

Abendschein, Michael; Grundke, Peter

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On the ranking consistency of global systemic risk measures: empirical evidence

Michael Abendschein¹, Peter Grundke²

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Abstract:

We empirically analyze to which extent popular global systemic risk measures (SRMs) yield comparable results with respect to the systemic importance of a financial institution and, in particular, from which determinants the degree of consistency of the classification by the various SRMs depends. In this study, we investigate the rank correlations of SRMs in order to detect common drivers that might explain (in-)consistent ranking outcomes. This could allow to facilitate the interpretation of the outcome of SRMs and to increase the reliability of their usage in academic and practical applications. Our results show that rank correlations are particularly sensitive towards a bank's leverage and towards tightening economic conditions. This finding holds across various different specifications.

Keywords: systemic risk, risk rankings, financial regulation

JEL classification: G01, G21, G28, G32

¹ Osnabrück University, Chair of Banking and Finance, Katharinenstraße 7, 49069 Osnabrück, Germany, Phone: +49 (0)541 969 6109, Fax: +49 (0)541 969 6111, E-mail: michael.abendschein@uni-osnabrueck.de.

² Osnabrück University, Chair of Banking and Finance, Katharinenstraße 7, 49069 Osnabrück, Germany, Phone: +49 (0)541 969 4720, Fax: +49 (0)541 969 6111, E-mail: peter.grundke@uni-osnabrueck.de.

1 Introduction

The question on how systemic risk, i.e. the risk that many banks simultaneously suffer large losses and that these losses are then spread through the system (see Benoit et al. (2017)), and the systemic importance of single banks could be measured has been intensively discussed in the academic research in the past few years. During the financial crisis of 2007-2009, it became obvious that a purely microprudential regulation of banks is not sufficient to ensure the stability of the financial system as a whole, but that this method has to be supplemented by a macroprudential approach. Since then, global systemic risk measures (SRM) have been developed, on one hand, to identify those financial institutions whose collapse would have the most harmful effect on the financial system, and, on the other hand, to identify those financial institutions who would be most significantly affected by a financial distress on the system level.

Such SRMs could enable regulators to classify banks according to their systemic risk potential (for instance, to impose stricter capital requirements for these banks) or help to estimate and assess the aggregate systemic risk level in an economy. However, up to now, a scenario where banks are regulated based on their individual systemic risk measure is far from being realistic since all the developed SRMs deliver strongly divergent results when classifying banks as systemically risky or not (see, e.g., Benoit et al. (2013), Grundke (2018), Nucera et al. (2016)). It is of particular interest to regulators and the financial industry as a whole to understand the drivers behind the outcomes of different systemic risk measures and their rankings. At first glance, it seems to be desirable that SRMs assign very similar systemic risk rankings to individual banks but in this work it is shown that the correlation between the ranks of popular systemic risk measures are only between 0.35 and 0.64 on average. However, as long as these differences can be explained by underlying bank or market characteristics, different outcomes might even give valuable additional insights in how to measure the systemic risk potential of financial institutions and how to interpret these values.

Given that several risk measures have already proved to contain valuable information (see Benoit et al. (2017) for an overview), it is not advisable to focus on one single metric. Still, it is hard to draw conclusions from systemic risk measures that inconsistently assign systemic risk rankings.

This work aims to shed light on the puzzle of inconsistent systemic risk rankings by investigating drivers of rank correlations of popular systemic risk measures. Being able to explain potential factors that influence the rank correlation could allow for a more stringent and more accurate application of SRMs in practice that could lead to a more efficient regulation. Given

that particular bank characteristics or macroeconomic variables have a pronounced effect on rank correlations, the outcome of systemic risk measures and especially the rankings thereof can be interpreted more reliably. For instance, the leverage of a bank is found in the following to be negatively associated with SRM rank correlations, whereas the asset size of a bank does not have a measurable influence on rank correlations. Hence, for banks with a lower leverage systemic risk measures of different kinds show more similar results compared to more indebted banks. On the contrary, even though larger banks are often suspected to be more systemically important, the investigation of ranks based on different SRMs does not reveal consistent results that could be associated with their asset size. That is, the ranking outcomes of different SRMs do not show more similar patterns for larger banks which could imply the necessity to study several different SRMs for assessing their systemic risk potential.

The results of a baseline panel regression with a sample of 80 large international banks indicate, however, that few specific drivers can be detected that might explain differences in ranking outcomes, with in particular leverage as an exception. These results are highlighted and confirmed with the help of several robustness checks. It turns out that rank correlations are particularly sensitive towards leverage during periods of increased market uncertainty. Furthermore, the analysis with respect to an alternative way of computing correlations in the framework of a dynamic panel setting reveals similar results. Rank correlations are further investigated on an aggregate level, that is, we shift the focus from a purely bank-individual viewpoint and investigate drivers of correlations across various banks in a cross-sectional perspective.

This work confirms theoretical and empirical findings that show that ranks based on different systemic risk measures vary considerably and, hence, the rank correlations are not too large. Still, parts of the variation of rank correlations can be explained by bank-level variables and macroeconomic characteristics. Given the considerable amount of remaining variation in our data, we suspect the underlying processes that lead to different systemic risk ranks to be not fully satisfactorily captured.

The paper is structured as follows: The literature on systemic risk measures is shortly sketched in Section 2. Section 3 explains methodological foundations with respect to systemic risk measures, rank computations and the baseline regression specification. Section 4 presents and summarizes the data employed in the study. Section 5 discusses the results of the panel regressions that include the baseline regression, a subsample analysis as well as a dynamic panel setting. Section 6 deals with the analysis of rank correlations on the macro-level includ-

ing several subsample analyses. Section 7 discusses the achieved results while Section 8 summarizes and concludes.

2 Literature

Up to now, the regulatory authorities use an indicator-based approach to classify banks according to their systemic importance. The indicators are related to five broad categories: size, interconnectedness, lack of readily available substitutes or financial institution infrastructure, global (cross-jurisdictional) activity and complexity (see BCBS (2013)). In contrast to this, many other seemingly more sophisticated global SRMs relying on market and/or accounting data have been developed.

With respect to the literature on SRMs, various strands can be identified (for the following, see Grundke (2018)). First, there are papers in which the SRMs are introduced, motivated and empirically estimated the first time. Examples are Acharya et al. (2012), Acharya et al. (2017), Adrian and Brunnermeier (2016) or Brownlees and Engle (2016). Acharya et al. (2017) introduce the Marginal Expected Shortfall (MES) which measures how much an individual bank contributes to the overall risk of the banking system. Using bank equity return data, MES is defined as the expected equity return of a bank conditional on the market return being smaller than some low quantile (e.g., 95%-quantile). The ΔCoVaR measure of a bank, proposed by Adrian and Brunnermeier (2016), corresponds to the increase of the conditional Value-at-Risk (VaR) of bank i , given that the market return of the whole banking system switches from its median to values at (below) some low quantile. This value is called the “exposure ΔCoVaR ” of bank i by Adrian and Brunnermeier (2016); it measures the extent to which an individual bank is affected by systemic financial distress. To measure the influence that financial stress of one bank i has on the whole banking system, Adrian and Brunnermeier (2016) also define the ΔCoVaR of the system where the conditioning is reversed (“contribution ΔCoVaR). The ΔCoVaR of the system (with respect to bank i) denotes the increase of the VaR of the banking system conditional on bank i being in financial distress.

The SRISK-index proposed by Acharya et al. (2012) and Brownlees and Engle (2016) is the expected capital shortfall of a bank conditional on a system crisis. The capital shortfall is understood as the capital reserves that a bank has to hold due to regulatory or prudential requirements minus its equity value. This SRM can be interpreted as an extension of the MES taking into account both the volume of the bank liabilities and its size (measured by the bank’s market capitalization).

Second, in a large body of follow-up papers, existing SRMs are taken (more or less) as they are and empirically estimated on various kinds of data sets. Partly, it is tried to identify determinants that have a significant influence on the SRMs (e.g., features of the individual bank such as size or leverage or of the regulatory framework in which a bank operates). Examples of papers belonging to this second group are Döring et al. (2016), López-Espinosa et al. (2012) or Weiß et al. (2014a, 2014b). Döring et al. (2016) and Giglio et al. (2016) are also examples in which, the other way round, the prognostic power of SRMs for financial market and macroeconomic variables is checked. Buch et al. (2017) try to distinguish between contributions to systemic risk on the national and the European level.

Third, in another group of papers, modifications, extensions or enhanced strategies for the empirical estimation of existing SRMs are proposed. Examples are Girardi and Ergün (2013), Gravelle and Li (2013) or López-Espinosa et al. (2012, 2015). While, for example, Girardi and Ergün (2013) modify the conditioning event in the ΔCoVaR , López-Espinosa et al. (2012, 2015) modify it to capture asymmetric co-movements between system-wide and individual bank returns in case of a positive and a negative shock.

Finally, a fourth group is formed by papers in which the ability of the proposed SRMs to consistently measure the systemic importance of financial institutions and the robustness of the SRMs are analyzed. Examples are Benoit et al. (2013), Benoit et al. (2017), Danielson et al. (2016a, 2016b), Grundke (2018), Jiang (2012), Löffler and Raupach (2017), and Nucera et al. (2016). Benoit et al. (2013) and Benoit et al. (2017) formally derive conditions that explain how the risk ranks based on MES, SRISK and ΔCoVaR are interrelated. Moreover, they show how the aforementioned SRMs can be computed solely with the help of systematic risk measures such as a firm's beta. This finding translates into interesting characteristics with respect to their joint rankings. While risk ranks of systemic and systematic risk measures can be identical in the cross-sectional perspective, i.e. for a given point of time across a sample of financial institutions, they can diverge in the times-series dimension for a given bank. Furthermore, Grundke (2018) investigates the rank consistency of different SRMs in a simulation-based banking network model and tests the ability of bank-specific variables as well as variables capturing network characteristics to explain rank consistency. Potential explanatory variables are found to be only weakly related to rank consistency. In this paper, we embark on investigating rank correlations in an empirical setting and confirm theoretical results. Furthermore, factors that have already proved to influence the outcomes of SRMs themselves are suspected to influence the consistency of SRMs as well. This approach aims at explaining which factors can contribute to a better understanding of the outcomes of SRMs.

3 Methodology

3.1 Systemic risk measures

Even though meanwhile there is a plethora of systemic risk measures available, in this study we focus on the seemingly three most popular ones in the academic literature, namely Marginal Expected Shortfall (MES), SRISK and the exposure ΔCoVaR measure as well as modifications thereof as explained in the following. It has to be noted that systemic risk in this work is solely measured with respect the extent a bank is exposed to systemic risk, that is how much an individual bank suffers when the whole system experiences a stress period.³

Marginal Expected Shortfall (MES)

The MES was originally proposed by Acharya et al. (2017) and extensively estimated in various empirical studies as the marginal contribution of a bank i to the overall systemic risk of an economy. In this study, a dynamic version of MES is used that is based on Brownlees and Engle (2016). MES is defined as

$$MES_{it}(C) = \frac{\partial ES_{m,t}(C)}{\partial w_{i,t}} = E_{t-1}(R_{i,t} | R_{m,t} < C) \quad (1)$$

where $ES_{m,t}$ is the expected shortfall of the market at time t given event C defined as

$$ES_{m,t}(C) = E_{t-1}(R_{m,t} | R_{m,t} < C) = \sum_{i=1}^N w_{i,t} E_{t-1}(R_{i,t} | R_{m,t} < C). \quad (2)$$

Thus, $ES_{m,t}$ is the expected market equity return R_m at time t given the market equity return, computed as the sum of the weighted individual equity returns $R_{i,t}$, is below some specified threshold C . The $MES_{it}(C)$ of bank i at time t is hence the marginal contribution of bank i to the overall expected shortfall of the market. Following among others Acharya et al. (2017), the event C is set equal to the 5%-quantile of the market return R_m . Acharya et al. (2017) mention that MES alone does not capture systemic risk effects that result from size and in particular leverage of specific firms. In order to obtain a measure that takes the size of a bank into account, Homar et al. (2016) suggest computing a modification of MES by multiplying a

³ On the contrary, systemic risk can also be addressed by measuring how much the financial stress of an individual institution affects the stability of the financial system as a whole. Thereby, the potential of a single institution to harm the financial system is attributed to systemic risk. Extensive analyses have also been performed considering SRMs that measure the contribution of a financial institution to the overall systemic risk. Due to space constraints the results cannot be discussed here.

bank's value for MES with its equity value. We follow this approach, too (MES-EQ in the following).⁴

SRISK

The SRISK-measure proposed by Acharya et al. (2012) and Brownlees and Engle (2016) is the expected capital shortfall of a bank i conditional on a systemic crisis. The capital shortfall is understood as the capital reserves that a bank has to hold due to regulatory or prudential requirements minus its equity value. This SRM can be interpreted as an extension of the MES taking into account both the volume of the bank liabilities and its size (measured by the bank's market capitalization). SRISK is defined as (see Brownlees and Engle (2016)):

$$SRISK_t^i = k \cdot L_{i,t} - (1 - k) \cdot (1 - LRMES_t^i) \cdot W_{i,t} \quad (3)$$

where $LRMES_t^i$ is the long-run *MES* of bank i at time t . The term “long-run” means that instead of daily equity returns, equity returns over some longer time horizon (e.g., 6 months) are employed. As a crisis scenario, Acharya et al. (2012) propose to consider situations in which the market drops by more than 40% over the next six months. They argue that $LRMES_t^i$ can be approximated by $1 - \exp(18 * MES_{i,t}^{2\%})$. This approximation is also used for our estimation (see also Benoit et al. (2013) for a detailed methodological discussion). Furthermore, k is the required prudential or regulatory capital ratio. It is chosen at 8% since this is the standard in the academic literature, see for example Brownlees and Engle (2016). $L_{i,t}$ is the book value of total liabilities of bank i at time t and $W_{i,t}$ is the equity value of bank i at time t .

ΔCoVaR

The third SRM is the (exposure-) ΔCoVaR measure as developed by Adrian and Brunnermeier (2016). The prefix “Co-“ can be understood as “Conditional” since this SRM measures the Value-at-Risk of a bank's market equity return conditionally on the market being at its own Value-at-Risk $Var_{m,t}(\alpha)$. That is:

⁴ A similar procedure is discussed in Adrian and Brunnermeier (2016) for their ΔCoVaR measure. They advocate both the use of (market valued) equity or assets to account for a bank's size. The subsequent analysis is performed with MES multiplied with a bank's asset value as well and the results are qualitatively similar to the ones when equity value is used as a multiplier.

$$P\left(R_{i,t} \leq CoVaR_t^{i|R_{m,t}=VaR_{m,t}(\alpha)} \mid R_{m,t} = VaR_{m,t}(\alpha)\right) = \alpha. \quad (4)$$

In order to compute $\Delta CoVaR_t$, the difference between the VaR of a bank given the market is in financial distress and the VaR of the bank given the market is not in financial distress is calculated. Financial distress of the market is defined as the market being at its VaR, whereas not being financially constrained is defined as the market being at its median state. That is:

$$\Delta CoVaR_t(\alpha) = CoVaR_t^{i|R_{m,t}=VaR_{m,t}(\alpha)} - CoVaR_t^{i|R_{m,t}=Median(R_{m,t})} \quad (5)$$

Similar to MES, a modified measure of $\Delta CoVaR$ is computed by multiplying the $\Delta CoVaR$ -value of a specific bank with its equity value to account for size effects ($\Delta CoVaR$ -EQ).

The computation of MES, SRISK and $\Delta CoVaR$ follows exactly the procedure of Benoit et al. (2013).⁵ They stress the well-known fact that there are several different ways to compute values for $\Delta CoVaR$. While, originally, Adrian and Brunnermeier (2016) suggest using quantile regressions, another popular approach is to employ a GARCH-DCC model (see for example Benoit et al. (2013) and Döring et al. (2016)). The conditional volatility modelling allows to measure time-varying $\Delta CoVaR$ directly, while the quantile estimation approach requires time varying macroeconomic (state) variables to estimate the conditional VaR. We follow Benoit et al. (2013) and compute $\Delta CoVaR$ via a GARCH-DCC model, a procedure similarly used to compute MES and SRISK.

