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A Quantitative Evaluation of Systemic Risk in the European Banking Sector

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Abstract

This paper proposes a cross-section analysis of systemic risk in the European banking sector. The absence of a general definition of systemic risk makes it difficult to use a single, practically relevant model. Therefore, we empirically compare four methods of measuring systemic risk, namely Value-at-Risk (VaR), Marginal Expected Shortfall (MES), Systemic Risk Index (SRISK), and ΔCoVaR. We use a sample of 69 listed European banks over the period 2005–2019. The renewal of financial supervision following the global financial crisis was a consequence of the unveiled shortcomings in the regulation and monitoring of systemic risk, along with a greater focus on the 'too big to fail' institutions. We find that this thesis different risk measures seem to be good indicators of the aggregate systemic risk in the financial system, all reacting to major real events. We pool systemic risk rankings of the European banks prior to the global financial crisis, the European debt crisis, and per today. The differences in underlying inputs reflect the mixed outcome on an individual level. We cannot identify a leading indicator. However, SRISK privileges size and leverage which are the main components to be considered when examining systemically important banks. The empirical application verifies the ability of SRISK to identify the banks that contributes the most to the overall systemic risk, labeled as G-SIB by the Financial Stability Board.

Keywords: Systemic risk measures; Systemic risk contribution; European banking supervision; Risk rankings

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1 Introduction

In this paper, we examine systemic risk within the European banking sector. Systemic risk corresponds to an event at firm level that could trigger severe instability or collapse of an entire economy. We identify how the risk exposure in the European banking industry has evolved between 2005 and 2019, i.e., during the global financial crisis and the European debt crisis. We compare various econometric models that have gained a great deal of attention in both the academic discussion and the policy debate. The analysis is performed both on an aggregate and an individual level and we aim to identify systemically important banks.

The methodology of this paper follows the cross-sectional measures of Acharya et al. (2017), Adrian and Brunnermeier (2011), and Brownlees and Engle (2017) who measure systemic risk by Marginal Expected Shortfall (MES), ΔCoVaR and Systemic Risk Index (SRISK). Cross-sectional measures quantify the contribution to each bank to the overall risk of the financial system. The common features of the cross-sectional measures are that they rely on public market data and consider an aggregate risk measure, the Value-at-Risk (VaR) or the Expected Shortfall (ES). This paper adds to their results by also taking into account the measures of Kritzman et al. (2011) and Billio et al. (2012) to compute financial turbulence and dynamic causality respectively.

It has been more than a decade since the previous global financial crisis took place and the consequences are still visible across the world. The collapse of Lehman Brothers on September 15, 2008 marked the peak of the global financial crisis and would make such a severe impact on the financial industry that it was, up until this date, only to be compared with the Great Depression in the 1930s. Reinhart and Rogoff (2009) find evidence of extreme run-ups in housing prices, equity values, and large current account deficits, similar to previous crises. Bank insolvencies, declines in global stock markets, and negative shocks to the real economy are all typical causes of financial crises, according to, e.g., Acharya et al. (2017), Altman (2009), and Fackler (2008),

In the aftermath of the global financial crisis, new financial regulations were introduced with the aim to stabilize the financial sector and to prevent further crises of the same kind. Even though the adopted regulatory frameworks, such as Basel III, seem to contribute to a more secure financial market there are still hazards to be aware of. Acharya and Plantin (2017) claim that the banking sector could fail as a whole even if banks are individually solvent and Stiroh (2018) argues this is more likely as financial institutions are becoming more and more alike. These similarities can potentially contribute to systemic risk, since major banks become more of a financial supermarket, rather than part of the financial market itself. Hence, banks offer a full range of services to diversify themselves which in fact can develop the banking sector to become a "systemic as a herd" where a shock, or financial distress, can lead to large-scale disruption in the financial sector once again.

Following the global financial crisis, and the European debt crisis, the governments were forced to intervene and organize bailouts of financial institutions that they considered either 'too big to fail' or 'too interconnected to fail'. The rescue efforts that have been made for financial institutions have entailed large government costs in several countries, while the failure of Lehman Brothers led to the largest bankruptcy filing in history. In this context, Banulescu and Dumitrescu (2015) claim that a key issue for regulators is the essential, but complex, identification of the so-called Systemically Important Financial Institutions (SIFIs). As stated by the Financial Stability Board (FSB) (2020), the SIFIs can be seen as financial institutions "whose disorderly failure, because of their size, complexity, and systemic interconnectedness, would cause significant disruption to the wider financial system and economic activity". In this paper, we choose to focus on the Systemically Important Banks (SIBs) in an European setting.

The issue with regulating and measuring systemic risk is to determine if it is possible to use quantitative indicators to identify systemically important banks and if so, what those indicators are and how they should be used and what policy response to expect. For a systemic risk measure to be a useful tool for policy makers, the signals need to be seen well in advance since regulations require time to adapt. The recent crises have thus renewed the common interest in the definition, measurement, and regulation of systemic risk.

In previous literature, systemic risk is divided into systemic-risk taking, financial contagion, and amplification mechanisms. Schwaab et al. (2011) claim that financial imbalances build up gradually over time creating asset market bubbles that finally burst affecting the entire financial system. Additionally, Caballero and Simsek (2013) claim financial contagion to be caused by idiosyncratic problems that evolve, becoming widespread in the cross-section, then affecting the whole market. Lastly, shared exposure to the financial market and macroeconomic shocks may lead to simultaneous problems for all participants. International Monetary Fund (2009) offers a different definition of systemic risk where failures of a major financial institution spillover to the real economy, thereby affecting otherwise solvent firms.

The lack of consensus on the definition of systemic risk makes it difficult to find a single way to measure it. Acharya et al. (2017) admit the difficulties in finding a systemic risk measure that is both practically relevant and justified by a general equilibrium model. The absence of such models has contributed to the institution-level VaR measure serving as a leading indicator for systemic risk, which is not fully appropriate according to Allen and Saunders (2004).

In our research, we empirically compare the systemic risk measures of MES, ΔCoVaR, and SRISK. In addition, we include the VaR as a measure of market perceptions regarding a firm's business risk and evaluate its commonality with the original systemic risk measures. Based on our results, these measures appear to be good indicators for the aggregate systemic risk in the European banking sector. The movement of the indicators slightly differs but they react similarly to real events, that support their ability to identify the actual level of systemic risk in the system. Moreover, turbulence increases following a systemic risk event, particularly validated in September 2008—July 2009 (global financial crisis) and November 2011—February 2012 (European debt crisis). In addition, we show that the number of causal relationships increases in crisis periods, indicating the risk of financial contagion and spillover effects between the banks to be particularly high.

We investigate the systemic risk on an individual level by constructing rankings of the banks. We find that the different systemic risk measures lead to different results in this aspect and our results indicate that the level of systemic risk for each particular bank varies considerably between the indicators. First, VaR seems to measure the systematic risk rather than the systemic, pinpointing banks with the highest asset price volatility. The simplest method to measure systemic risk is the marginal procedure of MES, that reflects an increase in the level of risk to a unit change in a bank's market share. The MES approach does not take size and leverage into account, thus neglecting the firm's characteristics in line with the 'too big to fail' paradigm. The shortcomings for MES are addressed in the SRISK model where size and leverage are included. SRISK measures the bank's expected undercapitalization in the event of a systemic crisis. Here, we identify all the European systemically important banks, as they were included in the Globally Systemically Important Banks (G–SIB) list of 2019, which implies SRISK allows us to recognize the systemically important banks as done by FSB. This signifies quantitative indicators to be used for distinguishing systemically important banks from non systemically-important banks by scoring, as well as rankings by their individual contribution to the overall systemic risk. In turn, ΔCoVaR acts as an intermediate of MES and SRISK in terms of both input and output values.

Finally, we fit vector autoregressive models and estimate impulse responses to predict future movements in the cross-sectional measures. However, we experience high autocorrelation. To address this, we perform a multivariate linear regression of the systemic risk measures on lagged principal components. Despite this, we cannot determine a leading indicator. We can conclude that the level of systemic risk is highly dependent on the set of definitions and criteria that are used to compute each systemic risk measure. This is further complicated by the complexity and vague definition of systemic risk. Despite the difficulties developing methods for the identification of systemically important banks, the progress is important if it can help to reduce the level of risk in the overall financial system.

