Measuring the Systemic Importance of Banks

Georgios Moratis[1] Plutarchos Sakellaris[2]

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Abstract

We measure the systemic importance of all banks that issue publicly traded CDS contracts among the world's biggest 150. Systemic importance is captured by the intensity of spillovers of daily CDS movements. Our new empirical tool uses Bayesian VAR to address the dimensionality problem and identifies banks that may trigger instability in the global financial system. For the period January 2008 to June 2017, we find the following: A bank's systemic importance is not adequately captured by its size. European banks have been the main source of global systemic risk with strong interconnections to US banks. For the global system, we identify periods of increased interconnections among banks, during which systemic and idiosyncratic shocks are propagated more intensely via the network. Using principal components analysis, we identify a single dominant factor associated with fluctuations in CDS spreads. Individual banks' exposure to this factor is related to their government's ability to support them and to their retail orientation but not to their size.

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

1. Introduction

Macroprudential policy entails bank supervision from a system-wide perspective, rather than that of the individual institution. The objective is to limit the risk of system-wide financial crisis as well as to contain the costs to the real economy, if a crisis erupts. In order to ensure that each institution pays for the externality it imposes on the global system, the measures applied to each bank should be calibrated to the systemic importance of each bank. In this paper, we provide a measure of systemic importance of all banks that issue publicly traded CDS contracts among the world's biggest 150 banks, for the period January 2008 to June 2017. We capture systemic importance by the intensity of spillovers of daily CDS movements. This measure captures institutional externalities such as "too big to fail", or "too correlated to fail."

We obtain some strong and, in some respects, surprising results. A bank's systemic importance is not adequately captured by its size. In addition, there is a considerable number of banks officially designated as GSIBs that are not ranked in the first quartile in terms of our novel measure of systemic importance.[3] Throughout the examined period, European banks have been the main source of global systemic risk with strong interconnections to US banks. Looking at the time dimension for global systemic risk, we identify periods of increased interconnections among banks, during which systemic and idiosyncratic shocks are propagated more intensely via the network. Using principal components analysis, we identify a single dominant factor associated with fluctuations in banks' CDS spreads. Individual banks' exposure to this factor is related to their

[3] See FSB (2013) for a description of the methodology for assessing the systemic importance of global systemically important banks (GSIBs) and the higher loss absorbency requirements imposed on them.

government's ability to support them and to their retail orientation but not to their size.

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 bank system. Vulnerability is captured by the shocks it receives from each bank in the global system. In particular, we find that more systemically important banks display relatively higher externalities than vulnerability to 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, and supervisory review actions. Arguably, this is an improved approach to safeguarding financial stability.

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.[4] CDS spreads are a better measure of credit risk than bond spreads, equity returns or other market variables. Second, we use Bayesian VAR to confront the high dimensionality of bank networks. Past work on this topic had to limit attention to a subset of global banks because of the dimensionality problem.[5] The closest to our approach is Alter and Beyer (2012), which builds upon the framework of Diebold and Yilmaz (2009, 2012). We deviate from

[4] These linkages may arise from correlated exposures, counterparty relationships or other structural channels.

[5] 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. (2016) for the U.S. financial system.

common practice in the literature by removing any market-wide shocks through the inclusion of a set of common external systemic variables. Thus, we allow each bank to become a source of systemic risk after idiosyncratic shocks through spillovers.

The remainder of this document is structured as follows. Section 2 presents the existing literature and section 3 describes the process of measuring systemic risk, the existing frameworks and the motivation. Section 4 presents the methodology and the data, while section 5 presents the results and section 6 concludes.

2. Relevant Literature

Our paper is closely related to four literature strands. First, it is related to studies concerning macroprudential policy. The aim of macroprudential policy is to increase the resilience of individual financial institutions and of the financial system as a whole, by limiting the build-up of vulnerabilities in order to mitigate systemic risk (ECB, 2016). It is also used to smooth-out the financial cycle, driven by fluctuations in credit, leverage and asset prices, which may otherwise result in a pattern of boom and bust (Dell'Ariccia et al., 2013; Elliot et al., 2013; Cerutti et al., 2015). Appropriate policies should be designed toward limiting the ex ante externalities that lead to an excessive build-up of systemic risk, and the ex post externalities that can generate inefficient failures of otherwise sound institutions in a crisis. All in all, macroprudential policy is the usage of primarily prudential tools to limit systemic risk (Crockett, 2000; FSB/IMF/BIS, 2011; IMF 2013). The literature on macroprudential policy is growing at a fast pace but is still at an early stage and historical experience is thin. The most relevant part of the literature aims at assessing the systemic importance of G-SIBs. The most important framework is the one developed by Basel Committee on Banking Supervision (BCBS). The framework compares each bank's activity over twelve indicators and finally assigns a score to each bank. The indicators include the size, the interconnectedness, the substitutability, the complexity and the cross-jurisdictional activity of each bank.

The BCBS methodology has also been used by Financial Stability Board for the identification of G-SIBs. This methodology has been transposed in the EU regulatory framework (see Article 131 of the Capital Requirements Directive IV (CRDIV)), which defines global systemically important institutions or G-SIIs. The BCBS/FSB framework for determining systemic risk has some deficiencies. It assigns primal importance to size, as all bank characteristics considered are directly related to size. This is a premise that is not necessarily backed by empirical evidence that the biggest banks are the most dangerous ones for financial stability. In addition, the weights assigned to the characteristics are arbitrary. Finally, it does not provide any information on the degree of externalities between a systemically important bank and any other one in the system. Our contribution is to use direct observations on credit risk to measure externalities between any two banks in the global system. In this way, we quantify the degree of danger that any bank may pose to the financial system or parts of it defined broadly or narrowly. Our methodology flexibly updates the classification dynamically as new information is obtained.

The second relevant field of literature has to do with the alternative systemic risk rankings for financial institutions. There is an important number of methodologies for calculating the exposure of financial institutions to changes in current economic conditions, how concentrated the risks are among the financial institutions and how closely linked they are with each other. The first stream has to do with price-based systemic risk rankings such as banks' VaR (Adams, Fuss, and Gropp, 2014; White, Kim, and Manganelli, 2015), ΔCoVaR (Adrian and Brunnermeier, 2014; Castro and Ferrari, 2014) and MES (Acharya, Pedersen, Philippon, and Richardson, 2010). These measure the VaR or MES of financial institutions conditional on the entire set of institutions performing poorly. The second group of such metrics incorporates book values as well and includes SRISK (Acharya, Engle, and Richardson, 2012; Brownlees and Engle, 2010), leverage ratio (Fostel and Geanakoplos, 2008; Geanakoplos and Pedersen, 2014), and CAPM beta times market capitalization (Benoit, Colliard, Hurlin, and Perignon, 2015). 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 key weakness, which is that they do not provide information on the pairwise directional connectedness, i.e. the direction of externalities 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. However, Granger causality is unable to consider contemporaneous movements, control for exogenous variables, quantify intensities of effects, or consider multi-dimensional networks. These are all aspects that our methodology and measure enables.

The third group of relevant papers deals with the estimation of high-dimensional VAR models. Our approach is closely related to the approach developed by Alter and Beyer (2013), which is based on the framework of

Diebold and Yilmaz (2009, 2011). The high-dimensionality problem had forced this research on global bank connectedness to limit their analysis to small samples of banks. Needless to say 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. Our distinct approach is to use Bayesian VAR in order to resolve the dimensionality problem.

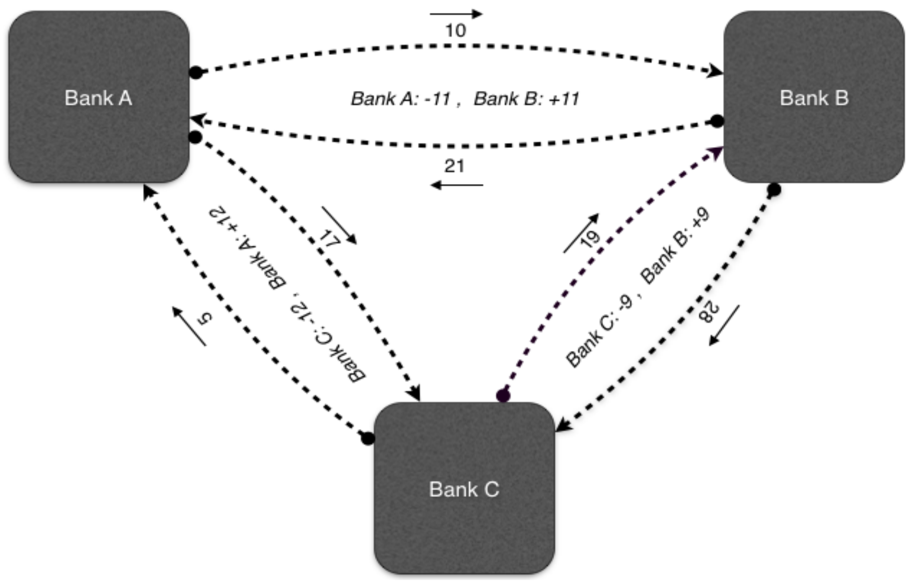
Finally, our paper relates to studies that apply principal components methods to analyze systemic risk. Billio et al. (2012) suggested that an important symptom of systemic risk is the presence of sudden regime shifts. Giglio et al. (2015) proposed dimension-reduction estimators for constructing systemic risk indexes from the cross section of measures and prove their consistency in a factor model setting. We differ by examining the individual bank loadings on the dominant factor associated with fluctuations in bank CDS spreads and determining which bank and country characteristics are related to these. This provides solid empirical basis for using relevant characteristics as indicators to measure systemic importance indirectly.