3.2 Rank correlations

To analyze the ranking consistency of the various SRMs, rank correlations are computed. For each day t and for each considered SRM $d \in \{1, \dots, D\}$, the rank $R_{d,i}^t \in \{1, \dots, N_t\}$ of bank i within the group of N_t banks that have survived until time t is computed. Larger values of the respective SRM at time t correspond to a larger systemic importance and, hence, lead to a higher rank ($R_{d,i}^t = N_t$: bank i has highest SRM d at time t , $R_{d,i}^t = 1$: bank i has smallest SRM d at time t).

Figure 1 and Figure 2 illustrate SRM ranks for two banks, one being rather more systemically risky (Bank of Piraeus) and the other turning out to be less risky (Wells Fargo) in terms of SRMs.

⁵ Benoit et al. (2013) kindly provide their MATLAB code that they use to compute MES, SRISK and $\Delta CoVaR$ via their own open source project runmycode.org. Extensive technical details are provided in the appendix of their paper.

– Figure 1 about here –

– Figure 2 about here –

Afterwards, for each bank $i \in \{1, \dots, N_t\}$ and for each combination of two SRMs $d_1, d_2 \in \{1, \dots, D\}$, the Spearman correlation coefficient $Corr_{i,q}(R_{d_1,i}, R_{d_2,i})$ of the bank's ranks for a given quarter q is computed. This is what we call ‘time-series rank correlation’ in the following. Alternatively, in Section 6.1, a ‘cross-sectional rank correlation’ is computed.

Figure 3 and Figure 4 illustrate the movement of rank correlations for the mentioned banks.

– Figure 3 about here –

– Figure 4 about here –

The time window is chosen to contain all daily ranks during one quarter. That means the rank correlation $Corr_{i,q}(R_{d_1,i}, R_{d_2,i})$ for quarter q is based on all daily SRM ranks during this quarter. This procedure is chosen in the baseline specification for two main reasons. First, with approximately 65 daily ranks per quarter, a sufficiently large number of ranks is considered to compute meaningful correlations. Second, since each correlation is based on non-overlapping data, that is, each rank is only used to compute one specific correlation, one reason for auto-correlated correlations is avoided. This is important for the subsequent panel regression analysis, where the correlations are used as dependent variables. For auto-correlated dependent variables, a dynamic panel regression setting might have to be chosen that requires more sophisticated techniques. This will be done in the robustness section.

Nucera et al. (2016) reject this time-series analysis since they assume (and confirm in their data based on a univariate Augmented-Dickey-Fuller test) that time series of ranks are frequently non-stationary. In contrast, applying the same procedure for our data, the hypothesis of a unit-root can be rejected for each SRM rank series for the vast majority of periods (not reported). This different finding might be explained by the different bank sample considered.

3.3 Baseline specification

For each pair $d_1, d_2 \in \{1, \dots, D\}$ of SRMs and based on quarterly data, panel regressions of the following type are run (with bank-fixed effects to account for unobserved heterogeneity):

$$\begin{aligned}
Corr_{i,q}(R_{d_1,i}, R_{d_2,i}) = & \beta_0 + \alpha_i + \sum_{m=1}^M \beta_m^{d_1,d_2} \cdot \text{Bank variables}_{m,i,q-1} \\
& + \sum_{r=1}^R \beta_r^{d_1,d_2} \cdot \text{Country/market variables}_{r,i,q} + \varepsilon_{i,q}^{d_1,d_2}
\end{aligned} \tag{6}$$

where $Corr_{i,q}(R_{d_1,i}, R_{d_2,i})$ denotes the (time-series) correlation of bank i 's rank in quarter q within the sample according to the SRMs d_1 and d_2 .

The employed bank-specific and macroeconomic variables are described in the following section.

4 Data and hypotheses

We investigate a sample consisting of large US-American, Canadian as well as European banks. Many related studies focus on US-American banks, in particular the early studies such as Acharya et al. (2017), Billio et al. (2012) or Brownlees and Engle (2016). US-American financial institutions are a natural starting point for the analysis due to their predominant role during the financial crisis. After establishing some risk measures, research focused on European banks as well, examples are Döring et al. (2016), Engle et al. (2015) or Nucera et al. (2016). While the crisis started in the US-financial system, it spread over to Europe soon thereafter illustrating the fragility of the European banking system and, hence, the need to understand and anticipate problems arising therein. As opposed to the US, the financial system in Europe is mainly marked by few very large banks per country (a notable exception is for example Germany which also has large savings banks and cooperative banks sectors). It is up to now doubtful whether or not those countries were able (again) to save their banks in case of a systemic crisis. In addition, our sample selection is based on the asset size of banks, following i.e., Beltratti and Stulz (2012) or Döring et al. (2016). Banks are included if they are larger than 50 bn in assets (in US-Dollar) at the end of 2008. In addition, all banks are included that are considered to be systemically important by the Basel Committee on Banking Supervision as of 2013, both on global and local level. However, some banks had to be excluded due to missing data. Subsidiaries are not included as long as their mother institution is part of the sample. This results in a sample of 80 banks (see Table 1).

– Table 1 about here –

Bank specific variables, mainly balance sheet items, are used at a quarterly frequency as they are reported from Bureau van Dijk's Bankscope database and cover a sample range from 2009 Quarter 3 to 2016 Quarter 3.

Macroeconomic variables are retrieved from WDI Database, the IMF and national central banks. In this database, they are only available on an annual basis and, hence, they are transformed into quarterly data by using cubic splines. This is a standard technique in related work such as López-Espinosa et al. (2012) or Döring et al. (2016).

Market data, namely daily closing stock prices, daily closing price of the MSCI world index as well as daily data on market capitalization for the computation of the various systemic risk measures stem from Thomson Reuters Eikon database. Data on total liabilities that is required to compute SRISK stems from Bureau van Dijk's Bankscope as well.

Potential explanatory variables are in particular those that in previous empirical studies on drivers of SRMs have been found to have an impact (see, e.g., Adrian and Brunnermeier (2016), Bostandzic et al. (2014), Buch et al. (2017), Cai et al. (2017), Girardi and Ergün (2013), López-Espinosa et al. (2012), Weiß et al. (2014a, 2014b), Zhou and Tarashev (2013)). The idea behind this specification is that if variations of these variables have a differential impact on the level of different SRMs, they might also have a significant impact on the ranking consistency of SRMs. However, the aforementioned studies reveal very ambiguous results. It turns out that the relation between bank- or macro-variables on the one hand and the outcome of systemic risk measures on the other hand is very sensitive to the specific setting. While Döring et al. (2016), for instance, find a rather negative relation between leverage and various systemic risk measures using a VAR model, the results of Bostandzic et al. (2014) show in a standard regression setting that leverage and systemic risk of individual banks are rather positively connected. Similarly, inflation and GDP growth is found to negatively influence the degree of systemic risk of financial institutions measured by means of SRISK by Bostandzic et al. (2014) and Buch et al. (2017) while Döring et al. (2016) find a rather positive relation. A common finding in the literature is the rather weak explanatory power of most of the employed variables in terms of statistical significance. There is hardly any bank characteristic or macroeconomic variable that explains the outcome of SRMs significantly across different specifications. Table 3 lists a summary of linkages between bank- or macro-variables and systemic risk found in the literature.

– Table 2 about here –

Note, that there are no ex-ante hypotheses concerning the relation between the rank correlation of SRMs and the explanatory variables. The presented bank- and macro-variables, however, have been widely associated with systemic risk in previous studies. We embark on this approach and investigate their relation towards rank correlations of SRMs as well. In this study and according to the related literature, the following bank-specific and country-specific macroeconomic variables are used as potential explanatory factors for the correlation of SRM ranks:

Assets: Assets are measured as the natural logarithm of total assets of a bank, a standard variable in the literature. It accounts for the size of the bank. A bank's size is one of the five indicators that the Basel Committee on Banking Supervision uses to define systemically important banks (see BCBS (2013)). Larger banks could take on more (systemic) risk since they could assume to be protected by implicit government guarantees (see, e.g., Bostandzic et al. (2014), Gandhi and Lustig (2015)).

Reserves-to-loans: This ratio measures potential losses that might occur due to a bank's bad performing credit portfolio. The higher the fraction of loss reserves compared to the overall amount of granted loans, the more negative might be the performance expectations of the bank (see e.g., Bostandzic et al. (2014)). Especially during economic downturns, this might be associated with increasing fragility of the bank.

Market-to-book: The market-to-book ratio is computed as the ratio of market valued equity to book valued equity and is often used in order to compare the market view (i.e., forward looking) with the valuation based on balance sheet data. Higher market-to-book ratios are associated with a lower system-wide risk potential (see Döring et al. (2016)).

Leverage: It is computed as the ratio of total debt to total assets (see, e.g., Weiß et al. (2014b)). It is associated with a higher default risk and also a higher systemic risk (see e.g., Brunnermeier et al. (2012), Bostandzic et al. (2014)).

Return on assets: This is a typical profitability measure (see, e.g., Buch et al. (2017)). Its influence on financial stability is suspected to be ambiguous. While on the one hand, profitable banks can be expected to be more stable, on the other hand, excessive rent seeking can be a sign for a particularly risky business model as well.

Long-term funding: This variable measures the ratio of long-term funding to total funding. During the crisis, it has become apparent that a short-term funding structure, sometimes on a day-to-day basis, can pose considerable threat to the stability of a bank. Whenever roll-over funding becomes difficult or expensive, banks with a larger share of short-term funding can

get into serious trouble. Hence, larger values of the ratio of long-term funding to total funding are associated with a more stable capital structure because banks are less prone to liquidity risk (see, e.g., Brunnermeier and Pedersen (2009)).

Non-interest income: It is measured as the ratio of non-interest income to total interest income (see, e.g., Weiß et al. (2014a), Buch et al. (2017)). The lower the ratio, the stronger a bank's business model is supposed to be associated with classical banking business in form of granting loans and receiving deposits which is assumed to be less risky in terms of systemic risk. On the contrary, the higher the fraction of non-interest income, the stronger banks are assumed to be connected to global financial markets and, hence, more dependent and vulnerable to global financial stability concerns.

Loans-to-deposits: This ratio is typically used to account for liquidity risk of a bank (see, e.g., Döring et al. (2016)). Higher ratios can be found for banks that do not mainly rely on deposits in order to finance their loans. Hence, they are expected to face a higher liquidity risk in case of financial distress.

Tier1 ratio: This is a standard measure to account for the quality of the capital base. Higher Tier1 ratios are in a straightforward manner associated with more stable banks (see e.g., Bostandzic et al. (2014), Cihák et al. (2013)).

Z-Score: It is a risk measure for banks that is also interpreted as a metric for a bank's distance to default. It is computed as the ratio of the sum of the equity-to-assets capital ratio and the return on assets and the standard deviation of the return on assets. A low value of the z-score of a bank is associated with a risky business model of a bank. It is also used as a proxy for systemic risk (see, e.g., Anginer et al. (2014), Li et al. (2017)).

As country-specific variables, unemployment, inflation and GDP growth are used. While the former is suspected to have a negative influence on financial stability, the latter two should positively affect financial and economic stability, at least in case of a moderate range of values (see e.g., Döring et al. (2016)).

Further macroeconomic indicators include the Herfindahl-Hirschman-Index as a measure for market concentration. Its influence on financial stability and systemic risk is ambiguous. While for instance Uhde and Heimeshoff (2009) find a positive relation between stability and market concentration, Bostandzic et al. (2014) state an inverse relation with respect to several systemic risk measures. Finally, a country's stock market conditions, that is, its stock market return and volatility as well as long-term sovereign interest rates are used as independent variables. All detailed definitions of the variables are given in Table 3.

– Table 3 about here –

Table 4 gives an overview on summary statistics of the employed dependent and independent variables. Note that all explanatory variables are winsorized at the 1% and 99% level. A larger set of additional variables has initially been available. The absence of multicollinearity, however, could not be confirmed in many cases. Thus, the final set of exogenous regressors is the result of eliminating any regressors that are found to induce multicollinearity.

It is interesting to see that all correlations contain values for approximately the whole range of possible outcomes from -1 to 1, illustrating the inconsistency of SRM ranks. The ranks of MES and exposure- Δ CoVaR seem to be more closely related than those of SRISK and one of the aforementioned SRMs. While the mean correlation for the former pair is between 0.7 and 0.9 depending on whether or not modifications multiplied with equity are considered, the mean correlations between SRISK and the other SRMs is around 0.3 to 0.4 only. Similarly, the standard deviations of rank correlations based on SRISK are larger than for other correlation pairs, indicating a stronger inconsistency between ranks of SRISK and the other SRMs.

– Table 4 about here –

5 Results panel regressions

5.1 Baseline panel regression

Results of the baseline regression can be found in Tables 5. All estimations use bank-fixed effects to account for bank-individual heterogeneity.

– Tables 5 about here –

It can be seen that the influence of bank- and macro-variables is ambiguous. Interestingly, the size of a bank does not seem to be too strongly connected to the SRM rank consistency. The coefficient for asset size is insignificant for the majority of rank correlations. Still, in case the asset size is found to be significant, the coefficient is negative indicating that SRM ranks of larger banks – if at all – tend to be less consistent.

On the contrary, a bank's leverage, measured as the ratio of debt to assets, is found to be significantly negatively associated with eight out of ten rank correlations. This is a first indication that the systemic risk ranks of more indebted banks are less consistently estimated by the various SRMs. Given a sample standard deviation for leverage of around 0.03, an increase of

leverage of one standard deviation would translate into a reduction of the respective rank correlations between 0.03 and 0.06 points. With respect to the other bank-specific variables, only the market-to-book ratio and the long-term funding ratio are found to be statistically significant for at least three out of ten correlations. The former shows a positive sign and a similar size around 0.05 throughout all of the different specifications. However, the size indicates a rather low economic significance since an increase of the market-to-book ratio around one standard deviation would only lead to an increasing rank correlation of around 0.03. Similarly, the long-term funding ratio is statistically significant with a positive sign for several rank correlations, but the economic significance is in the same range as for the market-to-book ratio.

Turning to macroeconomic factors, it can be seen that in particular the return of a country's stock market is negatively related to rank consistency. Around half of the respective coefficients are statistically significantly negative while all of the remaining ones, even though insignificant, still exhibit a negative sign. For some rank correlations this relation is particularly strong, even in economic terms.

Most of the other macroeconomic factors cannot be significantly associated with SRM rank correlations. The long-term interest rate is partially significant (and mostly positive) but with a very low economic influence. Inflation, finally, turns out to be significantly related to rank correlations in few cases as well, however, the sign of its coefficient is changing across the different correlation specifications

In a nutshell, two factors show a strong influence on SRM rank correlation, that is leverage on bank level as well the stock market development on country level. On the bank level, an increasing indebtedness might reduce the consistency of systemic risk ranks. This could be ascribed to the different consideration of debt in the computation of SRMs.

On the contrary, negative overall stock market conditions seem to be promote the ranking consistency of SRMs. Rank correlations are higher for countries and periods with lower stock market performance.

The remaining variables, such as the long-term funding ratio or the market-to-book ratio, seem to have a certain relationship with rank correlations, however, this relationship is rather weak and unstable. In addition, even though statistical significance is found in some cases, the magnitude of the estimated coefficients is too small to capture true economic significance.

These ambiguous results are in line with those derived in Grundke (2018) within a simulation-based dynamic banking network model. Similar to the results achieved here, several bank-

specific factors were found to be statistically significantly related to rank correlations, but not in a consistent manner and without translating into larger economic significance.

Up now, the baseline specification partly reveals that some factors might be indeed associated with rank correlations. Note that the (adjusted) R^2 is low throughout the different regressions. This is a typical result for panel data analyses with respect to systemic risk measures, see for instance Mühlnickel and Weiß (2015) for similar values.