The remainder of the paper is structured as follows. Section 2 consists of a literature review that examines systemic risk-taking, financial contagion, and amplification mechanisms. Afterwards, Section 3 gives a thorough description of the European bank data that we use. Section 4 describes the methodology behind the thesis. Section 5 presents the main empirical results and the analysis of the research while Section 6 consists of robustness tests. Finally, we make concluding remarks and give suggestions for further research in Section 7.

2 Literature Review

Although there is an extensive literature of systemic risk a precise definition has not been agreed upon. All result in the familiar domino effect[1]. For instance, Benoit et al. (2017) define systemic risk as the risk that many financial institutions are affected by severe losses, at the same time, which spread through the system threatening the stability of the entire financial system. This general, but minimal, definition is common to most of the papers we refer to.

Previous research has mainly focused on the U.S. market during the global financial crisis and it suggest a multitude of sources to give rise to such a crisis. The question of how to measure systemic risk has grown in importance from a regulatory perspective and has become a key topic of interest for policy makers (Lucas et al., 2013). As an effect, regulators have learned that cross-sectional correlations between assets and credit exposures[2] can have detrimental effects, even though single banks might qualify as solvent when considered in isolation, as stated by Schwaab et al. (2011). Kaufman and Scott (2003) claim this direct-causation is particularly intimidating since economically solvent firms cannot avoid systemic risk events. Therefore, despite banks being individually solvent, underlying risk factors may cause financial instability on the occasion of interconnectedness rather than the idiosyncratic risk of individual banks (Hautsch et al., 2015).

To get some further intuition of this topic, we now discuss systemic risk-taking (asset bubbles, correlated investments), financial contagion (networks, spillover effects) and amplification mechanisms (small shocks with large impacts). These subtopics are overlapping but we separate them below for presentation purposes.

2.1 Systemic Risk-Taking

The global financial crisis of 2008 escalated after the bankruptcy of Lehman Brothers. The bank's failure shed light on major consequences a single bank's collapse can have for the whole economy. Common characteristics of the global financial crisis are investigated by Bezemer (2019) who concludes that the source of the crisis could be traced to the balance sheet accounting. Bernanke (2013) claims that many warning signs often are similar before crises and that economists constantly aim to identify such risk factors in the financial market. Despite this, our inability to foresee a crisis may cause grave damage to the broader economy.

According to Glasserman and Young (2016), the limited understanding of the increasing

[1] Smaga (2014) refer domino effect to a chain reaction that emerge due to failures of one bank leading to failures of other banks. The domino effect is often synonymous with financial contagion, which is to be considered later in this section.

[2] Credit exposure is defined as the maximum potential loss to a lender if the borrower defaults. It is considered as the risk to doing business as a bank.

interconnectedness of global financial systems as well as of the relationship between interconnectedness and financial stability specifically contributed to the crisis of 2008. Financial imbalances built up gradually over time, leading to an asset market bubble that was hard to identify well in advance. Hautsch et al. (2015) argue that theoretical literature on financial contagion and network models is inhibited by an information deficit on intra-bank and liability exposures.

The loss spiral[3] and spillover effects within the banking industry are highly dependent on the individual investments of banks. Brunnermeier and Oehmke (2013) point out that short-term financing, increased leverage, and over-investment in illiquid assets (e.g., loans) create an excessive short-term debt that may trigger a systemic risk event in case of a negative shock. Acharya (2009) anticipates negative externalities to arise even if a single bank fails and risky investments decrease, leading to an increase in the rate of return of safe assets. This may lead to behavioural change in other banks and, in turn, contribute to the herding behaviour of banks' investment strategies.

Kaufman and Scott (2003) and Kodres and Pritsker (2002) describe this unpleasant scenario by referring to the banks risk awareness and consequentially, at least temporarily, a run to quality (i.e., well-recognized, safer assets). Meanwhile, Acharya and Yorulmazer (2007) motivate the incentives to invest in similar assets by referring to the problem that some institutions are believed to be 'too big to fail', which implies similar investment strategies can act as a protection for banks that cannot be allowed to fail.

Risk exposures may be higher by default in pre-crisis years due to government guarantees, or beliefs of government guarantees, according to Atkeson et al. (2019). This trust supports the risk-taking incentives if government bailouts are likely, even though guarantees normally are restrained to a certain degree in crisis periods. Rather than bailing out, Perotti and Suarez (2002) suggest we should allow surviving banks to profit from other banks' failures, at least in the short-run, since the lack of competition would be favourable. This last-man-standing-approach could also be beneficial in terms of mergers or acquisitions, as in the case of Bank of America's purchase of Merrill Lynch in 2008.

2.2 Financial Contagion

The global financial crisis showcased how problems in one part of the banking sector can transfer to other parts of the sector due to their interconnectedness. Slijkerman et al. (2013) describe common exposures to be a perfect example of financial contagion, exemplified by European

[3] Brunnermeier and Pedersen (2009) define a loss spiral as a negative shock in the financial sector that potentially generates a liquidity crisis, leading to reduced asset prices, forcing companies to sell off its assets when prices are low to maintain their leverage ratio.

banks exposure to U.S. sub-prime mortgages that was to about the same degree as American banks in the global financial crisis.

Greenwood et al. (2015) and Allen and Babus (2009) discusses two main factors that are able to create financial contagion. The first one, fire sales, consists of selling assets in distressed periods at highly discounted prices. Kaminsky and Schmukler (1999) claim changes driven by fire sales are leading to intensified liquidity problems, emerging to financial contagion. In turn, Kaufman and Scott (2003) claim that liquidation and portfolio rebalancing are (very) likely to press prices downwards. Here, Kodres and Pritsker (2002) define contagion as price movements in one market resulting from a shock in another. The second main factor includes contractual obligations in financial contracts (e.g., swap agreements) that may result in a negative shock transmitting to other actors if one bank cannot fulfill the agreement.

The fragility of the banking sector is strongly affected by broad networks, which makes the financial system particularly sensitive to systemic events. Goyal (2012), among others, uses graph theory to explain the networks in the financial system whilst Bae et al. (2003) compare contagion with a disease that spreads rapidly through direct or indirect contact. This goes hand in hand with Schwaab et al. (2011) and Allen and Gale (2000) who explain the interbank market to either be completely or incompletely connected. In the case of a completely connected market, a bank exposed to financial distress would immediately infect all other banks whilst just a few banks would be affected otherwise. Chen (1999) argue banks' returns to be correlated too, meaning a run on one bank to result in run on other banks, turning the financial system into a banking panic.

Following the global financial crisis, there was a bloom of new regulations aiming at preventing future bubbles. The reform that got the highest international impact was Basel III, which requires higher capital ratios and stricter definitions of capital held (BCBS, 2011). However, the regulations may lead to banks holding similar assets in their portfolios, thus becoming more and more alike. Therefore, regulatory actions may be counterproductive as proposed by Slijkerman et al. (2013) and Kaufman and Scott (2003). Apart from the Basel Committee on Banking Supervisions (BSBS) post-crisis reforms, the Financial Stability Board (FSB) was founded. At this point, Banulescu and Dumitrescu (2015) claim a key issue for regulators was the identification of the so-called Systemically Important Financial Institutions (SIFIs). These institutions are often referred to as 'too big to fail' (Financial Stability Board, 2020). The riskiest firms are being ranked in terms of highest contribution to the overall systemic risk and these rankings are often used as a proxy for systemically important banks in several papers, e.g., Brownlees and Engle (2017).

2.3 Amplification Mechanisms

The regulatory framework renewals described above seem to be focusing on individual banks, rather than the overall risk in the system. Regulatory incentives to monitor the solvency of individual banks may be ineffective due to transmitted losses through the interbank agreements, affecting already solvent firms, as stated by Elliott et al. (2014), Eisenberg and Noe (2001), and Freixas et al. (2000).

Brunnermeier and Oehmke (2013) define amplification mechanism as small shocks in one part of the banking sector that lead to huge losses for the entire financial system. Amplification mechanisms increase the magnitude of the correction of the affected part, caused by direct or indirect links. The latter are to be compared with spillover effects because of common exposure (c.f., contagion). Further, Brunnermeier and Oehmke (2013) claim the catalyst that triggered the global financial crisis was not of major economic significance, from a holistic perspective, since the subprime mortgage market made up only about 4% of the overall mortgage market. This shows how relatively small shocks can lead to large aggregate impacts, particularly when they simultaneously affect many institutions, as stated by Benoit et al. (2017).

