

A Service of

ZBW

Leibniz-Informationszentrum Wirtschaft Leibniz Information Centre for Economics

Jokivuolle, Esa; Tunaru, Radu; Vioto, Davide

## Working Paper Testing the systemic risk differences in banks

Bank of Finland Research Discussion Papers, No. 13/2018

**Provided in Cooperation with:** Bank of Finland, Helsinki

*Suggested Citation:* Jokivuolle, Esa; Tunaru, Radu; Vioto, Davide (2018) : Testing the systemic risk differences in banks, Bank of Finland Research Discussion Papers, No. 13/2018, ISBN 978-952-323-234-1, Bank of Finland, Helsinki, https://nbn-resolving.de/urn:nbn:fi:bof-201806011601

This Version is available at: https://hdl.handle.net/10419/212421

#### Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

#### Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



# WWW.ECONSTOR.EU



Bank of Finland Research Discussion Papers Editor-in-Chief Esa Jokivuolle

Bank of Finland Research Discussion Paper 13/2018 1 June 2018

Esa Jokivuolle – Radu Tunaru – Davide Vioto Testing the systemic risk differences in banks

ISBN 978-952-323-234-1, online ISSN 1456-6184, online

Bank of Finland Research Unit

PO Box 160 FIN-00101 Helsinki

Phone: +358 9 1831

Email: research@bof.fi Website: <u>www.bof.fi/en/research</u>

The opinions expressed in this paper are those of the authors and do not necessarily reflect the views of the Bank of Finland.

# Testing the Systemic Risk Differences in Banks

Esa Jokivuolle<sup>\*a</sup>, Radu Tunaru <sup>b</sup>, and Davide Vioto <sup>b</sup>

<sup>a</sup>Bank of Finland <sup>b</sup>Kent Business School, University of Kent

May 30, 2018

#### Abstract

This paper contains a testing framework for the reliability of systemic risk measurement of banks, using the three leading market-based measures of systemic risk. We test whether the difference within the same category and across different categories of systemic risk of individual banks is significant. We find that in general the systemic risk categories defined by the Financial Stability Board are different from those constructed in a full pairwise comparison approach based on the market measures. Moreover, these differences were more pronounced during episodes of high market turbulence. To account for model risk we introduce a more robust ranking method based on nonparametric confidence intervals. We show that there is a large number of banks with overlapping confidence intervals of their market-based systemic risk measures. Further, similarity measures indicate that the scoring based rankings are not perfectly aligned with rankings produced by market based systemic risk measures.

**Keywords:** Systemic risk measures, Systemic risk ranking validation, Dominance tests, Confidence intervals, Financial stability, Concordance measures.

JEL classification: G01, G32

<sup>\*</sup>Corresponding author: Bank of Finland, PO Box 160, 00101 Helsinki, Finland, e-mail: esa.jokivuolle@bof.fi

## 1 Introduction

The Global Financial Crisis and the European Sovereign-Debt Crisis emphasized the importance of systemic risk, increasing the interest of regulators, supervisory authorities and the academia alike on these topics. Silva et al. (2017) analyzed and classified 266 articles on systemic risk that were published no later than September 2016. The increasing number of studies has resulted in a large number of systemic risk measures (SRM). Bisias et al. (2012) carried-out a meta-analysis on the measures of systemic risk, surveying 31 quantitative measures for systemic risk, which can be classified according to data requirements, supervisory perspective and research perspective.

In this paper we provide further tests for how reliably the systemic risk of banks can be measured, using the three leading market-based measures of systemic risk, the delta conditional value at risk ( $\Delta CoVaR$ ) developed by Adrian and Brunnermeier (2016), the marginal expected shortfall (MES) of Acharya et al. (2017) and the SRISK proposed by Brownlees and Engle (2016). We test whether the difference between banks within the same category and across different categories of systemic risk is significant. We find that in general the systemic risk categories defined by the Financial Stability Board (FSB) are different from those constructed in a full pairwise comparison approach based on the market measures. In addition, we identify banks that were not marked as systemically important by the scoring method of the FSB but that are systemically important based on SRMs. The ranking results are sensitive to the SRM used for comparison and the difference in results becomes more evident during the three major events analysed here, the Chinese market crash in 2015, the Brexit vote result and the US presidential election of 2016. Our Granger causality analysis indicate that only during the subprime crisis there was a two-way effect of systemic risk transmission between the US and the European banking sectors, for all three SRMs. Interestingly, in different time periods, there is more evidence of a Granger causality of systemic risk from US to Europe.

Further, we introduce a more robust ranking method of banks' systemic risk based on

nonparametric confidence intervals. Tracking banks' confidence intervals overlap year on year we find that there is a large number of banks with overlapping confidence intervals of systemic risk measures, from 45% in the 2015 and 2016 in Europe to almost 97% in 2009 in the US. The degree of overlap is very high for all banks in both the US and Europe. Moreover, this new ranking method leads to a different classification of the US and European systemicly important banks within the 5 categories defined by the FSB. In particular, while the classification made by the FSB allocates most banks in the less risky category, our method allocates the banks in categories according to their contribution to the reference banking sector, resulting in different capital requirement that are strictly linked to the reference banking sector. This could improve the stress test exercises run by the Federal Reserve Board (FED) and the European Banking Authority (EBA), entailing different additional capital requirement, for the same bank, in the US and Europe.

The importance of reliably measuring the systemic risk of banks can be motivated on several grounds. Crockett (2000) argued that macroprudential policy should be targeting only financial firms that can be proved to be systemically risky and only those firms should be asked to increase their capital ratios. Companies may start litigations against the regulator for being given a systemic risk status that will imply operating under more stringent capital requirements than their commercial competitors, as in the case of MetLife suing Financial Stability Oversight Council (FSOC)<sup>1</sup> in the US. Moreover, the House Financial Services Committee released a staff report highlighting pitfalls on the FSOC methodology for the systemically important financial institutions (SIFI) designation<sup>2</sup>. Ideally the regulator should have a mechanism that automatically and transparently rates a company as systemically

<sup>&</sup>lt;sup>1</sup> "MetLife to mount legal challenge to systemic risk label," Financial Times, January 13, 2015. The insurance company first won the case at a U.S. district court, but afterwards the Obama administration appealed the ruling in 2016. Then, under the Trump administration MetLife and the Financial Stability Oversight Council (FSOC) filed a joint motion to dismiss the earlier FSOC appeal. Moreover, The FSOC voted in September 2017 to remove a similar designation for American International Group Inc, and GE Capital was able to reverse the labelling in 2016 after overhauling its business. Prudential Financial Inc now is the only non-bank SIFI still under stricter government oversight.

<sup>&</sup>lt;sup>2</sup> "Does 'Too Big to Fail' Mean Too Big for the Rule Law?," The Wall Street Journal, March 31 - April 2, 2017.

risky. Then, banks and other firms could self-test their position in the market and the risk of ad-hoc categorizing would be reduced. However, proving with high confidence that a company is posing systemic risk to a financial system is not straightforward and at least in the case of the most used SRMs the estimation uncertainty may cloud the results, as demonstrated by Danielsson et al. (2016).

While the FSOC focuses on the designation of nonbanks as systemically important the Basel Committee on Banking Supervision (BCBS) implemented a regulation targeting higher bank capital requirements for Global Systemically Important Banks (G-SIB)<sup>3</sup>. The BCBS focuses on banks "given that their business models have generally placed greater emphasis on trading and capital markets-related activities". The FSB decides on the list of the G-SIBs according to this assessment methodology. The Basel Committee on Banking Supervision (BCBS) and the Financial Stability Board (FSB) use a systemic-risk scoring methodology constructed by aggregation of data across five categories related to size, interconnectedness, substitutability, complexity and cross-jurisdictional activity. Benoit et al. (2017) find two major shortcomings in the current systemic-risk scoring methodology designed by the BCBS: the first is linked to the categories that, as defined by the official methodology, are quite volatile in the cross section; and, the second is related to the reference currency used to aggregate bank data across currency zones. They empirically demonstrate that these two shortcomings may affect the final ranking.

In our paper we take a different route. We consider the current systemic risk categorisation as a given benchmark and we try to compare the ranking results produced by the categorisation obtained by using the three main SRMs discussed widely in this literature strand. Since a change of systemic risk categorization leads to substantial change in regulatory capital requirement, we are motivated in this paper to provide further tests for the official ranking issued by the FSB using market-based SRMs, and furthermore, to develop an innovative ranking methodology based on nonparametric confidence intervals.

 $<sup>^3</sup>$  "Global systemically important banks: updated assessment methodology and the higher loss absorbency requirement", Basel Committee on Banking Supervision, July 2013.

In particular, we estimate over the period from 2003 Q1 to 2016 Q4 the systemic risk of the large banks in the US and Europe based on the three commonly used marked-based measures of systemic risk using daily observations on the US Bank Holding Companies (BHCs) covered by the Dodd-Frank Act Stress Test 2016 and European large banks covered by the EU-Wide Stress Test 2016. The focus on market-based SRMs is motivated by their transparency (in that anyone can, in principle, replicate them) and the fact that decision making based on public data, such that our results can be easily implemented, compared, and backtested.

The systemic risk assessments based on  $\Delta CoVaR$ , MES and SRISK may lead to different<sup>4</sup> conclusions so categorizing a financial firm as systemically risky may be SRM dependent<sup>5</sup>. The three SRMs collectively are efficient in discriminating between systemic and non-systemic banks. However, it is also necessary to be able to differentiate across, and within, different categories of systemic risk. A relative overestimation of systemic risk may lead to litigations and a lack of confidence in supervisory systems while any systematic underestimation of systemic risk may be perceived as a regulatory arbitrage opportunity and may ultimately lead to an increase of the externalization of risk. The SRMs provide a useful tool to test whether the G-SIBs assigned by the FSB do contribute more than the other banks to the overall systemic risk. Moreover, we also test whether the G-SIBs significantly increase their contribution to the overall systemic risk in the light of the SRMs during periods of financial instability. Lastly, as the ranking with SRMs is subject to estimation risk, the ranking process can be improved by employing confidence intervals.

Our paper is adjacent to Danielsson et al. (2016) who analyze the use of two SRMs as "riskometer" for policies targeted at reducing systemic risk<sup>6</sup>. They compare the MES and

<sup>&</sup>lt;sup>4</sup>Drehmann and Tarashev (2013) also found out that other measures of systemic risk can disagree substantially about the systemic importance of individual banks.

<sup>&</sup>lt;sup>5</sup>Löffler and Raupach (2018), considering as SRM the  $\Delta CoVaR$  and the MES, found that changes in the company's systematic risk, idiosyncratic risk, size or contagiousness, affect the systemic risk rankings. According to different SRMs, regulators could benefit banks estimating a lower systemic contribution, entailing banks to take actions that could increase the risk of the system rather than reduce it.

<sup>&</sup>lt;sup>6</sup>A targeted macroprudential policy, as developed by the FSB, requires only banks designated as systemically risky to operate with a higher capital requirement.

the  $\Delta CoVaR$  and evaluate the reliability of the riskometers built on these two measures. The riskometer reliability is estimated as the proportion of risky banks<sup>7</sup>. They find that while the bank with the highest estimated systemic risk score is generally susceptible of creating systemic risk, the risky probabilities decline rapidly. This implies that the riskometers are far less reliable than an optimal use of policies targeted at systemic risk would require.

Our approach continues also the line of research developed in Huang et al. (2012), Benoit et al. (2013), Rodríguez-Moreno and Peña (2013), Bernal et al. (2014), Castro and Ferrari (2014), Nucera et al. (2016), Ahnert and Georg (2017), Kleinow et al. (2017), van de Leur et al. (2017), and investigates the differences of the systemic risk estimates and rankings generated by the three main SRMs. Dividing our sample in sub-periods, we inspect the Granger causality between the systemic risk in the US and Europe. Moreover, we apply the bootstrap Kolmogorov-Smirnov (KS) test to formally test the capability of these SRMs to identify the same G-SIBs as the FSB using their scoring method. First, we test whether the difference in the systemic risk associated to each category defined by the FSB are pairwise significantly different; and, secondly, we apply the Wilcoxon signed rank sum test, as in Ahnert and Georg (2017), to verify whether or not the systemic risk of the G-SIBs significantly increases during high volatile periods of the financial market. Moreover, using the bootstrap KS test we rank the G-SIBs according to their systemic risk based on our methodology at the cutoff points of November 2015 and 2016, the periods when FSB reported their calculations. Finally, for  $\Delta CoVaR$ , we introduce a new and more robust method<sup>8</sup> of ranking systemically important banks based on nonparametric confidence intervals, thus accounting for the estimation risk. This ranking method entails that banks with different ranking may have similar systemic risk, because their confidence intervals overlap. We find evidence that the confidence intervals overlap up to the 96.67% of the cases. This new ranking methodology

<sup>&</sup>lt;sup>7</sup>According to Danielsson et al. (2016), a bank is designed as systemically risky, ie "guilty", if its probability to stay in the upper tail of the bank risk distribution is greater than or equal to 90%. They set the riskometer reliability of an optimal TMP as 75%.

<sup>&</sup>lt;sup>8</sup>One attractive feature of the new ranking methodology based on confidence intervals is that it can be used to build confidence intervals for the other market-based SRMs as well.

represents a dynamic support for regulators and supervisory authorities in order to develop, choose and employ their plan to monitor the systemic risk level of the SIFIs.

Despite the increasing literature on this topic, there is still no widely accepted definition of systemic risk (Lo, 2008; Billio et al., 2012; Rodríguez-Moreno and Peña, 2013). This remains a challenge also to public policy that explicitly aims to reduce this risk. Billio et al. (2012) define systemic risk as a set of events or circumstances that influence the stability of the financial system. For Acharya et al. (2017) the systemic risk may be seen as a situation of market freezing, which could cause a significant reduction in financial intermediation activities while Adrian and Brunnermeier (2016) argue that this risk is described by the possibility that the entire financial system being impaired, with potential adverse consequences for the real economy. Because of the partly different definitions, we believe it is important to study the three main SRMs jointly.

The remainder of this paper is organized as follows. In Section 2 we discuss the tests that are going to be applied to the systemic risk results in both the US and Europe to decide whether to different entities are significantly different when it comes to their contribution to systemic risk. Section 3 summarizes the characteristics of the data used in this study. The empirical results are presented in Section 4. Finally, Section 5 concludes the discussion.

## 2 Testing the systemic risk contribution

Testing the systemic contribution of a financial institution to the overall systemic risk is fundamental to the identification with a high degree of confidence of the systemic risky institutions. Bernal et al. (2014) apply the bootstrap KS test developed by Abadie (2002) for testing the systemic contribution of different financial sectors during the period from 2004 to 2012. Castro and Ferrari (2014) use the same test to determine whether or not a financial institution can be identified as systemically important<sup>9</sup>. The resampling method

 $<sup>^{9}</sup>$ Our approach is adjacent to Castro and Ferrari (2014) who develop a test of significance aimed at testing whether or not a financial institution can be classified as systemically important and ranked according to

introduced by Abadie (2002) is superior to the standard KS test because of the Durbin problem (see Durbin, 1973). Ahnert and Georg (2017) use the Wilcoxon signed rank sum test for paired data to test whether or not information contagion due to counterparty risk increases systemic risk.

In our study we test the systemic contribution of the G-SIBs, as identified by the FSB in November 2015 and 2016, to the overall systemic risk of the US and European banking sector, respectively. In particular, considering the G-SIBs covered by the Dodd-Frank Act Stress Test 2016 and the EU-Wide Stress Test 2016 in the US and Europe, respectively, we test whether or not the systemic contribution of these banks is greater than the systemic contribution of the US/European banking sector. We try to verify if the G-SIBs as identified by the FSB are effectively the systemically riskier banks. For testing our hypothesis we use the bootstrap KS test because it compares the cumulative distribution functions (CDFs) instead of considering only the means that could be sensitive to outliers. Moreover, its nonparametric nature does not require any assumptions about the distribution of the SRMs.

We also run a dominance test to measure the significance of the rankings listed by the FSB using as SRMs: (i) the  $\Delta^{\CoVaR_{99^{th}}}$ , (ii) the  $MES^{\Solution}$  and (iii) the SRISK<sup>10</sup>. Table 1 presents the G-SIBs identified by the FSB in November 2016, which are the same as of November 2015. We are interested to verify if the estimates of the three SRMs for our pool of banks confirm the systemically importance of the G-SIBs. In order to test this hypothesis, we compare the stressed 5% systemic risk contribution  $SRM_{5\%}^i$  of each SRM measure with the stressed 5% systemic risk contribution  $SRM_{5\%}^i$  of all the banking sector for 2015 and 2016. The systemic risk of the banking sector is represented by the panel distribution of

the  $\Delta CoVaR$ . They provide an empirical application based on a sample of 26 European large banks. We conduct this test for a wider sample of banks, considering the US and European banking sector and the MES and the SRISK in addition to the  $\Delta CoVaR$ . Moreover, we differentiate our test from their because we test the equality and the dominance for each pair of G-SIBs as identified by the FSB. In case no statistical difference between a pair of banks has found, the two banks have the same ranking position. If a bank *i* has an higher ranking position than bank *j* necessary means that bank *i* dominates bank *j* and all the other banks ranked below bank *j*; or in simple terms, that bank *i* is statistically systemically riskier than bank *j* and all the other banks ranked below bank *j*.