5.2 Panel regressions for (non-) crises periods

The results of the baseline panel analysis in 5.1 have already allowed to gain first insights on how SRM rank correlations can be associated with bank- and macro-variables. As a next step, we want to investigate whether or not these statistical relations differ during crises and non-crises periods. The need to ascribe systemic risk potential and ranks to financial institutions is particularly relevant during times of financial distress when regulators need to identify the most vulnerable banks. Therefore, we use data from the CBOE Volatility Index (VIX) to rank the quarters in our sample based on its VIX value. In a next step, the quarters of the upper 50% quantile are used as a subsample for rather distressed periods whereas the quarters of the lower 50% quantile are used as the subsample for stable periods. Given the comparably low number of quarters in our sample, a further reduction of, say, only the upper and lower 25% quantile would result in an unreasonable loss of data.

Finally, the ranks and rank correlations are computed for only the specific subsample and the same regression analyses from above are repeated. A first look at the correlations itself illustrates that they tend to increase during the stress period. Both the mean and the median of the correlations are larger for the crisis subsample, as can be seen in Table 6. This increase is robust across all of the then different rank correlations.

– Tables 6 to 8 about here –

The results of the subsample regression analyses are illustrated in Table 7 and Table 8.

Still, the asset size of a bank does not play an important role for either of the two subsamples. The leverage of a bank, however, does show a different behavior for the two samples. During rather rough market conditions its coefficient is found to be significantly and consistently negatively related to any of the ten SRM rank correlations. The size of the coefficient has on average doubled compared to the analysis of the complete sample. Consequently, during calmer market conditions, leverage cannot be ascribed a statistically significant influence on

rank correlations. This is a very important finding since it illustrates the role of a bank's leverage for the consistency of its risk ranks in particular during more severe market conditions, when risk ranks become increasingly important.

The other factors investigated do not show such a strong differentiated behavior for the two subsamples. The long-term funding ratio seems to be more important in terms of statistical significance for calmer periods, similar to the loans-to-deposits ratio which now turns out to be negatively related to rank consistency. Macroeconomic factors still do not affect rank correlations to a larger extent with the exception of a country's stock market return. Its coefficient is found to be negative for most correlations during both subsamples but the coefficients are particularly significant during times of financial distress. Hence, both effects that have been found to be importantly related to rank correlations have a particularly strong influence during times of higher market uncertainty.

5.3 Dynamic panel regression

While the correlations for the estimation of the regressions up to now are computed based on purely non-overlapping time windows, in a next step more ranks will be considered. Thus, rank correlations will not only be based on the ranks of the single respective quarter, but on a longer history of ranks out of overlapping time windows. This procedure could allow studying the behavior of correlations in case they exhibit features that only become apparent when taking a longer perspective. To be more precise, the correlations are based on a rolling window of length two quarters. That is, the correlation for Quarter 2, 2016 is based on the daily ranks from Quarter 1 and 2, 2016. The correlation for Quarter 1, 2016 is based on daily ranks from Quarter 1, 2016 and Quarter 4, 2015 and so on.

However, rank correlations based on overlapping time periods will lead to auto-correlated correlations and, hence, to auto-correlated dependent variables in the regression. This is known to cause serious endogeneity issues since the difference of the lagged dependent variable is correlated with the differenced contemporaneous error term. Such a setting cannot be treated with standard panel data techniques as it has been done so far. Thus, a GMM estimation technique that accounts for dynamic panel data will be used. A popular approach is to use the Blundell-Bond estimator.

The Blundell-Bond estimator uses lagged values of the dependent variable as instruments for the difference of the lagged dependent variable as well as lagged values of the exogenous regressors as instruments, too, in order to avoid endogeneity (see Blundell and Bond (1998)). In a two-step procedure, the instruments are regressed on the dependent variable. This procedure

is particularly suitable for panels with a small number of time periods and a large number of cross-sections as it is the case for this study. In addition, as opposed to other possible GMM estimators such as the Arellano-Bond estimator (see Arellano and Bond (1991)), the Blundell-Bond estimator is unbiased in settings with persistent dependent variables. Since persistence in the rank correlations cannot be excluded, the often also called System-GMM approach based on Blundell and Bond (1998) is employed. It has been proven to perform best in the presence of persistent time-series (see Blundell and Bond (2000)). We employ the two-step procedure with Windmeijer (2005) corrected standard errors (see, e.g., Köhler (2014)).

The System-GMM estimation techniques require two conditions to be fulfilled. First, the Hansen J-test for overidentifying restrictions has to be applied. This test is used to check for the validity of the moment conditions that are used in the GMM estimation (see Sargan (1959) and Hansen (1982)).

Second, the estimation of the Blundell-Bond System-GMM estimator requires the absence of second-order autocorrelation in the residuals. The Arellano-Bond-test can be used to check for the absence of autocorrelation. This test helps to determine the number of lags of the dependent variable to be included in the regression. The model is misspecified whenever second-order autocorrelation can be found in the residuals. The test statistics can be found together with the regression results. Note that H0 for the Hansen J-test is the validity of the overidentifying restrictions. H0 for the Arellano-Bond-test is the absence of autocorrelation of the respective order.

The regression equation has the following form:

$$\begin{aligned}
Corr_{i,q}(R_{d_1,i}, R_{d_2,i}) &= \beta_0 + \alpha_i + \sum_{l=1}^L Corr_{i,q-l}(R_{d_1,i}, R_{d_2,i}) \\
&+ \sum_{m=1}^M \beta_m^{d_1, d_2} \cdot Bank\ variables_{m,i,q-1} \\
&+ \sum_{r=1}^R \beta_m^{d_1, d_2} \cdot Country/market\ variables_{r,i,q} + \varepsilon_{i,q}^{d_1, d_2}
\end{aligned} \tag{9}$$

with $l = 1, \dots, L$ being the number of lags of the dependent variable.

The results of the dynamic panel regression can be found in Table 9. The conditions for applying the GMM techniques are mostly fulfilled, the test for overidentifying restrictions is only once rejected but no second-order serial correlation is detected in the residuals.

The results for the dynamic panel setting are rather similar with respect to the bank-individual variables. Leverage is still significantly negatively related with the majority of rank correlations. The size of the coefficients is also in the same range as before. This finding confirms previous results and strengthens the hypothesis that leverage has indeed a noticeable influence on rank consistency. The size of a bank in terms of its assets turns out to be an insignificant driver of correlations in this alternative setting as well. It is remarkable that more coefficients are found to be statistically significant when investigating the dynamic setting. In particular those variables that have already been found to be partially significant, such as the long-term funding ratio turn out to be more strongly significant. Similar to before, its influence is very small with comparably small coefficients such that its economic influence and significance is still negligible.

The number of macroeconomic variables that are found to be significant, on the contrary, increases considerably in this alternative setup. Unemployment and GDP-growth, to mention the most important ones, seem to have an important influence when correlations are computed based on a larger set of systemic risk ranks. The stock market return, however, cannot serve as a strong predictor anymore. Nevertheless, even though the number of significant coefficients for macroeconomic variables increases, the economic significance does not increase with the same magnitude. Given a coefficient of GDP growth of around 1 and the standard deviation of 0.02, an increase of GDP of one standard deviation would solely result in an increasing rank correlation of around 0.02 points.

– Table 9 about here –

Having employed different model specifications, we revealed some interesting results. Firstly, leverage is the most prominent factor that can be attributed a significant influence on the ranking consistency of SRMs. Regardless of the specific pair of SRMs considered, there is a significant and negative relation between a bank's debt and its systemic risk rank correlation in the majority of cases. This finding is particularly strong during times of financial distress, as measured by an increasing VIX value, and rather weak during tranquil times. It is in addition robust to an alternative way of computing correlations. Second, with respect to macroeconomic variables, the stock market return of a country is found to be particularly influential, both in terms of statistical and economic significance. It is also stronger for crises periods, however, it is more sensitive to the computational procedure for determining correlations. The relation is particularly strong when correlations are computed based on a smaller sample, i.e., one quar-

ter of daily data, and weaker for correlations that are computed on a larger set of ranks. Note that this finding can also be influenced by the different econometric setup which is chosen in the two cases. Finally, the other variables are partly found to be associated with certain individual SRM rank correlations, but there is hardly evidence for a more general relation. Their influence is in most of the cases limited to a statistical one since the value of the coefficient is mostly too small to realize a noticeable economic effect on rank correlations.

6 Alternative time-series regression

In addition to the estimation of the panel regression specifications, another correlation and regression analysis is conducted to shed more light on the behavior of rank correlations.

While so far bank-individual rank correlations in a time-series dimension have been considered, it is also interesting to study the rank correlation for a given point of time (i.e., quarter) across all banks (as done by Nucera et al. (2016)). Hence, it is no longer studied how the ranking consistency of specific banks is influenced in a time-series dimension, but if there are common patterns in the behavior of cross-sectional rank correlations. For each quarter of the sample period, Spearman's rank correlation between any pair of the considered SRMs during this quarter is computed.⁶ For this, first, rank correlations between pairs of SRMs across all banks on one day are computed and, second, the average of the daily rank correlations during one quarter is determined. In addition, the explanatory variables are averaged over all countries for the given (quarterly) period. This analysis is conducted for the whole sample as well as for different groups of countries in a further step, too, in order to investigate whether or not the rank consistency of SRMs show differentiated patterns in different countries.

The regression equation has the following form:

$$\text{Corr}(R_{d_1}^q, R_{d_2}^q) = \beta_0 + \sum_{r=1}^R \text{Country/market variables}_{r,\emptyset,q-1} + \varepsilon_q^{d_1,d_2}. \quad (8)$$

Table 10 shows summary statistics for each considered pair of rank correlation.

Kendall's coefficient of concordance (see Kendall and Gibbons (1990)) is computed as an additional estimator of rank consistency. It measures the degree of agreement of ranks based on

⁶ As an alternative to Spearman's rank correlation, Kendall's rank correlation, also known as Kendall's tau coefficient, can be computed, too. The basic idea behind this ranking is not to measure the distance between the ranking outcomes of pairs of ranks but to simply measure whether or not the ranks of a series deviate in the same direction or not. This leads to a more robust procedure towards outliers. Therefore, Kendall's rank correlation coefficient is found to compute correlations that are more centred around zero compared to Spearman's rank correlation coefficient. The subsequent analysis is repeated with Kendall's tau instead of Spearman's rho. Results (not shown) are qualitatively similar and available upon request.

different SRMs. Its values range from zero to one with larger values indicating a stronger degree of agreement.

– Table 10 about here –

The correlations of ranks of exposure SRMs across all banks show similar values as for the bank-individual correlations before. It is interesting to note that in particular the correlation between MES and SRISK is among the smallest with a value of 0.17 on average, since those two measures are probably the most prominent in academia. On the contrary, the ranking outcome of MES and exposure- Δ CoVaR are more consistent with a mean rank correlation around 0.7. Kendall's coefficient of concordance shows a rather strong degree of consistency across all different systemic risk measures with a mean of around 0.7.

Turning to the results of the regression illustrated in Table 11, it can be seen that particularly the HHI as a measure for market concentration of a country's banking industry is found to be negatively related to the cross-sectionally measured rank correlations of SRMs. Hence, the more fragmented a financial market is, the more similar systemic risk ranks tend to be. On the contrary, the more market power is concentrated in few banks, the less consistent individual risk ranks based on different SRMs become. The country-specific analysis below shows that this pattern is particularly strong for specific countries whereas the relation is rather weak for others.

– Table 11 about here –

Generally, besides market concentration, the macroeconomic factors are not too strongly associated with this form of rank correlations. Only the coefficients of inflation and GDP growth are found to be significant in more than one correlation specification. While the sign of the coefficient for inflation is changing throughout the different correlations, its counterpart for GDP growth is predominantly negative indicating that the rank correlation increases during harsh market conditions. This result might resemble the previous result from the bank-individual panel analysis that found stock market returns to be inversely related to SRM rank consistency. However, for the aggregate analysis, the effect of growth is not too pronounced in terms of economic significance. A similar picture emerges for Kendall's coefficient of concordance. Not a single factor is found to be able to significantly explain parts of its variation.

Given that our sample consists of banks from several different countries, it is interesting to see if there are specific patterns with respect to rank correlations for different economies. An analysis on individual country-level, however, is not meaningful since there are some countries with only one or two banks. Therefore we aggregate countries to six different country groups that are marked by geographic proximity. The six groups are formed by banks from the USA and Canada (Group 1); the UK and Ireland (Group 2); Germany, Switzerland and Austria (Group 3); France, Belgium and the Netherlands (Group 4), Portugal, Spain, Italy and Greece (Group 5); and finally the Nordic countries Norway, Sweden and Denmark (Group 6). This allows a more nuanced analysis that might deliver valuable additional insights. In a straightforward manner, ranks, correlations and aggregated macroeconomic variables are computed for each group of countries separately.

The results of the regressions can be seen in Tables 12 to 17. Notably, there are two different patterns across the six groups. While rank correlations for the United States and Canada as well as the UK and Ireland can be very well explained by several different factors, the macro variables within the remaining groups can only partially explain their respective rank correlations.

Unemployment is particularly strongly related to rank correlations for Groups 1 and 2 with a positive sign for the majority of cases. Hence, and once more, tightening economic conditions expressed by an increase in the unemployment rate seems to increase the rank consistency of SRMs. This finding is confirmed for UK and Ireland with significantly negative coefficients for GDP growth. Interestingly, the HHI is only strongly significant for UK and Ireland while it seems to be rather unrelated to rank correlations within the US and Canada. The long-term sovereign interest rate is in return very important for both country groups. The lower they are the stronger ranks are correlated, yet again with very low economic significance.

Market concentration is also found to be an important driver for Group 3 countries, where similar to before an increase of market concentration is associated with a decrease of rank correlations. Unemployment is only partially found to be significantly related, as well as GDP growth. Group 4 is marked by very few significant variables with the exception of unemployment which is strongly positively associated, not only in terms of statistical but also economic significance. The coefficient for the HHI is partly significant for Group 5 countries as well as for the long-term interest rate, but the effects are small in magnitude. The rank correlations within the Nordic countries, finally, are rather ambiguously influenced by the considered factors. Unemployment and the HHI are partially significant but with changing signs,

while only GDP growth and their stock market volatility seem to be robustly negatively related to rank correlations.

– Tables 12 to 17 about here –

To sum up, the finding that market concentration in the banking industry is a significant driver of rank correlations can be confirmed within several groups of countries. In addition, it turns out that unfavorable economic conditions seem to boost rank correlations for several countries since an increase in unemployment is often found to increase rank correlations, similarly to a contraction of GDP.

7 Discussion

The extensive analyses have revealed several important insights with respect to the relation between systemic risk rank correlations and associated bank-specific and macroeconomic factors. Generally, it can be seen that rank correlations differ to a considerable extent depending on which SRM pair is regarded. This starting point serves as motivation to investigate the circumstances of the differences of ranks based on an analysis of their correlations. The bank-level rank correlations are investigated based on two different econometric techniques, a fixed effect panel analysis as well as a dynamic panel analysis as a result of two different ways of computing Spearman's rank correlations.

It turns out that in particular two factors can explain SRM rank correlations, namely the leverage in terms of the debt-to-assets ratio of a bank as well as - to a smaller degree - the stock market return of a country. Other factors are partially significant, however, their influence cannot be considered to be a more general one. When splitting the sample into a financially distressed subsample and a financially tranquil one, in particular leverage seems to be an important predictor of the behavior of rank correlations during stress periods. This is a very important finding, given that those are the times when the identification and ranking of financial institutions with respect to their systemic risk potential is of utmost importance. Still, larger parts of the variation of rank correlations cannot be explained.