Danielsson et al. (2004) explain financial instability by claiming financial institutions face a Value-at-Risk[4] (VaR) constraint that implies VaR increases in volatile periods. This is to be compared with Brunnermeier and Oehmke (2013) who agree that the run-up phase (in terms of risk) is common in a market of low volatility. Speculators lever up, potentially with short-term debt, while the return differential between risky and 'safe' assets gets lower. As market prices fall, liquidating assets may be particularly costly if investors are being forced to sell at fire-sale prices. Allen and Gale (2000) comment these sales to amplify the downturn, leading to additional sales and even more depressed prices.

Bernardo and Welch (2004) also introduce the idea of market runs, in which liquidity runs and crises are not directly caused by the liquidity shocks per se, but the fear of future liquidity shocks. This is a scenario where investors expect major sell-offs today, thus causing this run. In turn, prices decrease since investors are unaware of sales being information or liquidity-driven.

There are widespread sources of risk-taking in the banking industry, which to some extent are treated in this section. Schwaab et al. (2011) describe the identifying of risk indicators as "thermometers" that regulators can plug into the system to read off the current heat. The risk exposure of an individual bank, in terms of systemic risk, is being measured in the tails, which is introduced and discussed at large in the subsequent sections.

[4] VaR is a statistical measure that quantifies the level of financial risk within a firm with a given probability (e.g., 5%).

3 Data

3.1 Data Collection

We focus on European banks over the period 2005–2019 and follow Karimalis and Nomikos (2018) by selecting banks from the STOXX Europe 600 Banks Index (see Appendix A-1), which in turn is a sub-sample from the STOXX Europe 600 Index. We use a sample of 69 listed European banks. The component selection of the index is determined by the free float market capitalization[5] (STOXX, 2020). Due to our selection we are guaranteed a sample with large market caps and high international activity. All banks are major actors in their local markets. We do not include other important actors of the European financial market, such as insurance and investment companies or brokerage firms[6]. The data constitutes an unbalanced panel, where 26 banks exit during the sample period for various reasons (see Appendix A-2). We choose to retain the original sample for all of the 15 years to prevent a survivorship bias. This implies that, as a consequence, the sample size is shrinking to 43 banks in the final year[7].

Stock prices along with fundamental data are obtained from Bloomberg. We collect daily returns, market capitalization, total assets, total liabilities, and shareholder's equity along with return on a benchmark index, STOXX Europe 600 Index. We had some difficulties with the data collection because of missing values for some banks, especially those banks that exit early from the sample. We have collected this data manually from the banks' annual reports.

The returns are adjusted for stock splits and dividends to provide a more accurate evaluation. We take the perspective of an Euro investor and convert all prices and fundamentals[8] to Euro for all non-Eurozone banks at each specific day, with closing rates obtained from Bloomberg.

State variables are used to construct the time-varying ΔCoVaR measure. We restrict ourselves to the following risk factors: (i) Euro STOXX 50 Volatility Index (VSTOXX), to capture the implied volatility in the market, (ii) liquidity spread, defined as the difference between the three month Euro Interbank Offered Rate (EURIBOR) and the risk free rate, (iii) the change in the risk free rate, (iv) yield spread, defined as the difference between the ten year German government bond rate and the risk free rate, and (v) the change in the credit spread between

[5]The free float market cap is calculated by multiplying the asset price and the number of shares outstanding.

[6]We are limiting ourselves to the banking industry in this study. We are aware of the consequences this entails since other actors play an important role in the financial industry too. However, Billio et al. (2012) conclude that banks play a more important role in transmitting shocks than other institutions, and Acharya et al. (2017) claim the systemic risk models are more applicable to banks.

[7]Out of the banks that qualified to our sample in 2005, 37 banks still remain in the index as of December 2019 whereas the full sample size of the STOXX Europe 600 Banks Index contains 48 banks as of December 2019.

[8]This implies that a non-Euro zone bank will have their fundamental values collected quarterly, currency-adjusted for each day meaning that the fundamentals will differ from one day to another.

Moody's Seasoned Baa Corporate Bond Yield[9] and the ten year German government bond rate. We use the three month German government bond rate as risk free. All the presented state variables are in line with Adrian and Brunnermeier (2011) and obtained from Bloomberg.

3.2 Descriptive Statistics

In a normally distributed sample the observed variable should optimally exhibit skewness of 0 and kurtosis of 3. In our sample the return values deviate from the values for normality, as can be seen in Table 3-1.

Variable	N	Mean	Median	Min	Max	Skewness	Kurtosis	Std. deviation
Full sample	3849	0.00020***	0.00060	-0.15670	0.15700	-0.07***	10.77***	0.01
Sample of small banks	3849	-0.00018***	-0.00016	-0.12846	0.17028	0.37***	13.58***	0.02
Sample of large banks	3849	0.00001***	0.00004	-0.17076	0.20133	0.57***	17.15***	0.02

Asterisks are used to denote significance at standard significance levels (* $p<0.10$, ** $p<0.05$, and *** $p<0.01$).

Table 3-1: Descriptive statistics of the average return
The descriptive statistics contains the average return of (i) a full sample of 69 banks, (ii) a sample of the 10 smallest banks, and (iii) a sample of the 10 largest banks. The selection is based on the market capitalization, as in Appendix A-1. In (i) skewness is negative 0.07, kurtosis 10.77, and the daily mean return is 0.0002. The negative skewness (to the left) induce a slightly higher median return. In (ii) skewness is 0.37, kurtosis 13.58, and the daily mean return is negative 0.00018. In (iii) skewness is 0.57, kurtosis 17.15, and the daily mean return is 0.00001.

The banks that drop out (see Appendix A-2) are observed as long as they are publicly traded. For the other banks there are 3849 daily returns. The banks are traded differently since the amount of public holidays are varying in the different countries. Therefore, the observations for each bank exceeds the common approximation of 252 trading days per year.

3.3 Sample Distribution

The histogram below shows that the stock return is bell-shaped and leptokurtically (fat-tailed) distributed. From Table 3-1 we can see that the distribution has fatter tails than the normal distribution and a Shapiro-Francia test of normality rejects the null hypothesis of normally distributed data. This implies that extreme events occur more frequently than what is proposed by a normal distribution.

[9] We used the yield on U.S. Baa rated corporate bonds since we did not find any comparable bonds on the European market.

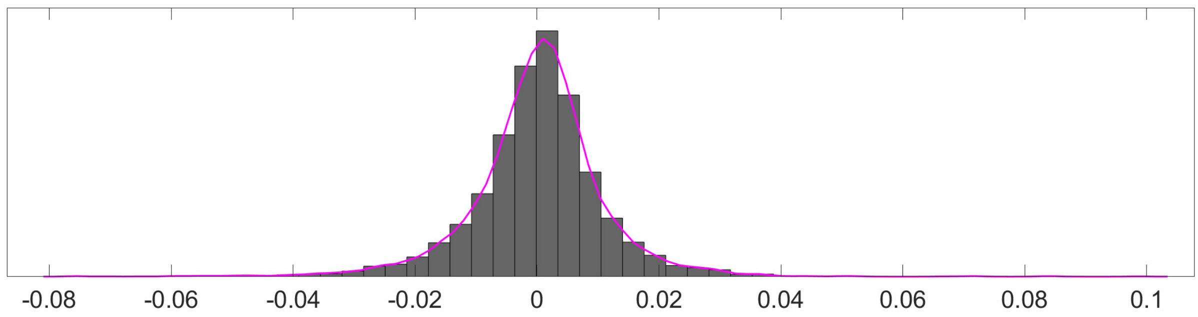

Figure 3-1: Histogram of the return distribution
This figure reports the sample distribution of the average returns for the full sample period (2005–2019). The line marks the the cumulative distribution function. We note fatter tails and higher kurtosis than in a normal distributed sample.

Variable	N	W'	V'	z	Prob>z
Full sample	3849	0.91773	188.581	13.061	0.00001

The normal approximation to the sampling distribution of W' is valid for 5 <= n <= 5000

Table 3-2: Shapiro-Francia test of normality

For the purpose of the empirical analysis, we compute daily log-returns from 2005–2019, which are illustrated in Figure 3-2. The time series exhibit several pronounced intervals of volatility. These periods are particularly visible during the global financial crisis (2008) and the European debt crisis (2010–2015). In this paper, these financial turmoil periods will suit as reference points for our further research.