<sup>&</sup>lt;sup>10</sup>Because the SRISK is a measure of capital shortfall in dollar term, for a full pairwise comparison among the SRMs we consider the equity weighted measure of the  $\Delta CoVaR_{99th}$  and the *MES*.

the measure without the bank under the analysis. The systemic contribution of the G-SIBs during a systemic event should be greater than the other banks in the banking sector. We test the following hypotheses:

$$H_0: SRM_{5\%}^i > SRM_{5\%}^{Banking-Sector} \tag{1}$$

$$H_1: SRM_{5\%}^i \le SRM_{5\%}^{Banking-Sector} \tag{2}$$

Reject the null (1) implies that the SRM disagrees with FSB's view of bank i's systemic risk<sup>11</sup>.

The FSB allocates five systemic categories corresponding to different requirement levels of additional capital buffers. Thus, any bank or financial institution belonging to any of these categories will be classified as a G-SIBs as having some systemic relevance. There is a canonic decreasing order of systemic relevance according to the categories. In particular, the banks contained in the  $n^{th}$ -category are systemically riskier than the banks contained in the  $(n-1)^{th}$ -category. These categories were built in such a way as to leave the highest  $(5^{th})$ empty as a deterrent for banks not to increase their global systemic importance.

In this paper we test whether or not higher ranked categories are effectively systemically riskier than the lower categories. To test this hypothesis, we consider all the G-SIBs classified in each category<sup>12</sup> and with the bootstrap KS test we compare the CDFs of the systemic risk contribution of each category. The two sample KS test statistic is given by:

$$D_{mn} = \sqrt{\left(\frac{mn}{m+n}\right)} sup_x |S_m(x) - T_n(x)| \tag{3}$$

<sup>&</sup>lt;sup>11</sup>We run the bootstrap KS dominance test with hypotheses (1) and (2) also for the banks not classified as G-SIBs, included in our sample, to investigate whether or not these banks present systemically importance.

<sup>&</sup>lt;sup>12</sup>G-SIBs covered by the Dodd-Frank Act Stress Test 2016: Citigroup Inc, JPMorgan Chase & Co (4); Bank of America Corp, Deutsche Bank AG, HSBC Holdings PLC (3); Goldman Sachs Group Inc/The, Mitsubishi UFJ Financial Group Inc, Wells Fargo & Co (2); Bank of New York Mellon Corp/The, Morgan Stanley, Banco Santander SA, State Street (1).

G-SIBs covered by the EU-Wide Stress Test 2016: BNP Paribas SA, Deutsche Bank AG, HSBC Holdings PLC (3); Barclays PLC (2); Crédit Agricole SA, Société Générale SA, ING Groep NV, Nordea Bank AB, Royal Bank of Scotland Group PLC, Banco Santander SA, Unicredit SpA (1).

Category	G-SIBs in alphabetical order within each category
5	(Empty)
(3.5%)	(Employ)
4	Citigroup Inc
(2.5%)	JPMorgan Chase & Co
3	Bank of America Corp
(2.0%)	BNP Paribas SA
	Deutsche Bank AG
	HSBC Holdings PLC
2	Barclays PLC
(1.5%)	Credit Suisse AG
	Goldman Sachs Group Inc/The
	Industrial and Commercial Bank of China Limited
	Mitsubishi UFJ Financial Group Inc
	Wells Fargo & Co
1	Agricultural Bank of China Ltd
(1.0%)	Bank of China Ltd
	Bank of New York Mellon Corp/The
	China Construction Bank Corp
	Groupe BPCE SA
	Crédit Agricole SA
	ING Groep NV
	Mizuho Financial Group Inc
	Morgan Stanley
	Nordea Bank AB
	Royal Bank of Scotland Group PLC
	Banco Santander SA
	Société Générale SA
	Standard Chartered PLC
	State Street Corp
	Sumitomo Mitsui Financial Group Inc
	UBS AG
	Unicredit SpA

Table 1: List of G-SIBs as of November 2016.

Note: The list contains the G-SIBs as of November 2016 allocated to categories corresponding to required levels of additional capital buffers. The 30 institutions identified as G-SIBs in 2016 remain the same as those on the 2015 list.

where  $S_m(x)$  and  $T_n(x)$  are the CDFs of the SRM within the same category, and, m and n represent the size of the two samples, respectively. The null and alternative hypotheses are defined as follows:

$$H_0: SRM^{i^{th}-Category} > SRM^{j^{th}-Category} \quad \text{with} \quad i > j \in \{1, 2, 3, 4, 5\}$$

$$\tag{4}$$

$$H_1: SRM^{i^{th}-Category} \le SRM^{j^{th}-Category} \quad \text{with} \quad i > j \in \{1, 2, 3, 4, 5\}$$
(5)

where  $SRM^{i^{th}-Category}$  and  $SRM^{j^{th}-Category}$  are the SRM for the  $i^{th}$  and the  $j^{th}$  categories. Rejecting the null hypothesis (4) implies that the SRM disagrees with the FSB's systemic categorization.

As an additional test, we investigate the contribution of the G-SIBs during the main high volatile events of 2015 and 2016. In particular, we investigate whether or not the contribution of the G-SIBs *h*-days after the volatile events is greater than *h*-days before. We consider the horizon *h* as one month (22 days), similar to Brownlees and Engle (2016). As main volatile events of 2015 and 2016, we examine the Chinese market crash on August  $24^{th}$ , the Brexit vote on June  $23^{th}$  and the presidential election in US of 2016 (November  $8^{th}$ ). The Wilcoxon signed rank sum test is applied to the following hypotheses:

$$H_0: SRM_{t:t+h-1}^i > SRM_{t-h:t-1}^i \tag{6}$$

$$H_1: SRM^i_{t:t+h-1} \le SRM^i_{t-h:t-1} \tag{7}$$

where SRM is the risk measure considered and i indicates the particular bank under study. The failure to reject the alternative hypothesis (7) means that the systemic risk level of the bank under the analysis did not increase during the high volatility events previously described.

#### 2.1 Testing systemic risk ranking

In order to test and rank the G-SIBs according to their systemic risk, we use the bootstrap KS test to investigate whether or not the G-SIBs included in higher categories are systemically riskier than the ones in lower categories. This dominance test defines the following null and alternative hypotheses:

$$H_0: SRM_{5\%}^i > SRM_{5\%}^j$$
 with  $i > j$   $i = 1, 2, ..., n$  and  $j = 1, 2, ..., n - 1$  (8)

$$H_1: SRM_{5\%}^i \le SRM_{5\%}^j \quad \text{with} \quad i > j \quad i = 1, 2, ..., n \quad \text{and} \quad j = 1, 2, ..., n - 1$$
 (9)

where SRM is the risk measure considered stressed at 5%, i and j indicate the G-SIB entities that are tested. The failure to reject the alternative hypothesis (9) means that bank j is systemically risker than bank i, entailing a higher<sup>13</sup> ranking position of j. Using the results from the KS dominance test, we rank the G-SIBs at 99% confidence level. We use this test to rank the G-SIBs and then to investigate the rankings produced by different SRMs, for 2015 and 2106.

#### 2.2 Systemic risk ranking with confidence intervals

The FSB publishes the list of the G-SIBs annually in November. Banks within the same systemic risk category should carry a similar systemic risk. However, the riskier banks in a given category could carry similar systemic risk to the less riskier banks in the upper next category. Hence, we propose a systemic risk ranking methodology based on confidence intervals, that should improve on the pointwise ranking previously used in literature.

We construct in this paper nonparametric confidence intervals based on bootstrapping. We build confidence intervals based on the mean with a re-sampling of (n=) 1000 considering

<sup>&</sup>lt;sup>13</sup>For the dominance test we carry out two tests, first with a null hypothesis that the SRM are identical for the two entities, and if this is rejected then we take one direction as the null hypothesis. Thus, in the end the testing results will indicate either equality or a strict inequality indicating dominance of systemic risk in one direction.

a 1-year moving window. If  $\overline{x}$  is the sample average, we estimate the bootstrapped mean  $\overline{x}^*$  with a (n=) 1000 resampling. The bootstrap differences are given by  $\delta^* = \overline{x}^* - \overline{x}$ . Repeating this exercise for 1000 times, we can estimate the critical values at 0.975 and 0.250 ( $\delta^*_{0.975}$  and  $\delta^*_{0.250}$ ) leading to the bootstrap confidence interval at 95% confidence level as:

$$[\overline{x} - \delta_{0.250}^*, \quad \overline{x} - \delta_{0.975}^*]$$
 (10)

In this paper, we built confidence intervals associated with the  $\Delta CoVaR_{99th}$ . However, the same methodology can be used for the other SRMs.

## 3 Data

In June and July 2016, the FED and EBA, respectively, released the results of their stress test exercises. Following the rules given by the supervisory authorities, the stress test involves only the larger banks. In particular, the EU-Wide Stress Test covers a sample of 51 banks with about 70% of the European banks total assets. The Dodd-Frank Act Stress Test included a sample of 33 BHCs that held USD50 billion or more in total consolidated assets. We then apply a set of data availability criteria to each bank<sup>14</sup>.

Our data consists of 32 US BHCs covered by the Dodd-Frank Act Stress Test 2016 and 35 European banks covered by the EU-Wide Stress Test 2016. Table 2 lists the banks included in the US and European sample, respectively.

We collect daily stock price and balance sheet data from Bloomberg over the period 2000 Q1 - 2016 Q4 in order to have estimations of the SRMs over the period from 2003 Q1 to 2016 Q4. For the US banking sector, all the series are in US dollar; while, for the European

<sup>&</sup>lt;sup>14</sup>In our study, we retain only banks that exist in the financial market during the study period and are listed. For this reason, we do not consider banks: (i) which are not listed or have become de-listed; (ii) for which market data is not available; (iii) with not enough available observations; in particular, we considered institutions with at least 1-year of daily observation; (iv) were involved in a M&A process, e.g. Banca Popolare that on the 1st of January 2017 merged with Banca Popolare di Milano creating Banco BPM.

Panel A: US banking sector			Panel B: European banking sector	
Bank Name	Starting Date	Country	Bank Name	Starting Date
Ally Financial Inc (ALLY)	28/01/2014	Austria	Erste Group Bank AG (EBS)	03/01/2000
American Express Co (AXP)	03/01/2000		Raiffeisen Bank International AG (RBI)	22/04/2005
Banco Bilbao Vizcaya Argentaria SA (BBVA)	03/01/2000	Belgium	Dexia SA (DEXB)	03/01/2000
Banco Santander SA (SAN)	03/01/2000		KBC Group NV (KBC)	03/01/2000
Bank of America Corp (BAC)	03/01/2000	Denmark	Danske Bank A/S (DANSKE)	03/01/2000
Bank of Montreal (BMO)	03/01/2000		Jyske Bank A/S (JYSK)	03/01/2000
Bank of New York Mellon Corp/The (BK)	03/01/2000	France	BNP Paribas SA (BNP)	03/01/2000
BB&T Corp (BBT)	03/01/2000		Crédit Agricole SA (ACA)	13/12/2001
Capital One Financial Corp (COF)	03/01/2000		Société Générale SA (GLE)	03/01/2000
Citigroup Inc (C)	03/01/2000	Germany	Commerzbank AG (CBK)	03/01/2000
Citizens Financial Group Inc (CFG)	23/09/2014		Deutsche Bank AG (DB)	03/01/2000
Comerica Inc (CMA)	03/01/2000	Hungary	OTP Bank PLC (OTP)	03/01/2000
Deutsche Bank AG (DB)	11/01/2000	Ireland	Allied Irish Banks PLC (ALBK)	04/01/2000
Discover Financial Services (DFS)	14/06/2007		Bank of Ireland (BKIR)	04/01/2000
Fifth Third Bancorp (FITB)	03/01/2000	Italy	Banca Monte dei Paschi di Siena SpA (BMPS)	03/01/2000
Goldman Sachs Group Inc/The (GS)	03/01/2000		Intesa Sanpaolo SpA (ISP)	03/01/2000
HSBC Holdings PLC (HSBC)	03/01/2000		Unicredit SpA (UCG)	03/01/2000
Huntington Bancshares Inc/OH (HBAN)	03/01/2000		Unione Di Banche Italiane SpA (UBI)	30/06/2003
JPMorgan Chase & Co (JPM)	03/01/2000	Netherlands	ING Groep NV (INGA)	03/01/2000
KeyCorp (KEY)	03/01/2000	Norway	DNB ASA (DNB)	03/01/2000
M&T Bank Corp (MTB)	03/01/2000	Poland	Powszechna Kasa Oszczedności Bank Polski SA (PKO)	09/11/2004
Mitsubishi UFJ Financial Group Inc (MTU)	02/04/2001	$\operatorname{Spain}$	Banco Bilbao Vizcaya Argentaria SA (BBVA)	03/01/2000
Morgan Stanley (MS)	03/01/2000		Banco de Sabadell SA (SAB)	18/04/2001
Northern Trust Corp (NTRS)	03/01/2000		Banco Popular Español SA (POP)	03/01/2000
PNC Financial Services Group Inc/The (PNC)	03/01/2000		Banco Santander SA (SAN)	03/01/2000
Regions Financial Corp (RF)	03/01/2000		Bankia SA (BKIA)	19/07/2011
State Street Corp (STT)	03/01/2000		CaixaBank SA (CABK)	10/10/2007
SunTrust Banks Inc (STI)	03/01/2000	Sweden	Nordea Bank AB (NDA)	03/01/2000
Toronto-Dominion Bank/The (TD)	03/01/2000		Skandinaviska Enskilda Banken AB (SEBA)	03/01/2000
US Bancorp (USB)	03/01/2000		Svenska Handelsbanken AB (SHBA)	03/01/2000
Wells Fargo & Co (WFC)	03/01/2000		Swedbank AB (SWEDA)	03/01/2000
Zions Bancorporation (ZION)	03/01/2000	United Kingdom	Barclays PLC (BARC)	04/01/2000
			HSBC Holdings PLC (HSBC)	04/01/2000
			Lloyds Banking Group PLC (LLOY)	04/01/2000
			Royal Bank of Scotland Group PLC (RBS)	04/01/2000
Note: The table lists the 32 US-BHCs an (Panel A) and the European banking sector	d the 35 European la rs, respectively. The c	arge banks that comp olumns (1-2) describe	ose the samples used to run the empirical analy the name of the bank and the first observation a	vailable for the US
US-BHCs. The list is sorted by bank name for the Furonean large banks. The list is a	e. The columns (3-5) control by Country	describe the country	name, the name of the bank, and the first observ	ation available
TOT ATT ATT A PARTY AND A PARTY A THAT AND A PARTY A	or we by country.			

Table 2: List of banks in the US and European samples.

14

banking sector, all series are converted into euros<sup>15</sup>. Our sample period covers the two main crises (2007-2009 and 2009-2012). In addition to stock prices, we use other measure-specific data from the Federal Reserve Economic Data, the U.S. Department of the Treasury and the European Money Markets Institute in the calculations of the SRMs, which are described in the next section.

We estimate the CoVaR using quantile regression, requiring a set of lagged state variables  $M_{t-1}$ . The Table 3 lists the variables used in the computation of the state variables for the US and Europe, respectively.

 $<sup>^{15}</sup>$ Engle et al. (2015) use the same method to analyse a sample of large financial institutions in Europe.