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) 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. More precisely, we adopt the "pure-contagion" (Gomez-Puig and Sosvilla Rivero, 2013) definition by controlling only for external common factors through the inclusion of a set of common external systemic risk factors, and assume that each bank could become itself a source of systemic risk as a result of an idiosyncratic shock.

The following example illustrates how we measure the systemic importance of banks (see Figure 1). Assume that there exist three banks. Focusing on bank A as the source of shocks, figure 1 presents the potential impact of an idiosyncratic shock on bank A to bank B and to bank C, respectively. Bank A sends a ten-unit shock to B and a seventeen-unit shock to C, a total of 27. Next, we focus on the shocks received by bank A from the other banks in the system. Bank A receives a twenty-one-unit shock from bank B and a five-unit shock from bank C, a total of 26. If we sum the shocks that bank A sends to and receives from the system, we obtain an estimate 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: Example of pairwise directional connectedness



Transforming this figure into a table, we construct the directional connectedness matrix.

Table 1: Directional connectedness matrix

Shock/Response	*Bank A*	*Bank B*	*Bank C*	***To Others (Sum_Out)***
Bank A	-	10	17	27
Bank B	21	-	28	49
Bank C	5	19	-	24
From Other(Sum_In)	26	29	45	100
Score (Sum_Out+Sum_In)	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.

Table 1 presents the entire picture for all three banks 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 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, as we are 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

4.1 Data

We study 77 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 77 banks to CDS prices from Thomson-Reuters Datastream and Bloomberg. CDS spreads cover the period from January 2008 to June 2017 and are at daily frequency. The sample contains all the banks that are designated as *"global systemically important banks"* ("GSIB'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). Table 2a (in the Appendix) classifies banks by assets and provides detail on the 77 banks in the sample, such as home-country and total assets, while table 2b (in the Appendix) classifies banks by home-country. We note that 40 out of the 77 banks (52%) in the sample are from Europe while 28 of them (34%) are headquartered in Eurozone members. Tables 3a and 3b (in the Appendix) provide the regional characteristics of the sample.

4.1.1 Systemic Risk factor

We will allow for the presence of a global systemic risk factor. This permits us to interpret robustly the results obtained from our model. Longstaff et al. (2011), for instance, has argued that credit risk appears related to global rather than country-specific factors while Aizenman et al. (2013) has established the importance of international economic factors in the pricing of credit risk. The variables we chose to 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; Aizenman et al., 2013; Ang and Longstaff, 2011). The global default risk conditions are represented by: 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, which is represented by the US 3-month treasury bills. The systemic factor is assumed to affect the endogenous variables contemporaneously. Table 4 contains the variable definitions and Table 5 provides descriptive statistics.

4.1.2 Bank-specific characteristics

A variety of bank- and country-specific variables are used for identifying the determinants of systemic risk fluctuation over time. The first bank-specific variable is bank size expressed as each bank's total assets (in log). According to BIS (2011a) the larger a bank is, the more likely it is to receive a bailout package. In this sense, we also take into consideration the "too-big-to-fail" (TBTF) issue (Acharya et al., 2013). The second bank-specific variable is the loan-to-asset ratio, which provides information on the bank's retail orientation. Ayadi et al. (2011) and Köhler (2013) suggest that retail-orientated banks appeared to be less risky than other banks during the recent financial crisis. Also, according to Altunbas et al. (2011) the non-interest income over total revenue is considered to be a measure of each bank's diversification, since the less a bank relies on interest income, the less exposed the bank is to a negative shock. Finally, we include each bank's nonperforming loans over total loans (see Tables 4 and 5).

4.1.3 Country-specific characteristics

It is important to include country-specific factors, since the impact of macroprudential policy might differ depending on the underlying economic conditions of each bank's home country. For example, the impact of shocks may be larger for economies that were under stress and hence rely more on rescue packages and foreign financing (IMF 2015a). These economies would not have the same ability to support effectively their banking systems in times of distress.

We investigate the role of sovereigns by searching among each *bank's home-country GDP growth*, the *primary surplus over GDP* and *public debt over GDP*.

4.2 Connectedness matrix

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

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

The vector of endogenous variables (y) consists of log differences of daily CDS spreads for the 77 banks. By including the exogenous variables, we account for common factors that affect at the same time all bank CDS spreads (Bekaert et al., 2005).

4.2.1 Bayesian VAR

The suggested model has many more parameters than observations, overfits the data in-sample, and, as a consequence, could perform poorly. 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. Their application to recursive forecasting exercises can, as a consequence, be prohibitive or even infeasible. The only exception is a variant of the Minnesota prior that 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 (2012), 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; see Koop and Korobilis (2010) for a further discussion of this aspect of the natural conjugate prior.

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), still dominates many applications of VAR models in economics. The recent contribution of Giannone, Lenza and Primiceri (2012), provides guidance on selecting the prior hyperparameter controlling shrinkage of the VAR coefficients.

Note that computational simplicity is a priority in this paper, so that the Gibbs sampler is preferred compared to other potentially more powerful and elegant Markov Chain Monte Carlo (MCMC) and Sequential Monte Carlo (SMC) algorithms for prior selection. However, we recognize that the flexibility of choosing the prior freely is one of the main controversial issues associated with Bayesian analysis and the reason why some researchers view the latter as subjective. It is also the reason why the Bayesian practice, especially in the early days, was dominated by non-informative priors, as these priors assign equal probabilities to all possible states of the parameter space with the aim of rectifying the subjectivity problem. We estimate the coefficients of a VAR(2) for 78 banks using the arithmetic returns 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 specify hyperparameters for the prior.

The Bayesian VAR(p) model can be written as:

$$y_t = a_0 + \sum_{j=1}^{p} A_j y_{t-j} + \varepsilon_t$$

where y_t for $t = 1,..., T$ is an $M \times 1$ vector containing observations on M time series variables, εt is an $M \times 1$ vector of errors, α_0 is an $M \times 1$ vector of intercepts and A_j is an $M \times M$ matrix of coefficients. We assume ε_t to be *i.i.d.* $N(0, \Sigma)$. Exogenous variables are added to the VAR and included in all the derivations below, but we do not do so to keep the notation as simple as possible.

4.2.2 The connectedness matrix framework

The construction of the diagnostic tool is based on a medium-size Bayesian vector autoregressive model with exogenous variables (Bayesian VARX) that accounts for common global and regional trends, and is able to include even bank-specific characteristics. Then, similar as 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 on Generalized Forecast Error Variance Decomposition (GFEVD) or on Generalized Impulse Response Functions (GIRF), obtained as shown in Pesaran and Shin (1998). Therefore, we derive Generalized Impulse Response Functions as functions of residuals together with the interdependent coefficients. According to Alter and Beyer (2012), it is of low importance which methodology we select, since they produce qualitatively similar results.

Table 6: Contagion/connectedness matrix

Shock\Response	y_1	y_2	..	y_n	To Others
y_1	-	$IR_{y1\to y2}$	..	$IR_{y1\to yn}$	$\sum_{j=1}^{N} IR_{y1\to yj}, j \neq 1$
y_2	$IR_{y2\to y1}$	-	..	$IR_{y2\to yn}$	$\sum_{j=1}^{N} IR_{y2\to yj}, j \neq 2$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
y_n	$IR_{yn\to y1}$	$IR_{yn\to y2}$	..	-	$\sum_{j=1}^{N} IR_{yn\to yj}, j \neq n$
From Others	$\sum_{j=2}^{N} IR_{yj\to y1}$	$\sum_{j=1}^{N} IR_{yj\to y2}$	..	$\sum_{j=1}^{N-1} IR_{yj\to yn}$	$CI = \frac{100}{N(N-1)} \sum_{i=1}^{N} \sum_{j=1, j\neq 1}^{N}$
Score	The sum between Shock_Sent and Shock_Received				

Note: Variables in the first column are the impulse origin, while variables on the top row are the respondents to the shock. The cumulative impact is bound between 0 and 1. A value of 0.5 means that the response variable would be impacted in the same direction with an intensity of 50% the initial unexpected shock in the impulse variable. The last column presents the aggregated impact sent (Sum OUT) by each row variable and on the bottom row the aggregated spillover received (Sum IN) by each column variable. The bottom-right cell shows total spillover in the system, and by dividing this value to the total number of non-diagonal cells we obtain the connectedness index (CI)

In table 2, row variables are the origin of the unexpected shock. Column variables are the respondents of contagion receivers. CI represents the connectedness index, calculated as the average response in the contagion matrix. The potential contagion effects are aggregated on each line and column and represent the total *to_others* and the total *from_others* as potential contributions to contagion from and to each bank. 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 evolve in the following period if bank A CDS increases by one unit shock?"*

We use accumulated Impulse Response functions over a 10-step horizon (10-days). Not all the banks respond to the shocks within the same period but the majority of the shocks are absorbed within 10-days. Nevertheless, the framework is flexible and it easily adapts to the needs of each study.