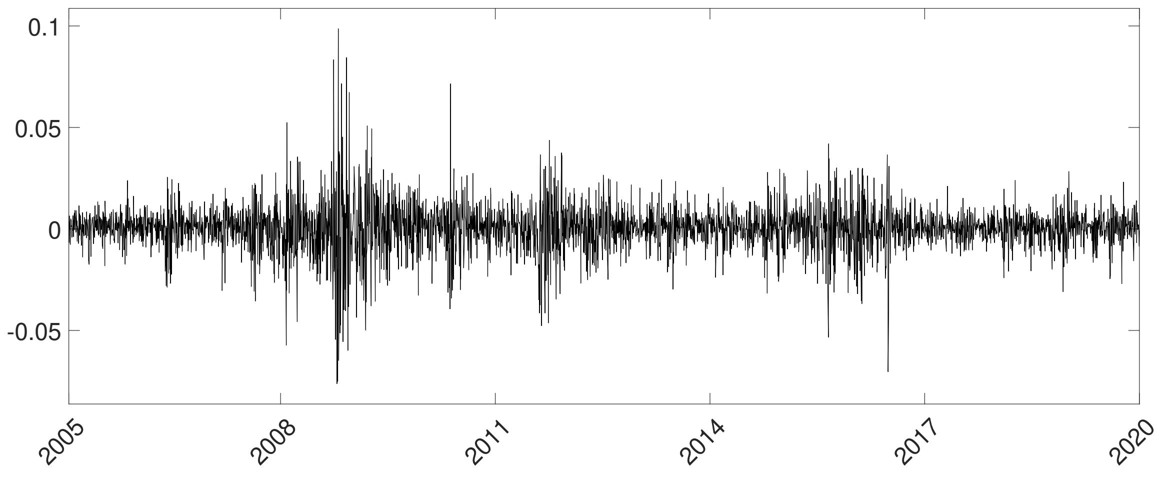

Figure 3-2: Log returns of the sample
This graph shows the average daily log returns for the full sample period (2005–2019).

4 Measurement of Systemic Risk

To measure systemic risk one could evaluate systemic-risk taking, financial contagion, and amplification mechanisms individually. This method could be appropriate if it is feasible to extract data to identify a specific risk factor within one category. There are also global measures that work as a multi-channel-approach to make use of more general risk measures to recognize systemic risk, rather than identifying specifically risk sources.

We present the following global measures in detail in this section: Marginal Expected Shortfall (MES) by Acharya et al. (2017), ΔCoVaR by Adrian and Brunnermeier (2011), Systemic Risk Index (SRISK) by Brownlees and Engle (2017), Turbulence Index by Kritzman et al. (2011) and Dynamic Causality by Billio et al. (2012). First, we introduce Dynamic Conditional Correlation GARCH (GARCH-DCC) which is to be found in VaR and all global measures.

Systemic risk measures	Definition
VaR*	The maximum amount to be lost over a given time period, at a pre-defined confidence level.
MES	The expected capital shortfall in the event of financial distress.
ΔCoVaR	The bank i's marginal contribution to system-level risk in the event of financial distress.
SRISK	The bank's expected undercapitalization in the event of a systemic crisis.
Financial turbulence	The condition in which asset prices, given their historical patterns of behaviour, behave in an uncharacteristic fashion.
Granger causality	The effect of one bank's stock price as a function of previous changes in the bank's stock prices and previous changes in another banks stock price.

Table 4-1: Overview of systemic risk measures
This table gives a brief overview of the systemic risk measures and their definitions. *Note that VaR is not considered to be a global measure, but it will be evaluated in accordance with the other measures.

4.1 Dynamic Conditional Correlation GARCH

In the GARCH-DCC we assume that conditional on information set F_{t-1}, the return with distribution D, with mean zero and time-varying covariance.

$$\begin{bmatrix} r_{it} \\ r_{mt} \end{bmatrix} \Bigg| F_{t-1} \sim D\left(\mathbf{0}, \begin{bmatrix} \sigma_{it}^2 & \rho_{it}\sigma_{it}\sigma_{mt} \\ \rho_{it}\sigma_{it}\sigma_{mt} & \sigma_{mt}^2 \end{bmatrix}\right) \tag{4.1.1}$$

where $r_{it} = log(1+R_{it})$ and $r_{mt} = log(1+R_{mt})$

We use specific equations for the correlation and development of the time varying volatilities. To calculate the volatilities Brownlees and Engle (2017) use GJR-GARCH according to Glosten et al. (1993), and to calculate the correlation Brownlees and Engle (2017) use the standard DCC correlation model of Engle (2002).

$$\sigma_{it}^2 = \omega_{Vi} + \alpha_{Vi} r_{it-1}^2 + \gamma_{Vi} r_{it-1}^2 I_{it-1}^- + \beta_{Vi} \sigma_{it-1}^2, \tag{4.1.2}$$

$$\sigma_{mt}^2 = \omega_{Vm} + \alpha_{Vm} r_{mt-1}^2 + \gamma_{Vm} r_{mt-1}^2 I_{mt-1}^- + \beta_{Vm} \sigma_{mt-1}^2, \tag{4.1.3}$$

If the firm return is less then zero ($r_{it} < 0$), then $I_{it}^- = 1$. The same applies if the market return is less than zero ($r_{mt} < 0$), then $I_{mt}^- = 1$. The correlations are computed through volatility adjusted returns, which are $\varepsilon_{it} = r_{it}/\sigma_{it}$ and $\varepsilon_{mt} = r_{mt}/\sigma_{mt}$. The model also consists of Q_{it} which is defined as the pseudo correlation matrix.

$$Cor \begin{pmatrix} \varepsilon_{it} \\ \varepsilon_{mt} \end{pmatrix} = R_t = \begin{bmatrix} 1 & \rho_{it} \\ \rho_{it} & 1 \end{bmatrix} = diag\,(Q_{it})^{-1/2}\, Q_{it}\, diag\,(Q_{it})^{-1/2} \tag{4.1.4}$$

Further, to the last step of the DCC-model, we need to specifie the dynamics of the pseudo-correlation matrix Q_{it} as

$$Q_{it} = (1 - \alpha_{Ci} - \beta_{Ci}) S_i + \alpha_{Ci} \begin{bmatrix} \varepsilon_{it-1} \\ \varepsilon_{mt-1} \end{bmatrix} \begin{bmatrix} \varepsilon_{it-1} \\ \varepsilon_{mt-1} \end{bmatrix}' + \beta_{Ci}\, Q_{it-1} \tag{4.1.5}$$

where r_{it} is the return and S_i is the unconditional correlation matrix of the firm. This is the final step and what we further on refers to as GARCH-DCC.

4.2 Value-at-Risk

Value-at-Risk (VaR) does not qualify for a global risk measure, but is included in several of the models. In general, VaR is a measure used to calculate the potential maximum loss one might suffer with a certain probability (probability often set to less than or equal to 5%). It is commonly used by firms and regulators to calculate the funds needed to cover possible losses. VaR reflects individual asset price volatility and we therefore use it as a proxy for market perceptions regarding a firm's business risk, as denoted by Nucera et al. (2016). Mathematically, VaR is implicitly defined as

$$5\% = Pr(R \leq -VaR_{5\%}) \tag{4.2.1}$$

For the purposes of this paper we estimate VaR by forecasting volatility using the GARCH-

DCC, assuming normal density. The calculation of VaR is then as follows

$$VaR = \sigma_{t+1} * q(p), \tag{4.2.2}$$

where σ_{t+1} is the volatility estimated from GARCH-DCC and $q(p)$ is $p\%$ quantile from the returns. Despite this method of calculating VaR is considered to be one of the most successful, a disadvantage being that the model completely ignores the presence of the fat-tailed distribution.

