemic risk upwards. In the meantime, in mid-2012, the ECB calmed financial markets by announcing unlimited support for all eurozone countries involved in a sovereign state bailout precautionary program from EFSF/ESM, through yield-lowering Outright Monetary Transactions (OMT). By 2014, non-performing loans (NPLs) amounting to almost €1 trillion had piled up on the balance sheets of large banks in the euro area, increasing TSR. However, the successful completion of both Ireland's and Portugal's bailout programs as

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[13] It is also the case that the rankings are stable over longer periods. Rank correlations measured five periods apart, that is between a point in time and 6-months later, and ten periods apart (1-year distance), average 0.84 and 0.75, respectively.

[14] As in the section above, the period of estimation for the impulse responses (and thus the ISRs) is the 70 days of the window and not the whole sample period of 1 January 2008 to 31 June 2017. In other words, there is a distinct ISR for each bank in every rolling window.

well as the targeted longer-term refinancing operations (TLTROs) that provided financing to credit institutions pushed TSR to low levels.

The threat of a Greek sovereign default in mid-2015 increased overall systemic risk. Eventually, Greece agreed to a third bailout package in August 2015. The liquidity problems in Italian banking system, the higher political uncertainty regarding UK membership in the EU and the US election, contributed to the build-up of higher levels of systemic risk. The major concern for global markets was the crisis in Deutsche Bank due to the bank's deep connections to global financial markets. However, the IMF's eventual announcement regarding its confidence that German and European authorities were working to ensure stability, calmed down financial markets.

[Figure 2 here]

Next, we calculate the systemic contribution of each bank as the ratio of individual systemic importance and total risk in the system:

$$Contribution_i = \frac{ISR_i}{TSR} * 100 \quad (5)$$

This transformation of the initial table allows comparison across samples that contain different number of banks and the comparison of a bank's systemic risk between different periods of time. The highest contribution that was calculated came from Deutsche bank in mid-2016 *(see section 5.3)*. This provides the impetus to study through the lens of our proposed systemic importance metric the case of Deutsche Bank in the summer of 2016. The case study will help us assess in a real-life situation whether our metric has behaved as an early warning indicator for global systemic risk developments.

5.3 A case study: Deutsche Bank in the summer of 2016

The turmoil around Deutsche Bank in mid-2016 revived memories of the meltdown of the global financial system back in 2008. In IMF (2016), it was argued that Deutsche Bank appeared to be the most important net contributor to systemic risk, followed by HSBC and Credit Suisse, making the bank the biggest potential risk to the wider financial system. The IMF announcement came just after the Federal Reserve said U.S. units of Deutsche Bank failed the final round of its "stress test" on June 29, 2016. However, this was not the most important Deutsche Bank event over this period, as in September 2016 the U.S. Department of Justice raised the prospect that Deutsche Bank could be fined $14 billion in relation to mis-sold mortgage-backed securities. On October, IMF (2016) did not mention Deutsche Bank's name when it warned in its financial stability report that cash-poor banks in Europe with outdated business models posed a threat to the financial system, but at the presentation of the study's findings the fund's economists have argued that Deutsche Bank, given its size and culture of risk-taking, poses more of a risk to financial markets that its peers in Europe and United States. The peak of the crisis was in September when Deutsche Bank's capital value was $16.8 bn. on September 28th, 2016.

According to our metric, the Deutsche bank crisis was the biggest global systemic event that was induced by a single bank. This was likely due to its intertwined relationships with other international lenders, aspects that our metric cannot by nature uncover. As may be seen in Figure 3, Deutsche Bank's ISR score peaked in July 2016 at a level more than double what it had attained a year earlier. Total systemic risk, TSR, did not move much in the run-up to the Deutsche Bank crisis but did jump 23% the period following the peak of the crisis: September 2016. Subsequently, it came back down. So, in this event, the substantial increase in Deutsche Bank's measured systemic risk was an early warning for the rise in global systemic risk that ensued.

[Figure 3 here]

Roughly half, 48%, of Deutsche Bank externalities emitted over the entire sample period affected just 16 banks. In other words, Deutsche bank was mostly connected to 22% of the sample. Twelve out of these 16 banks are designated as G-SIBs. None of these banks is headquartered in the US, while three out of four of the non-G-SIB banks are headquartered in Italy. Italian banks were vulnerable due to their NPE problems and the general instability of the Italian economy. From April 2015 to September 2016, Unicredit's share price fell from €6.45 to €2.40, while Monte dei Paschi's share fell from €9.45 to €0.24.

Figure 4 presents the percentage change between the average shocks sent by Deutsche Bank to each bank in its systemic risk network (as this is defined in section 5.1) over the whole sample period and the shocks it sent over the Deutsche Bank crisis period of March 2016 to July 2016. For example, the externalities of Deutsche Bank to Standard Chartered were 68% higher within two periods around the Deutsche Bank's crisis compared to the rest of the sample. Société Générale experienced a 54% increase over the same period.

[Figure 4 here]

An interesting question is: How did Deutsche Bank create global systemic risk during this period? To answer this, we investigate how the shocks that were generated by Deutsche Bank were distributed at a secondary level through its primary systemic network. We investigate how Standard Chartered propagated the shocks it received from Deutsche Bank (see Table 9). The reason why we choose to concentrate on Standard Chartered is because it was the bank most affected by the Deutsche Bank crisis.[15]

The first column in Table 5 contains the banks that respond to the shocks sent by Standard Chartered. The second column shows the average shock over the 56 rolling-window periods in the sample. The third column presents the shocks that were sent by Standard Chartered during the peak of the Deutsche Bank crisis while the fourth column presents the shocks sent by Standard Chartered one period after the peak of the Deutsche Bank crisis. The last column presents the % increase in the externalities of Standard Chartered between the t and t+1 of Deutsche crisis. For example, the shocks sent from Standard Chartered to Industrial Bank of Korea increased by 794.3%. Banks that respond to the shocks are ranked in terms of % increase between the t and t+1 of the Deutsche crisis peak.

In order to characterize a shock as part of a secondary effect it must satisfy two criteria. First, the shock should be directed outside of Standard Chartered bank's primary systemic network. Second, the received shock one period after the Deutsche Bank crisis peak must be higher than the average shock received throughout the sample and higher than the shock received during the peak period of the Deutsche Bank crisis. It is illustrative that the shocks towards banks outside

[15] The period after the Deutsche Bank crisis is suitable for identifying secondary effects for two reasons. First, this crisis displays undisputable global characteristics. Second, the lack of any other concurrent systemic events removes any potential noise created elsewhere in the bank market.

the systemic risk network of Standard Chartered increased dramatically one period after the Deutsche Bank crisis. Another interesting point depicted in Figure 5 is that the externalities of Standard Chartered to its systemic risk network fell by 35% from period *t* to *t+1* while the shocks sent to the banks not included to its network rose by 40% from period t to t+1, implying that banks inside the network react faster to a shock that is transmitted by the impulse bank.