5. Empirical results

5.1 Individual bank connectedness

We estimate the connectedness matrix as described in section 4.2.2 for the whole sample period, 1 January 2008 to 31 June 2017, and estimate the individual bank connectedness (table 7) which reports several notable results. The evidence do not offer support to the argument that systemic importance of a bank can be adequately captured by its size. According to table 7, the bank that creates the most systemic risk in the system is Intesa Sanpaolo, a medium-sized European bank that is ranked 27th in terms of total assets, with total contagion effects of 1.056 which is further decomposed into 0.505 vulnerability-score and 0.551 externalities-score. For instance, the Intesa Sanpaolo's 0.551 externalities score implies that one-unit shock in Intesa Sanpaolo will have an impact of 55.1% to the system, while the 0.505 vulnerability score means that one-unit shock to the market will affect Intesa Sanpaolo by 50.5%. Among the top-20 most connected banks can also be found smaller banks like BBVA (3rd), Credit Lyonnais (10th), Banca Monte dei Paschi (16th) and Mediobanca (20th), while the largest bank in the sample is listed 50th in terms of systemic importance.

The existing literature on the topic suggests that during crises periods, large banks behave differently than small or medium-sized banks (Laeven et al., 2014). This phenomenon could be partially attributed to some common characteristics that are shared by large banks and are associated with higher levels of risk, namely the increased portion of market-based activities, the reduced capital adequacy, the less stable funding and the higher organizational complexity. However, it remains unidentified the bank-size threshold above or below which these criteria are valid. Results presented in table 8 provide a more narrow response to the question whether systemic importance is related to size or not.

Size per se is a determinant of systemic importance, since when banks are ranked by systemic importance the first quartile compiles the largest percentage of total assets (34% of total assets). However, when the sample is ranked by total assets, and not in terms of connectedness, the first quartile represents 62% of total assets, indicating a severe leakage of assets to the other quartiles and revealing the existence of structural variables that interact with size.

The existing frameworks used by regulators and policy makers, such as the BCBS/FSB framework, rely heavily on size, either through size-related indicators or size per se, to calculate the capital adequacy ratios. Our results suggest that the measures taking strong size-effect as granted should also focus on the large banks' idiosyncratic characteristics that place 50% of G-SIBs in the first quartile of systemic importance.

Table 8: Banks ranked by systemic importance and by assets – Number of banks per quartile

	Quartile ranked by		Number of G-SIBs per quartile
	Score	Assets	
1st Quartile	34%	62%	48%
2nd Quartile	33%	22,4%	28%
3rd Quartile	18%	10,5%	10%
4th Quartile	14%	5,1%	14%

The next step is to calculate the systemic contribution of each bank in the system as the ratio between the total individual contagion effects and the total contagion in the system:

$$TSC_{y_i} = \frac{TIC_{y_i}}{TC} * 100$$

TSC is the total systemic contribution, *TIC* is the total individual contagion effects, and *TC* is the total contagion in the system. The bank with the highest ranking contributes 2.25% of the total contagion effects, while the bank at the bottom of the table contributes almost 0% (table 9). This measure allows us to compare the results among samples with different number of entities.

We define each bank's directional connectedness as the ratio between the *individual externalities* and the *total individual contagion*:

$$ID_{OUT,y_i} = \frac{IE_{OUT,y_i}}{TIC_{y_i}} * 100 \text{, or}$$

$$ID_{IN,y_i} = \frac{IV_{IN,y_i}}{TIC_{y_i}} * 100$$

ID is the individual directionality, *IE* is the individual externalities, *IV* is the individual vulnerabilities and *TIC* is total individual contagion. The followings should be always valid:

$$ID_{OUT,y_i} + ID_{IN,y_i} = 1,$$

$$ID_{OUT,y_i} > ID_{IN,y_i}$$

In case ID_{OUT,y_i} is larger than 50% it means than the bank that the systemic score of the bank it refers to, is externalities-driven. When breaking the results into quartiles that represent the average individual directionality for all the banks that belong in this quartile (table 10), we realize that banks with higher *TIC* tend to have higher ID_{OUT,y_i} ratios (54%) that their peers that belong in the last quartile (30%). We do not suggest that the directionality of contagion determines the systemic importance of banks because this is beyond control and difficult to interpret, but that in terms of systemic importance that may be interpreted into increased capital requirements is *"better to receive shocks than to send shocks to the system".*

Table 10: Average Individual Directionality (OUT) per quartile

	ID_{OUT,y_i}
1st Quartile	54%
2nd Quartile	53%
3rd Quartile	47%
4th Quartile	30%

Note: banks are ranked by systemic importance

5.2 Regional network connectedness

Prior quantifying the transmission of contagion effects, we focus on table 7 that reveals a very strong regional effect. This is that the first quartile of systemic importance is exclusively dominated by banks that are headquartered in Europe, implying the existence of a regional component and severe clustering. Table 11a shows the regional concentration per quartile and table 11b expresses the regional concentration as a percentage of the total number of banks that exist per region.

Table 11a: Concentration of banks per region

Quartile	*Europe*	*Eurozone (as % of EU)*	*N. America*	*Asia*	*Oceania*	*Africa*
1st Quartile	100%	75%	-	-	-	-
2nd Quartile	25%	25%	40%	25%	10%	-
3rd Quartile	50%	50%	10%	30%	10%	-
4th Quartile	35%	75%	12%	48%	-	5%

Table 11b: Regional concentration as a percentage of total banks per region

Quartile	*Europe*	*N. America*	*Asia*	*Oceania*	*Africa*
1st Quartile	47%	-	-	-	-
2nd Quartile	12%	73%	25%	25%	-
3rd Quartile	21%	9%	35%	75%	-
4th Quartile	16%	18%	40%	-	100%

The next step is to understand the flows of shocks among the different regions, the contagion effects and the degree of connectedness among the different regions (Table 12a and b). We focus on four regions, Europe, North America (expressed by U.S. banks), Asia and Oceania. Table 12a shows region's A externalities to the other regions as a percentage of region's A total externalities, while table 12b focuses on the vulnerabilities side. Combining the information obtained by tables 12a and b, European and U.S. appear to be strongly interconnected. More precisely, 58% of the aggregate shocks that are sent by U.S. banks are directed to Europe, while 64% of the aggregate shocks received by U.S. banks are generated in Europe. Also, another important finding is that 69% of the aggregate shocks that are sent by European banks remain within Europe.

Table 12a: Shocks sent per region as % of total shocks sent per region

	Asia	Europe	N.America	Oceania	**Sum**
Asia	41%	41%	9%	9%	100%
Europe	16%	69%	9.60%	5.40%	100%
N.America	19.50%	58%	16%	6.50%	100%
Oceania	33%	44.50%	9.50%	12%	100%

Table 12b: Shocks received per region as % of total shocks received per region

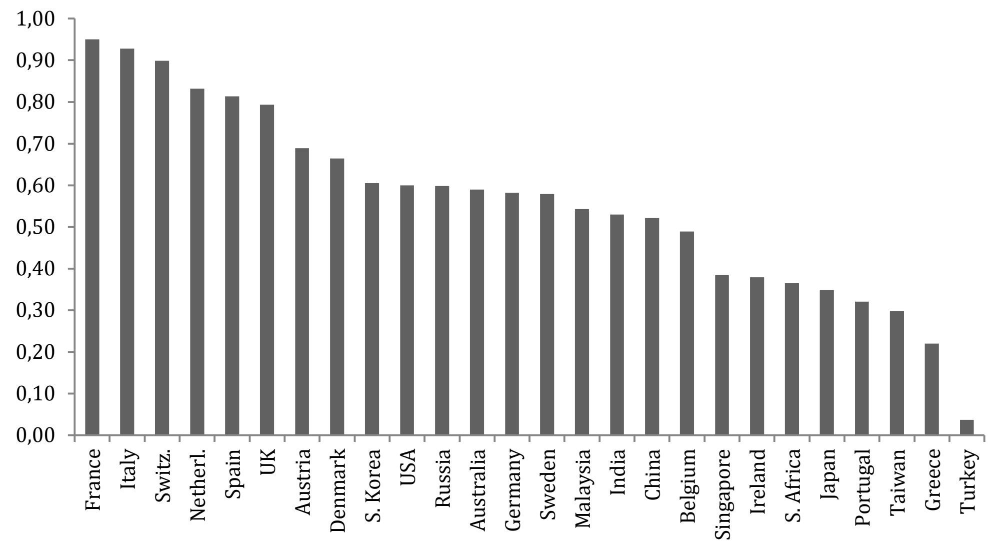
	Asia	Europe	N.America	Oceania
Asia	28%	10%	13%	21%
Europe	54%	75%	64%	59%
N.America	12%	12%	20%	13%
Oceania	6%	3%	3%	7%
Sum	100%	100%	100%	100%

All in all, it is obvious that there exists a regional factor that affects significantly the bank connectedness. However, it is interesting to find out the driving forces of this regional component, especially in the case of Europe which has been a special case due to the different transmission channels of the financial crisis, the highly interconnected banking system, the feedback loops among sovereigns and banks and the contagion from one country to the rest of Europe.