4.3 Marginal Expected Shortfall

Marginal Expected Shortfall (MES) is a systemic risk measure introduced by Acharya et al. (2017). To calculate MES we first specify the Expected Shortfall (ES). ES is defined as the expected loss under the assumption that the loss is greater than the VaR (i.e., when the portfolio's loss is greater than its VaR limit), illustrated below with 95% confidence level:

$$ES_{5\%} = -E[R|R \leq -VaR_{5\%}] \tag{4.3.1}$$

ES is the expected return on days when an asset exceeds its VaR. R is equal to the return of the aggregate banking sector. To see the effect in full, we rewrite equation (4.3.1) to the following:

$$ES_{5\%} = -\sum_i y_i E[r_i|R \leq -VaR_{5\%}], \tag{4.3.2}$$

where y_i is the weight of the individual firm and r_i is the return of firm i. The banks' return, R, is the value-weighted average of all banks' returns and it is equal to $\sum_i y_i r_i$. MES is the partial derivative of ES with respect to y_i, which is the market capitalizaton weight of bank i.

$$MES^i_{5\%} = \frac{\partial ES_{5\%}}{\partial y_i} = -E[r_i|R \leq -VaR_{5\%}] \tag{4.3.3}$$

$MES^i_{5\%}$ measures the increase of systemic risk as a cause of a marginal increase in the weight of bank i in the system. In summary, MES is the expected return on a financial firm conditional on a market return being in its lower tail.

4.4 ΔCoVaR

CoVaR is defined as the VaR of the financial system[10], conditional on institution i being in distress. ΔCoVaR captures the marginal contribution of an individual bank in terms of the

[10]The financial system is generally approximated by a market index. We choose to use the STOXX Europe 600 Index.

aggregate systemic risk. This means that ΔCoVaR is defined as the VaR of the financial system when institution i is in distress, less the VaR of the financial system when institution i is at their median state, as proposed by Adrian and Brunnermeier (2011). Mathematically, ΔCoVaR is defined as

$$\Delta CoVaR_{it}(q) = CoVaR_t^{system|\psi_{it}=VaR_{it}(q)} - CoVaR_t^{system|\psi_{it}=Median(\psi_{it})}, \tag{4.4.1}$$

where ψ_{it} is the return of market valued assets of the system and individual institutions. For institution i, the growth of market valued total assets is defined as

$$\psi_{it} = \frac{ME_{it} \cdot LEV_{it} - ME_{i,t-1} \cdot LEV_{i,t-1}}{ME_{i,t-1} \cdot LEV_{i,t-1}}, \tag{4.4.2}$$

where ME_{it} is the market value of firm i's equity and LEV_{it} is the ratio of total value of assets and book value of equity.

To estimate ΔCoVaR we use quantile regression[11]. First, we predict the return in a crisis situation with the individual banks return as the explanatory variables, where the estimation of the financial sector, $\hat{\psi}_q^{system,i}$, conditional on institution i for the q^{th}-quantile is

$$\hat{\psi}_q^{system,i} = \hat{\alpha}_q^i + \hat{\beta}_q^i \psi^i \tag{4.4.3}$$

This regression is for the q^{th} quantile, as in median level q is equal to 50%. By definition VaR is the conditional quantile given ψ^i, as following

$$VaR_q^{system}|\psi^i = \hat{\psi}_q^{system,i} \tag{4.4.4}$$

According to the definition by Adrian and Brunnermeier (2011), if we have a particular predicted value for $\psi^i = VaR_q^t$, it then yields the measure of $CoVaR_q^i$, $\left(CoVaR_q^{system|\psi^i=VaR_q^i}\right)$. We then obtain the unconditional CoVaR measure

$$CoVaR_q^{system|\psi^i=VaR_q^i} = VaR_q^{system}|VaR_q^i = \hat{\alpha}_q^i + \hat{\beta}_q^i VaR_q^i \tag{4.4.5}$$

With equation 4.4.1 in mind we can then conclude that the constant systemic risk measure of bank i for the q^{th} quantile is

$$\Delta CoVaR_q^{system|i} = CoVaR_q^i - CoVaR_q^{system|VaR_{50}^i}, \tag{4.4.6}$$

[11] There are several other ways to compute ΔCoVaR. Quantile regression is the method used in Adrian and Brunnermeier (2011). Alternatively, it could be estimated through models with time-varying second moments.

$$= \hat{\beta}_q^i (VaR_q^i - VaR_{50}^i), \tag{4.4.7}$$

which is the last step of the standard procedure to calculate the ΔCoVaR measure.

However, the quantile regression yields a ΔCoVaR measure that is constant over time. To estimate the time-varying ΔCoVaR, we use lagged state variables, M_t, which contain information on time variation in asset returns. The time-varying ΔCoVaR is calculated as follows

$$X_t^i = \alpha^i + \gamma^i M_{t-1} + \varepsilon_t^i \tag{4.4.8}$$

$$X_t^{system} = \alpha^{system|i} + \beta^{system|i} X_t^i + \gamma^{system|i} M_{t-1} + \varepsilon^{system|i}, \tag{4.4.9}$$

from which the estimated values are used to get:

$$VaR_t^i(q) = \hat{\alpha}_q^i + \hat{\gamma}_q^i M_{t-1} \tag{4.4.10}$$

$$CoVaR_t^i(q) = \hat{\alpha}^{system|i} + \hat{\beta}^{system|i} VaR_t^i(q) + \hat{\gamma}^{system|i} M_{t-1} \tag{4.4.11}$$

From this, the time-varying ΔCoVaR is given as

$$\Delta CoVaR_t^i(q) = CoVaR_t^i(q) - CoVaR_{t,50}^i \tag{4.4.12}$$

$$= \hat{\beta}^{system|i} (VaR_t^i(q) - VaR_{t,50}^i \tag{4.4.13}$$

4.5 Systemic Risk Index

Systemic Risk Index (SRISK) is a function of size, leverage, and the Long Run Marginal Expected Shortfall (LRMES) of the firm (Brownlees and Engle, 2017). This model generates an aggregate capital shortfall index ranking the financial institutions in terms of risk exposure in case of a systemic risk event. SRISK measures the expected capital shortfall under an assumption that market is in distress and is defined as the expected capital shortfall conditional on systemic events, illustrated below:

$$SRISK_{it} = E_t(CS_{i\,t+h} | R_{m\,t+1:t+h} < C), \tag{4.5.1}$$

where CS is the capital shortfall and C is a threshold value for an equity market decline, that happens over a time horizon h. The capital shortfall is taken as the capital reserves a firm needs to hold minus its equity, as proposed by Brownlees and Engle (2017). The intuition behind the measure is that a capital shortfall in the economy contributes to systemic risk. Capital shortfall of firm i on day t is defined as

$$CS_{it} = kA_{it} - W_{it} = k(D_{it} + W_{it}) - W_{it}, \tag{4.5.2}$$

where k[12] is the prudential capital fraction and is based on the capital maintained by large institutions in normal times. $A_{it} = D_{it} + W_it$ is the value of quasi assets, W_{it} is the market value of equity, while D_{it} is the book value of debt. If the capital shortfall is positive, the firm experiences distress, and if it is negative, the firm is working properly.

A systemic crisis is denoted by a equity market decline of C over a time period of h. The multiperiod market return between the first period $(t+1)$ to the last period $(t+h)$ is denoted as $R_{mt+1:t+h}$. In the case of systemic event, $\{R_{m\,t+1:t+h} < C\}$. By rewriting equation (4.5.1), we can conclude that SRISK equals

$$kE_t(D_{i\,t+h}|R_{m\,t+1} < C) - (1-k)E_t(W\,i\,t+h|R_{m\,t+1\,:\,t+h} < C) \tag{4.5.3}$$

It is assumed by theory that debt cannot be renegotiated in a crisis, therefore its book value stays constant as following

$$E_t(D_{i\,t+h}|R_{\,t+1\,:\,t+h} < C) = D_{it}, \tag{4.5.4}$$

with this assumption it follows that the formula expressed in equation (4.5.3) becomes

$$SRISK_{it} = kD_{it} - (1-k)W_{it}(1 - LRMES_{it}) \tag{4.5.5}$$

$$= W_{it}[kLVG_{it} + (1-k)LRMES_{it} - 1] \tag{4.5.6}$$

In equation (4.5.6) LVG_{it} denotes the quasi leverage ratio $\frac{D_{it}+W_{it}}{W_{it}}$. $LRMES_{it}$ stands for Long Run Marginal Expected Shortfall, which is the negative expected return on the firm's equity conditional on a systemic event. Brownlees and Engle (2017) denotes $LRMES$ as

$$LRMES_{it} = -E_t(R_{i\,t+1\,:\,t+h|Rm\,t+1\,:\,t+h} < C) \tag{4.5.7}$$

To estimate LRMES, we use the GARCH-DCC proposed by Brownlees and Engle (2017)[13], as can be seen in Section 4.1. We simulate a random sample of size S of h-period firm and market

[12] We set k to 5.5% which is in line with Engle et al. (2015), that also investigates European banks.