US State Variable	Source Variables	Source	Currency	Starting Date
Change in the three-month yield	Three-month Treasury bill rate	treasury.gov	Rate	03/01/2000
Change in the slope of the yield curve	Three-month Treasury bill rate	treasury.gov	Rate	03/01/2000
	Composite Long-term bond yield	treasury.gov	Rate	03/01/2000
$Short-term \ TED \ spread$	Three-month LIBOR rate	Bloomberg	Rate	04/01/2000
	Three-month secondary market Treasury bill rate	fred.stloiusfed.org	Rate	03/01/2000
Change in the credit spread	Moody's Baa-rated bonds	Bloomberg	Rate	03/01/2000
	Ten year Treasury bill rate	treasury.gov	Rate	03/01/2000
darket return	S&P500	Bloomberg	USD	03/01/2000
teal estate sector return in excess of the narket financial sector return	The Dow Jones U.S. Real Estate Index	Bloomberg	USD	03/01/2000
	The Dow Jones U.S. Financial Index	Bloomberg	USD	03/01/2000
Equity volatility	S&P500	Bloomberg	USD	01/12/1999
Juropean State Variable	Source Variables	Source	Currency	Starting Date
Thange in the three-month yield	Euro Generic Government Bond 3M	Bloomberg	Rate	04/01/2000
Change in the slope of the yield curve	Euro Generic Government Bond 3M	Bloomberg	Rate	04/01/2000
	Euro Generic Government Bond 10Y	Bloomberg	Rate	04/01/2000
$hort-term \ TED \ spread$	Three-month EURIBOR rate	euribor-rates.eu	Rate	03/01/2000
	Euro Generic Government Bond 3M	Bloomberg	$\operatorname{Rate}$	04/01/2000
Mange in the credit spread	BofA Merrill Lynch Euro High Yield Index Effective Yield	fred.stlouisfed.org	Rate	03/01/2000
	Euro Generic Government Bond 10Y	Bloomberg	Rate	04/01/2000
darket return	Euro STOXX 50	Bloomberg	EUR	03/01/2000
teal estate sector return in excess of the narket financial sector return	STOXX Europe 600 Real Estate	Bloomberg	EUR	29/12/2000
	STOXX Europe 600 Financial Services	Bloomberg	EUR	03/01/2000
Cquity volatility	STOXX600	Bloomberg	EUR	03/01/2000

Table 3: List of the state variables for the US and European banking sector.

16

## 4 Empirical evidence on systemic risk

#### 4.1 The magnitude of systemic risk

Figure 1 displays the magnitude of the systemic risk at aggregate level<sup>16</sup> for the US and Europe, during the period from 2003 Q1 to 2016 Q4. Following the previous studies by Adrian and Brunnermeier (2016), Black et al. (2016) and Brownlees and Engle (2016), we look closely at some of the major dates in order to measure the magnitude of this risk and the response of the SRMs to the two main crises and the events related to them. The dates considered are: (1) the freezing of BNP Paribas funds on August 8<sup>th</sup>, 2007; (2) the Lehman Brothers bankruptcy on September 15<sup>th</sup>, 2008; (3) the agreement between the Greek government and the IMF for the First bailout package of €110 billion on May 2<sup>nd</sup>, 2010; (4) the peak of 44.21% reached by the Greek 10-year bond yields on March 9<sup>th</sup>, 2012; (5) the Chinese market crash on August 24<sup>th</sup>, 2015; and, (6) the Brexit referendum result on June 24<sup>th</sup>, 2016.

As shown in Figure 1 different SRMs produce different systemic risk estimates. From a policy supervision point of view, this may suggest that systemic risk assessments based on a single measure may lead to contradictory assessments. However, the time-series patterns of the SRMs are very similar between the US and the European banking sector, although these three SRMs seem to provide inconsistent estimates with each other, similar to the conclusions in Zhang et al. (2015). Both banking sectors have a very low systemic value until the freezing of three funds by BNP Paribas (1) due to the subprime problem. The time-series patterns clearly highlight the subprime mortgage crisis, that reached its peak with the bankruptcy of Lehman Brothers (2). However, the peaks reached by these measures are not all observed during the same year. For instance, considering the US and Europe, the higher value of  $\Delta CoVaR$ , MES and SRISK are observed in October 2008, October 2009 and March 2009,

<sup>&</sup>lt;sup>16</sup>We estimate the CoVaR at aggregate level considering as  $X^i$  the return of the portfolio of all the banks included in the reference banking sector and as  $X^{system}$  the return of the bank industry index for the US and the Europe, respectively.



Figure 1: Evolution of systemic risk measures in the US and European zone.

Note: The graphs show the plot of the daily aggregate value of  $\Delta CoVaR_{99^{th}}^{\$}$ ,  $MES^{\$}$ , and SRISK for the US and European banking sector, respectively. The solid vertical lines mark: (1) the freezing of BNP Paribas funds; (2) the Lehman Brothers bankruptcy, (3) the First bailout package for the Greece,(4) the Greek 10-year bond yields peak, (5) the Chinese market crash , and (6) the Brexit referendum result.

respectively. It seems that the  $\Delta CoVaR$  reacts immediately<sup>17</sup>, with two peaks, to the first two events of the subprime crisis.

The three SRMs react differently to market downturns. The graphs in Figure 1 illustrate the dramatic increase of the three measures after the bankruptcy of Lehman Brothers; however, after the peak is reached,  $\Delta CoVaR$  and MES sharply reduce their value, while the SRISK decrease only at the beginning of 2013. The sovereign-debt crisis hits both banking sectors, which reach new peaks of the measures during the period form 2010 Q1 to 2013 Q4. All SRMs react to the Greece agreement of the First bailout package – marked by (3), decreasing their levels. A decreasing trend is observed after this event. However, the systemic risk level increases again when the Greek 10-year bond yields reach the peak of 44.21% as indicated by the event marked by (4). At the beginning of 2013, there is a stable, decreasing in case of the SRISK, trend for all SRMs in both banking sectors. Another interesting feature is that the systemic risk level after the subprime crisis is still high and the systemic risk level of the US and Europe has not reverted back so far, until the end of 2016, to the level experienced before the subprime crisis.

Table 4 presents the descriptive statistics for the aggregate value of the systemic risk estimates in dollar terms (ie equity weighted). Within each sub-panel, the SRISK has a higher mean and maximum value than the other two risk measures. The mean and the max value of the  $CoVaR_q^{\$}$  and the  $MES^{\$}$  are higher for the US while, in the case of SRISK, these values are higher for Europe<sup>18</sup>, confirming the results in Bostandzic and Wei (2018). These features could be probably explained analyzing the different characteristics of the US and the European banking sector and the methodology behind these three measures. Bernal

<sup>&</sup>lt;sup>17</sup>Zhang et al. (2015) inspect whether market-based SRMs offer early warning signals on the systemic importance of large financial institutions. In particular, considering as market-based SRMs the  $\Delta CoVaR$ as developed by Adrian and Brunnermeier (2016), its modified version of López-Espinosa et al. (2012), the SRISK (Brownlees and Engle, 2016), and the Expected Shortfall as implemented by Lehar (2005), they test whether the SRMs provide additional information that are not already provided by conventional risk proxies or simpler firm characteristics liked to systemic risk (e.g. the size of the company). They found that only the  $\Delta CoVaR$  as developed by Adrian and Brunnermeier (2016), in the case of the subprime crisis, slightly increased the predictive power of conventional early warning models.

<sup>&</sup>lt;sup>18</sup>Analyzing the systemic risk of the 196 largest European financial firms, Engle et al. (2015) found a similar trend for the SRISK of the European banks.

	Mean	Median	Std. dev.	Min	Max	No. obs.
Panel A: US banking	g sector					
$\overline{CoVaR_{50^{th}}^{\$}}$	953.68	600.64	$1,\!142.31$	11.49	$14,\!536.47$	2973
$CoVaR_{75^{th}}^{\$}$	$17,\!376.37$	$15,\!899.44$	7,024.35	6,330.12	$71,\!576.01$	2973
$CoVaR_{95^{th}}^{\$}$	$45,\!237.63$	42,515.21	$18,\!676.96$	$19,\!242.36$	$198,\!357.58$	2973
$CoVaR_{99^{th}}^{\$}$	$70,\!453.73$	$68,\!146.40$	$27,\!612.41$	$22,\!441.11$	$263,\!344.06$	2973
$MES^{\$}$	$52,\!237.28$	45,040.73	$28,\!966.83$	$18,\!021.67$	$189,\!817.51$	2973
SRISK	$650,\!451.19$	$650,\!029.36$	$446,\!642.36$	59,776.43	$1,\!553,\!885.22$	2973
Panel B: European b	banking sector					
$CoVaR_{50^{th}}^{\$}$	811.12	456.97	1,039.00	0.00	$23,\!926.69$	2955
$CoVaR_{75^{th}}^{\$}$	$10,\!240.54$	9,749.44	$3,\!659.79$	2,724.62	$37,\!522.77$	2955
$CoVaR_{95^{th}}^{\$}$	$25,\!665.28$	$24,\!618.34$	$8,\!309.69$	$7,\!211.98$	$85,\!983.43$	2955
$CoVaR_{99^{th}}^{\$}$	$38,\!512.82$	$37,\!873.78$	$10,\!329.61$	11,756.22	$97,\!896.28$	2955
$MES^{\$}$	$29,\!685.48$	29,562.88	$11,\!173.37$	$9,\!451.25$	$78,\!304.56$	2955
SRISK	1,023,772.58	$1,\!128,\!641.56$	$448,\!511.97$	$257,\!083.06$	1,785,800.21	2955

Table 4: Aggregate systemic risk statistics.

Note: The descriptive statistics of the aggregate systemic risk estimates are expressed in dollar terms  $(SRM^{\$} = Size \times SRM)$  for the US and European banking sector. The  $CoVaR_q^{\$}$  indicates the  $CoVaR_q$  weighted for the size of the portfolio of all the banks included in the reference banking sector; where, the  $CoVaR_q$  is the predicted value from a q% quantile regression of the bank industry index equity losses on the portfolio equity losses of all the banks included in the reference banking sector and on the lagged state variables. The  $MES^{\$}$  denotes the MES in dollar term of the banking sector computed as the weighted sum of the individual MESs of all the banks included in the reference banking sector. The SRISK is the sum of the individual SRISKs of all the banks included in the reference banking sector. The columns (2-7) describe average, median, standard deviation, minimum value, maximum value, and number of observation. All the estimates refer to the period from 2003 Q1 to 2016 Q4.

et al. (2014) demonstrated that the main systemic source of the US financial market is the insurance sector. In addition,  $\Delta CoVaR$  and MES are a function of: (i) the sensitivity of the financial institution to market decline and (ii) the size of the firm. The SRISK considers also the leverage of the financial institution and it requires a more severe decline condition<sup>19</sup> than the other two systemic measures. This may explain the comparative trends since, after a peak, the  $\Delta CoVaR$  and the MES reduce their values in a shorter period compared to the SRISK, which does not react immediately<sup>20</sup> to a change in market conditions because it must take into consideration balance-sheet variables. Analyzing the systemic risk level of the two banking sector, both US and European banks contribute more to systemic risk during the Global Financial Crisis, while the systemic risk threat seems to be more restrained during the Sovereign-Debt one. Overall, the information on systemic risk provided by the three measures is quite heterogeneous, confirming the criticism detailed in Danielsson et al. (2016) that it would be difficult for the regulator to select a single SRM for a targeted macro-prudential approach.

#### 4.2 Granger causality tests

Table 5 reports the value of the Granger causality test between the systemic risk in US and Europe (the lag length is chosen based on the Akaike information criterion). In particular, we test whether the systemic risk increases in the US (European) banking sector "does not Granger Cause" systemic risk increases in the European (US) banking sector. The Dickey-Fuller test (ADF) and KPSS tests indicate that the first difference of SRMs are stationary and these series are used for Granger causality testing. In order to have a more complete and detailed analysis, we run the Granger causality test for the full sample period (2003 Q1

<sup>&</sup>lt;sup>19</sup>The SRISK computation includes the long-run marginal expected shortfall (LRMES), which measures the expected capital shortfall of a financial institution in case of a financial crisis. To be specific, a financial crisis is defined as a fall of the broad index by 40 percent over the next six months (Acharya et al., 2012).

<sup>&</sup>lt;sup>20</sup>Homar et al. (2017) accounting for size reveals that the stress impact on bank capital implied by SRISK is only marginally correlated with the stress impact as modelled for the ECB/EBA stress test, and key components thereof such as credit losses and trading losses.

- 2016 Q4) and for five sub-periods<sup>21</sup>. Note that the Granger causality test does not imply that one variable is the effect of the other; more precisely, it indicates that one variable contains information about the other.

Table 5 highlights some interesting insights. First of all, there is not always a two-way Granger causality effect for all SRMs. In particular, for the full sample and the pre-subprime crisis periods, we do not find Granger causality in the SRISK from Europe to the US; while, we find it for the  $\Delta CoVaR_{99th}^{\$}$  and the  $MES^{\$}$ . During the subprime crisis, a two-way Granger causality effect has been found for all the three SRMs. However, the results are significant at 1% level from the US to Europe while, the significance level is 1%, 5% and 10% for the  $\Delta CoVaR_{99th}^{\$}$ , the  $MES^{\$}$  and the SRISK, respectively, from Europe to US. For the period in-between the two crises, we find Granger causality from the US to Europe for the  $\Delta CoVaR_{99th}^{\$}$  (at 10%) and the  $MES^{\$}$  (at 1%) and from Europe to the US for the SRISK (at 5%). Surprisingly, during the sovereign-debt crisis the results indicate the presence of Granger causality from the US to Europe at 1% confidence level for all the three SRMs and only for the SRISK from the European banking sector to the US one. A similar result has been found for the post-crises period.

### 4.3 Testing the contribution of the G-SIBs

Idier et al. (2014) argue that, as a financial crisis unfolds, regulators have to identify quickly the most endangered institutions. The FSB imposes higher capital levels for banks defined as

<sup>&</sup>lt;sup>21</sup>In order to examine the Granger causality between the systemic risk level of the US (European) banking sector and the European (US) one during different market periods, we split the full sample period (2003 Q1 - 2016 Q4) into five sub-periods. In order to determine the crisis periods we refer to the major events announced by the official sources (as per, on all, Forbes and Rigobon (2002) and Baur (2012)). We define the following sub-periods: (i) pre-subprime crisis, which begins the 1<sup>st</sup> January 2003 (starting of the sample period) and ends the 7<sup>th</sup> August 2007; (ii) subprime crisis, which starts with the freezing of BNP Paribas funds (8<sup>th</sup> August 2007) until the 31<sup>st</sup> March 2009, day in which the first signs of stabilization are evidenced according the 79<sup>th</sup> Annual Report of the Bank for International Settlements; (iii) pre-sovereign debt crisis; which has been identified as the period between the 1<sup>st</sup> April 2009 to the 1<sup>st</sup> May 2010; (iv) sovereign-debt crisis; which covers the period from the first bailout package to Greece on the 2<sup>nd</sup> May 2010 to the 30<sup>th</sup> September 2012, month in which the European Central Bank announced free unlimited support for all the European Stability Mechanism; (v) post crises; which includes the period from the end of the sovereign-debt crisis to the last observation of the sample, in 2016.

Table 5: Granger causality test between t	he systemic risk in the US and Europe.
---	--

	$\Delta CoVaR_{99^{th}}^{\$}$	$MES^{\$}$	SRISK
Full sample period			
US systemic risk does not Granger Cause European systemic risk	$14.9047^{***}$	$26.5294^{***}$	$24.0114^{***}$
European systemic risk does not Granger Cause US systemic risk	$3.4604^{***}$	$1.8702^{***}$	0.7027
Pre-subprime crisis period			
US systemic risk does not Granger Cause European systemic risk	$3.553^{***}$	$5.8084^{***}$	$11.0901^{***}$
European systemic risk does not Granger Cause US systemic risk	$3.0158^{**}$	$2.5516^{***}$	0.8202
Subprime crisis period			
US systemic risk does not Granger Cause European systemic risk	$4.9005^{***}$	$7.1906^{***}$	$15.5461^{***}$
European systemic risk does not Granger Cause US systemic risk	3.3278***	$2.2462^{**}$	2.7301*
Pre-sovereign debt crisis period			
US systemic risk does not Granger Cause European systemic risk	$2.136^{*}$	7.6405***	0.3504
European systemic risk does not Granger Cause US systemic risk	0.1969	0.0218	$2.1565^{**}$
Sovereign debt crisis period	0 5051***	<b>F FO</b> 4 C * * *	1 0005***
US systemic risk does not Granger Cause European systemic risk	8.7871	1.7246	4.6895****
European systemic risk does not Granger Cause US systemic risk	0.0794	1.783	3.3249***
Post grisss period			
US automia rick does not Cranger Cause Furenean automia rick	o 0599***	15 5100***	0 9957***
European systemic risk does not Granger Cause European systemic risk	1 1140	2 2744*	9.0001
European systemic risk does not Granger Cause US systemic risk	1.1149	3.3/44	4.34/2

Note: The Table reports the F-Statistics from the Granger causality test between the systemic risk in the US and Europe. The null hypothesis is that systemic risk level increases in the US (European) banking sector "does not Granger Cause" systemic risk level increases in the European (US) banking sector. The systemic risk level is measured with  $\Delta CoVaR_{99th}^{\$}$ ,  $MES^{\$}$  and SRISK, respectively. The lag length is chosen based on the Akaike information criterion. \*\*\*, \*\*, and \* indicate significance at 1%, 5%, and 10% levels, respectively.