5.3 National banking system connectedness

We approach the national banking system first of all by calculating the average systemic risk per bank for each one of the countries in the sample (Figure 2). Four out of the first five banks, that contributed the most to the global systemic risk, belong to Eurozone. French banks contributed the most to systemic risk, while Italy and Spain, both of which suffered from banking systems in distress, followed at close range. Banks in non-Euro-area countries, like Swiss and UK banks played an important role as well. Surprisingly, the average contagion effects for German banks place them almost in the middle of the table, indicating that German banking system may acted as a stability factor for the European region. Both Portuguese and especially Greek banking system appeared to be isolated from the global banking system.

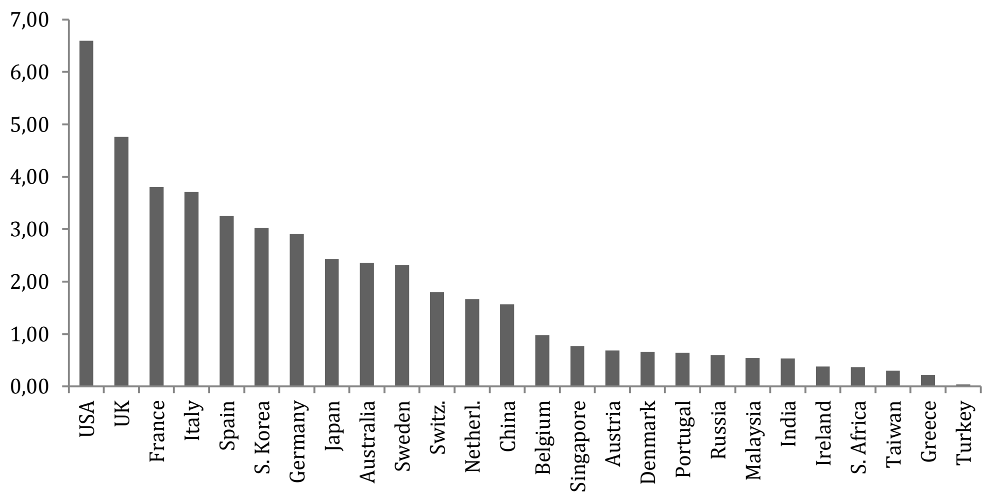
Figure 2: Average systemic risk per bank – Own shocks are excluded



Note: results concern the period January 2008-June 2017

In figure 3 we approach the total contagion from a different perspective, by presenting the total contagion effects for each sovereign. This approach may depends on the number of banks per sovereign but illustrates that U.S.-European cluster dominates in terms of systemic importance.

Figure 3: National systemic risk – Own shocks are excluded



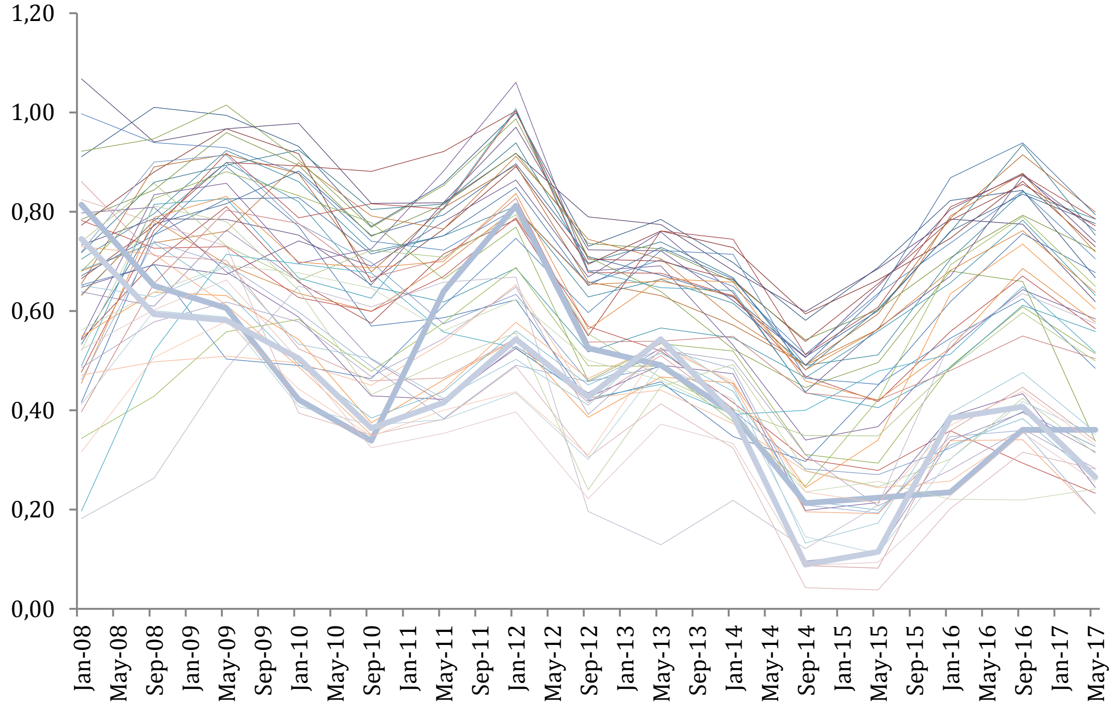
Note: results concern the period January 2008-June 2017

5.3 Rolling window

5.3.1 Individual Banks

In order to better understand the evolvement of systemic risk and how this fluctuated over the whole period we use rolling-window analysis, where the length of the window is 340 days and the step is 150 days. Figure 3 presents the evolution of total contagion over time where strong co-movement and interconnections among banks are obvious. We also discriminate periods where the cluster of TCI lines is shrinking and systemic risk is becoming more unified, which means that systemic and idiosyncratic shocks are propagated more intensely via the network.

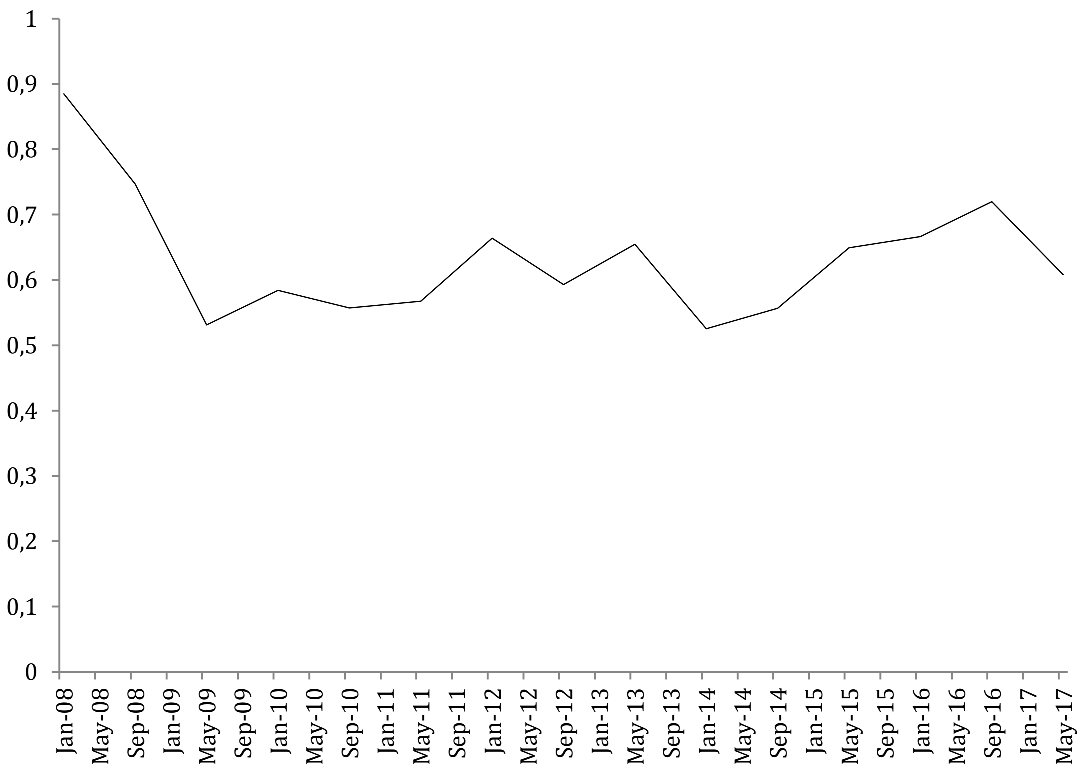
Figure 3: Total Individual Contagion



Note: The length of the window is 340 days and the step is 150 days.

We introduce the range as a new metric of systemic risk unification. Range at each point in time is defined as the difference between the highest and the lowest score in the system (Figure 4). The lowest the score the more unified the systemic risk is becoming. Given the predictive power of CDS spreads, this new measure could be used by regulators and policymakers as an early-warning tool. However, it remains an open question what is the threshold, below which the unification of systemic risk could consist a problem. It is remarkable that the most "loose" links were observed during the post-Lehman collapse in late 2008 and reached its lowest price at the beginning of Greek crisis.

Figure 4: Systemic risk range



Note: The length of the window is 340 days and the step is 150 days.

5.3.2 Global banking system

In this part we are interested in understanding the behavior of aggregate contagion effects. *Total Systemic risk (TSR)* is defined as the total of the offdiagonal entries in the connectedness matrix, or as the sum of the *"from" column* or *"to" row* measures total connectedness.