As a next step, we shift our focus to the aggregate rank correlation of SRMs across several banks for a given point in time. This analysis is performed both for the overall sample as well as for subsamples of country groups. It can be stated that some general findings hold quite stable across the different specifications while others solely realize for individual country groups. The market concentration within the respective bank industries is most strongly found

to be a significant driver of rank correlations. The stronger markets are concentrated the weaker rank correlations tend to become. In addition, overall economic conditions seem to have a negative effect on rank correlations as well. The higher certain macroeconomic factors such as GDP growth or stock market returns are, the lower rank correlations seem to be. However, there is still a considerable portion of variation in the results that hinder a straightforward explanation of correlations.

The weak consistency between the rankings of different SRMs could pose considerable problems to researchers working with those measures. To be more precise, it is unclear whether or not results based on one or two particular SRMs could hold when some other measures deliver quite different outcomes in terms of systemic risk potential. Bank-individual as well as macroeconomic variables are not able to explain those differences consistently. Thus, it seems to be rather difficult to identify some kind of ‘safe harbour’ (given by specific constellations of explaining variables), in which the SRM choice is likely not to influence the results of an analysis.

8 Conclusions

The need to rank financial institutions based on their systemic risk potential became apparent during the aftermath of the financial crisis. Ongoing efforts have led to the development of sophisticated measures for systemic risk that have been shown to deliver valuable insights with respect to a bank’s systemic importance. However, when ranking banks based on different systemic risk measures, ranks turn out to differ largely across those measures. In order to shed light on the diverging ranking outcomes, in this study, we look for explanatory factors for the correlations of ranks. In previous studies, a large set of bank-specific and macroeconomic factors have been exploited in order to explain the outcome of systemic risk measures. We embark on this strategy and investigate similar variables with respect to their relation towards rank correlations. A panel data approach could detect only few explicit bank characteristics that could be responsible for the behavior of rank correlations, amongst whom a bank’s leverage turns out to be most pronounced. This finding is further confirmed when the analysis is repeated for periods of particular financial distress and tranquillity. It turns out that the influence of leverage is even stronger during rough market conditions. This result can help practitioners and academics to better understand the rankings of systemic risk measures, particularly during times of heightened market uncertainty. An aggregate analysis that measures rank correlations across banks for a given point of time reveals in addition that unfavourable overall market conditions tend to increase the rank consistency. Extensions and further robustness

tests confirm these results but still they show that only a small part of the variation in rank correlations can indeed be explained by the regarded variables. Thus it can be suspected that the underlying process is more complex than assumed so far. More sophisticated analyses need to be conducted to elaborate further on rank correlations of systemic risk measures. Those results will enable e.g. regulators and policy makers to more precisely assign a bank its individual risk potential and could hence reduce the fragility of the global financial system as a whole.

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Appendix

Table 1: List of Banks

Aareal Bank	ING
Allied Irish Banks	Intesa Sanpaolo
Alpha Bank	JP Morgan Chase
American Express	Jyske Bank
Annaly Capital Management	KBC Group
Banca Monte dei Paschi di Siena	KeyCorp
Banca Popolare di Milano	Lloyds Banking Group
Banco BPI	Mediobanca
Banco Comercial Portugues	Morgan Stanley
Banco de Sabadell	M&T Bank
Banco Popular Espanol	National Bank of Greece
Banco Santander	Natixis
Bank of America	Nordea
Bank of Ireland	Northern Trust
Bank of Montreal	Permanent TSB
Bank of New York Mellon	PNC Financial Services
Bank of Nova Scotia	Raiffeisen Bank
Bank of Piraeus	Regions Financial
Bankinter	Royal Bank of Canada
Barclays	Royal Bank of Scotland
BB&T	SEB
BBVA	SNS Reaal
BNP	Societe Generale
Caixabank	Standard Chartered
Canadian Imperial Bank of Commerce	State Street
Capital One Financial	Storebrand
Charles Schwab	SunTrust
Citigroup	Svenska Handelsbanken
Comerica	Swedbank
Commerzbank	Sydbank
Credit Agricole	UBS
Credit Suisse	UniCredit
Danske Bank	Unione di Banche Italiane
Deutsche Bank	US Bancorp
Dexia	Wells Fargo
Discover Financial Services	Zions Bancorporation
DNB	
Erste Group	
Eurobank Ergasias	
Fifth Third Bank	
Goldman Sachs	
HSBC	
Hudson City	
Huntington Bancshares	

Table 2: Literature overview: Variables that could influence systemic risk measures

Variable	SRM	Direction	Statistical significance	Source
Total assets	MES	Positive Positive Mixed	Insignificant Insignificant Insignificant	Weiß et al. (2014a) Bostandzic et al. (2014) Weiß et al. (2014b)
	SRISK	Positive Positive Positive Positive	Significant Insignificant Significant Significant	Bostandzic et al. (2014) Homar et al. (2016) Buch et al. (2017) Laeven et al. (2016)
	Δ CoVaR	Positive Positive Positive Positive Positive	Insignificant Significant Insignificant Significant Significant	López-Espinosa et al. (2012) Girardi and Ergün (2013) Bostandzic et al. (2014) Adrian and Brunnermeier (2016) Laeven et al. (2016)
Loan loss provision	MES	Neutral	Weakly significant	Weiß et al. (2014a)
		Positive Neutral	Significant Insignificant	Bostandzic et al. (2014) Weiß et al. (2014b)
	SRISK	Positive	Significant	Bostandzic et al. (2014)
	Δ CoVaR	Mixed	Insignificant	Bostandzic et al. (2014)
Non-performing loans to total loans	MES	Positive	Insignificant	Döring et al. (2016)
	SRISK	Positive Positive	Insignificant Insignificant	Döring et al. (2016) Buch et al. (2017)
Market-to-book ratio	MES	Negative Positive Mixed Negative	insignificant Insignificant Partly insignificant Insignificant	Weiß et al. (2014a) Bostandzic et al. (2014) Weiß et al. (2014b) Döring et al. (2016)
		SRISK	Mixed Negative	Insignificant Significant
	Δ CoVaR	Neutral Negative Negative	Insignificant Insignificant Significant	López-Espinosa et al. (2012) Bostandzic et al. (2014) Döring et al. (2016)
Leverage	MES	Positive Neutral Negative	Partly significant Insignificant Insignificant	Bostandzic et al. (2014) Weiß et al. (2014b) Döring et al. (2016)
		SRISK	Positive Negative Positive	Insignificant Significant Insignificant

Table 2 (cont.)

	Δ CoVaR	Positive/neutral Neutral Negative	Partly significant (during market downturns) Insignificant Insignificant	Girardi and Ergün (2013) Bostandzic et al. (2014) Döring et al. (2016)
ROA	MES	Positive	Insignificant	Weiß et al. (2014a)
	SRISK	Mixed Positive	Insignificant Weakly significant	Homar et al. (2016) Buch et al. (2017)
Long-term funding to total funding	MES	Positive	Insignificant	Bostandzic et al. (2014)
	SRISK	Mixed	Insignificant	Bostandzic et al. (2014)
	Δ CoVaR	Negative	Insignificant	Bostandzic et al. (2014)
Non-interest to total interest income	MES	Mixed Negative Neutral	Insignificant Insignificant Insignificant	Weiß et al. (2014a) Bostandzic et al. (2014) Weiß et al. (2014b)
	SRISK	Mixed Negative	Insignificant Insignificant	Bostandzic et al. (2014) Buch et al. (2017)
	Δ CoVaR	Positive	Weakly significant	Bostandzic et al. (2014)
	MES	Positive	Weakly significant	Döring et al. (2016)
Loans to deposits	SRISK	Positive	Significant	Döring et al. (2016)
	Δ CoVaR	Positive	Significant	Döring et al. (2016)
	MES	Negative	Insignificant	Bostandzic et al. (2014)
Tier1 ratio	SRISK	Positive Positive	Insignificant Significant	Bostandzic et al. (2014) Laeven et al. (2016)
	Δ CoVaR	Positive Positive	Significant Insignificant	Bostandzic et al. (2014) Laeven et al. (2016)
	MES	Negative	Insignificant	Döring et al. (2016)
Unemployment	SRISK	Positive	Insignificant	Döring et al. (2016)
	Δ CoVaR	Negative	Significant	Döring et al. (2016)
	MES	Neutral Positive	Weakly significant Significant	Weiß et al. (2014b) Döring et al. (2016)
Inflation	SRISK	Positive Negative	Significant Insignificant	Döring et al. (2016) Buch et al. (2017)
	Δ CoVaR	Positive	Weakly significant	Döring et al. (2016)

Table 2 (cont.)

GDP growth	MES	Positive Negative Mixed Positive	Insignificant Weakly significant Significant Insignificant	Weiß et al. (2014a) Bostandzic et al. (2014) Weiß et al. (2014b) Döring et al. (2016)
	SRISK	Negative Positive Negative	Weakly significant Insignificant Insignificant	Bostandzic et al. (2014) Döring et al. (2016) Buch et al. (2017)
	Δ CoVaR	Neutral Neutral	Insignificant Insignificant	Bostandzic et al. (2014) Döring et al. (2016)
HHI	MES	Mixed	Significant	Weiß et al. (2014b)
		Positive	Significant	Bostandzic et al. (2014)
	SRISK	Positive	Significant	Bostandzic et al. (2014)
	Δ CoVaR	Positive	Weakly significant	Bostandzic et al. (2014)
Stock index return	Δ CoVaR	Mixed	Significant	Adrian and Brunnermeier (2016)
Stock index volatility	Δ CoVaR	Positive	Significant	Adrian and Brunnermeier (2016)

This table shows an overview of variables whose influence on the different systemic risk measures have been test in the literature. SRM indicates the specific systemic risk measure, Direction indicates if the SRM is positively or negatively affected (or not all) and statistical significance states the statistical significance of the relation.

Table 3: Variables

Variable name	Description	Source
Bank variables		
Assets	Natural logarithm of total assets (in thousands of US-Dollar)	Bankscope
Reserves-to-loans	Reserves against possible losses on impaired or non-performing loans/total loans (in thousands of US-Dollar)	Bankscope, Thomson Reuters Eikon (market capitalization)
Market-to-book	Market value equity (measured as market capitalization)/book value total equity (in thousands of US-Dollar)	Bankscope, Thomson Reuters Eikon (market capitalization)
Leverage	Ratio of total debt and total assets	Bankscope,
ROA	Return on assets	Bankscope
Long-term funding	Long-term funding/total funding (in thousands of US-Dollar)	Bankscope
Non-interest income	Non-interest income/total interest income (in thousands of US-Dollar)	Bankscope
Loans-to-deposits	Total loans/ total (customer) deposits (in thousands of US-Dollar)	Bankscope
Tier 1 ratio	Tier 1 capital ratio	Bankscope
Z-score	$((\text{Total equity}/\text{total assets})+\text{ROA})/\text{Std.Dev}(\text{ROA})$	Bankscope
Total liabilities	Total liabilities (in thousands of US-Dollar)	Bankscope
Equity (stock) prices	Daily closing prices of the respective banks	Thomson Reuters Eikon
MSCI world index	Daily closing prices of MSCI world index	Thomson Reuters Eikon

Table 3 (cont.)

Macro variables		
Unemployment	Unemployment as a fraction of total labor force	WDI Database
Inflation	Change in consumer price index (in %)/100	WDI Database
GDP growth	Nominal GDP growth rate at market prices in local currency (in %)/100	WDI database
Herfindahl-Hirschman-Index (HHI)	Sum of squared market shares based on total assets of a country's domestic and foreign banks	Thomson Reuters Eikon, ECB, national central banks, own calculation
Long-term interest rate	10-years government bond yield, in percent	IMF, OECD
Stock index return	Quarterly averages of daily log-returns of a country's major stock index, in percent	Thomson Reuters Eikon
Stock index volatility	Quarterly averages of daily annualized 22-days log-return volatility of a country's major stock index.	Thomson Reuters Eikon
VIX	Implied volatility index	Thomson Reuters Eikon

This table contains all the variables used as exogenous regressors in the panel analysis as well as for the computation of the systemic risk measures. All bank variables are – if not indicated differently – at a quarterly frequency. Unemployment, Inflation and GDP growth are at annual frequency and transformed to quarterly values via cubic splines. The remaining macroeconomic variables are at daily frequency and transformed to quarterly averages. The sample range covers the period 2009 Quarter 3 to 2016 Quarter 3.

Table 4: Summary statistics - Baseline regression

Variable	Mean	Median	Std. Dev.	Min	25%-Quantile	75%-Quantile	Max
Exposure systemic risk measures							
Corr MES-SRISK	0.3897935	0.4598	0.3699486	-0.81110	0.16277	0.68357	0.97508
Corr MES-MES-EQ	0.7383334	0.81151	0.2377833	-0.85572	0.66456	0.89965	1.0000
Corr MES-ExpΔCoVaR	0.9380233	0.960315	0.0699051	0.26198	0.926755	0.976515	0.99564
Corr MES-ExpΔCoVaR-EQ	0.7340121	0.8043	0.2329325	-0.79788	0.653765	0.8933	0.98836
Corr SRISK-MES-EQ	0.3493312	0.41891	0.3776547	-0.85184	0.092837	0.65231	0.9590
Corr SRISK-ExpΔCoVaR	0.3476388	0.41554	0.3795104	-0.85422	0.094419	0.65272	0.96735
Corr SRISK-ExpΔCoVaR-EQ	0.3476388	0.41554	0.3795104	-0.85422	0.094419	0.65272	0.96735
Corr MES-EQ-ExpΔCoVaR	0.7185345	0.79503	0.2451878	-0.86951	0.62852	0.88591	0.98437
Corr MES-EQ-ExpΔCoVaR-EQ	0.8898761	0.92233	0.1059881	-0.14427	0.86436	0.95602	1.0000
Corr ExpΔCoVaR – ExpΔCoVaR-EQ	0.7291439	0.80166	0.2376089	-0.82348	0.642875	0.893095	1.0000
Explanatory variables							
Assets	19.51999	19.45232	1.236592	17.12324	18.44933	20.54583	21.72232
Reserves-to-loans	0.0317198	0.0221852	0.0332632	0.002032	0.0108883	0.0392126	0.189159
Market-to-book	0.9877539	0.8551177	0.6641379	0.0083002	0.5693645	1.210746	4.06966
Leverage	0.9304834	0.9351989	0.030503	0.8578537	0.908684	0.9537057	0.9939634
ROA	0.0016203	0.0017208	0.0035156	-0.0162399	0.0005758	0.0029616	0.0128418
Long-term funding	0.1781765	0.1422877	0.1353937	0.0066399	0.08234	0.251993	0.6147417

Table 4 (cont.)