G-SIBs to make sure they could cope with the risk that a future stress event could cause. The FSB publishes the list of G-SIBs, every year in November. In this context, we compute the equity weighted systemic risk value for  $\Delta CoVaR_{99^{th}}$  and MES, which are also compared with the SRISK in order to verify if these measures are able to capture the G-SIBs as classified by the FSB as systemically riskier than the other banks in the banking system. There are 12 G-SIBs covered by the Dodd-Frank Act Stress Test 2016<sup>22</sup>; and there are 11 G-SIBs covered by the EU-Wide Stress Test 2016<sup>23</sup>.

Table 6 reports the results of the bootstrap KS dominance test for the US and the European banks classified as G-SIBs as of November 2015 and 2016, respectively. Excepting few cases, we always reject the null hypothesis at 1% critical level, implying that G-SIBs are individually systemically riskier than the pool of other banks in the banking sector. This result, for most of the banks considered, is consistent for all three SRMs.

Table 7 shows that the success ratio of each measure for the US G-SIBs is above 75% at 1% critical level and 92% at 5% for 2015 and it is above 83% and 92% at 1% and 5% critical level, respectively, for 2016. Thus, for the European banks, the three SRMs completely succeed to classify the European G-SIBs as systemically risky within the banking sector. There is a bank with a rejected systemic risk status based on the  $\Delta CoVaR$  within the US banking sector. This is State Street Corp that is classified in the less risky systemic category by the FSB<sup>24</sup>. According to the bootstrap KS test results, the systemic risk contribution of State Street Corp is not significantly greater than the other banks in 2015, while the null hypothesis is rejected at 10% in 2016. Relaxing the critical level at 10% would allow to include State Street Corp as systemic risky. Overall, the results suggest that the G-SIBs are indeed the banks that contribute more to the systemic risk of the banking sector.

<sup>&</sup>lt;sup>22</sup>In alphabetical order: Bank of America Corp, Bank of New York Mellon Corp/The, Banco Santander SA, Citigroup Inc, Deutsche Bank AG, Goldman Sachs Group Inc/The, HSBC Holdings PLC, JPMorgan Chase & Co, Morgan Stanley, Mitsubishi UFJ Financial Group Inc, State Street Corp, Wells Fargo & Co.

<sup>&</sup>lt;sup>23</sup>In alphabetical order: Banco Santander SA, Barclays PLC, BNP Paribas SA, Crédit Agricole SA, Deutsche Bank AG, HSBC Holdings PLC, ING Groep NV, Nordea Bank AB, Royal Bank of Scotland Group PLC, Société Générale SA, Unicredit SpA.

<sup>&</sup>lt;sup>24</sup>In Section 4.4, State Street Corp is always ranked as one of the less systemically risky among the G-SIBs.

Panel A: US l	banking sector			Panel B: Europe	an banking sector	r	
$H_1: \ SRM^i_{5\%} \le SRM^{Banking-Sector}_{5\%}$	$\Delta CoVaR_{99th}$	MES	SRISK	$H_1: SRM_{5\%}^i \leq SRM_{5\%}^Banking-Sector$	$\Delta CoVaR_{99^{th}}$	MES	SRISK
2015							
Bank of America Corp	$0.932^{***}$	$0.933^{***}$	$0.972^{***}$	Banco Santander SA	$0.968^{***}$	$0.989^{***}$	$0.898^{***}$
Bank of New York Mellon Corp/The	$0.477^{**}$	$0.532^{***}$	$0.905^{***}$	Barclays PLC	$0.799^{***}$	$0.851^{***}$	$0.971^{***}$
Banco Santander SA	$0.693^{***}$	$0.866^{***}$	$0.979^{***}$	BNP Paribas SA	$0.941^{***}$	$0.941^{***}$	$1.000^{***}$
Citigroup Inc	$0.864^{***}$	$0.899^{***}$	$0.958^{***}$	Crédit Agricole SA	$0.607^{***}$	$0.648^{***}$	$0.956^{***}$
Deutsche Bank AG	$0.454^{**}$	$0.561^{***}$	$0.993^{***}$	Deutsche Bank AG	$0.716^{***}$	$0.645^{***}$	$0.985^{***}$
Goldman Sachs Group Inc/The	$0.750^{***}$	$0.766^{***}$	$0.936^{***}$	HSBC Holdings PLC	$1.000^{***}$	$0.971^{***}$	$0.929^{***}$
HSBC Holdings PLC	$0.867^{***}$	$0.833^{***}$	$0.986^{***}$	ING Groep NV	$0.845^{***}$	$0.877^{***}$	$0.884^{***}$
JPMorgan Chase & Co	$0.966^{***}$	$0.966^{***}$	$0.965^{***}$	Nordea Bank AB	$0.759^{***}$	$0.616^{***}$	$0.796^{***}$
Morgan Stanley	$0.625^{***}$	$0.717^{***}$	$0.943^{***}$	Royal Bank of Scotland Group PLC	$0.521^{***}$	$0.587^{***}$	$0.927^{***}$
Mitsubishi UFJ Financial Group Inc	$0.704^{***}$	$0.799^{***}$	$1.000^{***}$	Société Générale SA	$0.687^{***}$	$0.688^{***}$	$0.913^{***}$
State Street Corp	0.352	$0.431^{**}$	$0.899^{***}$	Unicredit SpA	$0.588^{***}$	$0.749^{***}$	$0.869^{***}$
Wells Fargo & Co	$1.000^{***}$	$1.000^{***}$	$0.915^{***}$				
<u>2016</u>							
Bank of America Corp	$0.935^{***}$	$0.921^{***}$	$0.971^{***}$	Banco Santander SA	$0.941^{***}$	$0.971^{***}$	$0.914^{***}$
Bank of New York Mellon Corp/The	$0.544^{***}$	$0.616^{***}$	$0.860^{***}$	Barclays PLC	$0.794^{***}$	$0.882^{***}$	$0.957^{***}$
Banco Santander SA	$0.693^{***}$	$0.828^{***}$	$0.962^{***}$	BNP Paribas SA	$0.968^{***}$	$0.941^{***}$	$1.000^{***}$
Citigroup Inc	$0.871^{***}$	$0.905^{***}$	$0.952^{***}$	Crédit Agricole SA	$0.602^{***}$	$0.701^{***}$	$0.942^{***}$
Deutsche Bank AG	$0.449^{**}$	$0.489^{***}$	$0.989^{***}$	Deutsche Bank AG	$0.634^{***}$	$0.618^{***}$	$0.984^{***}$
Goldman Sachs Group Inc/The	$0.744^{***}$	$0.746^{***}$	$0.914^{***}$	HSBC Holdings PLC	$1.000^{***}$	$1.000^{***}$	$0.971^{***}$
HSBC Holdings PLC	$0.899^{***}$	$0.873^{***}$	$0.981^{***}$	ING Groep NV	$0.842^{***}$	$0.853^{***}$	$0.856^{***}$
JPM organ Chase & Co	$0.967^{***}$	$0.987^{***}$	$0.943^{***}$	Nordea Bank AB	$0.762^{***}$	$0.647^{***}$	$0.798^{***}$
Morgan Stanley	$0.644^{***}$	$0.759^{***}$	$0.923^{***}$	Royal Bank of Scotland Group PLC	$0.733^{***}$	$0.741^{***}$	$0.899^{***}$
Mitsubishi UFJ Financial Group Inc	$0.741^{***}$	$0.791^{***}$	$1.000^{***}$	Société Générale SA	$0.706^{***}$	$0.735^{***}$	$0.928^{***}$
State Street Corp	$0.372^{*}$	$0.454^{**}$	$0.865^{***}$	Unicredit SpA	$0.558^{***}$	$0.666^{***}$	$0.882^{***}$
Wells Fargo & Co	$1.000^{***}$	$0.946^{***}$	$0.885^{***}$				

Table 6: Dominance test results for the G-SIBs.

determine whether or not the systemic risk of the G-SIBs, as identified by the FSB in 2015 and 2016, is greater than the systemic risk of the reference banking sector. The hypothesis tested is  $H_1$ :  $SRM_{5\%}^i \leq SRM_{5\%}^{Banking-Sector}$ . The failure to reject this hypothesis means that the FSB identified incorrectly bank *i* as systemically riskier. The systemic risk of the bank is measured with  $\Delta CoVaR_{99th}^0$ , MES Note: The results, for the G-SIBs in US (Panel A) and Europe (Panel B), of the bootstrap Kolmogorov-Smirnov tests, which aims to and SRISK. The columns contain the test statistic. \*\*\*, \*\*, and \* indicate significance at 1%, 5%, and 10% levels, respectively. As reported in Section 2, we run this test also for the other banks not classified as G-SIBs. In both banking sectors, we find that the three SRMs pinpoint more systemically important banks than the FSB. In particular, considering a critical level of 1%, the  $\Delta CoVaR$ , the MES and the SRISK respectively identify 13 (18) and 16 (17), 15 (18) and 17 (18), 25 (33) and 28 (33) G-SIBs in the US (Europe) in 2015 and 2016<sup>25</sup>. The high number of banks identified as systemically important by the SRISK can be explained by the high volatility, but not systemic, periods experienced by the US and European banking sectors in 2015 and 2016, the characteristics of the SRISK explained in Section 4.1 and the sizes of the banks included in the two samples.

Table 7:	Success	ratios	of	the	SRMs.

Significance level	$\Delta CoVaR$	MES	SRISK
<u>US G-SIBs - 2015</u>			
0.01	75%	92%	100%
0.05	92%	100%	100%
<u>US G-SIBs - 2016</u>			
0.01	83%	92%	100%
0.05	92%	100%	100%
European G-SIBs -	2015		
0.01	100%	100%	100%
0.05	100%	100%	100%
European G-SIBs -	2016		
0.01	100%	100%	100%
0.05	100%	100%	100%

Note: The success ratio at 0.01 and 0.05 critical levels for the US and European G-SIBs as identified by the systemic risk measure. This ratio is computed as the fraction of G-SIBs identified riskier than the reference banking sector (US/European) at 0.01 and 0.05 critical levels – according to  $\Delta CoVaR$  (column 1), MES (column 2) and SRISK (column 3) – over the number of G-SIBs announced by the FSB within the sam banking sector. The test used is the bootstrap KS test.

<sup>&</sup>lt;sup>25</sup>Relaxing the critical level at 5% and 10% the number of banks identified as systemically important, according to  $\Delta CoVaR$  and MES, slightly increases both in the US and Europe. The results are available upon request.

Table 8 contains the results of the bootstrap KS dominance test for the systemic categories identified by the FSB as of November 2015 and 2016. In the US we work with four categories while in Europe there are only three categories, see Table 1. The results in Table 8 point out to a difference in the risk of different categories. In 2015, for the G-SIBs in US, the null hypothesis is not rejected in the case of the SRISK for the comparison of the  $2^{nd}$  and the  $1^{st}$ categories, but the null hypothesis is rejected at 5% for the  $\Delta CoVaR$  and the MES, when testing for significant difference between  $3^{rd}$  and  $2^{nd}$  categories. For all the other cases, in both banking sectors, the null hypothesis is always rejected at the 1% critical level.

The results of the Wilcoxon signed rank sum test for the G-SIBs within the US and European banking sector during the Chinese market crash in 2015, the Brexit vote in 2016, and the US presidential election of 2016 are illustrated in Table 9. We run this test to inspect whether or not the systemic risk of the G-SIBs significantly increases after a volatile event or a period of financial instability. The null hypothesis is rejected at 1% critical level in most of the cases. In particular, high volatile periods increase significantly the systemic risk of the G-SIBs. These results may motivate the supervisory authority to carefully monitor and keep under control these banks during these periods. Despite the increase in systemic risk following the Chinese market turbulence and the Brexit vote, the US and European G-SIBs showed resilience, which allowed the banking sector to avoid<sup>26</sup> a new systemic crisis.

The results related to the presidential election of 2016 in the US show an asymmetric increase in the systemic risk of the G-SIBs for the US and Europe, respectively. For the US, considering the MES, the hypothesis is rejected at 1% for all the G-SIBs, excepting Banco Santander SA. The  $\Delta CoVaR_{99^{th}}$  produces similar results, failing to reject the null hypothesis for Banco Santander SA and State Street Corp. However, when using the SRISK the hypothesis is not rejected for all the G-SIBs, except Banco Santander SA. Thus, the  $\Delta CoVaR_{99^{th}}$  and the MES are more sensitive to changes in market conditions. In Europe,

<sup>&</sup>lt;sup>26</sup>The increase in systemic risk may trigger other market reactions. Flannery et al. (2017) discovered statistically significant average cumulative abnormal returns around many of the stress test disclosure dates, and in general there is more information about riskier banks being generated post-stress disclosures.

Panel A: US banking sector		Panel B: European banking secto	r
$\Delta CoVaR_{95}$	9th MES SRISK	$\Delta CoVaR_{99^{4}}$	MES SRISK
$\frac{2015}{SRM^{4^{th}}-Category} \leq SRM^{3^{th}}-Category \ 0.500^{***}$	$0.667^{***} \ 0.734^{***}$	$SRM^{3^{th}-Category} \leq SRM^{2^{th}-Category}  0.667^{***}$	**** 0.667***
$SRM^{4^{th}-Category} \leq SRM^{2^{th}-Category} 0.667*** SRM^{4^{th}-Category} \leq SRM^{1^{th}-Category} 1.000***$	$0.667^{***}$ $0.954^{***}$ $1.000^{***}$ $0.750^{***}$	$SRM^{3^{th}-Category} \leq SRM^{1^{th}-Category} 0.524^{***}$ $SRM^{2^{th}-Category} \leq SRM^{1^{th}-Category} 0.714^{***}$	$0.524^{***}$ $0.740^{***}$ $0.714^{***}$ $1.000^{***}$
$SRM^{3^{th}-Category} \leq SRM^{2^{th}-Category} 0.333^{**}$ $SRM^{3^{th}-Category} \leq SRM^{1^{th}-Category} 0.667^{***}$ $SRM^{2^{th}-Category} < SRM^{1^{th}-Category} 0.806^{***}$	$0.333^{**}$ $0.954^{***}$ $0.472^{***}$ $0.750^{***}$ $0.750^{***}$ $0.045$		
2016			
$\frac{CRM}{SRM}^{4^{th}-Category} \leq SRM^{3^{th}-Category} 0.500^{***}$	0.667*** 0.681*** 0.0077*** 0.0681***	$SRM^{3th}-Category \leq SRM^{2th}-Category 0.667***$	0.667*** 1.000***
$SRM^{4^{th}-Category} \leq SRM^{1} - Category 1.000***$	$1.000^{***} 0.750^{***}$	$SRM^{2^{th}-Category} \leq SRM^{1^{th}-Category} 0.054^{mm}$	$0.857^{***}$ $1.000^{***}$
$SRM^{3th}$ - Category $\leq SRM^{2th}$ - Category 0.333*** $CRM^{3th}$ - Category $\sim CRM^{1th}$ - Category 0.667***	0.333 0.667*** 0.667*** 0.750		
$SRM^{2^{th}-Category} \leq SRM^{1^{th}-Category} 1.000^{***}$	$0.500^{***} 0.500$		
Note: The results of the bootstrap Kolmogorov-S.	inirnov tests, which aim	is to determine whether or not the systemic risk of t	ne G-SIBs classified
III à IIIBIIET Cavegoly is greaver vilair vile sysvenire Foulting coston of of the FCD concentration Vi	TISK 01 ULE U-DILE CLUSS	The house category, for the US (Fairer A) and The house the set of $T$	ыпореан (ганет <i>р)</i> Дл.( <i>n-i</i> ) <sup>th</sup> -Categoru

Table 8: Dominance test results for the categories as defined by the FSB.

banking sector as of the FSB announcements in November 2015 and 2016. The hypothesis tested is  $H_1$ :  $SRM^{n''-Category} \leq SRM^{(n-j)''-Category}$ , with j=1,2,...,n-1. The failure to reject this hypothesis means that the FSB identified incorrectly the systemic categories. The systemic risk of the categories is measured with  $\Delta CoVaR_{99th}$ , MES and SRISK. The columns contain the test statistic. \*\*\*, \*\*, and \* indicate significance at 1%, 5%, and 10% levels, respectively. the MES signals an increase in the systemic risk of all G-SIBs, except the Royal Bank of Scotland Group PLC, Banco Santander SA and Unicredit SpA. For the  $\Delta CoVaR_{99^{th}}$ , the hypothesis is rejected for the same entities rejected by the MES. The SRISK identifies an increase of the systemic risk for Royal Bank of Scotland Group PLC only.