[13] Brownlees and Engle (2017) present two other models in their paper. The static bivariate normal model and a time-varying copula model, also described by Patton (2006). According to Brownlees and Engle (2017), a static bivariate normal model does not provide a timely measure of SRISK. It should therefore only be used for a short time horizon.

arithmetic returns, conditional on the information set available on day t. Then we compute the cumulative logarithmic returns and convert them into arithmetic h-period return. By performing Monte Carlo simulation, we then obtain the average of the simulated arithmetic h-period returns,

$$LRMES_{it}^{dyn} = -\frac{\sum_{s=1}^{S} R_{it+1:t+h}^{s} I\{R_{mt+1:t+h}^{s} < C\}}{\sum_{s=1}^{S} I\{R_{mt+1:t+h}^{s} < C\}} \tag{4.5.8}$$

SRISK can be defined at the aggregate level, where the total amount of systemic risk in the financial system is measured as

$$SRISK_t = \sum_{i=1}^{N} (SRISK_{it})_{SRISK>0} \tag{4.5.9}$$

The aggregate SRISK can be thought of as the funds needed for a government to bail out the financial system, conditional on a systemic event. In the event of crisis, a nonpositive SRISK_{it} means that a firm_i would still have enough capital at time t to cover its prudential requirements. In percentage form, the risk share of a particular institution takes its form in

$$SRISK\%_{it} = \frac{SRISK_{it}}{SRISK_t} \tag{4.5.10}$$

if $SRISK_{it} > 0$, zero otherwise.

4.6 Financial Turbulence Indicator

Financial turbulence is a measure developed by Kritzman et al. (2011) that is based on the Mahalanobis distance[14]. The model is defined as a condition in which asset prices, given their historical patterns, move by an uncharacteristically large amount. Mathematically, the financial turbulence indicator is defined as

$$TurbulenceIndex_t = (r_t - R)\,\Sigma^{-1}\,(r_t - R), \tag{4.6.1}$$

where r_t is the asset return for period t, R is an average vector of historical return, Σ is a static/unconditional matrix of historical returns. The value of financial turbulence is conditional on two statements. First, if asset prices move by an uncommon large amount. Second, if the movement of asset prices violates the existing correlation structure. If both conditions are satisfied, the market experiences higher turbulence compared to if only one condition is satisfied.

[14]Mahalanobis distance is a measure of the distance between a point (p) and a distribution (d), in terms of standard deviations. The measure is used to identify outliers in a certain set of data.

4.7 Dynamic Causality Index

Dynamic Causality Index (DCI) is a Granger-causality test proposed by Billio et al. (2012), used to measure interconnectedness. We use DCI to investigate whether the return for one bank can forecast the return of another bank, where an increase in DCI indicates a higher level of interconnectedness. If there is such a causality, shocks can propagate throughout the banking industry, and can give rise to financial contagion between the banks. Mathematically we need to define a Granger causality for a pair of time series with zero mean and unit variance, as given below

$$X(t) = \sum_{i=1}^{L} A_i X_{t-i} + \sum_{i=1}^{L} B_i X_{t-i} + \varepsilon_t, \tag{4.7.1}$$

$$Y(t) = \sum_{i=1}^{L} C_i X_{t-i} + \sum_{i=1}^{L} D_i X_{t-i} + \eta_t, \tag{4.7.2}$$

where L is the maximum lag considered and in absolute value significantly larger then zero. A_i, B_i, C_i, and D_i are coefficients of the model. Both error terms (ε and η) are assumed to be uncorrelated and i.i.d. Causality occurs when Y causes X when B_i is significantly different from zero. Billio et al. (2012) define the dynamic causality index as

$$DCI_t = \frac{Number\, of\, casual\, relationship}{Total\, possible\, number\, of\, causal\, relationship} \tag{4.7.3}$$

DCI is the number of connections as a percentage of the total amount of possible connections, at the 5% level of statistical significance, as in the formula above.

5 Results and Analysis

In this section we present the results of the systemic risk measures VaR, MES, ΔCoVaR, and SRISK. The four measures are computed using code made available by Belluzzo (2020). We compare the systemic risk time series results with systemic and economic events. Apart from presenting the aggregate systemic risk level in the market, and its development over time, we investigate which banks that are most prone to suffer from systemic risk. Here, we provide a rank correlation analysis to measure rank similarity and ranking stability. We add a Granger causality test to investigate connectedness as well as a financial turbulence indicator to support our findings. In addition, we include several principal component analyses. Lastly, we estimate vector autoregressive (VAR) models and attempt to explain the relationship among the systemic risk measures, and fundamental values, with orthogonalized impulse response functions (OIRF).

5.1 Comparison of Systemic Risk Measures

There are several periods during our observation period where the individual assets, on an aggregate level, are very sensitive to shocks that occur in the market. These shocks correspond to events in the real economy, implicating lower return in distressed periods. We apply the methodology as presented in Section 4 and obtain the results given in Figure 5-1.

We confirm that the systemic risk measures are separately working appropriately to monitor the development of systemic risk over the past fifteen years. This can be shown by comparing the systemic risk time series with systemic and real events. We note that the systemic risk was especially prominent during the global financial crisis. This demonstrates that aggregate risk becomes larger during periods of financial distress, and the asset returns contribute to the tails of the market returns. After the crisis, it is clear that the systemic risk starts to decrease and the graphs show a downward movement. Changes in regulatory frameworks may have helped to stabilize the market with stricter regulations and monitoring giving rise to a lower systemic risk level. The European debt crisis is also visible in the graphs below but that crisis was more protracted, and therefore harder to pin-point.

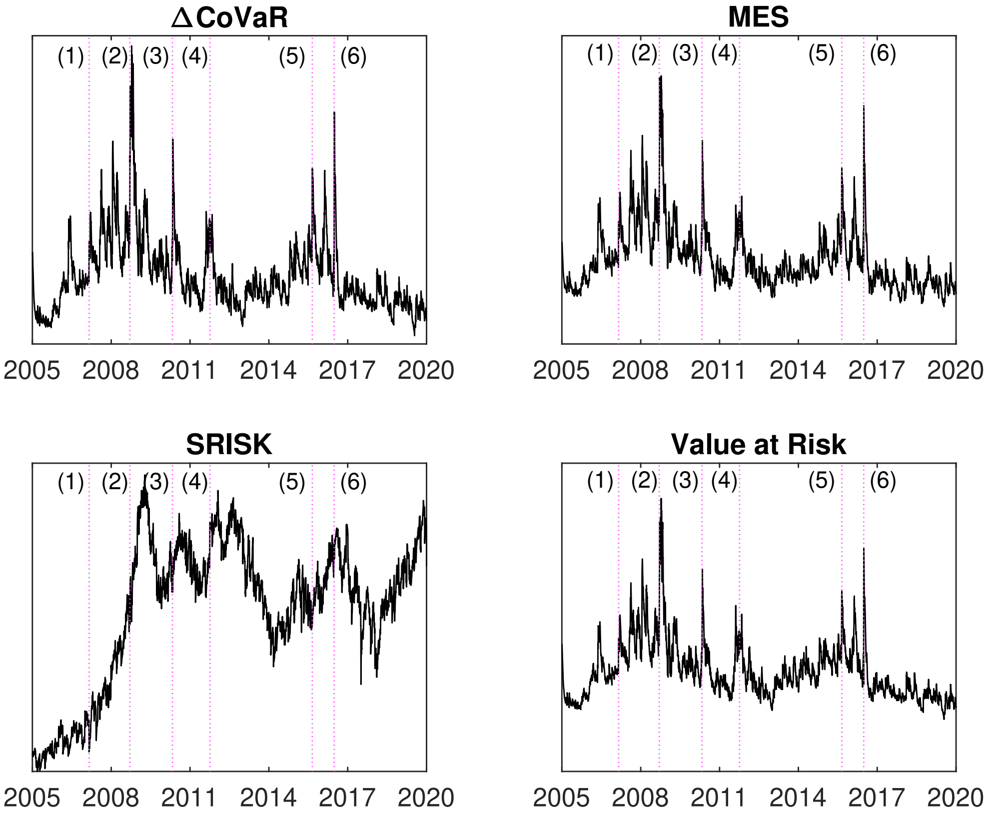

Figure 5-1: Systemic risk comparison with financial events
This figure shows the time series of systemic risk measures from January 2005 to December 2019. The vertical dashed line correspond to some major financial and political events. (1) February 27^{th}, 2007: The Chinese stock bubble. (2) September 15^{th}, 2008: Lehman Brothers bankruptcy. (3) May 2^{nd}, 2010: Greek government bailout. (4) November 30^{th}, 2011: Federal Reserve agreed with European Central Bank and other central banks to revise, extend, and expand its swap lines. In the announcement it was published that the pricing of overnight index swap rates were reduced, from a spread of 100 basis points to 50 basis points. (5) August 24^{th}, 2015: Black Monday in China that send a global echo on the financial markets. (6) June 23^{th}, 2016: Brexit vote is published and Great Britain began its path to break free from the European Union. Due to comparison reasons and the focusing on the dynamics of the models, the values of the individual models (on the y-axis) are dropped.