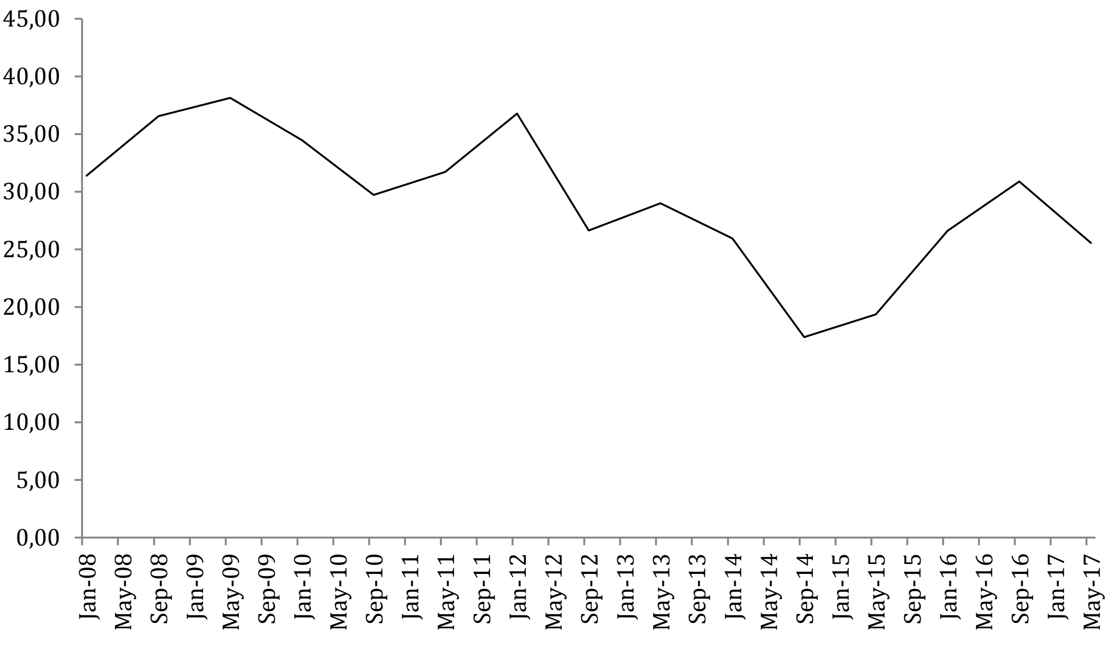
$$TSR^H = \sum_{\substack{i,j=1 \\ j\neq i}}^{N} IR_{ij}^H$$

We could plot a moving contagion measure, defined as the sum of all *IRFs "to others* but we go one step further and we choose to present the *Total Contagion index (TCI)* which is calculated as the average response per bank in the connectedness matrix and is calculated as the sum of all non-diagonal cells divided by the total number of entities:

$$TCI = \frac{1}{N}\sum_{i=1}^{N}\sum_{j\neq 1} IR_{y_i \to y_j}$$

Cumulative IRs interval is [0,1], the index will be bound between 0 and 100. Higher contagion index implies a tightening of the nexus among banks (Figure 5).

Figure 5: Total Connectedness (TC)



Note: The length of the window is 340 days and the step is 150 days.

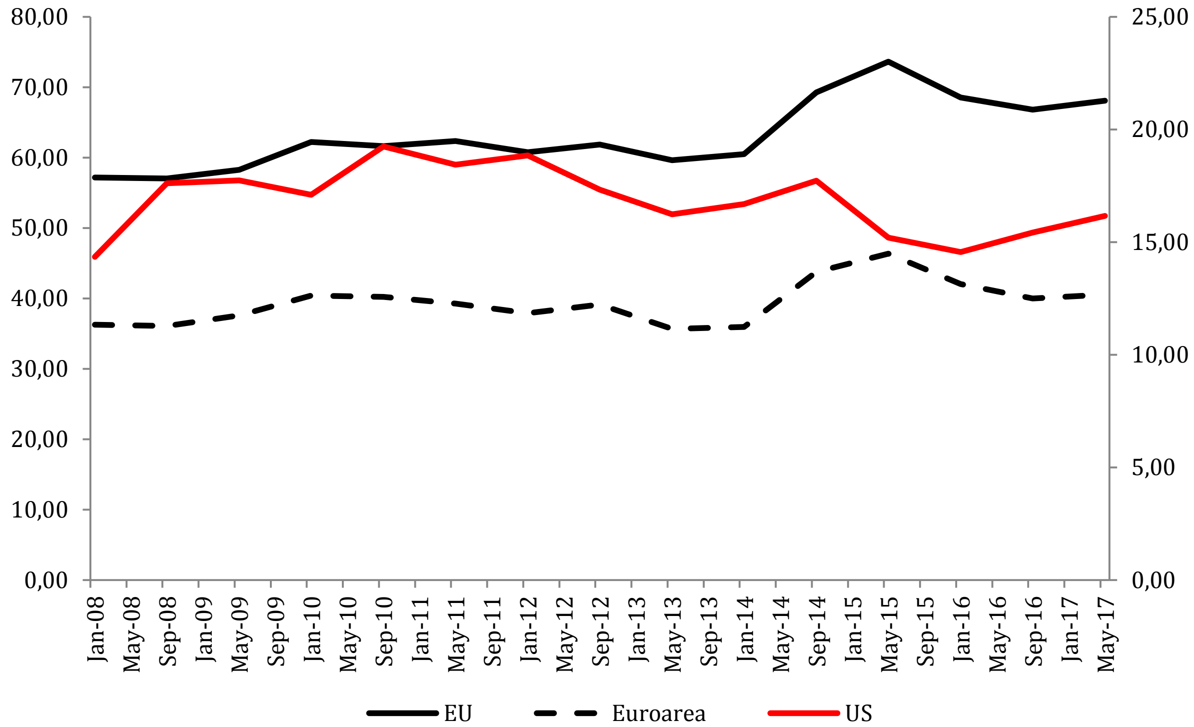
Total connectedness reached its peak after Lehman collapse and was severely affected by the developments in the European banking and sovereign debt markets that shocked some EU member countries until mid-2012. The Greek crisis and then the fact that in the early 2011 Italy and Spain joined the countries with stressed banking systems pushed total connectedness upwards. After the early 2012, the actions taken by the ECB constrained total contagion but after early 2015 higher political uncertainty following the outcomes of the UK referendum on EU membership and the US election as well as market concerns about euro area banks' longer-term profitability prospects, played their role and contributed to the severe increase in the index. At the same time, continued accommodative monetary policy in advanced economies and abating market concerns about the possibility of a sharp slowdown in China have dampened spikes in systemic stress. Also, a major concern for global markets was the crisis in Deutsche Bank and its deep connections to global financial institutions.

From a policy perspective, the most pressing issue for euro area financial institutions remains the high level of NPLs, which needs to be addressed. The resolution of systemic NPL problems will take time and requires a comprehensive strategy, involving coordination of all relevant stakeholders.

5.3.3 Rolling Window – Regional Systemic Contribution (RSC)

We calculate the systemic contribution of each region as the ratio between the total regional contagion effects and the total contagion in the system. We focus on Europe, North America (US) and Euro-area since these regions dominated in terms of systemic risk during the period. Figure 8 compares the systemic contribution of these regions. Surprisingly, the share of systemic risk that European banks hold increased after 2014, while the contribution of US banks remains increasingly lower than European banks' contribution after mid-2012. The difference between the systemic contribution of European and US banks fluctuates between 40% and 55%.

Figure 8: European, US and Euro-area banks' contribution to total systemic risk (as a % of total systemic risk)



Note: US banks' contribution is presented in secondary axis

5.4 Principal Component Analysis

We use PCA analysis, in which the banks' CDS spreads are decomposed into orthogonal factors of decreasing explanatory power, to identify the increased commonality among the default risk of banks (see Muirhead, 1982 for an exposition of PCA).

Let Y_t be the log difference of bank's *i* CDS, *i=1,...,77*, let the system's aggregate credit risk be represented by the sum $Y^S = \sum_i Y_i$, and let $E\left[Y^i\right] = \mu_i$ and $\mathrm{Var}\left[R^i\right] = \sigma_i^2$. Then we have

$$\sigma_s^2 = \sum_{i=1}^{N}\sum_{j=1}^{N}\sigma_i\sigma_j E[z_i z_j]$$

where $z_k = (R^k - \mu_k)/\sigma_k$, *k=i,j,*

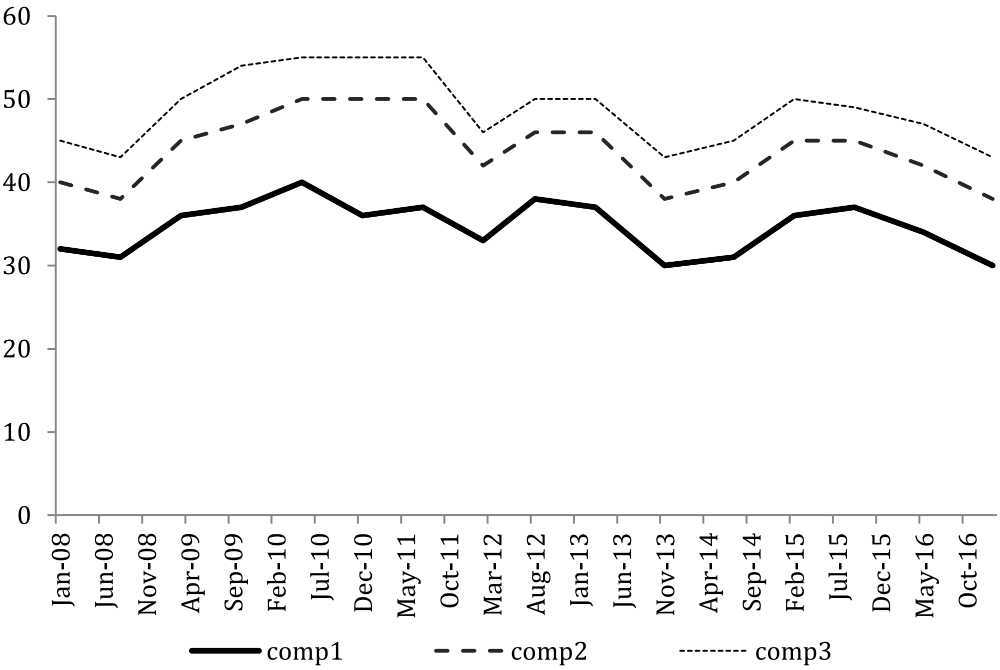
where z_k is the CDS of bank *k* and σ_s^2 is the variance of the system.