Therefore, the US presidential election of 2016 affected mainly the systemic risk of the G-SIBs in the US, and less the Europe. The SRISK does not capture a significant increase in the risk of the G-SIBs in any of the two banking sectors, contrary to the results estimated for the Chinese market crash in 2015 and the Brexit vote result in 2016. Laeven et al. (2016) argue that the SRISK, contrary to the  $\Delta CoVaR$  that captures the contagion risk, is sensitive only to the exposure to common shocks that affect the entire financial market.

#### 4.4 Testing the ranking of the G-SIBs

Here the bootstrap KS dominance test is run for each pair of G-SIBs using the SRMs stressed at 5% with a one-year moving window. Then, the G-SIBs are ranked as of November 2015 and 2016 with a significance level of 1%.

Tables 10 and 11 report the rankings resulting from the dominance test at 1% critical level. The results indicate that the G-SIBs that are classified in the higher categories by the FSB are not always riskier than the G-SIBs classified in the lower categories! It is therefore very important to have a categorising or systemic risk rating process that is replicable using market data such that companies can self-check their status every year.

#### 4.5 Rankings based on confidence intervals

In this section we present a new contribution to the systemic risk ranking based on nonparametric confidence intervals. As described in Section 2.2, we build nonparametric confidence intervals for the  $\Delta CoVaR_{99th}$  of the US and the European banks, through bootstrapping.

In order to estimate confidence intervals for the  $\Delta CoVaR_{99^{th}}$ , we use resampling of (n=) 1000 simulations, considering a one-year moving window. Figures 2 and 3 show the confidence

	Chinese.	Market Crash	2015	ш	rexit 2016		US Preside	ntial Election 201
$: SRM^{i}_{t:t+h-1} \leq SRM^{i}_{t-h:t-1} $	$\Delta CoVaR_{99t}$	h MES S	RISK	$\Delta CoVaR_{99^{t1}}$	1 MES	SRISK	$\Delta CoVaR_{99th}$	MES SRISH
nel A: US banking sector								
nk of America Corp	$-4.009^{***}$	-4.475***	$4.009^{***}$	-3.427***	$-2.341^{**}$	$-4.009^{***}$	$-4.009^{***}$	$-4.621^{***}$ 0.000
nk of New York Mellon Corp/The .	$-4.009^{***}$	-4.475***	$4.009^{***}$	$-3.170^{***}$	$-4.475^{***}$	-4.009***	$-2.640^{***}$	$-4.621^{***}$ 0.000
nco Santander SA	$-4.009^{***}$	0.000	$4.009^{***}$	-2.309**	-4.475***	-4.009***	-0.346	-0.140 -0.168
igroup Inc	$-4.009^{***}$	-4.235***	$4.009^{***}$	-3.523***	-2.428**	$-4.009^{***}$	-3.523***	-3.874*** 0.000
utsche Bank AG	$-4.009^{***}$	-1.837*	$4.009^{***}$	-2.784***	-2.298**	$-4.009^{***}$	$-4.009^{***}$	$-4.621^{***}$ 0.000
ldman Sachs Group Inc/The	$-4.009^{***}$	-4.475***	$4.009^{***}$	$-3.611^{***}$	-1.505	$-2.184^{**}$	$-4.009^{***}$	-3.874*** 0.000
BC Holdings PLC	$-4.009^{***}$	-4.475***	$4.009^{***}$	$-3.741^{***}$	$-4.621^{***}$	$-4.009^{***}$	-2.857***	$-4.621^{***}$ 0.000
Morgan Chase & Co	$-4.009^{***}$	-4.475***	$4.009^{***}$	$-3.741^{***}$	$-3.194^{***}$	$-4.009^{***}$	-2.857***	$-4.621^{***}$ 0.000
organ Stanley	$-4.009^{***}$	-4.235***	$4.009^{***}$	$-3.741^{***}$	-3.707***	$-4.009^{***}$	-3.427***	$-4.621^{***}$ 0.000
tsubishi UFJ Financial Group Inc	$-4.009^{***}$	-4.475***	$4.009^{***}$	$-3.611^{***}$	-2.320**	$-4.009^{***}$	$-4.009^{***}$	$-4.621^{***}$ 0.000
te Street Corp	$-4.009^{***}$	-4.475***	$4.009^{***}$	-1.499	-3.902***	-4.009***	-1.101	$-4.621^{***}$ 0.000
ills Fargo & Co	$-4.009^{***}$	-4.475*** 0	000'	-3.335***	-0.219	$-2.184^{**}$	-3.335***	$-4.621^{***}$ 0.000
nel B: European banking sector								
nco Santander SA	$-3.741^{***}$	0.000	$4.009^{***}$	-3.842***	-2.882***	$-4.009^{***}$	-0.793	-0.291 -1.009
rclays PLC	0.000	-4.475***	$4.009^{***}$	-0.002	-4.475***	$-4.009^{***}$	-4.009***	-4.475*** 0.000
IP Paribas SA	-1.009	-0.415	$4.009^{***}$	$-4.009^{***}$	$-4.118^{***}$	$-4.009^{***}$	-1.827*	-4.475*** 0.000
édit Agricole SA	$-3.741^{***}$	0.000	$4.009^{***}$	$-4.009^{***}$	$-3.731^{***}$	-4.009***	-4.009***	-4.475*** 0.000
utsche Bank AG	-2.062**	-3.731***	$4.009^{***}$	$-4.009^{***}$	-0.001	$-4.009^{***}$	$-2.504^{**}$	-4.475*** 0.000
BC Holdings PLC	-3.741***	-4.475***	$4.009^{***}$	$-4.009^{***}$	$-4.475^{***}$	$-4.009^{***}$	-2.373**	-4.475*** 0.000
G Groep NV	-3.842***	-3.278***	$4.009^{***}$	$-4.009^{***}$	-4.040***	$-4.009^{***}$	-3.335***	$-4.475^{***}$ 0.000
rdea Bank AB	-1.055	-1.468	$4.009^{***}$	-2.438**	-3.956***	-4.009***	-2.857***	-4.475*** 0.000
yal Bank of Scotland Group PLC .	-0.085	0.000	$4.009^{***}$	-3.335***	-3.218***	-0.002	0.000	0.000 -4.009
ciété Générale SA	-3.842***	-4.235***	$4.009^{***}$	-3.088***	-3.463***	$-4.009^{***}$	-2.002**	$-4.475^{***}$ 0.000
irredit SnA	-0.168	0.000	$2.640^{***}$	-0.346	-1.024	$-4.009^{***}$	-0.004	-0.001 -1.827

Table 9: Wilcoxon signed rank sum test for the C-SIBs during the main volatile events of 2015 and 2016.

determine whether or not the systemic risk of the G-SIBs h-days after a volatile event is greater than the systemic risk of the same h-days before. The hypothesis tested is  $H_1$ :  $SRM^i_{t:t+h-1} \leq SRM^i_{t-h:t-1}$ , with h=22-days. The failure to reject this hypothesis means that the systemic risk level of the bank i did not increase during the high volatility event considered. This test consider the main volatile events of 2015 and 2016. The systemic risk of the bank is measured with  $\Delta CoVaR_{99th}$ , MES and SRISK. The columns contain the test statistic. \*\*\*, \*\*, and \* indicate significance at 1%, 5%, and 10% levels, respectively. Note

				Ч. Т.	Inc	AG	s PLC	merica		er SA	ase &	>	Sachs	с	rp	York he
		2016	ion	shi IIF	Group j	te Bank	Holding	of Aı	ıp Inc	Santand	çan Chi	Stanley	n nc/The	argo & '	rreet Co	of New Corp/T
		Nov.	Instituti	Mitenbi	nancial	Deutsch	HSBC I	Bank Corp	Citigrou	Banco S	JPMorg Co	Morgan	Goldma Group I	Wells Fa	State St	Bank o Mellon
ЗK	_		Rank	<del>.</del>	;	2.	с;	4.	ы.	.9	7.	×.	9.	10.	11.	12.
SRIS	(3)	Nov. 2015	Institution	Mitenhishi IIFI Fi.	nancial Group Inc	Deutsche Bank AG	HSBC Holdings PLC	Banco Santander SA	Bank of America Corp	JPMorgan Chase & Co	Citigroup Inc	Morgan Stanley	Goldman Sachs Group Inc/The	Wells Fargo & Co	Bank of New York Mellon Corp/The	State Street Corp
			Rank	<del>.</del>	;	2.	с;	4.	ю.	6.	7.	×.	9.	10.	11.	12.
		Nov. 2016	Institution	IDMorran Chase &	Co	Bank of America Corp	Citigroup Inc	Wells Fargo & Co	HSBC Holdings PLC	Banco Santander SA	Morgan Stanley	Mitsubishi UFJ Financial Group Inc	Goldman Sachs Group Inc/The	Bank of New York Mellon Corp/The	Deutsche Bank AG	State Street Corp
ES			Rank	<del>, -</del>	;		2.	3.	4.	5.	6.	7.	×.	9.	10.	11.
MI	(5	Nov. 2015	Institution	Walls Farm & Co		JPMorgan Chase & Co	Bank of America Corp	Citigroup Inc	Banco Santander SA	HSBC Holdings PLC	Goldman Sachs Group Inc/The	Mitsubishi UFJ Fi- nancial Group Inc	Morgan Stanley	Deutsche Bank AG	Bank of New York Mellon Corp/The	State Street Corp
			Rank	<del>.</del>	÷	2.	ς.	4.	ы. С	6.	7.	×.	9.	10.	11.	12.
		Nov. 2016	Institution	Walls Farm & Co		JPMorgan Chase & Co	Bank of America Corp	HSBC Holdings PLC	Citigroup Inc	Goldman Sachs Group Inc/The	Mitsubishi UFJ Financial Group Inc	Banco Santander SA	Morgan Stanley	Bank of New York Mellon Corp/The	Deutsche Bank AG	State Street Corp
${}^{\imath R_{99th}}$			Rank	-	÷	2.	<del>.</del> с	4.	<u>о</u> .	9.		7.	×.	9.	10.	11.
$\Delta CoV_{c}$	(1	Nov. 2015	k Institution	Walls Farm & Co		JPMorgan Chase $\&$ Co	Bank of America Corp	Citigroup Inc	HSBC Holdings PLC	Goldman Sachs Group Inc/The	Mitsubishi UFJ Fi- nancial Group Inc	Banco Santander SA	Morgan Stanley	Bank of New York Mellon Corp/The	Deutsche Bank AG	State Street Corp
			Ran	<del>.</del>	÷	2.	3.	4.		<u>.</u>			6.	7.	×.	9.

Table 10: Ranking of the G-SIBs in the US as of November 2015 and 2016.

test with 0.01 significance level. The hypothesis tested is  $H_1$ :  $SRM_{5\%}^i \leq SRM_{5\%}^j$ , with i > j, i=1,2,...,n and j=1,2,...,n-1. The failure to reject this hypothesis means that bank j is systemically risker than bank i, entailing an higher ranking position of j. The systemic risk Note: The ranking of the G-SIBs in the US as of November 2015 and 2016. The ranking results from the bootstrap Kolmogorov-Smirnov of the bank is measured with  $\Delta CoVaR_{99th}$  (1), MES (2) and SRISK (3). All the systemic risk measures are stressed at 5%.

	$\Delta CoV_{\ell}$	$R_{99t}$	ų		ME	SE			SRIS	SK	
(1)					(2	<u> </u>			(3)	<b>.</b>	
Nov. 2015			Nov. 2016		Nov. 2015		Nov. 2016		Nov. 2015		Nov. 2016
Institution Rank	Rank		Institution	Ranl	t Institution	Rank	Institution	Ranl	: Institution I	Rank	: Institution
HSBC Holdings PLC 1.	Η.		HSBC Holdings PLC	i.	Banco Santander SA	1.	HSBC Holdings PLC	1.	BNP Paribas SA	Ŀ.	BNP Paribas SA
Banco Santander SA 2.	2.		BNP Paribas SA	2.	HSBC Holdings PLC	5.	Banco Santander SA	5.	Deutsche Banks AG	6.	Deutsche Banks AG
BNP Paribas SA 3. ]	с. Г	-	Barclays PLC	З.	BNP Paribas SA	З.	BNP Paribas SA	З.	Barclays PLC	с.	HSBC Holdings PLC
ING Groep NV 4.	4		Banco Santander SA	4.	ING Groep NV	4.	Barclays PLC	4.	Crédit Agricole SA	4.	Barclays PLC
Barclays PLC 5. ]	5.	_	ING Groep NV	5.	Barclays PLC	ъ.	ING Groep NV	5.	HSBC Holdings PLC	ы. С	Crédit Agricole SA
Nordea Bank AB 6.	.9		Nordea Bank AB	6.	Unicredit SpA	9.	Société Générale SA		Royal Bank of Scot- land Group PLC	6.	Société Générale SA
Deutsche Banks AG 7. I 1	7. I 1		Royal Bank of Scot- and Group PLC	7.	Société Générale SA	7.	Royal Bank of Scot- land Group PLC	6.	Société Générale SA	7.	Banco Santander SA
Société Générale SA 8. S	м. М	01	ociété Générale SA		Deutsche Banks AG	×.	Crédit Agricole SA		Banco Santander SA	ò	Royal Bank of Scot- land Group PLC
Crédit Agricole SA 9. I	9. I	Н	<b>Deutsche Banks AG</b>	×.	Crédit Agricole SA	9.	Nordea Bank AB	×.	ING Groep NV	9.	Unicredit SpA
Unicredit SpA 10. 0	10.	$\overline{}$	<b>Crédit Agricole SA</b>	9.	Nordea Bank AB	10.	Unicredit SpA	9.	Nordea Bank AB	10.	ING Groep NV
Royal Bank of Scot- 11. <sup>1</sup> land Group PLC	11.	-	Unicredit SpA	10.	Royal Bank of Scot- land Group PLC	11.	Deutsche Banks AG	10.	Unicredit SpA	11.	Nordea Bank AB

Table 11: Ranking of the G-SIBs in Europe as of November 2015 and 2016.

Smirnov test with 0.01 significance level. The hypothesis tested is  $H_1$ :  $SRM_{5\%}^i \leq SRM_{5\%}^j$ , with i > j, i=1,2,...,n and j=1,2,...,n-1. The failure to reject this hypothesis means that bank j is systemically risker than bank i, entailing an higher ranking position of j. The Note: The ranking of the G-SIBs in the Europe as of November 2015 and 2016. The ranking results from the bootstrap Kolmogorovsystemic risk of the bank is measured with  $\Delta CoVaR_{99th}$  (1), MES (2) and SRISK (3). All the systemic risk measures are stressed at 5%. intervals at 95% of the  $\Delta CoVaR_{99^{th}}$  for the US and the European large banks<sup>27</sup>, respectively. The US and European large banks are allocated in 5 categories that are associated with the required levels of additional capital buffers defined by the FSB. The categories have the same property of the FSB ones. In particular, higher categories are associated with higher systemic importance of the bank and higher additional capital requirements. The confidence intervals of the top systemically important institutions overlap, implying that institutions with different systemic risk level, but confidence intervals overlapped, may have the same true systemic risk, even if they are in different ranking positions.

Figures 2 and 3 show that the confidence intervals are wider during the crises (2008-2009 and 2011), while they shrink during calm periods. The most important feature coming out is that, considering both banking system, the confidence intervals frequently overlap, especially during a crisis. Thus, while the overlapping is expected for the banks in the middle of the ranking, the overlapping in the top positions of the rankings entails that banks ranked lower may have similar systemic risk contribution with higher ranked banks. Second, because the size of the confidence intervals become wider during crises and there are more overlapping of confidence intervals, it implies that there is more uncertainty about the real level of systemic risk during turmoil periods.

Table 12 summarizes the ranking for each year of the top ten systemic US BHCs and European large banks according to the systemic risk value estimated by  $\Delta CoVaR_{99^{th}}$  over the period from 2007 to 2016. The systemic risk value ( $\Delta CoVaR_{99^{th}}$ ) of each bank has been estimated as the mean over one year estimates moving window, in order to consider all the market downturns and upturns. Table 12 reports the estimated lower and upper bounds, the size of the confidence interval and the systemic ranking of the bank.

For the evolution of systemic risk, we notice that the top ten systemically institutions change from one year to the other. It is interesting to see that the width of the confidence

 $<sup>^{27}</sup>$ We normalize the confidence intervals by their upper bound. This allows us to maintain constant the absolute distance among them. As an additional exercise, we do the normalization of the confidence intervals by the midpoint as well. The results are very similar and available upon request.



Figure 2: Confidence intervals 95% of the  $\Delta CoVaR_{99^{th}}$  for the US BHCs.



Figure 3: Confidence intervals 95% of the  $\Delta CoVaR_{99th}$  for the European large banks.