[Table 5 here]

[Figure 5 here]

5.4 Explanatory Power of the ISR metric

In order to check the validity of the ISR metric further, we investigate the lead-lag relationship of this metric with a set of variables that capture market-wide risk, namely *iTraxx*, *VIX*, *EONIA* and *CISS*. The aim is to quantify the amount of information that our metric contributes to these variables and vice versa. We construct a new systemic risk index based on our ISR metric and test whether it contributes more to the variation of the above-mentioned market-wide risk variables than vice versa. Indeed, we find strong evidence that a systemic risk index based on our metric has strong explanatory power.

We construct two systemic risk indexes: one constructed from the top-5 ISR banks and one for the bottom-5 ISR banks. The ranking that determines the top and bottom 5 banks is performed at each of the 56 rolling-window periods, and the indexes are constructed through principal component analysis. We examine two joint hypotheses. First, that the top-5 ISR index has higher explanatory power over standard measures of global systemic risk than vice versa. Second, that the bottom-5 ISR index does not have higher explanatory power over standard measures of global systemic risk than vice versa. The predictive strength among the variables in the sample is investigated through Generalized Forecast Error Variance Decomposition analysis, which is not subject to Cholesky ordering (Pesaran and Shin, 1998), and each variable of interest affects all other variables contemporaneously as well as with a lag.

Table 6 (Panels C and D) shows that *top-5 ISR index* contributes strongly to each one of the global systemic risk variables in the system, while none of these variables has important explanatory power on the *top-5 ISR index*. The *top-5 ISR* *index* explains 33% of iTraxx variance and 59,9% of EONIA variance, while iTraxx contributes only 5.7% and OIS 16% respectively to the *top-5 ISR index* variance. A similar but less pronounced pattern is observed in the explained variance between top-*5 ISR index* and VIX or CISS. On the other hand, the *bottom-5 ISR* index does not display more significant explanatory power over the other variables in the system than these have over that index. This shows that the banks that are estimated to contribute little to TSR do not affect the global systemic risk (Table 6 - Panels A and B).

Finally, we investigate the relationship between the *top-5 ISR* and *bottom-5 ISR* indices through a Granger causality test. As expected, the results suggest that a shock that is experienced by the banks in the top of the systemic importance list is finally transmitted to the rest of the system, while the opposite path does not exist *(*see *Table 7).*

[Tables 6,7 here]

5.5 Regional and country – level analysis

The estimation of CDS spillovers between any pair of banks in the system allows us to explore further regional or national effects. We now investigate the flows of contagion between different regions. The banks with the strongest systemic presence are European, adding to the evidence that most of the turmoil during 2009– 2017 stemmed from the interior of the European Union.

Figure 6 presents and compares the externalities of banks belonging to a region to every other region. The largest portion of shocks generated in the European banking system remains within the region. Of course, European banks are not immune to the banks outside the European Union, but throughout the examined period they have been more vulnerable to shocks that emanated from within. This is consistent with the eurozone crisis being of primal importance. European banks seem to be also the favorite target of shocks emanating from all other world regions. It seems that over the period Jan. 2009 – Jun. 2017 European banks absorbed most shocks that were being transmitted in the global banking system, being by far the most vulnerable banking block. Table 8 displays evidence that 64% of the aggregate shocks that are received by U.S. banks are generated in

Europe.[16] Thus, we conclude that the European and U.S. banking sectors have been strongly interconnected and strongly exposed to each other. The highly interconnected banking system, the feedback loop among sovereigns and banks, and the high transmission of contagion effects from one country to the other, put the European banking system in the eye of the storm throughout the examined period.

[Figure 6 here]

[Table 8 here]

6. Characteristics Related to Bank Systemic Importance

What characteristics of a bank itself, or of the country in which it is headquartered are associated with its systemic importance? We proceed to such an analysis in this section. Our novel measure of bank systemic importance identifies separately the degree of externalities originating in a bank from its vulnerability to the global system. We will analyze separately these two components of systemic importance in a panel data framework.

Our choice of bank-specific characteristics is guided by theory and empirical findings from past literature. We include the following as explanatory variables. Net interest margin (*NIM*), defined as the difference between interest income and interest expense as a ratio to total assets, is inversely related to bank diversification. Return on equity (*ROE*), the ratio of net income over total equity is also included as a performance indicator. Bank size is measured by total bank assets (*TotalAssets)*. There are several theories supporting the view that large and complex banks contribute to systemic risk, either because they engage more in risky activities and finance more with short-term debt (Gennaioli, Shleifer, and Vishny, 2013; Boot and Ratnovski, 2012) or due to too-big-to-fail considerations (see, Farhi and Tirole, 2012). To control for the influence of a bank's loan portfolio quality (credit risk), we include the share of Non-performing loans to the total book value of loans (*NPLTA*). To control for capital adequacy and capacity of loss absorption we include the regulatory *TIER1* ratio, which is the ratio of core equity

[16] In corroborating evidence, and using a different methodology, Bostandzic and Weiss (2018) find that European banks contribute more to global systemic risk than banks in the United States.

capital to total risk-weighted assets. Finally, we include an indicator of whether the bank has been assigned G-SIB status.

To control for the impact of macroeconomic conditions we include four country-related variables. The set includes domestic *GDP* (in logs), country indebtedness (*DEBT*), captured by the ratio of government gross debt and GDP, country fiscal space (*DEFICIT*), measured by the ratio of government deficit to GDP, and a business confidence indicator (*BCI*). BCI is a leading indicator providing information on future developments, e.g. output growth, and captures economic uncertainty and fluctuations in credit availability.

Furthermore, we analyze whether the degree of concentration of the domestic banking industry is associated with financial stability. *Concentration* is defined as the sum of assets of the three largest national commercial banks as a share of total national commercial banking assets. Prior research disagrees regarding the influence of concentration on the stability of a banking system (see Ijtsma et al. (2017) for a review of results and a proposed resolution). A *concentration–stability* view argues that banks in more concentrated markets tend to be more stable. On the other hand, a *concentration–fragility* view argues the opposite.

The data used in this section, their sources, and some descriptive statistics are summarized in Tables 9 and 10. The sample contains 45 banks for which we had complete data over the whole period. Table 2 contains the names of the banks used in this subsample. The two components of bank systemic importance, externalities and vulnerability, are estimated in 56 rolling windows over the sample period. Each window has a length of 70 days and a step of 35-days. Bank-specific variables are mapped into these windows from annual financial statements. Country-specific variables are mapped from annual data.