PCA produces the decomposition of the variance-covariance matrix of CDS spreads of the 77 banks contained in the sample into the orthogonal matrix of loadings L (eigenvector of the correlation matrix of CDS spreads) and the diagonal matrix of eigenvalues Λ.

We focus on the first three eigenvalues as they explain most of the variation in the system. These three eigenvalues are supposed to explain a larger portion of the total volatility in the system when the CDS spreads are moving together, or in other words when systemic risk in more unified. So periods, when the first three components explain most of the total volatility indicates the existence of increased interconnectedness among banks. The first component that is extracted accounts for the maximum amount of total variance in the observed variables. In other words, the proportion of explained variance by the first component shows how much of the variations in the CDS spreads can be explained by one common factor. This result is in line with Fontana and Scheicher (2010) who finds there to be a single large determinant dominating the variation in the CDS spread, where the proportion of explained variance by factor 1 exceeds 80%. According to Billio et al. (2012) during periods of distress fewer components explain larger part of the volatility which means that the fluctuation of the first principal component, while taking into account the predictive power that CDS carry, reveal periods of increased systemic risk.

We run rolling window analysis; where the length of the window is 200 days and the step is 100 days, over the period January 2008 to June 2017 and the results indicate the existence of a single dominant component that determines the fluctuations of CDS spreads (Figure 9).

Figure 9: Rolling Principal Components analysis



Note: The length of the window is 200 days and the step is 100 days

Investigating the determinants of the loadings of each bank to the first principal component through rolling cross-sectional analysis will reveal the driving forces of systemic risk on a yearly basis over the period 2008-2016. For that reason we use rolling cross-sectional analysis:

$$y_i = a + \beta_1 Assets_i + \beta_2 Loans_i + \beta_3 NPLs_i + \beta_4 NII_i + \beta_5 GDP_i + \beta_6 Surplus_i + \beta_7 Debt_i + \varepsilon_i$$

y_i is each bank's loading to the first component.

We search among the following bank-specific characteristics: total value of bank assets (logs), retail orientation the total loans/total assets (levels), NPLs/ total loans (levels), and non-interest income / total revenue, and among the following home-country specific characteristics: GDP growth, primary surplus/GDP (levels), public debt/GDP (levels). We manage to match 47 banks to bank-specific characteristics

Table 13: Determinants of each bank's loadings in the first component over the nine periods

	2008	2009	2010	2011	2012	2013	2014	2015	2016
Size	-0.012	-0.002	-0.007	-0.012**	0.001	0.004	0.001	-0.002	-0.003
	(0.008)	(0.007)	(0.006)	(0.006)	(0.007)	(0.006)	(0.010)	(0.008)	(0.009)
Loan-to-assets	-0.048	-0.142***	-0.113***	-0.136***	-0.135***	-0.114***	-0.212***	-0.210***	-0.239***
	(0.043)	(0.051)	(0.051)	(0.051)	(0.054)	(0.051)	(0.078)	(0.069)	(0.074)
NPLs	0.844***	0.414	0.352**	0.035	0.004	-0.097	0.333	0.304***	0.194
	(0.349)	(0.253)	(0.187)	(0.183)	(0.054)	(0.139)	(0.187)	(0.147)	(0.174)
Non-interest-income	0.000	0.000	0.001**	0.000	0.001	0.000	0.001	0.000	0.000
	(0.000)	(0.000)	(0.006)	(0.006)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GDP	-0.004	-0.003	-0.006***	-0.003	-0.009***	-0.009***	-0.011***	-0.004***	-0.007
	(0.004)	(0.002)	(0.001)	(0.003)	(0.054)	(0.003)	(0.005)	(0.001)	(0.006)
Primary Surplus/GDP	0.000	-0.002	0.002	0.000	-0.002	-0.004	-0.009***	-0.014***	-0.012***
	(0.002)	(0.001)	(0.001)	(0.170)	(0.054)	(0.003)	(0.004)	(0.004)	(0.005)
Debt/GDP	-0.001***	-0.0005***	-0.0006***	-0.001***	-0.0007***	-0.0005***	-0.0005***	0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.054)	(0.000)	(0.000)	(0.000)	(0.000)
_cons	0.300	0.235	0.297	0.372	0.248	0.229	0.252	0.283	0.323
	(0.080)	(0.076)	(0.068)	(0.078)	(0.054)	(0.072)	(0.111)	(0.094)	(0.107)

Note: ***1%, **5%,*10%

6 Conclusions

Macroprudential policy is still in its infancy. Much work is still needed on developing good and timely analysis, effective policy instrument tools, and effective implementation. Our paper makes a contribution on the dimension of analysis and measurement. The key aim of macroprudential policy is to address externalities and spillovers among financial institutions in an effort to safeguard financial stability. These interactions are complex. We provide a tool for clarifying and quantifying these interactions. Our measures can guide appropriate macroprudential policies that aim to internalize these externalities. A key conclusion from our study is that the focus on size does not adequately address the systemic importance of banks.

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Part B

We study 77 banks from 26 developed and emerging economies. Data are downloaded from Thomson-Reuters and cover the period from January 1st 2008 to June 30th 2017. The first sample contains 77 banks are from 19 developed economies, while the rest are from 6 emerging economies (as of IMF's list). The sample contains most of the banks that are designated as *"global systemically important banks"* ("GSIB's") as designated 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. 43 out of the 77 banks (54,4%) in the sample are from Europe while 28 of them (35,44%) are headquartered in Eurozone members. The sample is extended by adding 19 smaller European banks.

B Sample Presentation, Bank Details, Descriptive Statistics

Tables 2a and b presents the 77 banks in the sample in the world's top 150 as they ordered by assets (Q4 2016). Table A3 presents the share of assets that each home-country holds in the sample as well as the share of assets per developed and emerging countries, while Table A4 presents the share of assets per region. Table A5 presents the 14 European banks that are added to the initial sample.

Table 2a: Banks ordered by Total Assets *(in US $ billion)*

Rank	Bank Name	Country	Total assets,

			US$B
1	Bank of China	China	2,613
2	Mitsubishi UFJ Financial Group	Japan	2,597
3	JPMorgan Chase & Co	USA	2,490
4	HSBC Holdings	UK	2,374
5	BNP Paribas	France	2,196
6	Bank of America	USA	2,187
7	Wells Fargo	USA	1,930
8	China Development Bank	China	1,904
9	Credit Agricole Group	France	1,821
10	Citigroup	USA	1,792
11	Mizuho Financial Group	Japan	1,757
12	Deutsche Bank	Germany	1,682
13	Sumitomo Mitsui Financial Group	Japan	1,654
14	Barclays PLC	UK	1,490
15	Societe Generale	France	1,461
16	Banco Santander	Spain	1,416
17	Lloyds Banking Group	UK	1,004
18	Norinchukin Bank	Japan	984
19	Royal Bank of Scotland Group	UK	981
20	UBS Group AG	Switzerland	919
21	Unicredit S.p.A.	Italy	908
22	ING Groep NV	Netherlands	893
23	Goldman Sachs Group	USA	860
24	Morgan Stanley	USA	814
25	Credit Suisse Group	Switzerland	806

Table 2a – Continued from previous page

26	BBVA	Spain	773
27	Intesa Sanpaolo	Italy	766
28	Commonwealth Bank of Australia	Australia	703
29	Rabobank Group	Netherlands	700
30	Australia & New Zealand Banking Group	Australia	661
31	Nordea	Sweden	651
32	Standard Chartered Plc	UK	646
33	Westpac Banking Corp	Australia	607
34	National Australia Bank	Australia	562
35	Commerzbank	Germany	549
36	Danske	Denmark	495
37	State bank of India	India	492
38	U.S. Bancorp	USA	445
39	The Export-Import Bank of China	China	427
40	Sberbank of Russia	Russia	420
41	Resona	Japan	412
42	Sumitomo Mitsui T.H.	Japan	406
43	Nomura Holdings	Japan	370
44	PNC Financial Services	USA	366
45	Capital One Financial Corporation	USA	357
46	DBS Group Holdings	Singapore	332
47	Shinhan Financial Group	South Korea	328
48	KBC Group NV	Belgium	291
49	Svenska Handelsbanken	Sweden	289
50	Skandinaviska Enskilda Banken	Sweden	289
51	Hana Financial Group	South Korea	288
52	Nationwide Building Society	UK	276
53	Korea Development Bank	South Korea	268