US	Midpoint	Lower	Upper	$\mathbf{Width}$	Ranking	Europe	Midpoint	Lower	Upper	Width	Ranking
31/12/2007 STT HBAN GS FITB USB MTB WFC ZION BMO MS	$\begin{array}{c} 6.57 \\ 6.51 \\ 6.18 \\ 5.56 \\ 5.54 \\ 5.33 \\ 5.29 \\ 5.28 \\ 5.11 \end{array}$	$5.98 \\ 6.05 \\ 5.72 \\ 5.05 \\ 5.08 \\ 5.06 \\ 4.87 \\ 4.89 \\ 5.04 \\ 4.79 \\$	$\begin{array}{c} 7.20 \\ 6.99 \\ 6.63 \\ 6.01 \\ 6.01 \\ 5.98 \\ 5.79 \\ 5.67 \\ 5.51 \\ 5.46 \end{array}$	$\begin{array}{c} 1.22\\ 0.93\\ 0.91\\ 0.95\\ 0.93\\ 0.93\\ 0.92\\ 0.77\\ 0.47\\ 0.67\end{array}$	1.2.3.4.5.6.7.8.9.10.	LLOY BKIR SHBA UCG SWEDA ALBK BNP BMPS BARC JYSK	$\begin{array}{c} 4.65 \\ 4.52 \\ 4.45 \\ 4.29 \\ 4.23 \\ 4.16 \\ 4.01 \\ 3.95 \\ 3.84 \\ 3.78 \end{array}$	$\begin{array}{c} 4.48 \\ 4.34 \\ 4.27 \\ 4.15 \\ 4.06 \\ 3.98 \\ 3.80 \\ 3.77 \\ 3.63 \\ 3.65 \end{array}$	$\begin{array}{c} 4.82\\ 4.69\\ 4.65\\ 4.45\\ 4.39\\ 4.34\\ 4.24\\ 4.11\\ 4.05\\ 3.92 \end{array}$	$\begin{array}{c} 0.34\\ 0.35\\ 0.38\\ 0.30\\ 0.32\\ 0.36\\ 0.45\\ 0.34\\ 0.42\\ 0.27\\ \end{array}$	1. 2. 3. 4. 5. 6. 7. 8. 9. 10.
31/12/2008 DFS HBAN KEY AXP WFC STI PNC STT C ZION	$\begin{array}{c} 13.89\\ 10.62\\ 10.34\\ 10.31\\ 10.18\\ 10.17\\ 9.96\\ 9.90\\ 9.89\\ 9.89\\ 9.82 \end{array}$	$\begin{array}{c} 13.07 \\ 9.92 \\ 9.35 \\ 9.55 \\ 9.38 \\ 9.46 \\ 9.21 \\ 9.40 \\ 8.90 \\ 9.10 \end{array}$	$\begin{array}{c} 14.67 \\ 11.30 \\ 11.37 \\ 11.09 \\ 10.94 \\ 10.85 \\ 10.61 \\ 10.37 \\ 10.85 \\ 10.53 \end{array}$	$\begin{array}{c} 1.60 \\ 1.38 \\ 2.02 \\ 1.54 \\ 1.56 \\ 1.39 \\ 1.40 \\ 0.98 \\ 1.95 \\ 1.44 \end{array}$	1. 2. 3. 4. 5. 6. 7. 8. 9. 10.	BKIR ALBK DEXB LLOY RBS SAN BARC SHBA BNP SWEDA	$\begin{array}{c} 9.30\\ 9.15\\ 8.63\\ 8.61\\ 7.89\\ 7.77\\ 7.38\\ 7.36\\ 7.36\\ 7.36\\ 7.32\end{array}$	$\begin{array}{c} 8.66\\ 8.35\\ 7.93\\ 8.02\\ 7.13\\ 7.33\\ 6.97\\ 6.99\\ 6.92\\ 6.97\end{array}$	$\begin{array}{c} 9.92 \\ 9.88 \\ 9.21 \\ 9.15 \\ 8.62 \\ 8.19 \\ 7.77 \\ 7.71 \\ 7.76 \\ 7.66 \end{array}$	$\begin{array}{c} 1.26 \\ 1.53 \\ 1.27 \\ 1.13 \\ 1.48 \\ 0.86 \\ 0.80 \\ 0.72 \\ 0.84 \\ 0.69 \end{array}$	1. 2. 3. 4. 5. 6. 7. 8. 9. 10.
31/12/2009 DFS C USB CMA ZION FITB WFC KEY MS BK	$\begin{array}{c} 9.16 \\ 8.90 \\ 8.41 \\ 8.30 \\ 8.02 \\ 7.92 \\ 7.90 \\ 7.76 \\ 7.63 \\ 7.42 \end{array}$	$\begin{array}{c} 8.83\\ 8.18\\ 7.82\\ 7.80\\ 7.45\\ 7.37\\ 7.33\\ 7.13\\ 7.15\\ 7.06 \end{array}$	9.44 9.60 8.99 8.75 8.51 8.45 8.43 8.35 8.08 7.82	$\begin{array}{c} 0.60 \\ 1.42 \\ 1.17 \\ 0.95 \\ 1.06 \\ 1.08 \\ 1.11 \\ 1.22 \\ 0.93 \\ 0.76 \end{array}$	$\begin{array}{c} 1.\\ 2.\\ 3.\\ 4.\\ 5.\\ 6.\\ 7.\\ 8.\\ 9.\\ 10. \end{array}$	LLOY ISP BARC DANKSE BNP BMPS INGA BKIR ALBK JYSK	8.87 8.05 8.02 7.88 7.81 7.63 7.57 7.50 7.48	$\begin{array}{c} 8.22 \\ 7.68 \\ 7.57 \\ 7.61 \\ 7.45 \\ 7.37 \\ 7.34 \\ 7.21 \\ 7.14 \\ 7.28 \end{array}$	$\begin{array}{c} 9.50 \\ 8.40 \\ 8.41 \\ 8.15 \\ 8.21 \\ 7.96 \\ 7.94 \\ 7.89 \\ 7.83 \\ 7.68 \end{array}$	$\begin{array}{c} 1.28 \\ 0.72 \\ 0.84 \\ 0.54 \\ 0.76 \\ 0.59 \\ 0.60 \\ 0.68 \\ 0.69 \\ 0.41 \end{array}$	1.2.3.4.5.6.7.8.9.10.
31/12/2010 DFS USB HSBC CMA FITB MS TD BK DB ZION	$\begin{array}{c} 7.63 \\ 5.68 \\ 5.33 \\ 5.27 \\ 5.14 \\ 5.08 \\ 5.08 \\ 4.99 \\ 4.94 \end{array}$	$\begin{array}{c} 7.45 \\ 5.49 \\ 5.13 \\ 5.18 \\ 5.10 \\ 4.98 \\ 4.91 \\ 4.95 \\ 4.76 \\ 4.75 \end{array}$	$\begin{array}{c} 7.81 \\ 5.88 \\ 5.53 \\ 5.49 \\ 5.44 \\ 5.30 \\ 5.28 \\ 5.20 \\ 5.21 \\ 5.12 \end{array}$	$\begin{array}{c} 0.37 \\ 0.39 \\ 0.40 \\ 0.31 \\ 0.32 \\ 0.38 \\ 0.25 \\ 0.45 \\ 0.37 \end{array}$	$ \begin{array}{c} 1.\\ 2.\\ 3.\\ 4.\\ 5.\\ 6.\\ 7.\\ 8.\\ 9.\\ 10.\\ \end{array} $	RBI UCG SHBA JYSK OTP ISP ALBK DANKSE BNP CBK	$\begin{array}{c} 6.00\\ 5.95\\ 5.95\\ 5.74\\ 5.72\\ 5.69\\ 5.60\\ 5.49\\ 5.43\\ 5.42\end{array}$	5.87 5.88 5.82 5.60 5.55 5.47 5.38 5.24 5.24	$\begin{array}{c} 6.14 \\ 6.02 \\ 6.08 \\ 5.89 \\ 5.87 \\ 5.83 \\ 5.73 \\ 5.61 \\ 5.62 \\ 5.61 \end{array}$	$\begin{array}{c} 0.27 \\ 0.14 \\ 0.27 \\ 0.29 \\ 0.32 \\ 0.28 \\ 0.26 \\ 0.24 \\ 0.38 \\ 0.36 \end{array}$	1. 2. 3. 4. 5. 6. 7. 8. 9. 10.
31/12/2011 DFS USB HSBC TD CMA MS ZION BK COF STI	$\begin{array}{c} 6.72 \\ 6.26 \\ 6.12 \\ 5.96 \\ 5.93 \\ 5.92 \\ 5.88 \\ 5.82 \\ 5.78 \\ 5.66 \end{array}$	$\begin{array}{c} 6.52 \\ 5.98 \\ 5.81 \\ 5.67 \\ 5.76 \\ 5.69 \\ 5.63 \\ 5.59 \\ 5.52 \\ 5.45 \end{array}$	$\begin{array}{c} 6.92 \\ 6.56 \\ 6.43 \\ 6.26 \\ 6.09 \\ 6.14 \\ 6.15 \\ 6.05 \\ 6.02 \\ 5.87 \end{array}$	$\begin{array}{c} 0.39 \\ 0.58 \\ 0.63 \\ 0.58 \\ 0.33 \\ 0.45 \\ 0.52 \\ 0.46 \\ 0.51 \\ 0.43 \end{array}$	$ \begin{array}{c} 1.\\ 2.\\ 3.\\ 4.\\ 5.\\ 6.\\ 7.\\ 8.\\ 9.\\ 10.\\ \end{array} $	SHBA RBI BNP BARC KBC DEXB OTP ISP SAB UCG	$\begin{array}{c} 7.52 \\ 7.08 \\ 6.83 \\ 6.71 \\ 6.65 \\ 6.61 \\ 6.54 \\ 6.53 \\ 6.49 \\ 6.30 \end{array}$	$\begin{array}{c} 7.15 \\ 6.85 \\ 6.48 \\ 6.41 \\ 6.33 \\ 6.24 \\ 6.26 \\ 6.24 \\ 6.25 \\ 6.12 \end{array}$	$\begin{array}{c} 7.86 \\ 7.30 \\ 7.16 \\ 6.99 \\ 6.95 \\ 6.96 \\ 6.78 \\ 6.82 \\ 6.70 \\ 6.50 \end{array}$	$\begin{array}{c} 0.71 \\ 0.45 \\ 0.69 \\ 0.58 \\ 0.62 \\ 0.73 \\ 0.51 \\ 0.57 \\ 0.45 \\ 0.37 \end{array}$	$ \begin{array}{c} 1.\\ 2.\\ 3.\\ 4.\\ 5.\\ 6.\\ 7.\\ 8.\\ 9.\\ 10.\\ \end{array} $
31/12/2012 DFS USB CMA STI JPM MS COF WFC HBAN STT	$\begin{array}{c} 6.52 \\ 6.33 \\ 6.30 \\ 5.76 \\ 5.70 \\ 5.69 \\ 5.69 \\ 5.58 \\ 5.51 \end{array}$	$\begin{array}{c} 6.44\\ 6.22\\ 6.19\\ 5.66\\ 5.61\\ 5.60\\ 5.59\\ 5.55\\ 5.48\\ 5.41\\ \end{array}$	$\begin{array}{c} 6.60 \\ 6.45 \\ 6.43 \\ 5.85 \\ 5.79 \\ 5.79 \\ 5.78 \\ 5.75 \\ 5.67 \\ 5.61 \end{array}$	$\begin{array}{c} 0.17 \\ 0.23 \\ 0.24 \\ 0.20 \\ 0.17 \\ 0.18 \\ 0.19 \\ 0.20 \\ 0.19 \\ 0.19 \\ 0.19 \end{array}$	$\begin{array}{c} 1.\\ 2.\\ 3.\\ 4.\\ 5.\\ 6.\\ 7.\\ 8.\\ 9.\\ 10. \end{array}$	SHBA RBI KBC UCG BARC BNP BKIA SAB DEXB DNB	$\begin{array}{c} 6.61 \\ 6.25 \\ 5.96 \\ 5.91 \\ 5.87 \\ 5.82 \\ 5.82 \\ 5.82 \\ 5.65 \\ 5.64 \end{array}$	$\begin{array}{c} 6.42 \\ 6.10 \\ 5.75 \\ 5.79 \\ 5.70 \\ 5.65 \\ 5.43 \\ 5.59 \\ 5.45 \\ 5.51 \end{array}$	$\begin{array}{c} 6.80 \\ 6.40 \\ 6.16 \\ 6.04 \\ 6.05 \\ 6.00 \\ 6.18 \\ 5.88 \\ 5.85 \\ 5.77 \end{array}$	$\begin{array}{c} 0.38\\ 0.30\\ 0.41\\ 0.26\\ 0.34\\ 0.75\\ 0.30\\ 0.41\\ 0.26\\ \end{array}$	$ \begin{array}{c} 1.\\ 2.\\ 3.\\ 4.\\ 5.\\ 6.\\ 7.\\ 8.\\ 9.\\ 10.\\ \end{array} $

Table 12: Ranking of the top 10-systemic US and European large banks over the period from 2007 to 2016.

Table: 12 (Continued)