< Tables 9,10 here>

6.1 Results

We run a dynamic linear model with bank fixed effects.[17] The results in Table 11 reveal a common pattern of relationships for both vulnerabilities and externalities. *Grosso modo*, the set of statistically significant determinants is the same for vulnerabilities and externalities, and coefficients are in the same direction. Bank size is significantly related to systemic importance, *ceteris paribus*. This confirms the size effect on systemic risk found in other studies, e.g. Laeven et al., (2016). The economic magnitude is rather weak though: a one-standard-deviation increase in size increase vulnerabilities (externalities) by 0.05 (0.04) standard deviations. Classification as G-SIB is highly related to a bank's estimated systemic importance, as one would expect. G-SIBs have vulnerability score 0.23 standard deviations higher than average and externality score 0.19 standard deviations higher than average, controlling for other relevant systemic characteristics.

The fiscal weakness variables, DEBT and DEFICIT, are both negatively related to measures of bank systemic importance. This is consistent with banks in countries with a weak sovereign not expecting to be bailed out easily in case of trouble, thus choosing less risky portfolios and behavior.

Finally, our empirical results provide support for the concentration-stability view in banking. The estimated coefficient is negative, statistically significant but economically small. Banks in systems whose concentration is one standard deviation below the average country rate are estimated to have vulnerability or externalities 0.02 standard deviations above average, *ceteris paribus*.

<Table 11 here>

7. Comparing ISR and other metrics of systemic importance.

In this section, we compare and contrast our systemic risk measure, ISR, with three widely used market-based systemic risk metrics that are based on daily publicly available data. These are the Long Run Marginal Expected Shortfall

[17] The specification is dynamic since we observed evidence of serial correlation in the residuals of a corresponding static specification. The estimation method is System Generalized Method of Moments (GMM) (see Blundell and Bond, 1996) and the individual bank fixed effects are removed through first differencing. In order to choose optimal instrument lag, we use the Andrews and Lu (2001) proposed consistent moment and model selection criteria (MMSC) for GMM models based on Hansen's (1982) *J* statistic of over-identifying restrictions.

(LRMES) of Acharya et al. (2012), the Systemic Risk (SRISK) measure of Brownlees and Engle (2017), and the Delta Conditional Value-at-Risk (ΔCoVaR) of Adrian and Brunnermeier (2016). ΔCoVaR is a bottom-up approach where risk directs from individual bank distress to the entire system. On the other hand, SRISK is a top-down approach where, first, a total amount of systemic risk is calculated that is then allocated to individual banks. Finally, Long Run Marginal Expected Shortfall (LRMES) tries to quantify the contribution of each institution to overall risk in the financial system. LRMES builds upon the literature of dynamic volatility and correlation modeling by adapting a DCC-GARCH approach.

We selected these three measures based on two criteria. First, the computations need to involve readily available public data that cover the period under analysis. Second, the measures need to be computed for a relatively large dataset, overcoming any dimensionality issues. SRISK and LRMES require both market and accounting data in the estimation. Hence, differences in accounting standards used by banks may affect consistency of results across jurisdictions. We provide details on the construction of these three measures in the Internet Appendix.

First, we examine to what extent the ISR metric and the three selected metrics produce similar rankings of systemic importance for the banks in our sample. We find that ΔCoVaR rankings deviate largely from those obtained from the other metrics. In particular, the rank correlation with ISR rankings is zero (see Table II.3 in the Internet Appendix). In fact, relatively smaller banks in terms of assets exhibit higher ΔCoVaR than their peers, whereas it is exactly the opposite with ISR rankings. For example, Societe Generale, BNP Paribas, Deutsche Bank and Credit Agricole are placed in the bottom quartile when ranked by ΔCoVaR. SRISK and LRMES produce systemic importance rankings similar to ISR during the period 2009-2017 (see Tables III.1 and IV.1 in the Internet Appendix, respectively). The rank correlation of bank ISR is 50% with SRISK and 60% with LRMES.

Next, we compare how well these measures perform as an early warning indicator in the case study of the Deutsche Bank Crisis. ΔCoVaR reacted to the crisis with a significant but short-lasting increase. If this was an early indicator of a crisis, it showed that it resolved itself way before it had done so actually (see Figure II.2 in the Internet Appendix). The fact that Deutsche Bank is ranked 44th out of 49 banks in terms of ΔCoVaR explains this failure partly (Table II.4).

SRISK displays a similar reaction to ISR during the Deutsche Bank crisis. Both $SRISK_{Deutsche}$ and $ISR_{Deutsche}$ increased, placing Deutsche Bank in the second and first place respectively of the systemic importance ranking table (see Table III.2 in the Internet Appendix). However, the magnitude of the increase is considerably lower for $SRISK_{Deutsche}$ (see Figure III.1 in the Internet Appendix) and not comparable to the increase in $ISR_{Deutsche}$ (see Figure 3). LRMES seems to behave similarly to ISR as an early warning indicator of the Deutsche Bank crisis. The magnitude and duration of changes in $LRMES_{Deutsche}$ (Figure IV.1 in the Internet Appendix) and $ISR_{Deutsche}$ (Figure 3) are quite similar.

In summary, from the three metrics, LRMES appears to produce the most similar systemic rankings and measures to ISR, with high rank correlation and similar dynamics during the Deutsche Bank crisis. Our analysis supports previous findings of conflicting results among the three established systemic risk measures (see, among others, Löffler and Raupach, 2016). Nonetheless, we find a high level of coherence between ISR and LRMES, and to a lesser extent between ISR and SRISK.

In the Internet Appendix, we replicate the panel regression analysis in sub-section 6.1 for each one of the three different metrics. Bank size seems to be related to SRISK. Business confidence index relates negatively to LRMES and SRISK, while ROE is negatively related with all metrics. ”

8. Conclusions

This paper provides a novel empirical framework to measure the systemic importance of banks based on publicly available CDS data alone. Our methodology has several advantages. It is directly derived from market information on the degree of spillovers among banks. It is easily implementable by regulators and may be updated even daily. It may be applied to a network of banks at the global, regional, or national level. It provides estimates of bilateral interdependence for all pairs of banks in the system.

Our novel measure of bank systemic importance identifies separately the degree of externalities originating in a bank from its vulnerability to the system. Externalities are captured by the degree to which a shock experienced by a bank is propagated to each individual bank in the global banking system. Vulnerability is captured by the shocks it receives from each bank in the global system. This decomposition better allows the macroprudential supervisor to differentiate the "cure" according to the individual bank's systemic "disease". The "cure" usually consists of a combination of capital requirements, quantitative restrictions, resolution regimes, and supervisory review actions among others. Arguably, our decomposition facilitates an improved approach to safeguarding financial stability.