54	Woori Bank	South Korea	257
55	Landesbank Baden-Wurttemberg	Germany	257
56	Cathay Financial Holding	Taiwan	252
57	Swedbank	Sweden	237
58	United Overseas Bank (UOB)	Singapore	235
59	Dexia	Belgium	225
60	Banco Sabadell	Spain	224
61	Bayerische Landesbank	Germany	224
62	Erste Group Bank AG	Austria	220
63	Banco Popular Espanol	Spain	204
64	Industrial Bank of Korea	South Korea	196
65	Bank of Ireland	Ireland	182
66	Malayan	Malaysia	161
67	Standard Bank Group	South Africa	161
68	Banca Monte dei Paschi di Siena	Italy	161
69	American Express	USA	158
70	National Bank of Greece	Greece	153
71	Macquarie	USA	143
72	Credit Lyonnais	France	120
73	Comercial Portuguese	Portuguese	113
74	Banco Espirito Santo	Portugal	112
75	Turkiye is bankasi	Turkey	112
76	Mediobanca	Italy	95
77	Landesbank Hessen	Germany	92

Table 2b: Banks ordered by Country

Rank	Bank	Country	Total assets, US$B
1	Commonwealth Bank of Australia	Australia	703
2	Australia & New Zealand Banking Group	Australia	661
3	Westpac Banking Corp	Australia	607
4	National Australia Bank	Australia	562
5	Erste Group Bank AG	Austria	220
6	KBC Group NV	Belgium	291
7	Dexia	Belgium	225
8	Bank of China	China	2,613
9	China Development Bank	China	1,904
10	The Export-Import Bank of China	China	427
11	Danske	Denmark	495
12	BNP Paribas	France	2,196
13	Credit Agricole Group	France	1,821
14	Societe Generale	France	1,461
15	Credit Lyonnais	France	120
16	Deutsche Bank	Germany	1,682
17	Commerzbank	Germany	549
18	Landesbank Baden-Wurttemberg	Germany	257
19	Bayerische Landesbank	Germany	224
20	Landesbank Hessen	Germany	92
21	National Bank of Greece	Greece	153
22	State bank of India	India	492
23	Bank of Ireland	Ireland	182
24	Unicredit S.p.A.	Italy	908
25	Intesa Sanpaolo	Italy	766

26	Banca Monte dei Paschi di Siena	Italy	161
27	Mediobanca	Italy	95
28	Mitsubishi UFJ Financial Group	Japan	2,597
29	Mizuho Financial Group	Japan	1,757
30	Sumitomo Mitsui Financial Group	Japan	1,654
31	Norinchukin Bank	Japan	984
32	Resona	Japan	412
33	Sumitomo Mitsui T.H.	Japan	406
34	Nomura Holdings	Japan	370
35	Yamaguchi Financial Group	Japan	93
36	ING Groep NV	Netherlands	893
37	Rabobank Group	Netherlands	700
38	Banco Espirito Santo	Portugal	111
39	Sberbank of Russia	Russia	420
40	DBS Group Holdings	Singapore	332
41	United Overseas Bank (UOB)	Singapore	235
42	Standard Bank Group	South Africa	161
43	Shinhan Financial Group	South Korea	328
44	Hana Financial Group	South Korea	288
45	Korea Development Bank	South Korea	268
46	Woori Bank	South Korea	257
47	Industrial Bank of Korea	South Korea	196
48	Banco Santander	Spain	1,416
49	BBVA	Spain	773
50	Banco Sabadell	Spain	224
51	Banco Popular Espanol	Spain	204

Table 2b – Continued from previous page

53	Nordea	Sweden	651
54	Svenska Handelsbanken	Sweden	289
55	Skandinaviska Enskilda Banken	Sweden	289
56	Swedbank	Sweden	237
57	UBS Group AG	Switzerland	919
58	Credit Suisse Group	Switzerland	806
59	Cathay Financial Holding	Taiwan	252
60	Turkiye is bankasi	Turkey	112
61	HSBC Holdings	UK	2,374
62	Barclays PLC	UK	1,490
63	Lloyds Banking Group	UK	1,004
64	Royal Bank of Scotland Group	UK	981
65	Standard Chartered Plc	UK	646
66	Nationwide Building Society	UK	276
68	JPMorgan Chase & Co	USA	2,490
69	Bank of America	USA	2,187
70	Wells Fargo	USA	1,930
71	Citigroup	USA	1,792
72	Goldman Sachs Group	USA	860
73	Morgan Stanley	USA	814
74	U.S. Bancorp	USA	445
75	PNC Financial Services	USA	366
76	Capital One Financial Corporation	USA	357
77	American Express	USA	158
78	Macquarie	USA	143

Table 3a: Banks' home-countries ordered by the sum of total bank assets

Developed	Total Assets	Developing	Total Assets
USA	11547	China	4944
Japan	7867	India	492
UK	6936	Russia	420
France	5599	Taiwan	252
Germany	2994	South Africa	161
Spain	2617	Turkey	112
Australia	2534		
Italy	1933		
Switzerland	1725		
Netherlands	1584		
Sweden	1467		
South Korea	1340		
Singapore	568		
Belgium	516		
Denmark	495		
Ireland	344		
Austria	220		
Greece	153		
Portugal	111		
Total Assets of banks that are headquartered in:			
Developed	**50553.66**	Emerging	**6382.3**
% of total assets	**88,8%**	% of total assets	**11,2%**

Table 3b: Regional details

Region	Number of Banks	Total bank assets	% of total assets
Europe	40	26696,73	47,3
Asia	21	15576,58	27,5
N. America	11	11547,24	20,4
Oceania	4	2534	4,5
Africa	1	161	0,3

B. Data Definitions and Descriptive Statistics

Table 4: Data Definitions

Variable	Description
Endogenous	
CDS	CDS 5-year spread
Exogenous	
Systemic risk	
CDX	The family of CDS indeces covering North America
VIX	The volatiliy index of S&P 500
US 3-month T Bill	The short-term obligation backed by the Treasury Dept. of the U.S. goverment
Bank-specific	
Size	Total assets
Retail orientation	Total Loans / Total assets
Diversification	Non-interest income / Total revenues
NPLs	Non-performing loans / Total Loans
Country-specific	
GDP	Each bank's home-country GDP growth
Budget Balance	Current Account/GDP
Public Debt	Public Debt/GDP

Table 5: Descriptive Statistics

Panel A: Systemic risk factor

	CDX	VIX	TED
Mean	2.69E-06	-0.000123	-0.00121
Median	0.000	-0.001	0.000
Maximum	0.020	0.176	0.250
Minimum	-0.009	-0.152	-0.750
Std. Dev.	0.001	0.031	0.033
Skewness	4.689	0.689	-17.326
Kurtosis	106.047	6.789	377.496
Jarque-Bera	1105896	1679.364	14610377
Probability	0.000	0.000	0.000
Sum	0.007	-0.304	-3.000
Sum Sq. Dev.	0.003	2.427	2.746

Note: CDX and VIX are in log differences. TED spread is in first differences.

Panel B: Bank specific

	Assets	Loans_to_Assets	Non_Interest_Inc.	NPLs
Mean	732.382	55.596	24.42	4.601
Median	458009	59.921	23.78	2.411
Maximum	3030645	86.64	86.40	35.217

Minimum	43543,87	9.070	-59.62	0.1082
Std. Dev.	746001.3	17.017	14.81	5.612
Skewness	1.081	-0.641	-0.694	2.376
Kurtosis	30.129	2.584	6.193	9.630
Jarque-Bera	7.023	272.888	1821.17	9995.01
Probability	0.000	0.000	0.000	0.000
Sum	2.64E+09	200370.2	88037.46	16584.30
Sum Sq. Dev.	2.01E+15	1043392.	790803.6	113486.7

Note: Data are in levels

Part C – Global Sample

Table 7: Individual systemic importance

Panel A – Ranked by total score

Rank by score	Rank by bank assets	Bank Name	Home-Country	Region	Assets (billion US $)	Score	To others (Aggr.)	From others (Aggr.)
1	27	Intesa Sanpaolo	Italy	Europe	766	1.056	0.505	0.551
2	16	Banco Santander	Spain	Europe	1416	1.038	0.464	0.574
3	26	BBVA	Spain	Europe	773	0.987	0.454	0.533
4	5	BNP Paribas	France	Europe	2196	0.982	0.445	0.537
5	21	Unicredit S.p.A.	Italy	Europe	908	0.975	0.489	0.485
6	14	Barclays PLC	UK	Europe	1490	0.961	0.454	0.507
7	12	Deutsche Bank	Germany	Europe	1682	0.954	0.428	0.526
8	9	Credit Agricole Group	France	Europe	1821	0.942	0.424	0.518
9	15	Societe Generale	France	Europe	1461	0.940	0.427	0.512
10	72	Credit Lyonnais	France	Europe	120	0.938	0.445	0.493
11	17	Lloyds Banking Group	UK	Europe	1004	0.925	0.438	0.487
12	25	Credit Suisse Group	Switz.	Europe	806	0.907	0.376	0.531
13	35	Commerzbank	Germany	Europe	549	0.904	0.410	0.494
14	20	UBS Group AG	Switz.	Europe	919	0.890	0.387	0.503
15	32	Standard Chartered Plc	UK	Europe	646	0.870	0.419	0.451
16	68	Banca Monte dei Paschi	Italy	Europe	161	0.861	0.429	0.433