US	Midpoint	Lower	Upper	$\mathbf{Width}$	Ranking	Europe	Midpoint	Lower	Upper	$\mathbf{Width}$	Ranking
31/12/2013 DFS USB COF CMA BMO MS MTB TD HBAN WFC	$5.59 \\ 4.68 \\ 4.53 \\ 4.49 \\ 4.48 \\ 4.45 \\ 4.41 \\ 4.41 \\ 4.37 \\ 4.36$	$5.50 \\ 4.58 \\ 4.44 \\ 4.42 \\ 4.43 \\ 4.39 \\ 4.36 \\ 4.33 \\ 4.31 \\ 4.30$	$5.67 \\ 4.77 \\ 4.62 \\ 4.57 \\ 4.54 \\ 4.52 \\ 4.46 \\ 4.49 \\ 4.43 \\ 4.42$	$\begin{array}{c} 0.17 \\ 0.18 \\ 0.18 \\ 0.16 \\ 0.11 \\ 0.13 \\ 0.10 \\ 0.16 \\ 0.12 \\ 0.12 \end{array}$	1. 2. 3. 4. 5. 6. 7. 8. 9. 10.	BKIA RBI DANKSE SHBA UCG PKO DEXB CABK UBI NDA	$5.29 \\ 4.94 \\ 4.64 \\ 4.63 \\ 4.60 \\ 4.59 \\ 4.32 \\ 4.27 \\ 4.22 \\ 4.22$	$5.13 \\ 4.88 \\ 4.58 \\ 4.58 \\ 4.56 \\ 4.52 \\ 4.25 \\ 4.21 \\ 4.17 \\ 4.17 \\ 4.17 \\$	$5.44 \\ 4.99 \\ 4.71 \\ 4.69 \\ 4.63 \\ 4.66 \\ 4.40 \\ 4.33 \\ 4.27 \\ 4.27 \\ 4.27 \\$	$\begin{array}{c} 0.31 \\ 0.11 \\ 0.14 \\ 0.11 \\ 0.07 \\ 0.14 \\ 0.15 \\ 0.13 \\ 0.10 \\ 0.10 \end{array}$	1. 2. 3. 4. 5. 6. 7. 8. 9. 10.
31/12/2014 DFS BMO BK TD PNC MTB HSBC SAN USB MS	$\begin{array}{r} 4.97\\ 3.96\\ 3.92\\ 3.86\\ 3.82\\ 3.77\\ 3.72\\ 3.70\\ 3.69\\ 3.67\end{array}$	$\begin{array}{c} 4.88\\ 3.90\\ 3.84\\ 3.76\\ 3.74\\ 3.71\\ 3.64\\ 3.63\\ 3.59\\ 3.58 \end{array}$	5.06 4.03 4.00 3.95 3.89 3.83 3.81 3.76 3.77 3.75	$\begin{array}{c} 0.17\\ 0.13\\ 0.16\\ 0.19\\ 0.15\\ 0.12\\ 0.17\\ 0.14\\ 0.18\\ 0.17\\ \end{array}$	1.2.3.4.5.6.7.8.9.10.	BKIA SHBA PKO RBI DANKSE BNP UCG DEXB POP CABK	$\begin{array}{c} 4.58\\ 4.30\\ 4.28\\ 4.18\\ 4.14\\ 4.13\\ 4.09\\ 4.05\\ 3.97\\ 3.93\end{array}$	$\begin{array}{c} 4.43 \\ 4.26 \\ 4.20 \\ 4.12 \\ 4.08 \\ 4.06 \\ 4.06 \\ 3.99 \\ 3.90 \\ 3.87 \end{array}$	$\begin{array}{c} 4.71 \\ 4.35 \\ 4.35 \\ 4.24 \\ 4.21 \\ 4.21 \\ 4.13 \\ 4.10 \\ 4.04 \\ 3.99 \end{array}$	$\begin{array}{c} 0.28 \\ 0.09 \\ 0.15 \\ 0.12 \\ 0.13 \\ 0.15 \\ 0.07 \\ 0.12 \\ 0.14 \\ 0.11 \end{array}$	1. 2. 3. 4. 5. 6. 7. 8. 9. 10.
31/12/2015 DFS USB TD BMO HSBC COF WFC MTB CMA PNC	5.75 5.36 5.11 4.92 4.91 4.88 4.84 4.84 4.84 4.79 4.77	$5.59 \\ 5.18 \\ 4.96 \\ 4.81 \\ 4.77 \\ 4.71 \\ 4.70 \\ 4.73 \\ 4.64 \\ 4.62$	$5.92 \\ 5.52 \\ 5.25 \\ 5.02 \\ 5.05 \\ 5.05 \\ 4.99 \\ 4.95 \\ 4.95 \\ 4.90$	$\begin{array}{c} 0.33 \\ 0.33 \\ 0.29 \\ 0.22 \\ 0.29 \\ 0.34 \\ 0.28 \\ 0.22 \\ 0.31 \\ 0.28 \end{array}$	$ \begin{array}{c} 1.\\ 2.\\ 3.\\ 4.\\ 5.\\ 6.\\ 7.\\ 8.\\ 9.\\ 10.\\ \end{array} $	SHBA PKO BNP DANKSE RBI POP SAN OTP UBI DNB	$5.11 \\ 5.04 \\ 4.90 \\ 4.81 \\ 4.73 \\ 4.69 \\ 4.60 \\ 4.55 \\ 4.52 \\ 4.49$	5.05 4.91 4.81 4.72 4.64 4.62 4.51 4.45 4.47 4.42	$5.17 \\ 5.16 \\ 4.99 \\ 4.90 \\ 4.81 \\ 4.75 \\ 4.69 \\ 4.65 \\ 4.58 \\ 4.55$	$\begin{array}{c} 0.12 \\ 0.25 \\ 0.19 \\ 0.18 \\ 0.13 \\ 0.18 \\ 0.20 \\ 0.10 \\ 0.13 \end{array}$	$ \begin{array}{c} 1.\\ 2.\\ 3.\\ 4\\ 5.\\ 6.\\ 7.\\ 8.\\ 9.\\ 10.\\ \end{array} $
31/12/2016 DFS USB ALLY WFC TD BMO CMA STT HSBC MS	$\begin{array}{c} 5.47\\ 5.28\\ 5.15\\ 5.14\\ 5.04\\ 5.02\\ 4.91\\ 4.83\\ 4.83\\ 4.78\end{array}$	$5.33 \\ 5.10 \\ 4.78 \\ 5.01 \\ 4.90 \\ 4.92 \\ 4.77 \\ 4.71 \\ 4.69 \\ 4.65 \\$	$\begin{array}{c} 5.61 \\ 5.45 \\ 5.52 \\ 5.25 \\ 5.17 \\ 5.13 \\ 5.04 \\ 4.95 \\ 4.96 \\ 4.90 \end{array}$	$\begin{array}{c} 0.28 \\ 0.34 \\ 0.74 \\ 0.24 \\ 0.28 \\ 0.21 \\ 0.27 \\ 0.23 \\ 0.28 \\ 0.25 \end{array}$	1. 2. 3. 4. 5. 6. 7. 8. 9. 10.	SHBA BNP UBI POP RBI PKO CABK DANKSE DNB SAN	$\begin{array}{c} 5.69 \\ 5.35 \\ 5.24 \\ 5.17 \\ 5.13 \\ 5.12 \\ 5.11 \\ 5.03 \\ 5.00 \\ 4.93 \end{array}$	5.62 5.21 5.14 5.07 5.01 4.93 5.03 4.92 4.88 4.82	$\begin{array}{c} 5.76 \\ 5.47 \\ 5.34 \\ 5.27 \\ 5.25 \\ 5.19 \\ 5.14 \\ 5.10 \\ 5.03 \end{array}$	$\begin{array}{c} 0.15 \\ 0.26 \\ 0.21 \\ 0.20 \\ 0.24 \\ 0.35 \\ 0.15 \\ 0.22 \\ 0.22 \\ 0.21 \end{array}$	1. 2. 3. 4. 5. 6. 7. 8. 9. 10.

Note: The ranking of the top 10 US bank holding companies (column 1-6) and European large banks (column 7-12) according to the systemic risk value estimated by the  $\Delta CoVaR_{99^{th}}$  over the period from the 2007 to 2016. Columns report name of the institution (1 and 7), mean  $\Delta CoVaR_{99^{th}}$  (2 and 8), lower bound (3 and 9), upper bound (4 and 10), the size of the confidence interval at 95% (5 and 11) and the ranking (6 and 12).

intervals is greater during the crisis, while it decreases during calm periods. The width of the confidence intervals for both banking sectors reached its peak during the subprime crisis. The systemic risk and its confidence interval shrank after the crisis of 2007-09.

Table 13 presents the number, and the percentage, of cases in which we encountered a confidence intervals overlap. We consider only substantial overlap of confidence intervals. In particular, we define two confidence intervals to be overlapped only when the upper bound of the SRM for the bank rated less risky is above the midpoint of the bank rated as riskier.

Table 13 highlights some interesting insights. Analyzing the US banking sector (Panel A - All BHCs), we can see that the percentage of overlapping intervals is always consistent. In particular, the percentage of overlapping intervals never goes below the 70%, registered in 2012, and reaches the maximum value of 96.67% in 2009. A similar pattern has been found for the European banking sector (Panel B - All Banks). The percentage of overlapping intervals reaches a minimum value of 62.86% in 2014 and a maximum value of 94.12% in 2009 and 2012. Analyzing only the G-SIBs included in the US and European banking sector (Panel A and Panel B - G-SIBs), the rate of overlap remains solid, even if we document a decreasing number of cases in which the confidence intervals overlap.

Panel A: US banking sector									Pane	el B: Europea	an bank	ing se	ector
		All E	BHCs			G-S	SIBs		All B	anks		G-S	SIBs
Year	Ν	n	%		Ν	n	%	Ν	n	%	N	n	%
2007	29	26	89.66%		12	7	58.33%	33	31	93.94%	11	8	72.73%
2008	30	27	90.00%		12	8	66.67%	33	29	87.88%	11	8	72.73%
2009	30	29	96.67%		12	9	75.00%	34	32	94.12%	11	6	54.55%
2010	30	26	86.67%		12	6	50.00%	34	30	88.24%	11	7	63.64%
2011	30	28	93.33%		12	8	66.67%	34	32	94.12%	11	7	63.64%
2012	30	21	70.00%		12	7	58.33%	35	31	88.57%	11	7	63.64%
2013	30	24	80.00%		12	9	75.00%	35	26	74.29%	11	6	54.55%
2014	30	25	83.33%		12	8	66.67%	35	22	62.86%	11	6	54.55%
2015	31	26	83.87%		12	8	66.67%	35	26	74.29%	11	5	45.45%
2016	31	27	87.10%		12	8	66.67%	35	28	80.00%	11	5	45.45%

Table 13: Number of overlapping confidence intervals over the period from 2007 to 2016.

Note: The table presents the number (N) of banks, and G-SIBs, in the US and European banking sector, the number (n) of cases in which the confidence intervals overlap, and the percentage (%) of the "n" cases over the total "N".

Table 14 presents the classification of the US and European large banks at the end of 2016. The banks are allocated in the 5 categories considered by the FSB. Fist of all, it is highlighted that only few banks fill the 5<sup>th</sup> category. As we can observe, in the US there is a quasi-uniform allocation of banks from the 4<sup>th</sup> to the 2<sup>nd</sup> category; while, in Europe there is a major concentration of banks within the 4<sup>th</sup> and the 3<sup>rd</sup> category. This result contrasts the G-SIBs classification made by the FSB, which allocates most banks in the 1<sup>st</sup>

Category	United States	Europe
5	Ally Financial Inc	BNP Paribas SA
(3.5%)	Bank of Montreal	Svenska Handelsbanken AB
	Comerica Inc	
4	Discover Financial Services	Banco Popular Español SA
(2.5%)	HSBC Holdings PLC	Banco Santander SA
	Morgan Stanley	CaixaBank SA
	State Street Corp	Danske Bank A/S
	Toronto-Dominion Bank/The	DNB ASA
	US Bancorp	OTP Bank PLC
	Wells Fargo & Co	Powszechna Kasa Oszczedności Bank Polski SA
		Raiffeisen Bank International AG
		Unione Di Banche Italiane SpA
3	Banco Santander SA	Banca Monte dei Paschi di Siena SpA
(2.0%)	Bank of New York Mellon Corp/The	Banco Bilbao Vizcaya Argentaria SA
	Capital One Financial Corp	Banco de Sabadell SA
	Fifth Third Bancorp	Bankia SA
	Goldman Sachs Group Inc/The	Barclays PLC
	M&T Bank Corp	Crédit Agricole SA
	PNC Financial Services Group Inc/The	Deutsche Bank AG
	Zions Bancorporation	Dexia SA
		Erste Group Bank AG
		HSBC Holdings PLC
		ING Groep NV
		Intesa Sanpaolo SpA
		Jyske Bank A/S
		KBC Group NV
		Nordea Bank AB
2	American Express Co	Skandinaviska Enskilda Banken AB
(1.5%)	Banco Bilbao Vizcaya Argentaria SA	Société Générale SA
	Bank of America Corp	Swedbank AB
	Deutsche Bank AG	Unicredit SpA
	Huntington Bancshares Inc/OH	
	JPMorgan Chase & Co	
	KeyCorp	
	Northern Trust Corp	
	Regions Financial Corp	
	SunTrust Banks Inc	
1	BB&T Corp	Allied Irish Banks PLC
(1.0%)	Citigroup Inc	Bank of Ireland
	Mitsubishi UFJ Financial Group Inc	Commerzbank AG
		Lloyds Banking Group PLC
		Royal Bank of Scotland Group PLC

Table 14: List of US and European large banks allocated in categories according to the ranking based on confidence intervals as of November 2016.

Note: The list contains the US and European large banks allocated in categories according to the ranking based on confidence intervals as of November 2016. The required levels of additional capital buffers associated with each category refer to the FSB list of G-SIBs.

category (see Table 1). Further, because the  $\Delta$ CoVaR method does not take into account

bank size, some banks end up in high systemic risk categories because of their high degree of interconnectedness.<sup>28</sup>. Another important finding is that the banks overseen by both the FED and the EBA are not necessarily ranked in the same category. In particular, the same bank can be ranked in two different categories between the US and Europe. This is a strong finding because the systemic risk contribution of the same bank may be different according to the reference banking sector. A bank could be subject to different additional capital requirement in the stress test exercise in the US and Europe.

The classification of financial institutions according to their systemic risk level and the application of confidence intervals can provide valuable support for regulators and supervisory authorities in order to develop, choose and employ their plan to monitor the systemic risk level of the SIFIs. The usage of confidence intervals supports the estimation of the effective difference among the banks by degree of systemic risk contribution to the whole system. In addition, our methodology offers a more objective approach in deciding the classification categories for the G-SIBs based on the current market data information and taking into consideration the uncertainty surrounding rank estimates. Hence, the classification of banks and companies as systemically risky inherits a dynamic feature in our approach.

### 4.6 Measuring and testing rankings similarity

Finally, we are trying to answer whether rankings under different SRMs are very similar to the published ranking under the scoring system, and also what is the similarity between the results under different SRMs. In order to verify the similarity between the ranking list produced by FSB<sup>29</sup> we employ the Kendall's  $\tau_b$  ranking correlation coefficient measure and an

<sup>&</sup>lt;sup>28</sup>Castro and Ferrari (2014) reported a similar issue. In particular, they showed that scaling the  $\Delta CoVaR$  by the bank size, the classification of the financial firms changes, being strongly influenced by the bank size. In this case, the FSB could reduce its policy to an assessment of only the biggest (size) banks. However, in this study we only discuss a methodology to rank G-SIBs, and we built confidence intervals associated with  $\Delta CoV aR$ .

<sup>&</sup>lt;sup>29</sup>In order to estimate the correlation coefficients between the ranking (not the categories defined by the FSB) of the G-SIBs and each SRM, we download the G-SIB scores, used by the FSB to allocate the G-SIBs

improved theoretical variant of this coefficient –  $\tau_x$  introduced by Emond and Mason (2002). The methodologies of these two rank correlation coefficient are described in Appendix A. The  $\tau_b$  and  $\tau_x$  coefficients are measures of concordance for ranking lists. These measures take values between -1 and +1, with +1 when the lists are identical and -1 when the lists are in reverse order, respectively. The value 0 indicates the absence of any association.

Figures 4 and 5 present the daily estimates of  $\tau_b$  and  $\tau_x$  for each pair of SRMs for the US and European banking sector, respectively. The estimates of  $\tau_b$  and  $\tau_x$  are almost equivalent within the same banking sector and similar between the US and European banking sectors. Moreover, their values are always positive, suggesting a positive association between the various systemic risk methods. The daily-association between  $\Delta CoVaR_{99^{th}}$  and MES is the highest among all compared pairs, in both the US and Europe, the  $\tau_b$  and  $\tau_x$  between these two SRMs rarely go below the value of 0.75. This association decreases in the cases of  $\Delta CoVaR_{99^{th}}$  vs. SRISK and MES vs. SRISK<sup>30</sup> for the US. Moreover, for the  $\Delta CoVaR_{99^{th}}$ and MES versus the SRIS,  $\tau_b$  and  $\tau_x$  estimates drastically increase in the aftermath of the last two financial crises, suggesting that rankings between these two combinations of SRMs are in accordance during turbulent periods for the market.

Figures 6 and 7 present the daily estimates of  $\tau_b$  and  $\tau_x$  between the FSB ranking of the G-SIBs and each SRM, which we compute considering only the 12 G-SIBs covered by the Dodd-Frank Act Stress Test 2016 in the US<sup>22</sup> and the 11 G-SIBs covered by the EU-Wide Stress Test 2016 in Europe<sup>23</sup>. The estimates of  $\tau_b$  and  $\tau_x$  take only positive values, and they are almost equivalent within the same banking sector. The concordance tests with FSB list as a benchmark are different in the US vis-a-vis Europe<sup>31</sup>.

in categories, from 2014 to 2016. We rank the G-SIBs according to these scores to obtain a formal ranking. The G-SIBs scores are available at: https://www.financialresearch.gov/.

<sup>&</sup>lt;sup>30</sup>We conduct also the Kendall  $\tau_b$  test for each of the cases analyzed. We find that the  $\tau_b$  estimates, in percentage of total observation, in the US (Europe) are significant at 1%, 5% and 10%: 100% (100%) in the case of  $\Delta CoVaR_{99^{th}}$  vs. MES; 43.06%, 79.35% and 90.32% (89.79%, 99.57% and 99.89%) in the case of  $\Delta CoVaR_{99^{th}}$  vs. SRISK; and 53.38%, 83.22% and 93.51% (99.50%, 99.93% and 99.96%) in case of MES vs. SRISK.

<sup>&</sup>lt;sup>31</sup>Also in this case, we conduct the Kendall  $\tau_b$  test for each of the cases analyzed. We find that the  $\tau_b$  estimates in the US (Europe), in percentage of total observation, are significant at 1%, 5% and 10%: 0.17%, 41.91% and 84.52% (0%, 0% and 0.16%) in the case of FSB ranking vs.  $\Delta CoVaR_{99t^h}$ ; 1.91%, 41.22% and



Note: The Figure shows the daily  $\tau_b$  (a) and  $\tau_x$  (b) of each pair of systemic risk measures for the US banking sector. The  $\tau_b$  and  $\tau_x$  coefficients are computed using the ranking of all the US bank holding companies included in the sample.

## Figure 4: US banking sector: $\tau_b$ and $\tau_x$ .



Figure 5: European banking sector:  $\tau_b$  and  $\tau_x$ .

2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017

Note: The Figure shows the daily  $\tau_b$  (a) and  $\tau_x$  (b) of each pair of systemic risk measures for the European banking sector. The  $\tau_b$  and  $\tau_x$  coefficients are computed using the ranking of all the European large banks included in the sample.



Figure 6: US banking sector G-SIBs:  $\tau_b$  and  $\tau_x$ .

Note: The Figure shows the daily  $\tau_b$  (a) and  $\tau_x$  (b) that associate the FSB ranking with each systemic risk measures for the US G-SIBs. The  $\tau_b$  and  $\tau_x$  coefficients are computed considering only the G-SIBs included in the US banking system.