Some caveats are in order. On a broader perspective, no financial institution should receive an automatic exclusion from being designated systemically important. Our framework aims to measure the systemic importance of banks. It could be a useful tool for regulators and supervisors, but it is silent about systemic importance developments in other parts of the financial system. Tighter regulation of systemically important banks may cause risk-shifting to less regulated parts of the financial system. This risk should not be underestimated. A second caveat concerns the global scope of the empirical application of our tool in this paper. Our sample includes all banks that issued publicly traded CDS contracts among the world's biggest 150. As the BCBS (2012) consultative document for dealing with domestic systemically important financial institutions (D-SIFIs) clearly states, there might be several financial institutions that are not significant at the global level but could have an important impact on their domestic financial system and economy.

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TABLES

Table 1: Externalities/Vulnerabilities matrix

Shock/Response	*Bank A*	*Bank B*	*Bank C*	***To Others (Externalities)***
Bank A	-	10	17	27
Bank B	21	-	28	49
Bank C	5	19	-	24
From Others (Vulnerabilities)	26	29	45	100
Score	53	78	69	

Note: Variables in the first column are the impulse origin, while variables on the top row are the respondents to the shock. *To_Others* column sums the shocks that are sent to the system from each bank, while *From_Others* aggregates the shocks that each bank receives from the system. The *Score* row represents the systemic importance of each bank and is measured as the sum of each bank's externalities *(To_Others)* and vulnerabilities *(From_Others)*.

Table 2: Data Definitions

	Variable	Description
Bayesian VAR	**Endogenous**	
	Bank CDS	Bank 5-year CDS spread
	Exogenous	
	CDX	The family of CDS indexes covering North America
	VIX	The volatility index of S&P 500
	US 3-month T Bill	The short-term obligation backed by the Treasury Dept. of the U.S. government
VAR and Granger-Causality	*Itraxx*	One hundred twenty five (125) of the most liquid European entities with investment grade credit ratings as published by Markit
	CISS	Composite Indicator of Systemic Stress by ECB
	EONIA	Euro Overnight Index Average
	VIX	Cboe Volatility Index

Note: The table describes the variables used in the analysis.

Table 3: Descriptive statistics for the systemic risk factor variables

	CDX	**VIX**	***US 3-month T Bill***	***Itraxx***	***CISS***	***EONIA***
Mean	0.000	-0.000	-0.001	417.8	0.076	0.163
Median	0.000	-0.001	0.000	390.65	0.061	0.109
Maximum	0.020	0.176	0.250	242.68	0.188	1.2
Minimum	-0.009	-0.152	-0.750	803.49	0.009	-0.361
Std. Dev.	0.001	0.031	0.033	142.11	0.047	0.36
Skewness	4.689	0.689	-17.326	0,892	0.609	0.519
Sum	0.007	-0.304	-3.000	23,397	4.3	9.176

Note: CDX and VIX are in log differences.

Table 4: Externalities/Vulnerabilities matrix

Shock\Response	y_1	y_2	$\cdots$	y_n	Externalities
y_1	-	$IR_{y_1 \to y_2}$	$\cdots$	$IR_{y_1 \to y_n}$	$\sum_{j=1, j\neq 1}^{N} IR_{y_1 \to y_j}$
y_2	$IR_{y_2 \to y_1}$	-	$\cdots$	$IR_{y_2 \to y_n}$	$\sum_{j=1, j\neq 2}^{N} IR_{y_2 \to y_j}$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
y_n	$IR_{y_n \to y_1}$	$IR_{y_n \to y_2}$	$\cdots$	-	$\sum_{j=1, j\neq n}^{N} IR_{y_n \to y_j}$
Vulnerabilities	$\sum_{j=2}^{N} IR_{y_j \to y_1}$	$\sum_{j=1, j\neq 2}^{N} IR_{y_j \to y_2}$	$\cdots$	$\sum_{j=1}^{N-1} IR_{y_j \to y_n}$	$TSRI = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1, j\neq i}^{N} IR_{y_i \to y_j}$
Systemic Score	The sum of *Vulnerabilities* and *Externalities*				

Note: Variables in the first column are the impulse origin, while variables in the top row are the respondents to the shock. A value of 0.3 means that the response variable would be impacted in the same direction with an intensity of 30% of the initial unexpected shock in the impulse variable. The last column presents the aggregated impact sent (Externalities) by each row variable and the bottom row presents the aggregated spillover received (Vulnerabilities) by each column variable.

Table 5: Deutsche Bank crisis secondary effects analysis through the case of Standard Chartered

Response	Average Standard Chartered Impulse	Jul. 2016 (Deutsche Crisis)	Sep. 2016	% (Sep. 2016 - Jul. 2016)
Korea Development Bank	0,007	0,001	0,014	1513%
Industrial Bank of Korea	0,016	0,002	0,014	794%
Landesbank Hessen	0,001	0,000	0,002	687%
Landesbank Baden-Wurttemberg	0,003	0,000	0,003	595%
KBC Group NV	0,007	0,001	0,006	459%
Erste Group Bank AG	0,016	0,002	0,010	392%
Shinhan Financial Group	0,018	0,003	0,014	328%
Macquarie	0,009	0,002	0,008	262%
Sumitomo Mitsui Financial Group	0,018	0,002	0,005	242%
Woori Bank	0,006	0,004	0,014	233%
Lavoro Bank A.G.	0,000	0,005	0,015	231%
State bank of India	0,004	0,002	0,006	209%
Australia & New Zealand Banking	0,009	0,004	0,010	151%
National Australia Bank	0,004	0,004	0,008	125%
China Development Bank	0,015	0,006	0,013	124%
Westpac Banking Corp	0,008	0,004	0,009	111%
The Export-Import Bank of China	0,014	0,006	0,012	105%
DBS Group Holdings	0,008	0,002	0,004	105%
Commonwealth Bank of Australia	0,015	0,005	0,010	102%
Nomura Holdings	0,002	0,002	0,004	61%
Industrial & Comm Bank of China	0,003	0,004	0,006	45%
Nordea	0,007	0,006	0,008	45%
HSBC Holdings	0,007	0,012	0,017	42%
American Express	0,003	0,009	0,012	35%
Skandinaviska Enskilda Banken	0,009	0,005	0,007	20%
VTB Bank	0,004	0,009	0,011	20%
Dexia	0,012	0,002	0,003	17%
Sberbank of Russia	0,002	0,011	0,012	11%
Capital One Financial Corporation	0,005	0,006	0,007	10%
Banca Monte dei Paschi di Siena	0,002	0,010	0,011	9%

Note: The first column contains banks that respond to shocks sent by Standard Chartered. The second column shows the average shock over the 56 rolling-window periods in the sample. The 3rd column presents the shocks that were sent by Standard Chartered during the peak (t) of the Deutsche Bank crisis while the 4th column presents the shocks sent by Standard Chartered one period after the peak (t+1) of the Deutsche Bank crisis. The last column presents the % increase in the externalities of Standard Chartered between the t and $t+1$ of Deutsche crisis. For example, the shocks sent from Standard Chartered to Industrial Bank of Korea increased by 794.3%. Banks that respond to the shocks are ranked in terms of % increase between the t and $t+1$ of the Deutsche crisis peak.