Non-interest income	0.7383148	0.4466585	1.104151	-1.246757	0.2318795	0.7110439	6.04329
Loans-to-deposits	1.268424	1.126614	0.6605106	0.1064935	0.8649116	1.531341	4.711532
Tier1 ratio	0.1256099	0.12100	0.0322369	-0.06900	0.10800	0.13900	0.358700
Z-score	52.7103	43.97361	40.52473	0.0967388	21.33512	71.60466	190.0186
Unemployment	0.0966572	0.082	0.0506209	0.032	0.0715853	0.0977214	0.2683528
Inflation	0.0145205	0.0151496	0.0118969	-0.0142356	0.0051182	0.0239181	0.0420712
GDP growth	0.003869	0.0123291	0.0249173	-0.0744373	-0.0132994	0.0210348	0.059889
HHI	0.0834805	0.0527016	0.0552334	0.0273	.0511643	0.1068445	0.2254
Long-term interest rate	3.110331	2.623333	2.297669	0.1400	1.906667	3.583333	15.49667
Stock index return	0.0287472	0.0378002	0.1641536	-0.4581635	-0.0530674	0.1292129	0.4380493
Stock index volatility	0.2150427	0.18971	0.0981085	0.0842233	0.1394511	0.2665759	0.5086658

For a detailed description of the employed variables, see Table 3. All of the rank correlation pairs are computed based on one quarter of daily ranks for each systemic risk ranking and each individual bank for a sample. The sample of banks contains 80 large international banks. Data range is from 2009q2 to 2016q3. The explanatory variables are winso-rized at the 1% and 99% level

Table 5: Regression results – Baseline regression: exposure SRMs

	MES- MES-EQ	MES-SRISK	MES- ExpΔCoVaR	MES- ExpΔCo- VaR-EQ	MES-EQ- SRISK	MES-EQ - ExpΔCo- VaR	MES-EQ- ExpΔCo- VaR-EQ	SRISK- ExpΔCoVaR	SRISK- ExpΔCoVaR EQ	ExpΔCo- VaR- ExpΔCo- VaR-EQ
Assets	-0.104* (-1.83)	0.0524 (0.52)	-0.0387** (-2.08)	-0.0768 (-1.19)	0.104 (1.08)	-0.0660 (-1.25)	-0.0107 (-0.60)	0.0261 (0.25)	0.101 (0.95)	-0.0522 (-0.90)
Reserves-to- loans	-0.298 (-0.39)	0.206 (0.21)	-0.165 (-0.91)	-0.188 (-0.25)	-0.677 (-0.86)	0.122 (0.17)	-0.144 (-0.37)	0.0846 (0.09)	-0.688 (-0.85)	0.191 (0.26)
Market-to-book	0.0414 (1.49)	0.0360 (0.73)	0.00151 (0.21)	0.0492* (1.82)	0.0115 (0.22)	0.0552* (1.78)	-0.000412 (-0.04)	0.0464 (0.94)	0.0276 (0.56)	0.0588** (2.07)
Leverage	-2.077** (-2.27)	-2.431* (-1.90)	-0.383** (-2.56)	-1.992** (-2.36)	-1.380 (-0.90)	-1.810* (-1.77)	-0.701** (-2.52)	-2.123* (-1.68)	-1.644 (-1.05)	-1.735** (-2.03)
ROA	-1.360 (-0.54)	1.945 (0.53)	0.594 (1.34)	-1.418 (-0.57)	-0.543 (-0.16)	-0.499 (-0.17)	0.632 (0.38)	2.569 (0.64)	-1.480 (-0.40)	-0.682 (-0.27)
Long-term fund- ing	0.347* (1.98)	0.253 (1.13)	0.0144 (0.24)	0.305 (1.63)	0.188 (0.78)	0.319* (1.77)	0.125** (2.56)	0.190 (0.90)	0.208 (0.90)	0.284 (1.54)
Non-interest in- come	0.00913 (1.18)	-0.0158 (-1.18)	0.000320 (0.19)	0.00707 (0.94)	-0.0137 (-0.89)	0.00691 (0.84)	0.00156 (0.49)	-0.0146 (-1.05)	-0.0125 (-0.98)	0.00531 (0.67)
Loans-to- deposits	-0.0535 (-1.38)	-0.0799 (-1.02)	-0.00642 (-0.74)	-0.0667* (-1.69)	-0.112 (-1.40)	-0.0669* (-1.78)	0.00390 (0.25)	-0.0620 (-0.78)	-0.120 (-1.45)	-0.0586 (-1.58)
Tier1 ratio	0.00205 (0.41)	0.00740 (1.24)	-0.00106 (-0.80)	0.000487 (0.11)	0.00648 (1.14)	0.000914 (0.19)	-0.000756 (-0.41)	0.00633 (1.09)	0.000652 (0.11)	0.00286 (0.61)
Z-score	-0.000970 (-0.66)	-0.00192 (-0.95)	-0.00089*** (-3.02)	-0.00112 (-0.73)	-0.000465 (-0.22)	-0.00111 (-0.75)	-0.000638 (-1.25)	-0.00105 (-0.53)	-0.000214 (-0.10)	-0.000933 (-0.63)
Unemployment	-0.435 (-0.61)	-0.472 (-0.48)	0.0356 (0.20)	-0.412 (-0.54)	0.295 (0.30)	-0.465 (-0.66)	0.410 (1.45)	-0.310 (-0.30)	0.544 (0.58)	-0.470 (-0.61)

Table 5 (cont.)

Inflation	-1.782 (-1.61)	-2.078 (-1.48)	0.136 (0.59)	-1.425 (-1.28)	-2.401* (-1.95)	-1.649 (-1.54)	0.862** (2.60)	-1.856 (-1.27)	-1.688 (-1.43)	-1.487 (-1.37)
GDP growth	-0.175 (-0.36)	-0.114 (-0.21)	0.170 (1.39)	-0.281 (-0.62)	0.268 (0.50)	-0.126 (-0.29)	0.0685 (0.48)	-0.150 (-0.28)	0.336 (0.64)	-0.316 (-0.69)
HHI	0.313 (0.42)	0.0464 (0.03)	0.0866 (0.33)	0.618 (0.74)	-0.0869 (-0.06)	-0.0186 (-0.02)	0.0633 (0.23)	0.191 (0.12)	0.149 (0.10)	0.144 (0.17)
Stock market return	-4.011 (-1.04)	-6.546 (-1.09)	-1.483** (-2.28)	-3.779 (-1.03)	-12.85** (-2.06)	-4.028 (-1.05)	-2.850** (-2.11)	-2.300 (-0.38)	-15.33** (-2.41)	-3.109 (-0.85)
Stock market volatility	-0.0643 (-0.46)	-0.137 (-0.71)	0.0958*** (2.95)	-0.0395 (-0.31)	0.0731 (0.38)	-0.0230 (-0.18)	0.0454 (1.19)	-0.140 (-0.74)	0.0295 (0.16)	-0.0503 (-0.37)
Long-term interest	0.0130 (1.52)	0.0146 (1.39)	0.000854 (0.68)	0.0162* (1.86)	0.00337 (0.37)	0.0124 (1.54)	-0.00000213 (-0.00)	0.0152 (1.45)	0.00531 (0.61)	0.0151* (1.82)
Const.	4.702*** (3.41)	1.714 (0.70)	2.084*** (4.85)	4.084** (2.62)	-0.326 (-0.13)	3.737*** (2.85)	1.701*** (3.95)	1.845 (0.76)	-0.0318 (-0.01)	3.349** (2.40)
N	1394	1336	1395	1394	1334	1393	1393	1335	1334	1394
R²	0.032	0.020	0.050	0.029	0.023	0.028	0.031	0.017	0.024	0.026
Adj. R²	0.020	0.008	0.038	0.017	0.010	0.016	0.019	0.004	0.011	0.014

Dependent variable is the respective rank correlation mentioned at the top of each column. This table contains regression results for rank correlations between exposure-SRMs. A panel approach with fixed effects is applied; t-statistics are given in parentheses. The explanatory variables enter the equation with one lag. Regression coefficients are marked with stars if significant as follows: ***= 1% confidence level, **= 5% confidence level, *= 10% confidence level.

Table 6: Summary statistics - (non)-crisis rank correlations

		Subsample VIX – lower 50% quantile	Subsample VIX – upper 50% quantile
Corr MES-SRISK	Mean	0.3776	0.4050
	Median	0.4503	0.4697
Corr MES-MES-EQ	Mean	0.7290	0.7499
	Median	0.8037	0.8209
Corr MES-ExpΔCoVaR	Mean	0.9327	0.9446
	Median	0.9569	0.9636
Corr MES-ExpΔCoVaR-EQ	Mean	0.7218	0.7491
	Median	0.7957	0.8149
Corr SRISK-MES-EQ	Mean	0.3334	0.3692
	Median	0.4145	0.4262
Corr SRISK-ExpΔCoVaR	Mean	0.3788	0.3998
	Median	0.4457	0.4576
Corr SRISK-ExpΔCoVaR-EQ	Mean	0.3313	0.3680
	Median	0.3981	0.4329
Corr MES-EQ-ExpΔCoVaR	Mean	0.7096	0.7296
	Median	0.7893	0.8028
Corr MES-EQ-ExpΔCoVaR-EQ	Mean	0.8872	0.8932
	Median	0.9202	0.9260
Corr ExpΔCoVaR –ExpΔCoVaR-EQ	Mean	0.7197	0.74078
	Median	0.7920	0.8123

This table displays the sample mean and median of rank correlations for the non-crisis sample (lower 50% quantile) and the crisis sample (upper 50% quantile).

Table 7: Regression results – exposure SRMs based on upper 50% quantile of VIX values

	MES- MES-EQ	MES-SRISK	MES- ExpΔCoVaR	MES- ExpΔCo- VaR-EQ	MES-EQ- SRISK	MES-EQ - ExpΔCo- VaR	MES-EQ- ExpΔCo- VaR-EQ	SRISK- ExpΔCoVaR	SRISK- ExpΔCoVaR EQ	ExpΔCo- VaR- ExpΔCo- VaR-EQ
Assets	-0.143 (-1.53)	0.184 (1.21)	-0.0199 (-0.95)	-0.0978 (-1.05)	0.329** (2.36)	-0.0949 (-1.01)	-0.0455 (-1.28)	0.175 (1.15)	0.328** (2.24)	-0.0412 (-0.46)
Reserves-to- loans	-0.796 (-0.56)	1.827 (1.22)	0.279 (1.04)	-0.391 (-0.28)	0.506 (0.35)	-0.351 (-0.26)	-0.843 (-1.04)	1.315 (0.81)	0.0843 (0.05)	-0.220 (-0.16)
Market-to-book	-0.0160 (-0.35)	0.0225 (0.31)	0.00575 (0.59)	-0.00175 (-0.04)	0.0156 (0.20)	-0.00724 (-0.14)	-0.0268 (-1.62)	0.00456 (0.06)	0.0131 (0.17)	0.0131 (0.31)
Leverage	-2.959* (-1.88)	-6.675*** (-2.94)	-1.064* (-1.91)	-3.059** (-2.05)	-6.408*** (-3.12)	-3.018* (-1.79)	-1.174** (-2.47)	-4.822** (-2.02)	-6.420*** (-2.96)	-3.245** (-2.12)
ROA	-2.977 (-0.95)	0.233 (0.05)	1.265* (1.82)	-3.793 (-1.24)	-0.147 (-0.03)	-0.663 (-0.19)	-1.159 (-0.88)	1.952 (0.39)	-1.008 (-0.18)	-1.429 (-0.44)
Long-term fund- ing	0.467** (2.04)	0.430 (1.39)	-0.0237 (-0.45)	0.369 (1.56)	0.448 (1.37)	0.379 (1.47)	0.167** (2.09)	0.313 (1.07)	0.419 (1.24)	0.291 (1.14)
Non-interest in- come	0.0168 (1.24)	-0.0343 (-1.57)	-0.00546** (-2.13)	0.0110 (0.84)	-0.0231 (-0.89)	0.0123 (0.94)	0.00346 (0.78)	-0.0343 (-1.49)	-0.0237 (-1.25)	0.00936 (0.77)
Loans-to- deposits	0.00869 (0.22)	0.0129 (0.20)	0.00368 (0.43)	-0.00515 (-0.13)	-0.0593 (-0.95)	0.0104 (0.26)	0.0307* (1.78)	0.0426 (0.63)	-0.0432 (-0.72)	0.00699 (0.17)
Tier1 ratio	-0.0122 (-1.61)	0.00541 (0.56)	0.000585 (0.32)	-0.0113* (-1.75)	0.00418 (0.44)	-0.0119 (-1.44)	-0.00237 (-0.67)	0.00521 (0.52)	-0.00574 (-0.59)	-0.0122* (-1.74)
Z-score	-0.00222 (-1.26)	-0.00545* (-1.86)	-0.00157** (-2.49)	-0.00221 (-1.21)	-0.00397 (-1.56)	-0.00281 (-1.46)	-0.000993 (-1.64)	-0.00350 (-1.22)	-0.00359 (-1.35)	-0.00263 (-1.34)
Unemployment	-0.758 (-0.64)	-0.471 (-0.34)	-0.350 (-1.56)	-1.117 (-0.94)	0.673 (0.47)	-0.672 (-0.54)	0.394 (0.77)	-0.309 (-0.22)	0.993 (0.70)	-0.676 (-0.54)

Table 7 (cont.)

Inflation	-1.306 (-0.78)	-1.571 (-0.82)	-0.0347 (-0.12)	-1.005 (-0.63)	-3.185* (-1.73)	-1.830 (-1.09)	0.610 (1.36)	-1.143 (-0.58)	-2.066 (-1.11)	-1.766 (-1.10)
GDP growth	0.116 (0.19)	0.536 (0.82)	0.203 (1.43)	0.0457 (0.08)	0.743 (1.10)	0.332 (0.55)	0.295 (1.48)	0.286 (0.43)	0.780 (1.22)	0.354 (0.62)
HHI	1.179 (0.73)	-2.954 (-1.16)	-0.147 (-0.36)	1.661 (1.12)	-3.599 (-1.38)	0.295 (0.18)	0.415 (0.60)	-1.735 (-0.67)	-2.546 (-0.99)	0.235 (0.15)
Stock market re- turn	-11.51** (-2.31)	-2.247 (-0.27)	-1.824 (-1.57)	-9.793** (-2.03)	-7.968 (-0.93)	-9.759* (-1.78)	-4.704** (-2.63)	0.900 (0.11)	-13.33 (-1.58)	-7.213 (-1.41)
Stock market volatility	-0.257 (-1.24)	-0.123 (-0.46)	0.0591 (1.61)	-0.240 (-1.18)	0.0487 (0.16)	-0.149 (-0.69)	-0.0317 (-0.63)	-0.148 (-0.55)	-0.0391 (-0.13)	-0.145 (-0.67)
Long-term in- terest	0.00670 (0.62)	0.0250* (1.76)	0.00393 (1.57)	0.0103 (0.91)	0.0131 (0.93)	0.00594 (0.53)	-0.00316 (-0.79)	0.0227 (1.51)	0.0131 (0.92)	0.00887 (0.78)
Const.	6.522*** (3.32)	3.369 (1.00)	2.408*** (4.36)	5.707*** (2.76)	0.319 (0.10)	5.686*** (2.84)	2.866*** (3.75)	1.603 (0.47)	0.334 (0.10)	4.851** (2.52)
N	626	600	628	627	598	626	626	600	599	627
R²	0.061	0.031	0.077	0.049	0.042	0.049	0.061	0.020	0.047	0.043
Adj. R²	0.035	0.003	0.051	0.023	0.014	0.023	0.034	-0.008	0.019	0.016

Dependent variable is the respective rank correlation mentioned at the top of each column. This table contains regression results for rank correlations between exposure-SRMs. A panel approach with fixed effects is applied; t-statistics are given in parentheses. Regressions are performed for each quarter where the value of the VIX volatility index is part of its upper 50% quantile of the sample period. The explanatory variables enter the equation with one lag. Regression coefficients are marked with stars if significant as follows: ***= 1% confidence level, **= 5% confidence level, *= 10% confidence level.