17	19	Royal Bank of Scotland Group	UK	Europe	981	0.845	0.423	0.423
18	29	Rabobank Group	Netherl.	Europe	700	0.841	0.376	0.465
19	22	ING Groep NV	Netherl.	Europe	893	0.823	0.374	0.449
20	76	Mediobanca	Italy	Europe	95	0.821	0.389	0.433
21	24	Morgan Stanley	USA	N. Amer.	814	0.752	0.315	0.437
22	69	American Express	USA	N. Amer.	158	0.736	0.332	0.404
23	6	Bank of America	USA	N. Amer.	2187	0.716	0.318	0.398
24	23	Goldman Sachs Group	USA	N. Amer.	860	0.711	0.302	0.410
25	10	Citigroup	USA	N. Amer.	1792	0.706	0.313	0.393
26	4	HSBC Holdings	UK	Europe	2374	0.695	0.372	0.323
27	62	Erste Group Bank AG	Austria	Europe	220	0.688	0.314	0.375
28	49	Svenska Handelsbanken	Sweden	Europe	289	0.678	0.281	0.397
29	53	Korea Development Bank	S. Korea	Asia	268	0.677	0.393	0.284
30	60	Banco Sabadell	Spain	Europe	224	0.670	0.295	0.375
31	36	Danske	Denmark	Europe	495	0.663	0.296	0.367
32	45	Capital One Financial Corp.	USA	N. Amer.	357	0.662	0.260	0.401
33	3	JPMorgan Chase & Co	USA	N. Amer.	2490	0.658	0.257	0.401
34	7	Wells Fargo	USA	N. Amer.	1930	0.653	0.259	0.394
35	34	National Australia Bank	Australia	Oceania	562	0.622	0.376	0.247

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Table 3- Panel A continued from previous page

36	2	Mitsubishi UFJ Financial	Japan	Asia	2597	0.621	0.223	0.398
37	47	Shinhan Financial Group	S. Korea	Asia	328	0.615	0.331	0.283
38	54	Woori Bank	S. Korea	Asia	257	0.612	0.333	0.278
39	64	Industrial Bank of Korea	S. Korea	Asia	196	0.603	0.341	0.261
40	28	Commonwealth Bank	Australia	Oceania	703	0.599	0.388	0.211
41	40	Sberbank of Russia	Russia	Europe	420	0.598	0.294	0.305
42	30	Australia & N. Zealand	Australia	Oceania	661	0.597	0.383	0.214
43	50	Skandinaviska Enskilda	Sweden	Europe	289	0.578	0.262	0.316
44	31	Nordea	Sweden	Europe	651	0.574	0.289	0.285
45	71	Macquarie	USA	N. Amer.	143	0.572	0.321	0.251
46	48	KBC Group NV	Belgium	Europe	291	0.568	0.241	0.327
47	63	Banco Popular Espanol	Spain	Europe	204	0.558	0.297	0.261
48	61	Bayerische Landesbank	Germany	Europe	224	0.552	0.249	0.303
49	39	The Export-Import Bank	China	Asia	427	0.548	0.284	0.264
50	1	Bank of China	China	Asia	2613	0.548	0.276	0.272
51	66	Malayan	Malaysia	Asia	171	0.543	0.321	0.223
52	33	Westpac Banking Corp	Australia	Oceania	606	0.540	0.374	0.166
53	37	State bank of India	India	Asia	492	0.530	0.238	0.291
54	51	Hana Financial Group	S. Korea	Asia	288	0.518	0.290	0.227
55	57	Swedbank	Sweden	Europe	237	0.486	0.253	0.233
56	8	China Development Bank	China	Asia	1904	0.468	0.260	0.208

57	52	Nationwide Building Society	UK	Europe	276	0.463	0.217	0.246
58	59	Dexia	Belgium	Europe	225	0.409	0.197	0.212
59	46	DBS Group Holdings	Singapore	Asia	332	0.397	0.212	0.186
60	65	Bank of Ireland	Ireland	Europe	182	0.379	0.197	0.182
61	58	United Overseas Bank	Singapore	Asia	235	0.373	0.214	0.159
62	11	Mizuho Financial Group	Japan	Asia	1757	0.367	0.271	0.096
63	67	Standard Bank Group	S. Africa	Africa	161	0.365	0.123	0.242
64	74	Espirito Santos	Portugal	Europe	112	0.362	0.186	0.176
65	41	Resona	Japan	Asia	412	0.357	0.263	0.094
66	13	Sumitomo Mitsui Financial	Japan	Asia	1654	0.355	0.250	0.104
67	38	U.S. Bancorp	USA	N. Amer.	445	0.353	0.188	0.165
68	55	Landesbank Baden-Wurtt.	Germany	Europe	257	0.340	0.170	0.171
69	42	Sumitomo Mitsui T.H.	Japan	Asia	406	0.323	0.273	0.050
70	56	Cathay Financial Holding	Taiwan	Asia	252	0.298	0.189	0.109
71	73	Comercial Portuguese	Portugal	Europe	113	0.279	0.268	0.011
72	70	National Bank of Greece	Greece	Europe	153	0.220	0.176	0.044
73	18	Norinchukin Bank	Japan	Asia	984	0.215	0.164	0.050
74	43	Nomura Holdings	Japan	Asia	370	0.197	0.161	0.035
75	77	Landesbank Hessen	Germany	Europe	92	0.159	0.089	0.071
76	44	PNC Financial Services	USA	N. Amer.	366	0.078	0.034	0.043
77	75	Turkiye is bankasi	Turkey	Europe	112	0.037	0.030	0.007

Note: Results concern the period January 2008 – June 2017 and are of daily frequency

Table 9: Systemic contribution per bank (January 2008 – June 2017)

Rank	Bank Name	SC	Rank	Bank Name	SC	Rank	Bank Name	SC	Rank	Bank Name	SC
1	Intesa Sanpaolo	**2,25**	21	Morgan Stanley	**1,60**	41	Sberbank of Russia	**1,28**	61	United Overseas	**0,80**
2	Banco Santander	**2,21**	22	American Express	**1,57**	42	Australia & N. Zealand	**1,27**	62	Mizuho Financial	**0,78**
3	BBVA	**2,10**	23	Bank of America	**1,53**	43	Skandinaviska Enskilda	**1,23**	63	Standard Bank Group	**0,78**
4	BNP Paribas	**2,09**	24	Goldman Sachs Group	**1,52**	44	Nordea	**1,22**	64	Espirito Santos	**0,77**
5	Unicredit S.p.A.	**2,08**	25	Citigroup	**1,51**	45	Macquarie	**1,22**	65	Resona	**0,76**
6	Barclays PLC	**2,05**	26	HSBC Holdings	**1,48**	46	KBC Group NV	**1,21**	66	Sumitomo Mitsui	**0,76**
7	Deutsche Bank	**2,03**	27	Erste Group	**1,47**	47	Banco Popular	**1,19**	67	U.S. Bancorp	**0,75**
8	Credit Agricole	**2,01**	28	Svenska	**1,45**	48	Bayerische Landesbank	**1,18**	68	Landesbank.	**0,72**
9	Societe Generale	**2,00**	29	Korea Development Bank	**1,44**	49	The Export-Import	**1,17**	69	Sumitomo Mitsui T.H.	**0,69**
10	Credit Lyonnais	**2,00**	30	Banco Sabadell	**1,43**	50	Bank of China	**1,17**	70	Cathay Financial	**0,64**
11	Lloyds Banking	**1,97**	31	Danske	**1,41**	51	Malayan	**1,16**	71	Comercial Portuguese	**0,59**

12	Credit Suisse Group	**1,93**	32	Capital One Financial Corp.	**1,41**	52	Westpac Banking Corp	**1,15**	72	NBG	**0,47**
13	Commerzbank	**1,93**	33	JPMorgan Chase & Co	**1,40**	53	State bank of India	**1,13**	73	Norinchukin Bank	**0,46**
14	UBS Group AG	**1,90**	34	Wells Fargo	**1,39**	54	Hana Financial Group	**1,10**	74	Nomura Holdings	**0,42**
15	Standard Chartered	**1,86**	35	National Australia Bank	**1,33**	55	Swedbank	**1,04**	75	Landesbank Hessen	**0,34**
16	Banca Monte dei	**1,84**	36	Mitsubishi UFJ Financial	**1,32**	56	China Development	**1,00**	76	PNC Financial Services	**0,17**
17	RBS	**1,80**	37	Shinhan Financial Group	**1,31**	57	Nationwide Building	**0,99**	77	Turkiye is bankasi	**0,08**
18	Rabobank Group	**1,79**	38	Woori Bank	**1,30**	58	Dexia	**0,87**			
19	ING Groep NV	**1,75**	39	Industrial Bank of Korea	**1,29**	59	DBS Group Holdings	**0,85**			
20	Mediobanca	**1,75**	40	Commonwealth Bank	**1,28**	60	Bank of Ireland	**0,81**			