Table 6: Generalized Forecast Error Variance Decomposition

Panel A: Response of Bottom-5 index

iTraxx	*CISS*	*OIS*	*VIX*	*Bottom-5*
0,07	0,097	0,096	0,073	0,519

Panel B: Impulse of Bottom-5 index

iTraxx	*CISS*	*OIS*	*VIX*	*Bottom-5*
0,134	0,093	0,1	0,079	0,706

Panel C: Response of Top-5 index

iTraxx	*CISS*	*OIS*	*VIX*	*Top-5*
0,057	0,169	0,16	0,142	0,433

Panel D: Impulse of Top-5 index

iTraxx	*CISS*	*OIS*	*VIX*	*Top-5*
0,33	0,252	0,589	0,282	0,635

Note: *Panels A* and *C* refer to the response of *Bottom-5 ISR index* and *Top-5 ISR index,* respectively, to a shock to each one of the variables in the top row. *Panels B* and *D* refer to the response of *variables* in the top row to a shock to *Bottom-5 ISR index* and *Top-5 ISR index,* respectively.

Table 7: Granger Causality between Top-5 Index and Bottom-5 Index

Equation \ Excluded	**chi2**	**df**	**Prob > chi2**
Top-5 Index			
Bottom-5 Index	0.089	1	0.766
Bottom-5 Index			
Top-5 Index	3.285	1	0.070

Table 8: Regional systemic risk

	Asia	***Europe***	***Oceania***	***US***	***Vulnerabilities***
Asia	1,2	2,2	0,5	0,7	4,7
Europe	2,1	12,7	0,9	4,1	19,8
Oceania	0,4	0,7	0,3	0,2	1,7
US	0,8	4,6	0,3	2,1	7,9
Externalities	4,6	20,2	2,1	7,1	34,1
Score	9,3	40,1	3,8	15,0	

Note: Variables in the first column are the impulse origin, while variables on the top row are the respondents to the shock. The *Score* row provides the systemic importance of regions and is the sum of region banks' externalities and vulnerabilities.

Table 9 – Variables Description

	Variable	Source	Description
	Vulnerabilities	*Calculations*	Vulnerabilities per bank
	Externalities	*Calculations*	Externalities per bank
	ISR	*Calculations*	Total Systemic Index per Bank
Bank-Specific	*ROE*	*Datastream*	Return on Equity
	NIM	*Datastream*	Net Interest Margin
	Tier 1	*Datastream*	Tier 1 per bank
	Total Assets	*Datastream*	Total Assets per bank
	NPLTA	*Datastream*	Non-performing loans over Total Assets
Country-Specific	*Concentration*	*Bankscope*	Concentration Index. Raw data are from Bankscope.
	GDP	Bloomberg	Ln Values of Gross Domestic Product
	DEBT	Bloomberg	Debt as a % of GDP
	DEFICIT	Bloomberg	Deficit as a % of GDP
	BCI	Bloomberg	Business Confidence Index

Note: Description of variables used in section 6.

Table 10 - Descriptive Statistics

Panel A – Bank-specific Variables

Variable	Mean	Std. Dev.	Min	Max	Observations
Externalities	0,398	0,212	-0,361	0,941	N = 2263
Vulnerabilities	0,402	0,256	-0,411	1,240	N = 2263
ISR	0,800	0,453	-0,531	2,103	N = 2263
G-SIB	0,323	0,468	0,000	1,000	N = 2263
ROE	0,490	0,484	-1,300	4,500	N = 2263
NIM	19,530	44,681	-270,600	668,500	N = 2263
Tier1	13,457	3,537	6,400	28,700	N = 2263
Total Assets	2,681	11,630	-33,600	111,200	N = 2263
NPL	2,289	5,347	0,100	49,500	N = 2263

Panel B – Country specific Variables

Variable	Mean	Std. Dev.	Min	Max	Observations
lnGDP	12.014	1.161	12.314	16.786	N = 135
Debt	104	48.437	39.163	238.180	N = 135
Deficit	-4	3.583	-15.148	1.520	N = 135
BCI	100	1.073	96.220	102.517	N = 135
Concentration	48.696	13.262	34.615	78.600	N = 135

Note: *This Table reports* descriptive statistics for the variables used in Section 6 of the paper. Panel A contains the bank-specific variables and Panel B the country-specific variables. The variables' definitions are in the main text.

Table 11: Characteristics Related to Bank Systemic Importance

Panel A– Externalities under Investigation

Externalities	**Coef.**	**Std. Err.**
Externalities(-1)	**0.69919*** **	0.01149
Concentration	-0.00026	0.00018
ROE	**-0.03113*** **	0.00626
NIM	0.00007	0.00006
TIER1	0.00062	0.00067
Total Assets	**0.00069*** **	0.00018
NPLs	-0.00010	0.00065
LnGDP	-0.00362	0.00508
Debt	**-0.00069*** **	0.00014
Deficit	**-0.00267*** **	0.00129
BCI	0.00140	0.01076
G-SIB	**0.04003*** **	0.00697
_cons	0.09643	1.04565

Note: Dynamic panel-data estimation. Arellano-Bond test for AR(1) in first differences: z=-5.59, Pr>z =0.000. Sargan Test of overidentification restrictions chi2(1375) = 1530.06, Prob>chi2=0.002. Hansen Test of overidentification restrictions chi2(1319) = 40.14, Prob>chi2=1.000. Level equations with lagged differences as instruments in addition to the equations in first differences with lagged levels as instruments are included. Wald chi2(12) = 34282.87, Prob>chi2 = 0.000. Windmeijer's finite-sample correction for the two-step covariance matrix. Number of banks is 45 and total observations are 2263. Overall R-squared is 19%. Coefficients marked ***, **, and * are significant at the 1%, 5%, and 10% significance levels, respectively.