Table 8: Regression results – exposure SRMs based on lower 50% quantile of VIX values

	MES- MES-EQ	MES-SRISK	MES- ExpΔCoVaR	MES- ExpΔCo- VaR-EQ	MES-EQ- SRISK	MES-EQ - ExpΔCo- VaR	MES-EQ- ExpΔCo- VaR-EQ	SRISK- ExpΔCoVaR	SRISK- ExpΔCoVaR EQ	ExpΔCo- VaR- ExpΔCo- VaR-EQ
Assets	0.0169 (0.18)	0.147 (0.94)	-0.0309 (-1.65)	0.0320 (0.36)	0.237 (1.25)	0.0656 (0.73)	0.0365 (1.22)	0.0668 (0.42)	0.197 (1.06)	0.0542 (0.62)
Reserves-to- loans	0.0818 (0.12)	0.183 (0.16)	-0.136 (-0.81)	-0.0442 (-0.07)	-0.932 (-0.81)	0.701 (1.07)	0.379 (1.02)	0.185 (0.15)	-0.736 (-0.63)	0.643 (1.03)
Market-to-book	0.0957* (1.84)	0.0387 (0.68)	0.00675 (0.62)	0.0998** (2.23)	0.0303 (0.42)	0.117* (1.93)	0.0276 (1.61)	0.0622 (1.10)	0.0321 (0.46)	0.112** (2.24)
Leverage	-0.754 (-0.59)	-1.962 (-0.89)	-0.112 (-0.45)	-0.698 (-0.54)	-0.394 (-0.17)	-0.698 (-0.49)	-0.327 (-0.67)	-1.919 (-0.85)	-0.965 (-0.39)	-0.536 (-0.40)
ROA	-0.0546 (-0.01)	2.661 (0.42)	0.832 (1.64)	-0.247 (-0.06)	-4.144 (-0.79)	0.160 (0.03)	1.838 (0.69)	2.068 (0.30)	-4.885 (-0.94)	-0.104 (-0.03)
Long-term fund- ing	0.427* (1.79)	0.249 (0.73)	0.0997 (0.97)	0.454* (1.90)	0.0353 (0.12)	0.428* (1.92)	0.0835 (1.29)	0.281 (0.89)	0.123 (0.48)	0.451* (1.99)
Non-interest in- come	-0.00492 (-0.41)	0.00979 (0.47)	0.00159 (0.47)	-0.00549 (-0.54)	-0.00282 (-0.17)	-0.00815 (-0.63)	-0.00499 (-0.82)	0.0123 (0.55)	0.000803 (0.05)	-0.00685 (-0.65)
Loans-to- deposits	-0.119 (-1.66)	-0.161 (-1.04)	-0.0248 (-1.35)	-0.149** (-2.35)	-0.197 (-1.36)	-0.144** (-2.12)	-0.0175 (-0.75)	-0.155 (-0.99)	-0.237 (-1.62)	-0.142** (-2.10)
Tier1 ratio	0.00824 (1.25)	0.00296 (0.37)	-0.00186 (-0.83)	0.00477 (0.86)	0.00301 (0.39)	0.00624 (1.03)	-0.00131 (-0.62)	0.00213 (0.29)	0.000846 (0.11)	0.00850 (1.28)
Z-score	0.00256 (1.34)	-0.000867 (-0.29)	-0.000214 (-0.42)	0.00225 (1.09)	0.00304 (0.97)	0.00290 (1.62)	0.000639 (0.75)	-0.000450 (-0.15)	0.00284 (0.89)	0.00274 (1.53)
Unemployment	-0.137 (-0.15)	0.189 (0.12)	0.268 (1.37)	0.285 (0.30)	2.238 (1.57)	-0.161 (-0.18)	0.297 (0.69)	0.427 (0.26)	2.159 (1.42)	-0.0252 (-0.03)

Table 8 (cont.)

Inflation	-1.052 (-0.87)	-0.242 (-0.14)	0.159 (0.60)	-0.973 (-0.80)	-0.121 (-0.08)	-0.520 (-0.43)	1.080** (2.22)	-0.353 (-0.20)	0.246 (0.16)	-0.442 (-0.35)
GDP growth	-0.842 -0.842	-2.356* (-1.72)	0.125 (0.57)	-1.010 (-1.05)	-1.112 (-0.90)	-0.963 (-1.05)	-0.305 (-0.97)	-2.070 (-1.53)	-1.141 (-0.89)	-1.455 (-1.49)
HHI	0.658 (0.47)	0.906 (0.42)	0.0468 (0.17)	0.624 (0.40)	0.141 (0.05)	0.258 (0.17)	0.666 (1.10)	0.678 (0.32)	-0.613 (-0.26)	0.392 (0.25)
Stock market re- turn	-0.230 (-0.03)	-14.39 (-1.29)	-0.635 (-0.37)	-1.744 (-0.22)	-24.10* (-1.92)	-2.188 (-0.25)	-2.394 (-0.76)	-11.91 (-1.08)	-22.74* (-1.79)	-1.729 (-0.22)
Stock market volatility	-0.0397 (-0.09)	-0.313 (-0.74)	0.281*** (3.29)	-0.0217 (-0.06)	0.244 (0.60)	0.0515 (0.13)	0.381*** (3.73)	-0.320 (-0.76)	0.126 (0.33)	-0.155 (-0.38)
Long-term in- terest	0.0178 (1.49)	0.00245 (0.19)	-0.000269 (-0.15)	0.0221** (2.04)	-0.00105 (-0.09)	0.0183 (1.62)	0.00270 (0.73)	0.00372 (0.28)	-0.00165 (-0.14)	0.0220** (2.10)
Const.	0.747 (0.38)	-0.591 (-0.15)	1.602*** (3.20)	0.430 (0.20)	-4.145 (-0.94)	-0.260 (-0.13)	0.253 (0.37)	0.874 (0.21)	-2.679 (-0.60)	-0.202 (-0.10)
N	768	736	767	767	736	767	767	735	735	767
R²	0.041	0.033	0.067	0.042	0.034	0.043	0.060	0.031	0.032	0.049
Adj. R²	0.019	0.010	0.046	0.020	0.011	0.021	0.038	0.008	0.009	0.027

Dependent variable is the respective rank correlation mentioned at the top of each column. This table contains regression results for rank correlations between exposure-SRMs. A panel approach with fixed effects is applied; t-statistics are given in parentheses. Regressions are performed for each quarter where the value of the VIX volatility index is part of its lower 50% quantile of the sample period. The explanatory variables enter the equation with one lag. Regression coefficients are marked with stars if significant as follows: ***= 1% confidence level, **= 5% confidence level, *= 10% confidence level.

Table 9: Regression results dynamic panel: exposure SRM

	MES- MES-EQ	MES-SRISK	MES- ExpΔCo- VaR	MES- ExpΔCo- VaR-EQ	MES-EQ- SRISK	MES-EQ - ExpΔCo- VaR	MES-EQ- ExpΔCo- VaR-EQ	SRISK- ExpΔCo- VaR	SRISK- ExpΔCo- VaR EQ	ExpΔCo- VaR- ExpΔCo- VaR-EQ
L.1	0.484*** (5.28)	0.247** (2.20)	0.540*** (12.12)	0.436*** (5.54)	0.423*** (5.89)	0.424*** (4.63)	0.679*** (10.15)	0.228* (1.91)	0.400*** (4.15)	0.397*** (4.66)
L.2	-0.0262 (-0.35)	-0.0512 (-0.52)	-0.0403 (-1.14)	-0.0457 (-0.75)	0.112 (1.44)	-0.0375 (-0.50)	-0.145 (-1.14)	-0.0581 (-0.54)	-0.0104 (-0.12)	-0.0282 (-0.45)
Assets	0.00548 (0.58)	0.00120 (0.05)	-0.00321** (-2.04)	0.00500 (0.61)	0.00429 (0.37)	0.00232 (0.21)	0.000304 (0.23)	0.00253 (0.10)	-0.000918 (-0.04)	0.00570 (0.65)
Reserves-to-loans	-0.461 (-1.45)	-0.838 (-0.89)	0.0335 (0.29)	-0.447 (-1.29)	-0.741 (-1.15)	-0.401 (-1.19)	0.0508 (1.17)	-0.949 (-0.92)	-0.730 (-0.71)	-0.333 (-1.07)
Market-to-book	0.00860 (0.52)	0.0314 (0.54)	-0.00258 (-0.99)	0.0173 (1.01)	-0.000123 (-0.00)	0.0144 (0.77)	-0.00276 (-0.95)	0.0326 (0.51)	-0.0238 (-0.43)	0.0205 (1.10)
Leverage	-0.636 (-1.45)	-2.385* (-1.98)	-0.0592 (-0.70)	-0.808** (-2.04)	-1.574** (-2.27)	-0.928** (-1.97)	-0.0610 (-0.92)	-2.174* (-1.78)	-1.782* (-1.78)	-0.700* (-1.73)
ROA	-3.943 (-1.14)	-3.347 (-0.50)	0.265 (0.63)	-3.680 (-1.13)	-4.510 (-0.89)	-6.449* (-1.77)	0.804 (1.62)	-2.437 (-0.34)	-5.941 (-1.09)	-5.498* (-1.75)
Long-term funding	0.155 (1.46)	-0.237 (-0.89)	0.0353* (1.91)	0.182* (1.82)	-0.218 (-1.06)	0.179 (1.63)	-0.00598 (-0.18)	-0.253 (-0.87)	-0.123 (-0.47)	0.182** (1.97)
Non-interest income	-0.0128 (-0.99)	0.00512 (0.46)	-0.00123 (-1.28)	-0.0225** (-2.21)	0.0221 (1.20)	-0.0135 (-0.86)	0.00163 (1.07)	0.00542 (0.43)	0.0323* (1.74)	-0.0154 (-1.26)
Loans-to-deposits	-0.0295 (-0.91)	0.0244 (0.39)	-0.00695* (-1.70)	-0.0414 (-1.25)	0.0556 (1.11)	-0.0269 (-0.80)	0.00403 (0.39)	0.0146 (0.22)	0.0362 (0.59)	-0.0344 (-1.09)
Tier1 ratio	-0.000796 (-0.18)	0.0134** (2.28)	-0.000130 (-0.22)	0.00197 (0.48)	0.00593 (1.04)	0.00181 (0.40)	0.000159 (0.22)	0.0120** (2.03)	0.00509 (0.79)	0.00245 (0.66)

Table 9 (cont.)

Z-score	0.000135 (-0.52)	0.00103** (2.08)	0.0000256 (0.63)	-0.000148 (-0.57)	0.000342 (0.98)	-0.000136 (-0.54)	0.0000124 (0.41)	0.000815 (1.53)	0.000861 (1.26)	-0.000118 (-0.52)
Unemployment	0.152 (0.94)	0.859** (2.48)	-0.0193 (-0.41)	0.163 (0.90)	0.446* (1.88)	0.202 (1.01)	-0.0133 (-0.38)	0.893** (2.47)	0.759* (1.86)	0.150 (0.95)
Inflation	-0.537 (-0.80)	-1.532 (-1.27)	0.125 (1.03)	-0.389 (-0.53)	-1.822* (-1.85)	-0.202 (-0.24)	-0.0374 (-0.21)	-1.750 (-1.40)	-1.805 (-1.32)	-0.637 (-0.82)
GDP growth	0.857** (2.31)	0.972 (1.27)	0.112* (1.82)	0.921** (2.44)	1.229** (2.46)	1.007** (2.50)	0.304** (2.22)	1.151 (1.40)	1.588** (2.33)	0.868** (2.32)
HHI	0.275 (1.64)	0.425 (0.89)	0.0705 (1.34)	0.276* (1.73)	0.538* (1.75)	0.310 (1.54)	0.0101 (0.21)	0.359 (0.67)	0.263 (0.46)	0.165 (1.01)
Stock market return	1.778 (0.57)	5.727 (0.82)	0.523 (1.20)	1.151 (0.34)	1.808 (0.22)	-0.115 (-0.03)	-1.493** (-1.98)	3.511 (0.55)	-2.360 (-0.36)	1.963 (0.56)
Stock market volatility	-0.175* (-1.68)	0.219 (1.20)	0.0516*** (3.77)	-0.114 (-1.18)	0.218 (0.99)	-0.155 (-1.28)	0.0592*** (3.16)	0.227 (1.25)	0.268 (1.23)	-0.114 (-1.02)
Long-term interest	0.00885 (1.44)	0.0219** (2.34)	0.000306 (0.31)	0.0110* (1.86)	0.0104 (1.15)	0.00708 (1.09)	0.00214 (1.61)	0.0226* (1.91)	0.00904 (0.81)	0.00962* (1.83)
Const.	0.907** (2.17)	2.029** (2.12)	0.582*** (5.35)	1.076*** (2.67)	1.283** (2.00)	1.231*** (2.65)	0.124 (0.65)	1.857* (1.83)	1.612* (1.72)	0.972** (2.46)
N	1205	1176	1205	1205	1176	1205	1142	1176	1176	1205
Hansen J-Test	0.179	0.246	0.177	0.142	0.250	0.0788	0.554	0.225	0.139	0.194
Test for AR(1)	0.0000	0.0000	0.0174	0.0000	0.0000	0.0000	0.0230	0.0000	0.0000	0.0000
Test for AR(2)	0.924	0.859	0.121	0.712	0.167	0.947	0.449	0.895	0.937	0.817

This table contains regression results for rank correlations among exposure-SRMs. The correlations are based on a rolling window of length two quarters. L.1 and L.2 represent the lagged dependent variables of the respective order. The estimates stem from the Blundell-Bond (System GMM) estimation; z-statistics based on Windmeijer corrected standard errors are given in parentheses. The Hansen J-Test is expressed in terms of the p-value of its test statistic. The H0 states the validity of the overidentifying restrictions which is required for the application of GMM estimation. The Arellano-Bond test (with number of order in brackets) states the H0 of absence of serial correlation in the residuals of the given order. Serial correlation of order larger than one must be rejected in order to apply the Blundell-Bond estimator. The explanatory variables enter the equation with one lag; t-statistics are given in parentheses. Regression coefficients are marked with stars if significant as follows: ***= 1% confidence level, **= 5% confidence level, *= 10% confidence level.

Table 10: Summary statistics Spearman's rank correlation coefficients

Variable	Mean	Median	Std. Dev.	Min	25%-Quantile	75%-Quantile	Max
Exposure SRM:							
Corr MES-SRISK	0.1731487	0.1644273	0.1117411	0.0052296	0.0774247	0.266926	0.4032239
Corr MES-MES-EQ	0.3733782	0.3755426	0.0662323	0.2323271	0.3228555	0.4086375	0.5177163
Corr MES-ExpΔCoVaR	0.7008434	0.7009259	0.0779456	0.5836734	0.622972	0.7567826	0.8327345
Corr MES-ExpΔCoVaR-EQ	0.343312	0.3395214	0.0666597	0.2083404	0.3065039	0.3801951	0.522358
Corr SRISK-MES-EQ	0.4480284	0.4465832	0.1042688	0.2416642	0.3679721	0.5232778	0.673109
Corr SRISK-ExpΔCoVaR	0.6458564	0.6447139	0.0537802	0.5608017	0.6060844	0.6920841	0.7583867
Corr SRISK-ExpΔCoVaR-EQ	0.6775231	0.6693599	0.0721488	0.5717328	0.6104729	0.7255633	0.8190398
Corr MES-EQ-ExpΔCoVaR	0.3266603	0.3185012	0.0681743	0.1784721	0.3018085	0.3682488	0.4945535
Corr MES-EQ-ExpΔCoVaR-EQ	0.9969515	0.9971056	0.0014325	0.9915359	0.9967655	0.9977277	0.998803
Corr ExpΔCoVaR-ExpΔCoVaR-EQ	0.6216796	0.6353179	0.0712395	0.4909521	0.5807017	0.677437	0.7493474
Kendall's concordance coefficient							
K_Conc	0.6965653	0.6938632	0.0326917	0.6331134	0.67377	0.7215078	0.7625923

The table shows summary statistics for all correlation pairs. Correlations are computed in a cross-sectional dimension; that is for each day the rank correlations across the whole sample of banks based on a specific pair of SRMs is computed. In order to be used in a cross-sectional regression based on quarterly data, the daily rank correlations are averaged over all days of one quarter. This results in 30 rank correlations for each pair of SRMs. The correlations are computed based on Spearman's correlation coefficient. In addition, summary statistics for Kendall's coefficient of concordance are displayed.