SRISK begins to increase already in 2007 and reaches its peak not long after the Lehman crash. This is in contrast to the other measures that that appear to be be more fluctuating and not as smooth as SRISK. In fact, SRISK absorbs data from both the stock market and the balance sheet, thus distinguishes itself from the other measures. SRISK could therefore have an advantage over the other measures by incorporating more information. When we define ΔCoVaR and MES we use the 5% worst returns over the measured time period, which implies that a loss in the 5% quantile happens once a month (losses in the tail). When computing SRISK though, we calculate a market decline over a certain time span, e.g., if STOXX Europe 600 Index declines 40% over a period of six months. These are rare events that happen due to a 'real' financial crisis, or at least a significant economic downturn.

To get a better understanding of the movement of the global systemic risk measures (i.e., VaR excluded) we zoom into the global financial crisis in Figure 5-2. The systemic risk measures seem to be stable in advance of the crisis, but after BNP Paribas decided to freeze its hedge funds[15] in 2007 the level of risk increased. The systemic risk measures show a volatile movement over time but the collapse of Bear Stearns induced new spikes, as a result of increased fear of potential spillover effects. This is just in line with previous literature that explains the high level of interconnectedness in the market as the main cause of such spillover effects.

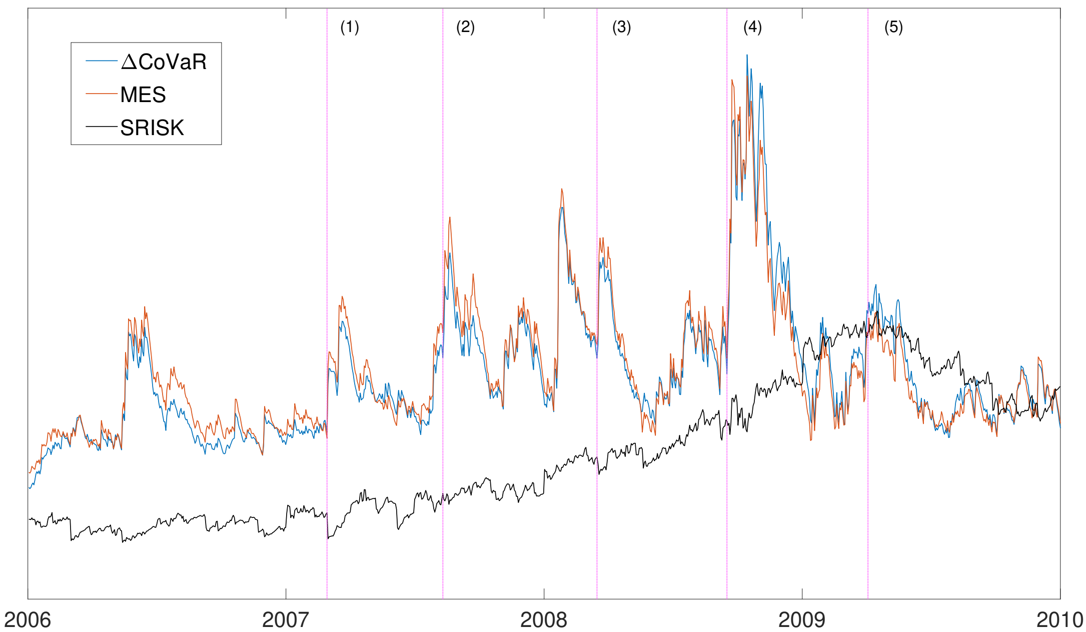

Figure 5-2: Systemic risk measures comparison during the global financial crisis
This figure zooms in on the global financial crisis to compare the global systemic risk measures. It shows the daily time series of the systemic risk measures from 2006–2010. The observations are normalized over the whole sample period to adjust for the scaling due to comparison reasons. The vertical dashed lines pinpoint major financial and political events. (1) August 9^{th}, 2007: France's BNP Paribas froze three of its investment funds due to its exposure to risky subprime loans. (2) February 27^{th}, 2007: The Chinese stock bubble. (3) March 14^{th}, 2008: Bear Stearns bailout and merger with JPMorgan Chase. (4) September 15^{th}, 2008: Lehman Brothers bankruptcy. (5) April 2^{nd}, 2009: G20 summit was held in London with the aim to restore the global economy.

At the G20 London Summit in 2009 stricter regulations and oversight were agreed to stabilize the market. The movement of the systemic risk measures in the European debt crisis are being displayed in Figure 5-3. The stabilized risk indicators in the European financial market would soon be about to change though, following the Greek government bailout.

The systemic risk measures increased (heavily), to reach new peaks. In the aftermath of the bailout, the systemic risk level decreased (temporarily). The risk of financial contagion and spillover effects would lead to a financial turmoil. The crisis was country-specific and tensions

[15] France's BNP Paribas froze three of its investment funds due to its exposure to risky subprime loans and difficulties calculating its net value (Kar-Gupta and Guernigou, 2007).

in between fiscally sound countries (e.g., Germany) and higher-debt countries (e.g., Greece) generated additional uncertainty in the market. Actions taken from the Federal Reserve and the European Central Bank would dampen the financial distress short-term, but not until the promises of the ECB to preserve the Euro the European financial market seemed to stabilize.

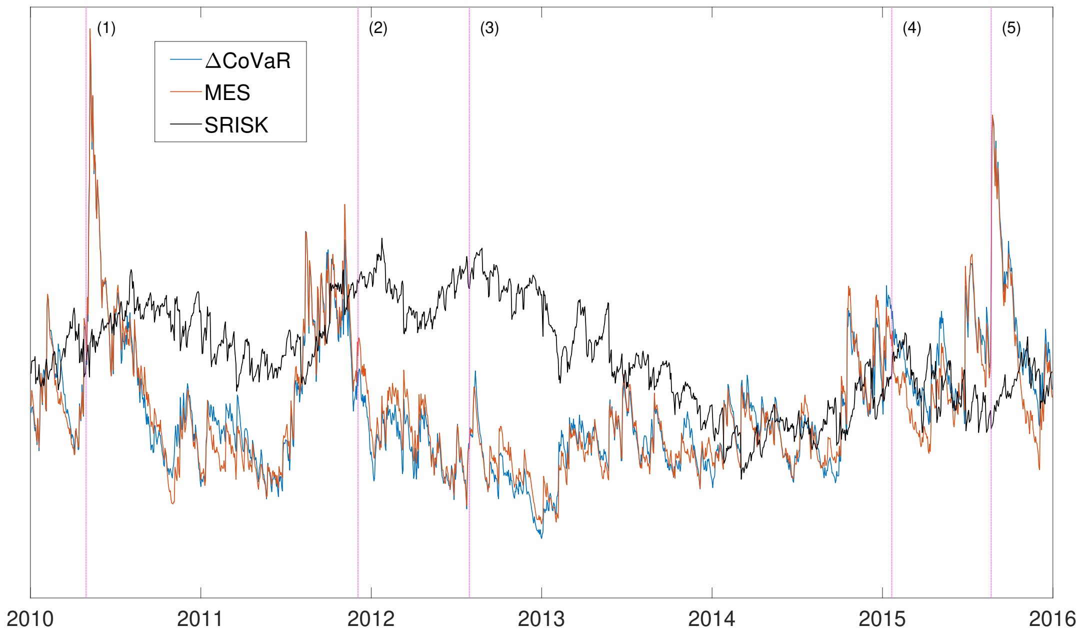

Figure 5-3: Systemic risk measures comparison during the European debt crisis
This figure zooms in on the European debt crisis to compare the global systemic risk measures. It shows the daily time series of the systemic risk measures from 2010–2019. The observations are normalized over the whole sample period to adjust for the scaling due to comparison reasons. The vertical dashed lines pinpoint major financial and political events. (1) May 2^{nd}, 2010: The Greek government bailout loan was launched. (2) November 30 th, 2011: Fed set up a swap-line with the European Central Bank to keep the financial market functioning. (3) July 26^{th}, 2012: At a speech in London Mario Draghi, President of the European Central Bank, demonstrated ECB would do 'whatever it takes' to save the Euro. (4) January 22^{nd}, 2015: ECB announces the plan to stimulate the eurozone's economy with a government bond-buying program of at least €1.1tn. (5) August 24^{th}, 2015: Black Monday in China that send a global echo on the financial markets.