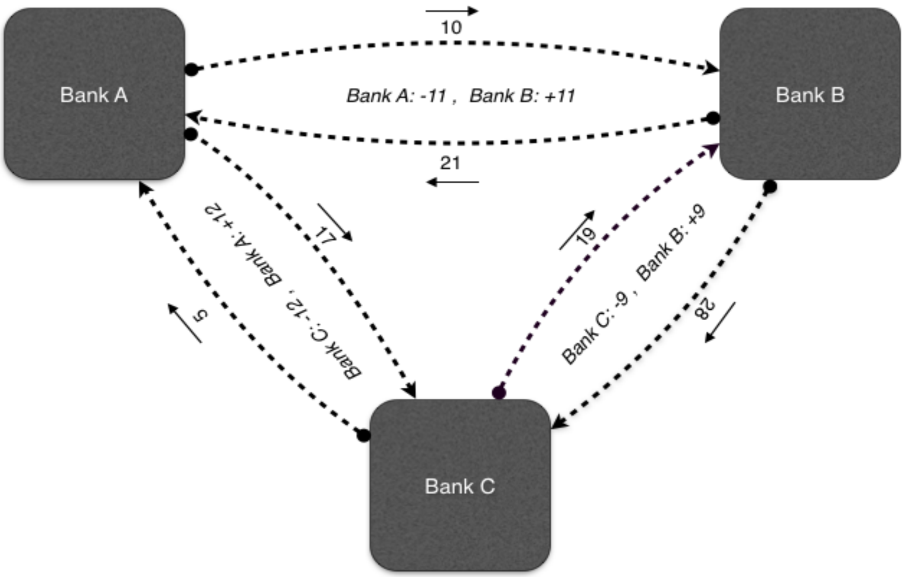
Panel B– Vulnerabilities under Investigation

Vulnerabilities	**Coef.**	**Std. Err.**
Vulnerabilities(-1)	**0.76586*** **	0.01182
Concentration	**-0.00044*** **	0.00022
ROE	**-0.03860*** **	0.00967
NIM	0.00008	0.00008
TIER1	0.00041	0.00081
Total Assets	**0.00102*** **	0.00017
NPLs	0.00051	0.00079
LnGDP	**-0.00754*** **	0.00441
Debt	**-0.00051*** **	0.00015
Deficit	**-0.00335*** **	0.00098
BCI	0.00832	0.00585
G-SIB	**0.05988*** **	0.00783
_cons	-0.58074	0.59086

Note: Dynamic panel-data estimation. Arellano-Bond test for AR(1) in first differences: z=-4.71, Pr>z =0.000. Sargan Test of overidentification restrictions chi2(1375) = 1520.51, Prob>chi2=0.003. Hansen Test of overidentification restrictions chi2(1319) = 39.21, Prob>chi2=1.000. Level equations with lagged differences as instruments in addition to the equations in first differences with lagged levels as instruments are included. Wald chi2(12) = 14313.96, Prob>chi2 = 0.000. Windmeijer's finite-sample correction for the two-step covariance matrix. Number of banks is 45 and total observations are 2263. Overall R-squared is 24%. Coefficients marked ***, **, and * are significant at the 1%, 5%, and 10% significance levels, respectively.

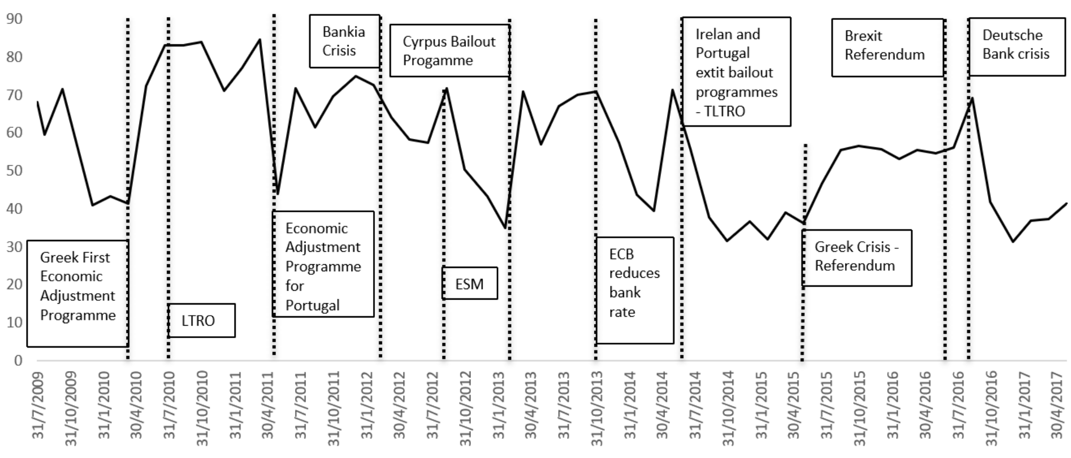
FIGURES

Figure 1: Example of pairwise directional connectedness



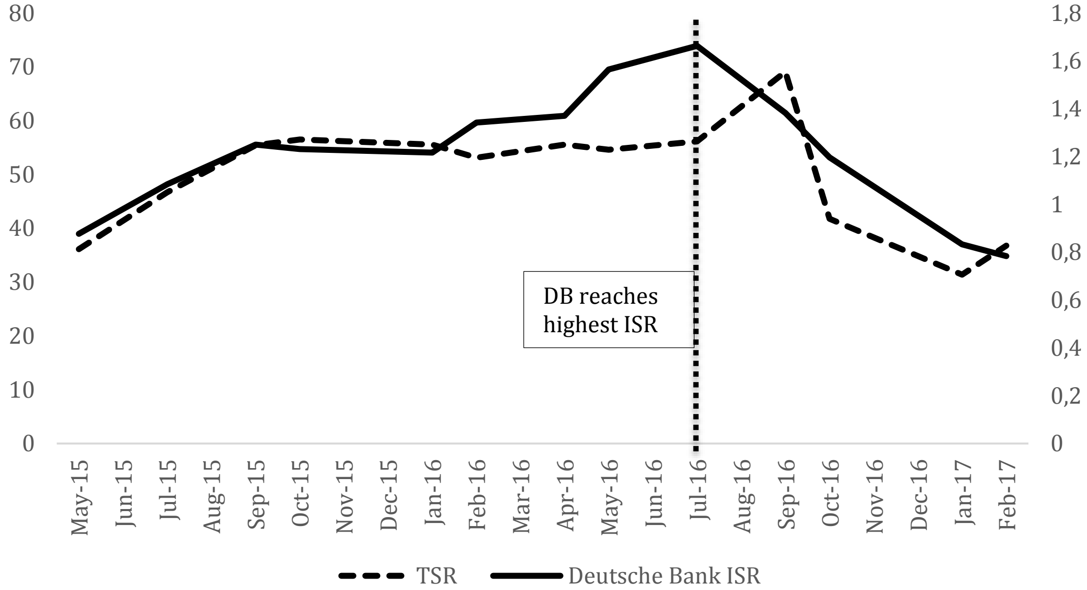
Note: Figure 1 presents the direct impact of an idiosyncratic shock on bank A to bank B and to bank C, separately. Bank A sends a shock to B, equivalent to 10% of its idiosyncratic shock and a shock to C equivalent to 17% of its idiosyncratic shock. In total, bank A generates externalities equal to 27% of its idiosyncratic shock. Bank A receives a shock from bank B equivalent to 21% of its idiosyncratic shock and from bank C equivalent to 5%, respectively. The total vulnerabilities of bank A amount to 26% of an equal idiosyncratic shock to the other banks in the system (bank B and C). If we sum the shocks that bank A sends to and receives from the system as a result of an equal shock hitting every bank in the system, we obtain a measure of the degree of connectedness for bank A. This is a valid measure of bank A's systemic importance. This procedure is repeated in order to calculate the systemic importance of bank B and bank C.