Table 11: Regression results – time series regression: exposure SRMs with Spearman’s correlation coefficient

	MES- MES-EQ	MES- SRISK	MES- ExpΔCo- VaR	MES- ExpΔCo- VaR-EQ	MES-EQ- SRISK	MES-EQ- ExpΔCo- VaR	MES-EQ- ExpΔCo- VaR-EQ	SRISK- ExpΔCo- VaR	SRISK- ExpΔCo- VaR EQ	ExpΔCo- VaR- ExpΔCo- VaR-EQ	K_Conc
Unemployment	2.014 (0.38)	5.831 (1.09)	-0.181 (-0.40)	2.285 (0.44)	-0.278 (-0.11)	0.266 (0.05)	0.00843 (0.14)	6.070 (1.22)	-0.136 (-0.06)	0.464 (0.09)	1.852 (0.88)
Inflation	-1.701 (-0.44)	1.537 (0.34)	0.730** (2.09)	-2.152 (-0.55)	1.367 (0.79)	-0.719 (-0.18)	0.0711* (2.01)	1.695 (0.40)	1.099 (0.66)	-1.475 (-0.36)	0.0900 (0.05)
GDP growth	-0.151 (-0.13)	-0.324 (-0.21)	-0.0187 (-0.18)	0.0437 (0.04)	-1.262* (-1.93)	-0.438 (-0.36)	-0.0245 (-1.42)	-0.395 (-0.28)	-1.089* (-1.73)	-0.211 (-0.17)	-0.303 (-0.61)
HHI	2.695 (0.24)	-29.05* (-2.07)	-2.927** (-2.09)	2.303 (0.21)	-10.54* (-1.88)	4.287 (0.36)	-0.0658 (-0.29)	-27.34* (-2.05)	-11.07* (-1.99)	5.128 (0.45)	-4.604 (-0.92)
Stock market return	-2.725 (-0.20)	-17.21 (-1.11)	-2.041** (-2.30)	-4.347 (-0.33)	5.836 (1.09)	-5.550 (-0.41)	-0.0938 (-0.55)	-15.22 (-0.99)	5.622 (1.10)	-6.470 (-0.47)	-2.590 (-0.46)
Stock market volatility	0.364 (0.99)	-0.423 (-0.97)	0.0352 (1.40)	0.397 (1.08)	0.785*** (4.18)	0.262 (0.70)	0.00200 (0.44)	-0.536 (-1.23)	0.753*** (4.22)	0.284 (0.77)	0.170 (1.06)
Long-term in- terest	-0.00736 (-0.19)	-0.0235 (-0.42)	-0.0105* (-2.02)	-0.00265 (-0.07)	-0.0319 (-1.43)	-0.0121 (-0.30)	-0.000140 (-0.15)	-0.0289 (-0.57)	-0.0326 (-1.48)	-0.00352 (-0.09)	-0.00694 (-0.37)
Const.	-0.113 (-0.13)	2.457* (2.04)	1.254*** (10.13)	-0.120 (-0.15)	1.508*** (3.00)	-0.0605 (-0.07)	1.001*** (52.77)	2.358** (2.09)	1.564*** (3.15)	-0.160 (-0.18)	0.890** (2.22)
N	29	29	29	29	29	29	29	29	29	29	29
R²	0.162	0.382	0.588	0.185	0.798	0.145	0.390	0.369	0.793	0.172	0.289
Adj. R²	-0.118	0.176	0.451	-0.087	0.731	-0.140	0.187	0.159	0.724	-0.104	0.052

Dependent variable is the (cross-sectional) rank correlation between the various exposure-SRMs that are based on Spearman’s correlations coefficient and Kendall’s coefficient of concordance, respectively, with t-statistics given in parentheses. An OLS approach with heteroscedasticity-robust standard errors is applied. Regression coefficients are marked with stars if significant as follows: ***= 1% confidence level, **= 5% confidence level, *= 10% confidence level.

Table 12: Regression results – time series regression: exposure SRMs – USA and Canada

	MES- MES-EQ	MES- SRISK	MES- ExpΔCo- VaR	MES- ExpΔCo- VaR-EQ	MES-EQ- SRISK	MES-EQ- ExpΔCo- VaR	MES-EQ- ExpΔCo- VaR-EQ	SRISK- ExpΔCo- VaR	SRISK- ExpΔCo- VaR EQ	ExpΔCo- VaR- ExpΔCo- VaR-EQ	K_Conc
Unemployment	0.679 (0.28)	7.240** (2.45)	-3.234 (-1.42)	-1.311 (-0.55)	4.329*** (3.53)	-2.987* (-1.77)	-0.375 (-1.26)	7.072*** (2.98)	3.324** (2.34)	-2.200 (-1.61)	1.082 (1.20)
Inflation	2.010 (0.66)	2.525 (0.68)	-2.950 (-1.19)	-0.682 (-0.23)	1.736 (1.30)	1.385 (0.76)	-0.539 (-1.47)	0.584 (0.22)	0.570 (0.39)	1.145 (0.71)	0.361 (0.34)
GDP growth	-1.879 (-1.12)	-4.323* (-1.84)	4.839** (2.71)	0.229 (0.15)	-3.422** (-2.59)	0.116 (0.10)	0.469** (2.28)	-2.544 (-1.47)	-2.341 (-1.65)	-0.387 (-0.50)	-0.521 (-0.82)
HHI	-23.21 (-1.10)	-8.913 (-0.37)	7.083 (0.43)	-11.35 (-0.55)	-21.67 (-1.55)	-5.746 (-0.48)	2.661 (1.43)	-21.32 (-1.06)	-17.59 (-1.23)	-6.423 (-0.64)	-7.220 (-0.77)
Stock market return	-13.14 (-0.86)	-16.42 (-0.73)	-18.50 (-1.32)	-5.197 (-0.39)	16.26* (1.83)	9.063 (1.00)	2.208 (1.22)	7.731 (0.57)	20.75* (1.88)	12.94* (1.92)	0.888 (0.18)
Stock market volatility	0.176 (0.46)	-1.490** (-2.50)	0.318 (1.15)	0.464 (1.30)	1.417*** (5.95)	0.118 (0.57)	0.0920** (2.63)	0.633 (1.58)	1.860*** (6.58)	0.119 (0.72)	0.284 (1.70)
Long-term in- terest	-0.0537* (-1.76)	-0.127*** (-3.26)	0.0821* (2.07)	-0.0373 (-0.98)	-0.0881*** (-4.09)	0.00104 (0.03)	0.00104 (0.21)	-0.109** (-2.25)	-0.0795*** (-4.06)	-0.0135 (-0.46)	-0.0354** (-2.70)
Const.	1.987 (1.39)	1.144 (0.71)	-0.260 (-0.24)	1.037 (0.74)	1.735* (1.92)	1.157 (1.52)	0.778*** (5.73)	1.381 (1.06)	1.340 (1.46)	1.260* (1.90)	1.031 (1.68)
N	29	29	29	29	29	29	29	29	29	29	29
R²	0.241	0.503	0.481	0.256	0.875	0.296	0.436	0.528	0.878	0.307	0.377
Adj. R²	-0.012	0.338	0.308	0.008	0.833	0.062	0.248	0.370	0.838	0.077	0.170

Dependent variable is the (cross-sectional) rank correlation between the various exposure-SRMs that are based on Spearman's correlations coefficient and Kendall's coefficient of concordance, respectively, with t-statistics given in parentheses. An OLS approach with heteroscedasticity-robust standard errors is applied. Regression coefficients are marked with stars if significant as follows: ***= 1% confidence level, **= 5% confidence level, *= 10% confidence level.

Table 13: Regression results – time series regression: exposure SRMs – UK and Ireland

	MES- MES-EQ	MES- SRISK	MES- ExpΔCo- VaR	MES- ExpΔCo- VaR-EQ	MES-EQ- SRISK	MES-EQ- ExpΔCo- VaR	MES-EQ- ExpΔCo- VaR-EQ	SRISK- ExpΔCo- VaR	SRISK- ExpΔCo- VaR EQ	ExpΔCo- VaR- ExpΔCo- VaR-EQ	K_Conc
Unemployment	-7.829 (-1.00)	15.29** (2.16)	22.75** (2.25)	6.882 (0.87)	-8.074** (-2.14)	29.54*** (2.94)	6.524*** (3.91)	5.072 (0.57)	-11.38*** (-2.93)	13.12* (1.87)	4.757 (1.45)
Inflation	6.277 (1.33)	-9.190** (-2.54)	-10.85* (-1.75)	3.003 (0.59)	0.782 (0.31)	-18.15*** (-3.85)	-1.788 (-1.58)	4.915 (1.16)	6.401*** (2.84)	-11.06*** (-3.62)	-1.991 (-1.08)
GDP growth	-4.289*** (-3.16)	-1.910** (-2.51)	0.0624 (0.04)	-4.724*** (-3.30)	-2.245** (-2.66)	1.566 (1.14)	-0.225 (-0.54)	-1.149 (-0.81)	-2.347*** (-4.06)	1.618 (1.45)	-1.102** (-2.32)
HHI	-17.38 (-0.72)	-38.26* (-1.91)	-58.27* (-1.79)	-43.06 (-1.58)	1.027 (0.08)	-74.03** (-2.79)	-12.23* (-1.94)	-22.71 (-1.15)	12.14 (0.96)	-33.75** (-2.22)	-18.77* (-1.93)
Stock market return	-22.71 (-1.06)	3.991 (0.20)	21.71 (0.69)	2.131 (0.08)	-11.65 (-1.32)	55.99*** (3.73)	14.16*** (3.27)	38.40** (2.18)	-10.93 (-1.39)	25.88** (2.34)	7.471 (0.76)
Stock market volatility	1.044** (2.20)	1.591*** (2.99)	2.769*** (3.74)	2.121*** (3.74)	0.127 (0.58)	0.841 (1.64)	0.432*** (3.37)	0.465 (1.00)	-0.175 (-0.67)	-0.0726 (-0.24)	0.722*** (2.94)
Long-term interest	-0.0459 (-1.58)	0.0483** (2.14)	-0.00177 (-0.04)	-0.0714** (-2.33)	-0.0170 (-0.74)	0.0970** (2.82)	-0.00203 (-0.15)	-0.0931** (-2.40)	-0.0731*** (-5.59)	0.0582** (2.67)	-0.00785 (-0.60)
Const.	2.087* (1.98)	0.856 (1.11)	0.674 (0.49)	1.812 (1.53)	1.518** (2.63)	1.450 (1.45)	0.913*** (3.33)	1.249 (1.52)	1.345** (2.81)	1.180* (2.00)	1.104*** (2.89)
N	29	29	29	29	29	29	29	29	29	29	29
R²	0.580	0.711	0.612	0.666	0.634	0.538	0.650	0.393	0.763	0.371	0.597
Adj. R²	0.440	0.614	0.483	0.555	0.513	0.383	0.533	0.191	0.684	0.161	0.462

Dependent variable is the (cross-sectional) rank correlation between the various exposure-SRMs that are based on Spearman's correlations coefficient and Kendall's coefficient of concordance, respectively, with t-statistics given in parentheses. An OLS approach with heteroscedasticity-robust standard errors is applied. Regression coefficients are marked with stars if significant as follows: ***= 1% confidence level, **= 5% confidence level, *= 10% confidence level.

Table 14: Regression results – time series regression: exposure SRMs – Germany, Switzerland, and Austria

	MES- MES-EQ	MES- SRISK	MES- ExpΔCo- VaR	MES- ExpΔCo- VaR-EQ	MES-EQ- SRISK	MES-EQ- ExpΔCo- VaR	MES-EQ- ExpΔCo- VaR-EQ	SRISK- ExpΔCo- VaR	SRISK- ExpΔCo- VaR EQ	ExpΔCo- VaR- ExpΔCo- VaR-EQ	K_Conc
Unemployment	17.97 (0.40)	41.86 (0.95)	-23.87 (-0.32)	33.59 (0.59)	19.55* (1.91)	9.577 (0.28)	18.86 (1.06)	47.04 (1.25)	12.51** (2.27)	-7.249 (-0.20)	13.60 (0.77)
Inflation	14.85 (0.60)	19.60 (0.81)	10.33 (0.26)	23.80 (0.73)	5.445 (0.88)	22.99 (1.09)	13.56 (1.28)	20.03 (1.07)	2.654 (0.83)	6.711 (0.36)	11.20 (1.09)
GDP growth	-1.616 (-0.39)	-1.801 (-0.50)	-2.918 (-0.66)	-0.550 (-0.12)	0.00749 (0.01)	-3.039 (-1.28)	-1.749 (-1.66)	-2.277 (-1.39)	-1.073** (-2.14)	0.0434 (0.03)	-1.197 (-0.85)
HHI	-48.98** (-2.14)	-61.03*** (-2.97)	-26.33 (-1.02)	-67.27** (-2.56)	-8.315 (-1.50)	-21.18 (-1.60)	-8.934 (-1.19)	-25.58** (-2.80)	1.145 (0.48)	-20.62** (-2.10)	-22.97** (-2.83)
Stock market return	-1.618 (-0.06)	3.720 (0.16)	-17.81 (-0.63)	0.845 (0.03)	-0.227 (-0.04)	16.28 (1.01)	1.254 (0.21)	3.887 (0.30)	-2.233 (-0.72)	9.037 (0.66)	1.055 (0.12)
Stock market volatility	0.726 (0.79)	0.233 (0.35)	1.256 (1.58)	0.711 (0.93)	-0.0115 (-0.07)	-0.535 (-1.43)	0.247 (1.60)	-1.332*** (-3.71)	0.0333 (0.41)	-0.949** (-2.57)	0.0302 (0.11)
Long-term in- terest	0.175 (0.82)	0.220 (1.28)	0.259 (0.93)	0.277 (1.39)	0.00485 (0.12)	0.0703 (0.61)	-0.0148 (-0.31)	-0.00935 (-0.06)	-0.0508** (-2.20)	0.120 (0.91)	0.0840 (1.34)
Const.	1.137 (0.61)	0.399 (0.24)	2.142 (0.74)	1.021 (0.50)	0.335 (0.87)	0.936 (0.74)	0.328 (0.55)	-0.506 (-0.34)	0.292 (1.34)	1.970 (1.44)	0.844 (1.28)
N	29	29	29	29	29	29	29	29	29	29	29
R²	0.240	0.435	0.294	0.358	0.386	0.483	0.368	0.623	0.695	0.631	0.404
Adj. R²	-0.013	0.246	0.059	0.144	0.182	0.311	0.158	0.498	0.593	0.507	0.205

Dependent variable is the (cross-sectional) rank correlation between the various exposure-SRMs that are based on Spearman's correlations coefficient and Kendall's coefficient of concordance, respectively, with t-statistics given in parentheses. An OLS approach with heteroscedasticity-robust standard errors is applied. Regression coefficients are marked with stars if significant as follows: ***= 1% confidence level, **= 5% confidence level, *= 10% confidence level.

Table 15: Regression results – time series regression: exposure SRMs – France, Netherlands and Belgium

	MES- MES-EQ	MES- SRISK	MES- ExpΔCo- VaR	MES- ExpΔCo- VaR-EQ	MES-EQ- SRISK	MES-EQ- ExpΔCo- VaR	MES-EQ- ExpΔCo- VaR-EQ	SRISK- ExpΔCo- VaR	SRISK- ExpΔCo- VaR EQ	ExpΔCo- VaR- ExpΔCo- VaR-EQ	K_Conc
Unemployment	34.52*** (3.66)	46.00** (2.52)	12.42 (0.95)	46.60*** (3.95)	12.46*** (4.00)	-3.408 (-0.27)	0.386 (0.24)	2.638 (0.19)	7.104** (2.28)	6.825 (0.64)	14.64** (2.33)
Inflation	6.504 (1.37)	6.054 (0.69)	5.304 (0.82)	6.718 (1.05)	0.881 (0.50)	-1.293 (-0.24)	0.0944 (0.15)	-1.324 (-0.22)	1.455 (0.85)	-2.297 (-0.46)	1.508 (0.47)
GDP growth	2.435 (0.98)	2.357 (0.64)	5.549** (2.44)	3.579 (1.14)	-0.153 (-0.21)	-3.114 (-1.67)	0.227 (0.99)	-2.756 (-1.12)	-0.363 (-0.49)	-4.059** (-2.25)	0.491 (0.38)
HHI	-12.44 (-0.67)	-61.31 (-1.60)	12.20 (0.53)	-28.26 (-1.20)	-10.21 (-1.49)	-5.756 (-0.29)	-1.019 (-0.41)	-33.75 (-1.34)	-2.006 (-0.29)	-16.85 (-0.94)	-14.55 (-1.10)
Stock market return	-9.242 (-0.49)	-23.30 (-0.63)	-18.84 (-0.78)	-16.75 (-0.72)	0.612 (0.12)	13.07 (0.87)	-2.051 (-1.04)	5.940 (0.29)	-2.396 (-0.40)	15.63 (1.08)	-4.398 (-0.38)
Stock market volatility	0.0812 (0.16)	0.957 (1.04)	-0.351 (-0.53)	0.205 (0.33)	0.431** (2.81)	-0.458 (-1.08)	0.00602 (0.11)	0.518 (0.84)	0.251 (1.20)	-0.351 (-0.83)	0.125 (0.45)
Long-term interest	-0.0253 (-0.54)	0.0608 (0.76)	-0.0277 (-0.44)	0.00708 (0.12)	0.0184 (1.22)	-0.0364 (-0.60)	0.00138 (0.19)	0.0266 (0.42)	0.00535 (0.37)	-0.00847 (-0.17)	0.00675 (0.22)
Const.	-0.651 (-0.27)	4.397 (0.93)	-2.099 (-0.98)	0.303 (0.10)	1.026 (1.29)	1.807 (0.92)	1.068*** (4.32)	4.546 (1.49)	0.427 (0.48)	2.412 (1.34)	1.369 (0.91)
N	29	29	29	29	29	29	29	29	29	29	29
R²	0.821	0.449	0.678	0.796	0.495	0.422	0.164	0.400	0.282	0.640	0.546
Adj. R²	0.761	0.265	0.571	0.727	0.327	0.229	-0.115	0.200	0.042	0.520	0.395

Dependent variable is the (cross-sectional) rank correlation between the various exposure-SRMs that are based on Spearman's correlations coefficient and Kendall's coefficient of concordance, respectively, with t-statistics given in parentheses. An OLS approach with heteroscedasticity-robust standard errors is applied. Regression coefficients are marked with stars if significant as follows: ***= 1% confidence level, **= 5% confidence level, *= 10% confidence level.