Figure 7: European banking sector G-SIBs:  $\tau_b$  and  $\tau_x$ .

Note: The Figure shows the daily  $\tau_b$  (a) and  $\tau_x$  (b) that associate the ranking of the FSB and each systemic risk measures for the European G-SIBs. The  $\tau_b$  and  $\tau_x$  coefficients are computed considering only the G-SIBs included in the European banking system.

In the US, the association ( $\tau_b$  and  $\tau_x$ ) between the FSB ranking and the  $\Delta CoVaR_{99th}$  is very close to 0.50 for the entire period of investigation. The estimates related to the cases of FSB ranking vs. MES and vs. SRISK show opposite patterns. In particular, the association between FSB ranking and MES slightly increases after 2015, while the concordance between the FSB list with SRISK list has a decreasing trend.

In Europe, we observe a very different picture. Between 2014 and 2015, the association between the FSB ranking and  $\Delta CoVaR_{99^{th}}$  ranking is almost zero, then this increases to almost 25% until 2017. Similar results emerge for the comparison between FSB scoring method and MES. However, the association between the FSB ranking and the SRISK, is most of the time between 50% and 75%, with an increasing time trend.

## 5 Concluding remarks

Our results on systemic risk estimation reveal that the information provided by  $\Delta CoVaR$ , MES and SRISK is heterogeneous. The SRMs may not reach their peak during the same period, suggesting that systemic risk assessments based on a single measure may lead to contradictory assessments.

The results provided by the bootstrap KS test suggest that the G-SIBs as identified by the FSB contribute more than the other banks in the banking sector to the overall systemic risk. The Wilcoxon signed rank sum test shows a significant increase of the systemic risk for most of the G-SIBs during high volatile periods. However, the ranking obtained using the bootstrap KS test does not indicate the same systemic risk categories as those on the FSB list. The risk of the G-SIBs can be different within the same risk category at 1% critical level. Moreover, different SRMs may rank the G-SIBs differently. Our approach emphasizes the potential of employing market-based SRMs in order to identify and rank SIFIs. We also identified banks that were not rated as systemically important by FSB but that came out

<sup>72.71%</sup> (0%, 1.15% and 11.99%) in the case of FSB ranking vs. MES; and 0%, 23.83% and 34.43% (56.16%, 79.31% and 94.58%) in case of FSB ranking vs. SRISK.

as important based on market based SRMs.

Determining the ranking based on confidence intervals, we demonstrate that institutions with different systemic risk level, but confidence intervals overlapped, may have similar systemic risk. Regulators and supervisory authorities could use SRMs estimates together with their confidence intervals in order to design their plan to monitor and regulate the SIFIs.

Our concordance testing suggests that in the US the FSB ranking has a 50% similarity with the  $\Delta CoVaR_{99^{th}}$  ranking and MES ranking, while the similarity with the SRISK has decreased over time. In the European banking sector the FSB ranking has been more disconnected with  $\Delta CoVaR_{99^{th}}$  and MES rankings, but it has about 62% similarity with SRISK between 2016 and 2017.

## References

- Abadie, A. (2002). Bootstrap tests for distributional treatment effects in instrumental variable models. *Journal of the American Statistical Association* 97(457), 284–292.
- Acharya, V., R. Engle, and M. Richardson (2012). Capital shortfall: A new approach to ranking and regulating systemic risks. *The American Economic Review* 102(3), 59–64.
- Acharya, V. V., L. H. Pedersen, T. Philippon, and M. Richardson (2017). Measuring systemic risk. *Review of Financial Studies* 30(1), 2–47.
- Adrian, T. and M. K. Brunnermeier (2016). CoVaR. The American Economic Review 106(7), 1705–1741.
- Ahnert, T. and C.-P. Georg (2017). Information contagion and systemic risk. *Available at* SSRN (2625575).
- Baur, D. G. (2012). Financial contagion and the real economy. Journal of Banking & Finance 36(10), 2680–2692.

- Benoit, S., G. Colletaz, C. Hurlin, and C. Pérignon (2013). A theoretical and empirical comparison of systemic risk measures. *HEC Paris Research Paper* (FIN-2014-1030).
- Benoit, S., C. Hurlin, and C. Pérignon (2017). Pitfalls in systemic-risk scoring. HEC Paris Research Paper (FIN-2013-1005).
- Bernal, O., J.-Y. Gnabo, and G. Guilmin (2014). Assessing the contribution of banks, insurance and other financial services to systemic risk. *Journal of Banking & Finance 47*, 270–287.
- Billio, M., M. Getmansky, A. W. Lo, and L. Pelizzon (2012). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics* 104(3), 535–559.
- Bisias, D., M. Flood, A. W. Lo, and S. Valavanis (2012). A survey of systemic risk analytics. Annu. Rev. Financ. Econ. 4(1), 255–296.
- Black, L., R. Correa, X. Huang, and H. Zhou (2016). The systemic risk of European banks during the financial and sovereign debt crises. *Journal of Banking & Finance 63*, 107–125.
- Bostandzic, D. and G. N. Wei (Forthcoming 2018). Why do some banks contribute more to global systemic risk? *Journal of Financial Intermediation*.
- Brownlees, C. and R. F. Engle (2016). SRISK: A conditional capital shortfall measure of systemic risk. *Review of Financial Studies* 30(1), 48–79.
- Castro, C. and S. Ferrari (2014). Measuring and testing for the systemically important financial institutions. *Journal of Empirical Finance* 25, 1–14.
- Crockett, A. (2000). Marrying the micro-and macro-prudential dimensions of financial stability. *BIS speeches 21*, 1–11.

- Danielsson, J., K. R. James, M. Valenzuela, and I. Zer (2016). Can We Prove a Bank Guilty of Creating Systemic Risk? A Minority Report. Journal of Money, Credit and Banking 48(4), 795–812.
- Drehmann, M. and N. Tarashev (2013). Measuring the systemic importance of interconnected banks. *Journal of Financial Intermediation* 22(4), 586–607.
- Durbin, J. (1973). Distribution theory for tests based on the sample distribution function.Society for Industrial and Applied Mathematics.
- Emond, E. J. and D. W. Mason (2002). A new rank correlation coefficient with application to the consensus ranking problem. *Journal of Multi-Criteria Decision Analysis* 11(1), 17–28.
- Engle, R., E. Jondeau, and M. Rockinger (2015). Systemic risk in Europe. Review of Finance 19(1), 145–190.
- Flannery, M., B. Hirtle, and A. Kovner (2017). Evaluating the information in the Federal Reserve stress tests. *Journal of Financial Intermediation* 29, 1–18.
- Forbes, K. J. and R. Rigobon (2002). No contagion, only interdependence: measuring stock market comovements. *The Journal of Finance* 57(5), 2223–2261.
- Homar, T., H. Kick, and C. Salleo (2017). Preparing for the Next Financial Crisis: Policies, Tools and Models, Chapter Making Sense of the EU-Wide Stress Test - Comparing SRISK and the ECB/EBA Measures of Bank Vulnerability, pp. 108–138. Cambridge: Cambridge University Press.
- Huang, X., H. Zhou, and H. Zhu (2012). Systemic risk contributions. Journal of Financial Services Research 42(1-2), 55–83.
- Idier, J., G. Lamé, and J.-S. Mésonnier (2014). How useful is the Marginal Expected Shortfall

for the measurement of systemic exposure? A practical assessment. Journal of Banking & Finance 47, 134–146.

- Kemeny, J. G. and J. L. Snell (1962). Mathematical Models in the Social Sciences, Chapter Preference rankings an axiomatic approach. The MIT Press.
- Kleinow, J., F. Moreira, S. Strobl, and S. Vähämaa (2017). Measuring systemic risk: A comparison of alternative market-based approaches. *Finance Research Letters* 21, 40–46.
- Laeven, L., L. Ratnovski, and H. Tong (2016). Bank size, capital, and systemic risk: Some international evidence. *Journal of Banking & Finance 69*, 25–34.
- Lehar, A. (2005). Measuring systemic risk: A risk management approach. Journal of Banking
   & Finance 29(10), 2577–2603.
- Lo, A. W. (2008). Hedge funds, systemic risk, and the financial crisis of 2007-2008: written testimony for the House Oversight Committee hearing on hedge funds. *Available at SSRN* (1301217).
- Löffler, G. and P. Raupach (2018). Pitfalls in the use of systemic risk measures. Journal of Financial and Quantitative Analysis 53(1), 269–298.
- López-Espinosa, G., A. Moreno, A. Rubia, and L. Valderrama (2012). Short-term wholesale funding and systemic risk: A global covar approach. *Journal of Banking & Finance 36*(12), 3150–3162.
- Nucera, F., B. Schwaab, S. J. Koopman, and A. Lucas (2016). The information in systemic risk rankings. *Journal of Empirical Finance* 38, 461–475.
- Rodríguez-Moreno, M. and J. I. Peña (2013). Systemic risk measures: The simpler the better? *Journal of Banking & Finance* 37(6), 1817–1831.
- Silva, W., H. Kimura, and V. A. Sobreiro (2017). An analysis of the literature on systemic financial risk: A survey. *Journal of Financial Stability* 28, 91–114.

- van de Leur, M. C., A. Lucas, and N. J. Seeger (2017). Network, market, and book-based systemic risk rankings. *Journal of Banking & Finance* 78, 84–90.
- Zhang, Q., F. Vallascas, K. Keasey, and C. Caif (2015). Are Market-Based Rankings of Global Systemically Important Financial Institutions Useful for Regulators? *Journal of Money, Credit and Banking* 47(7), 1403–1442.

# Appendices

## A Concordance Analysis

Here we shall study the concordance between the rankings obtained under each SRM and vis-a-vis the benchmark scoring obtained under the BCBS and FSB system.

#### A.1 Kendall $\tau$ distance

The Kendall tau rank distance is a metric that counts the number of pairwise disagreements between two ranking lists. The larger the distance, the more dissimilar the two lists are.

A concordant pair is a pair of observations, each on two variables,  $(X_1, Y_1)$  and  $(X_2, Y_2)$ , having the property that  $sgn(X_2 - X_1) = sgn(Y_2 - Y_1)$  where sgn is the sign function. A discordant pair is a pair of two-variable observations such that  $sgn(X_2 - X_1) = -sgn(Y_2 - Y_1)$ . The Kendall tau distance between two series is the total number of discordant pairs.

#### A.2 Kendall $\tau$ coefficient

Let  $(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)$  be a set of observations of the joint random variables X and Y respectively, such that all the values of  $x_i$  and  $y_i$  are unique. Any pair of observations  $(x_i, y_i) (x_j, y_j)$ , where  $i \neq j$ , are said to be concordant if the ranks for both elements (more

precisely, the sort order by x and by y) agree: that is, if both  $x_i > x_j$  and  $y_i > y_j$ ; or if both  $x_i < x_j$  and  $y_i < y_j$ . They are said to be discordant, if  $x_i > x_j$  and  $y_i < y_j$ ; or if  $x_i < x_j$  and  $y_i > y_j$ . If  $x_i = x_j$  or  $y_i = y_j$ , the pair is neither concordant nor discordant. The Kendall  $\tau$  coefficient is defined as:

$$\tau = \frac{(\text{number of concordant pairs}) - (\text{number of discordant pairs})}{n(n-1)/2}$$

Computationally this coefficient can be calculated using the formula

$$\tau = \frac{1}{n(n-1)} \sum_{i \neq j} \operatorname{sgn}(x_i - x_j) \operatorname{sgn}(y_i - y_j)$$

The denominator is the total number of pair combinations, so the coefficient must be in the range  $1 \le \tau \le 1$ . If the agreement between the two rankings is perfect the coefficient has value 1, if the disagreement between the two rankings is perfect the coefficient has value 1 while if X and Y are independent, then we would expect the coefficient to be roughly zero.

The Kendall rank coefficient can be applied as a test statistic to establish whether two variables may be regarded as statistically dependent. This test is non-parametric, as it does not rely on any assumptions on the distributions of X or Y or the distribution of (X,Y). Under the null hypothesis of independence of X and Y, the sampling distribution of  $\tau$  has an expected value of zero.

When there are ties the Kendall  $\tau_b$  coefficient is used. This is calculated as follows

$$\tau_b = \frac{n_c - n_d}{\sqrt{(n_0 - n_1)(n_0 - n_2)}}$$

where  $n_0 = n(n-1)/2$ ,  $n_1 = \sum_i t_i(t_i-1)/2$ , and  $n_2 = \sum_j u_j(u_j-1)/2$  where  $n_c$  is the number of concordant pairs,  $n_d$  is the number of discordant pairs,  $t_i$  is the number of tied values in the *i*-th group for the first variable and  $u_j$  is the number of tied values in the *j*-th group of ties for the second variable.

Another way to look at  $\tau_b$  is by considering for a given ranking X of n entities the  $n \times n$ score matrix  $\{x_{ij}\}$  defined as follows

$$x_{ij} = \begin{cases} 1, & \text{entity } i \text{ is ranked ahead of entity } j; \\ -1, & \text{entity } i \text{ is ranked behind entity } j; \\ 0, & \text{if the entities are tied, or if } i = j . \end{cases}$$

Then, for two different ranking systems X and Y we can calculate  $\tau_b$  as

$$\tau_b(X,Y) = \frac{\sum_{i=1}^n \sum_{j=1}^n x_{ij} y_{ij}}{\sqrt{\sum_{i=1}^n \sum_{j=1}^n x_{ij}^2 \sum_{i=1}^n \sum_{j=1}^n y_{ij}^2}}$$
(11)

Emond and Mason (2002) pointed out that Kendall's  $\tau_b$  is not a proper metric and, moreover, it has problems resulting from the way in which it handles ties. This problem led Kemeny and Snell (1962) to derive axiomatically another measure that is a metric for comparing ranking systems, given by

$$d(X,Y) = \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} |x_{ij} - y_{ij}|$$
(12)

Emond and Mason (2002) proposed an adjustment to Kendall's measure by redefining the scoring matrix. Thus, under their methodology

$$x_{ij} = \begin{cases} 1, & \text{entity } i \text{ is ranked ahead of or tied to, entity } j; \\ -1, & \text{entity } i \text{ is ranked behind entity } j; \\ 0, & \text{if } i = j . \end{cases}$$

Their new measure is called  $\tau_x$  and it is defined as

$$\tau_x(X,Y) = \frac{1}{n(n-1)} \sum_{i=1}^n \sum_{j=1}^n x_{ij} y_{ij}$$
(13)

Emond and Mason (2002) proved that the Kemeny-Snell metric is equivalent to  $\tau_x$ .

# Bank of Finland Research Discussion Papers 2018

ISSN 1456-6184, online

1/2018	Matthijs Lof – Jos van Bommel <b>Asymmetric information and the distribution of trading volume</b> ISBN 978-952-323-206-8, online
2/2018	Marcella Lucchetta – Michele Moretto – Bruno M. Parigi <b>Systematic risk, bank moral hazard, and bailouts</b> ISBN 978-952-323-209-9, online
3/2018	Ernesto Pasten – Raphael Schoenle – Michael Weber <b>Price rigidities and the granular origins of aggregate fluctuations</b> ISBN 978-952-323-211-2, online
4/2018	Jinill Kim – Francisco Ruge-Murcia <b>Extreme events and optimal monetary policy</b> ISBN 978-952-323-212-9, online
5/2018	Seppo Honkapohja – Kaushik Mitra <b>Price level targeting with evolving credibility</b> ISBN 978-952-323-213-6, online
6/2018	Guido Ascari – Anna Florio – Alessandro Gobbi <b>High trend inflation and passive monetary detours</b> ISBN 978-952-323-218-1, online
7/2018	Gonçalo Faria – Fabio Verona <b>The equity risk premium and the low frequency of the term spread</b> ISBN 978-952-323-219-8, online
8/2018	Mikael Juselius – Előd Takáts <b>The enduring link between demography and inflation</b> ISBN 978-952-323-220-4, online
9/2018	Jonathan Benchimol – Lahcen Bounader <b>Optimal monetary policy under bounded rationality</b> ISBN 978-952-323-222-8, online
10/2018	Mathias Drehmann – Mikael Juselius – Anton Korinek Going with the flows. New borrowing, debt service and the transmission of credit booms ISBN 978-952-323-224-2, online
11/2018	Kim Ristolainen Getting better? The effect of the single supervisory mechanism on banks' loan loss reporting and loan loss reserves ISBN 978-952-323-231-0, online
12/2018	Juho Anttila Measuring the effects of conventional and unconventional monetary policy in the euro area ISBN 978-952-323-232-7, online
13/2018	Esa Jokivuolle – Radu Tunaru – Davide Vioto <b>Testing the systemic risk differences in banks</b> ISBN 978-952-323-234-1, online