Figure 2: Total Systemic Risk



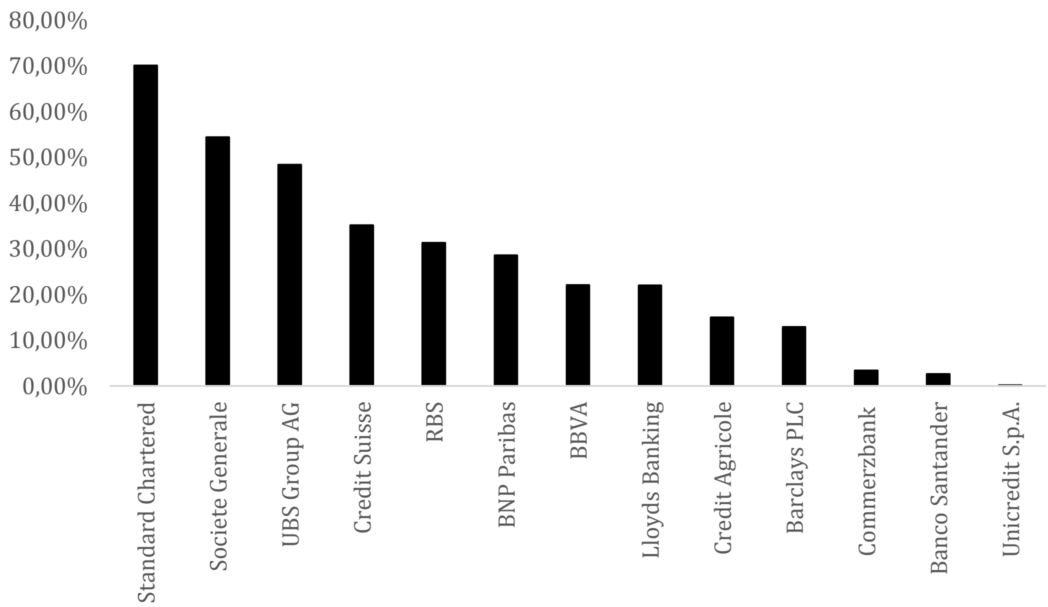
Note: Figure 2 presents the evolution of TSR over the 56 rolling windows during the period Jan. 2009 – Jun. 2017. Major financial systemic events are indicated.

Figure 3: Deutsche Bank ISR and TSR - Deutsche bank's contagion effect



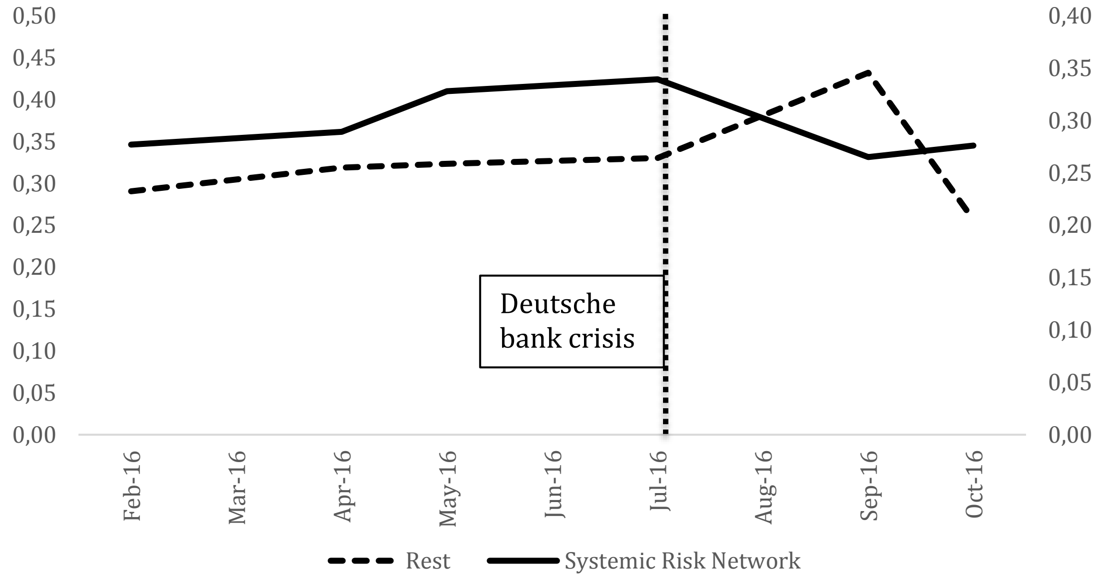
Note: Figure 3 presents Deutsche bank's ISR (solid line – RHS axis) and TSR (dashed line – LHS axis).