Table 16: Regression results – time series regression: exposure SRMs – Portugal, Spain, Italy and Greece

	MES- MES-EQ	MES- SRISK	MES- ExpΔCo- VaR	MES- ExpΔCo- VaR-EQ	MES-EQ- SRISK	MES-EQ- ExpΔCo- VaR	MES-EQ- ExpΔCo- VaR-EQ	SRISK- ExpΔCo- VaR	SRISK- ExpΔCo- VaR EQ	ExpΔCo- VaR- ExpΔCo- VaR-EQ	K_Conc
Unemployment	-3.600 (-1.16)	-1.068 (-0.55)	5.816 (1.21)	-3.598 (-0.95)	-2.807 (-1.53)	2.890** (2.29)	-0.198 (-0.25)	0.793 (0.25)	-4.365* (-1.93)	-0.000377 (-0.00)	-0.491 (-0.43)
Inflation	3.930 (0.43)	5.193 (0.75)	6.066 (0.60)	-6.192 (-0.59)	-2.999 (-0.69)	-6.885 (-1.66)	-4.246** (-2.59)	-5.732 (-0.74)	-7.452 (-1.02)	-5.001 (-1.36)	-1.865 (-0.55)
GDP growth	-0.221 (-0.11)	0.410 (0.28)	5.175** (2.51)	1.306 (0.61)	-1.380 (-1.53)	1.994** (2.45)	0.503* (1.75)	0.388 (0.21)	-1.452 (-0.93)	-0.0161 (-0.02)	0.537 (0.79)
HHI	4.655 (0.56)	-2.144 (-0.41)	-21.62* (-1.79)	-0.119 (-0.01)	5.486 (1.18)	-5.774* (-1.82)	-1.667 (-0.86)	-1.492 (-0.17)	8.337 (1.40)	2.963 (0.77)	-0.910 (-0.31)
Stock market return	8.954 (0.57)	-11.92 (-0.89)	6.848 (0.50)	18.86 (1.05)	4.095 (0.51)	-5.377 (-0.99)	4.017 (1.23)	0.982 (0.09)	15.59 (1.53)	-2.425 (-0.33)	3.169 (0.62)
Stock market volatility	0.479 (0.97)	-0.593* (-1.83)	0.0722 (0.13)	0.535 (0.90)	0.689* (1.89)	-0.385 (-1.62)	0.0317 (0.27)	0.731 (1.22)	1.315** (2.61)	-0.308 (-0.96)	0.205 (1.04)
Long-term in- terest	-0.00996 (-0.17)	-0.0250 (-0.49)	-0.0792 (-1.18)	0.0412 (0.57)	0.0139 (0.45)	0.0547* (1.88)	0.0285** (2.16)	0.00939 (0.17)	0.0428 (0.86)	0.0506* (1.79)	0.0102 (0.44)
Const.	0.343 (0.96)	0.959*** (3.26)	1.412*** (3.30)	0.382 (0.86)	0.545** (2.69)	0.521** (2.80)	0.997*** (10.26)	0.146 (0.40)	0.166 (0.63)	0.312 (1.52)	0.663*** (5.29)
N	29	29	29	29	29	29	29	29	29	29	29
R²	0.421	0.363	0.332	0.498	0.498	0.591	0.559	0.301	0.601	0.568	0.398
Adj. R²	0.228	0.151	0.110	0.331	0.331	0.455	0.412	0.068	0.468	0.424	0.197

Dependent variable is the (cross-sectional) rank correlation between the various exposure-SRMs that are based on Spearman's correlations coefficient and Kendall's coefficient of concordance, respectively, with t-statistics given in parentheses. An OLS approach with heteroscedasticity-robust standard errors is applied. Regression coefficients are marked with stars if significant as follows: ***= 1% confidence level, **= 5% confidence level, *= 10% confidence level.

Table 17: Regression results – time series regression: exposure SRMs – Norway, Sweden and Denmark

	MES- MES-EQ	MES- SRISK	MES- ExpΔCo- VaR	MES- ExpΔCo- VaR-EQ	MES-EQ- SRISK	MES-EQ- ExpΔCo- VaR	MES-EQ- ExpΔCo- VaR-EQ	SRISK- ExpΔCo- VaR	SRISK- ExpΔCo- VaR EQ	ExpΔCo- VaR- ExpΔCo- VaR-EQ	K_Conc
Unemployment	26.46 (1.35)	-2.824 (-0.16)	5.748 (0.38)	49.84** (2.47)	-15.92** (-2.20)	-15.32 (-0.63)	5.587 (0.81)	8.797 (0.37)	8.587 (1.04)	-25.72 (-1.18)	3.619 (0.40)
Inflation	10.44 (1.31)	7.229 (1.39)	-7.548 (-0.91)	3.660 (0.51)	3.544 (1.30)	-3.667 (-0.52)	-4.313* (-2.07)	12.47* (1.77)	10.80*** (4.92)	2.916 (0.35)	2.842 (1.02)
GDP growth	-10.14*** (-3.35)	-7.387** (-2.36)	2.507 (1.30)	-10.14*** (-3.26)	-3.206** (-2.59)	-0.742 (-0.17)	0.680 (0.62)	-0.269 (-0.06)	-6.606*** (-7.33)	-3.102 (-0.80)	-3.072* (-2.04)
HHI	22.42 (1.08)	17.22 (0.93)	-1.731 (-0.08)	24.46 (1.17)	4.089 (0.65)	-30.91 (-1.08)	-10.22 (-1.17)	-62.42* (-2.00)	13.90* (2.07)	-15.98 (-0.60)	-3.134 (-0.30)
Stock market return	-11.06 (-0.42)	-5.364 (-0.34)	3.359 (0.15)	-13.14 (-0.50)	6.159 (0.70)	-13.07 (-0.50)	-2.986 (-0.33)	32.71 (1.20)	7.367 (0.57)	2.087 (0.07)	0.485 (0.05)
Stock market volatility	-1.147 (-1.69)	-1.823*** (-4.24)	1.505** (2.32)	-0.769 (-1.25)	-0.658*** (-3.61)	-1.477* (-1.95)	0.0830 (0.36)	-1.311* (-1.93)	-0.537* (-1.95)	-2.333*** (-3.36)	-0.677** (-2.59)
Long-term interest	-0.0345 (-0.69)	0.0621 (1.53)	0.0482 (1.02)	-0.00708 (-0.14)	-0.0472** (-2.33)	0.0929 (1.18)	0.0254 (1.29)	0.131* (1.84)	-0.0994*** (-6.42)	0.0569 (0.86)	0.0183 (0.77)
Const.	-3.813 (-1.09)	-1.307 (-0.40)	-0.357 (-0.11)	-5.886 (-1.64)	1.557 (1.42)	5.200 (1.10)	1.741 (1.22)	7.172 (1.40)	-1.283 (-1.12)	4.373 (1.04)	0.792 (0.45)
N	29	29	29	29	29	29	29	29	29	29	29
R²	0.453	0.635	0.354	0.488	0.761	0.416	0.339	0.721	0.651	0.582	0.560
Adj. R²	0.270	0.514	0.139	0.317	0.681	0.222	0.118	0.628	0.535	0.443	0.414

Dependent variable is the (cross-sectional) rank correlation between the various exposure-SRMs that are based on Spearman's correlations coefficient and Kendall's coefficient of concordance, respectively, with t-statistics given in parentheses. An OLS approach with heteroscedasticity-robust standard errors is applied. Regression coefficients are marked with stars if significant as follows: ***= 1% confidence level, **= 5% confidence level, *= 10% confidence level.

Figure 1: SRM rankings: Bank of Piraeus

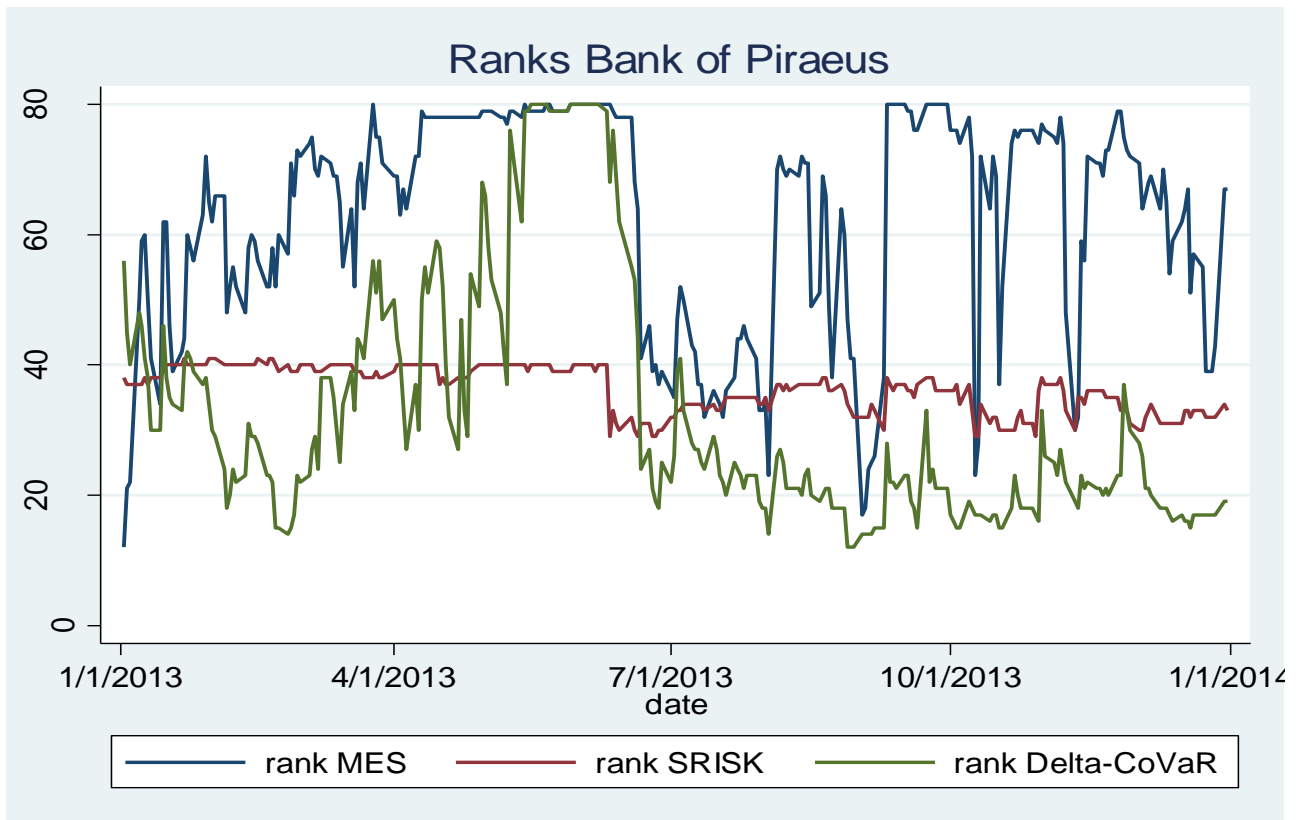


Figure 2: SRM rankings: Wells Fargo



Figure 3: Rank Correlations: Bank of Piraeus

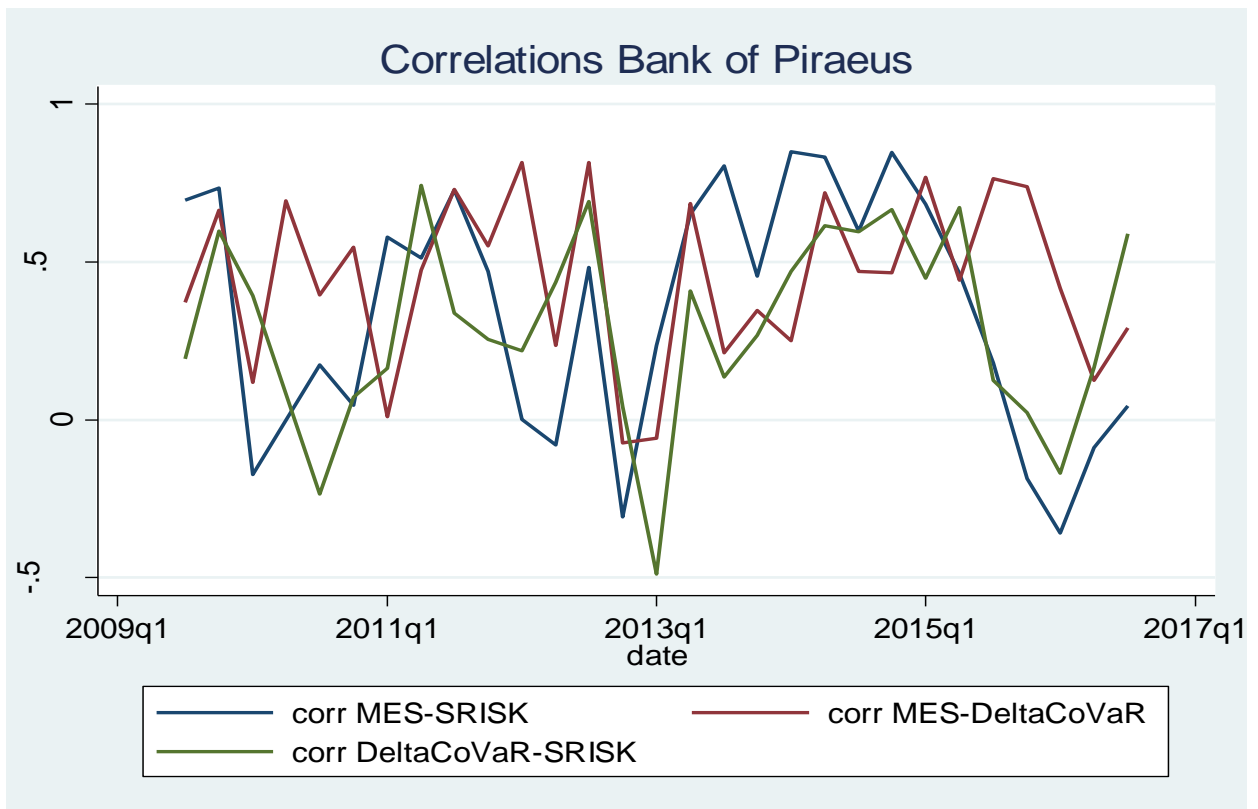


Figure 4: Rank Correlations: Wells Fargo