Figure 4: Deutsche Bank systemic risk network reaction - Average externalities vs. Externalities on July 2016



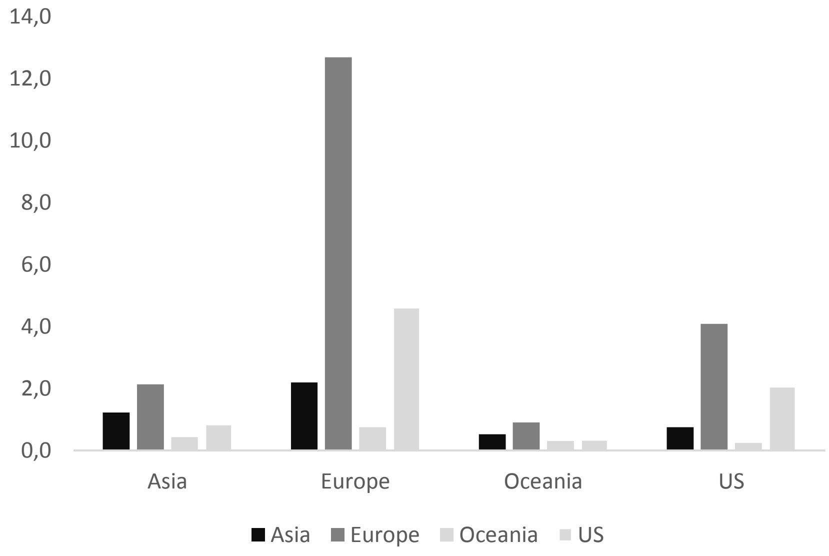
Note: Figure 4 presents the percentage change between the average shocks sent by Deutsche Bank to its systemic risk network over the period Jan. 2009 – Jun. 2017 and the shocks sent over the period Mar. 2016 – Jul. 2016. For example, the externalities of Deutsche bank to Standard Chartered increased by 68%.

Figure 5: Standard Chartered externalities to its systemic risk network and outside.



Note: The solid line presents the externalities of Standard Chartered to its systemic risk network (as this is defined in section 5.1) while the dashed line presents the externalities to the banks outside the bank's network. The vertical dashed line represents the period where Deutsche Bank's ISR reached its maximum value.

Figure 6: Externalities at regional level.



Note: Figure 6 depicts the shocks' origination and destination at regional level. Regions on the horizontal axis are the impulse origin. The bar heights in each group depict the sum of externalities sent by the originating region over the period January 2009 to June 2017.

Appendix

Table A.I : Individual Systemic Risk (ISR) (Jan. 2009 – June 2017)

Region	Country	Bank name	G-SIB	ISR	ISR Rank	Size Rank
Europe	France	BNP Paribas	*	1,925	1	4
Europe	Spain	Banco Santander	*	1,871	2	15
Europe	France	Credit Agricole Group	*	1,827	3	8
Europe	UK	Barclays PLC	*	1,825	4	13
Europe	Italy	Intesa Sanpaolo		1,82	5	25
Europe	Spain	BBVA	*	1,797	6	24
Europe	France	Societe Generale	*	1,779	7	14
Europe	Italy	Unicredit S.p.A.	*	1,755	8	19
Europe	Germany	Commerzbank	*	1,728	9	33
Europe	Germany	Deutsche Bank	*	1,717	10	11
Europe	Switzerland	Credit Suisse Group	*	1,684	11	23
Europe	UK	Lloyds Banking Group	*	1,674	12	16
Europe	UK	UBS Group AG	*	1,654	13	18
Europe	UK	Royal Bank of Scotland Group	*	1,569	14	17
Europe	UK	Standard Chartered Plc	*	1,476	15	30
Europe	Italy	Banca Monte dei Paschi di Siena		1,463	16	60
Europe	Netherlands	ING Groep NV		1,417	17	20
US	US	HSBC Holdings	*	1,413	18	3
US	US	Morgan Stanley	*	1,377	19	22
Europe	Netherlands	Rabobank Group		1,353	20	27
US	US	Citigroup	*	1,349	21	9
US	US	Goldman Sachs Group	*	1,339	22	21
US	US	Bank of America	*	1,33	23	5
US	US	JPMorgan Chase & Co	*	1,266	24	2
US	US	American Express		1,254	25	61
Europe	Italy	Lavoro Bank A.G.		1,222	26	68
Europe	Italy	Mediobanca		1,216	27	65
US	US	Wells Fargo		1,216	28	6
US	US	Capital One Financial Corp.		1,161	29	40
Europe	Portugal	Portuguese Comercial Bank		1,138	30	69
Europe	Sweden	Svenska Handelsbanken		1,092	31	44
Europe	Russia	Sberbank of Russia		1,082	32	37
Europe	Denmark	Danske		1,063	33	34
Europe	Spain	Banco Sabadell		1,036	34	55
Europe	Russia	VTB Bank		1,033	35	58
Europe	Spain	Banco Espirito Santo		1,012	36	64
Europe	Germany	Bayerische Landesbank		1	37	56
Europe	Sweden	Nordea		0,994	38	29
Europe	Austria	Erste Group Bank AG		0,952	39	57
Europe	Sweden	Skandinaviska Enskilda Banken		0,948	40	45
Europe	Austria	KBC Group NV		0,945	41	43

Table A.I (continued from previous page)

Region	Country	Bank name	GSIB	ISR	ISR Rank	Size Rank
Oceania	Australia	Commonwealth Bank of Australia		0,929	42	26
Asia	S. Korea	Industrial Bank of Korea		0,922	43	59
Asia	S. Korea	Korea Development Bank		0,914	44	48
Asia	S. Korea	Woori Bank		0,91	45	49
Asia	China	Shinhan Financial Group		0,881	46	42
Europe	Sweden	Swedbank		0,87	47	52
Oceania	Australia	Australia & New Zealand Banking		0,861	48	28
Asia	S. Korea	Hana Financial Group		0,839	49	46
US	US	Nationwide Building Society		0,816	50	47
Oceania	Australia	National Australia Bank		0,794	51	32
Asia	China	China Development Bank	*	0,787	52	7
Asia	China	The Export-Import Bank of China		0,758	53	36
Asia	India	State bank of India		0,713	54	35
Oceania	Australia	Westpac Banking Corp		0,702	55	31
Oceania	Australia	Macquarie		0,668	56	63
Europe	Belgium	Dexia		0,647	57	54
Asia	China	Ind. & Comm. Bank of China	*	0,547	58	1
Europe	Norway	DBS Group Holdings		0,515	59	41
Europe	Germany	Landesbank Baden-Wurttemberg		0,457	60	50
Asia	Singapore	United Overseas Bank (UOB)		0,368	61	53
Asia	Japan	Nomura Holdings		0,36	62	39
Asia	Japan	Resona		0,331	63	38
Europe	Greece	Alpha Bank		0,321	64	70
Asia	Japan	Mizuho Financial Group	*	0,291	65	10
Europe	Germany	Landesbank Hessen		0,26	66	67
US	US	Cathay Financial Holding		0,243	67	51
Europe	Greece	National Bank of Greece		0,232	68	62
Asia	S. Korea	Sumitomo Mitsui Financial Group	*	0,215	69	12
US	US	U.S. Bancorp		0,043	70	66

Note: Results cover the period January 2009 – June 2017. The above results concern 1-day horizon Bayesian VARs. ISR is the *Individual Systemic Risk* score. ISR rank is the ranking based on the ISR. Size Rank uses banks' Total Assets as of December 2016.

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