To summarize, the overall movement of the systemic risk measures seem to react similarly to the economic and political events, even though SRISK deviates from the other measures in terms of magnitude (not as heavy spikes as MES and ΔCoVaR). The dynamics of the measures seem to make sense since all of the measures react to major events, indicating that the measures are good indicators for systemic risk.

In addition to the systemic risk measures discussed above we construct a turbulence index to finalize our analysis of the systemic risk measures and real economic events. The turbulence index measures the systemic risk based on the abnormality of the asset returns on each particular day. These abnormalities can arise due to extreme events that move volatility up or down generated from abrupt changes in correlation between asset prices.

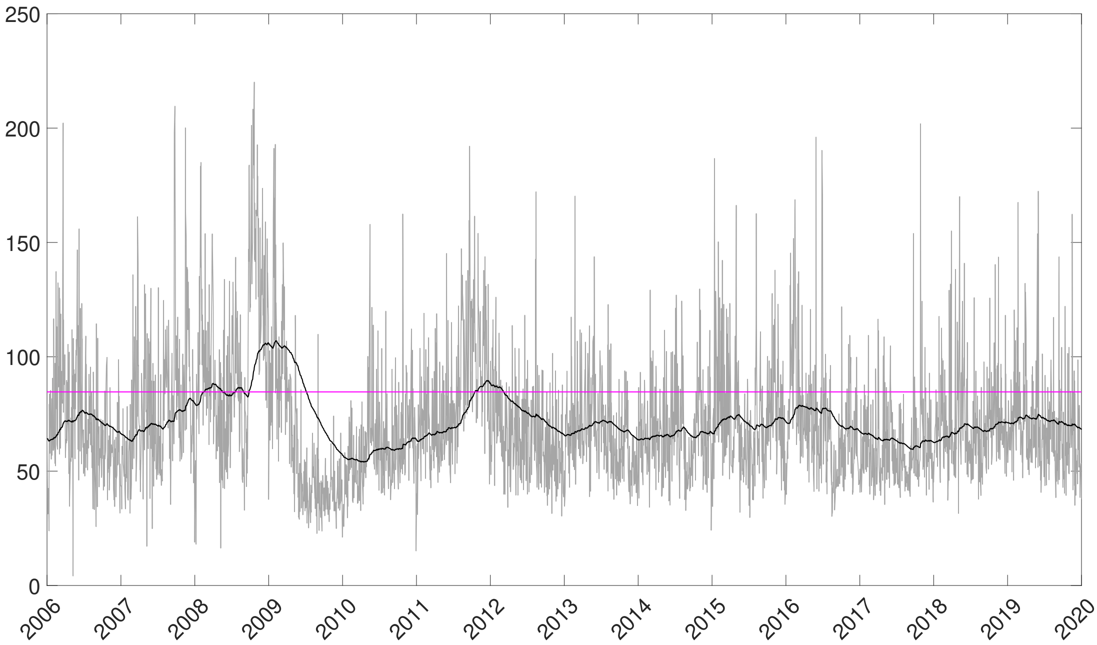

Figure 5-4: Turbulence Index
The financial turbulence indicator visualizes the turbulence in the market, with a threshold marked by the straight line. In times where the turbulence is above the threshold, its assumed to be a turbulent period whilst periods with low turbulence are being defined as quiet. Further, in line with Kritzman and Li (2010), an exponentially weighted moving average with a window size of 252 days is added to the graph to distinguish between the turbulent and quiet periods.

We identify February 2008–April 2008 and June 2008–July 2008 as turbulent periods, while particularly September 2008–July 2009 and November 2011–February 2012 are periods with most turbulence. It is interesting to observe that the most turbulent days appear in the aftermath of major events, suggesting that the turbulence indicator is lagging. If we follow this approach, we find that our indicator coincides remarkably closely with major financial events. Based on Figure 5-4 it seems like the systemic risk measures can predict future turbulence, which is expected according to the theory.

To be able to draw further conclusions about systemic risk and the impact on the financial market, we compare the systemic risk measures with fundamental values, as can be seen in Figure 5-5. The size factor match the stylized fact that SRISK was (heavily) increasing in the period of 2005–2010 and 2018–2019 (c.f., Figure 5-1). The same tendency can be seen for leverage and market to book. Figure 5-5 shows that before the global financial crisis, the leverage ratio and the market to book increased, which could potentially have been a sign of a build-up of overvalued assets. These results enforce the belief of systemic risk contributions of individual banks to be scaled up by the fundamentals, as concluded by Acharya et al. (2017).

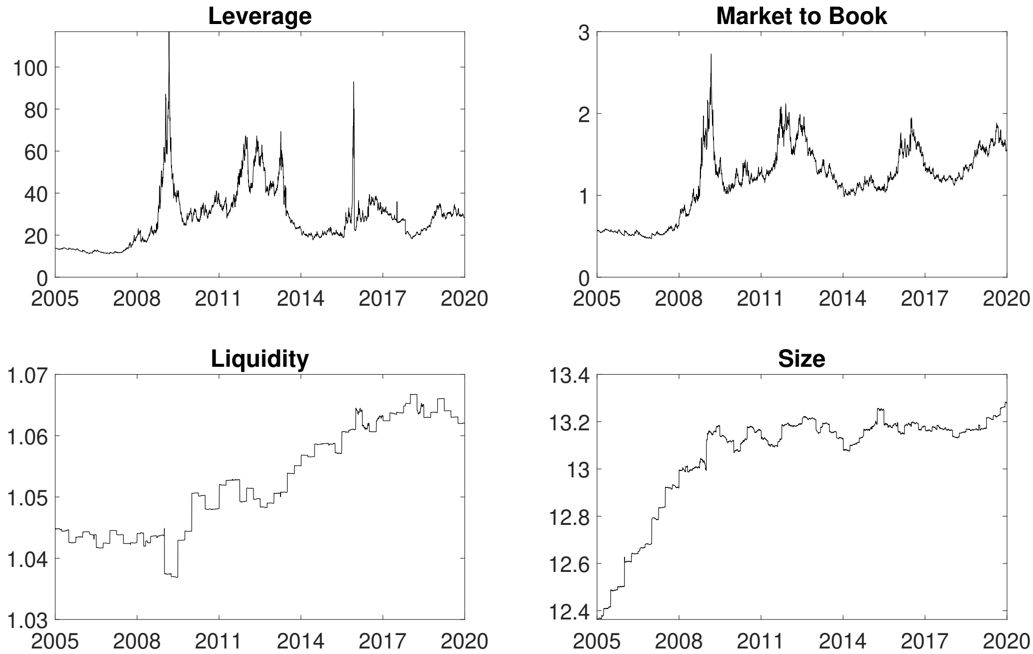

Figure 5-5: Comparison of fundamentals
This figure shows the average time series of different bank variables over the full sample from January 2005 to December 2019. For the fundamentals, quarterly reported data is used. Leverage is calculated, as proposed in the paper of Acharya et al. (2017), by taking the sum of Liabilities and Market capitalization and divide it by Market Capitalization. Market to Book is calculated by dividing the Market Capitalization with the Shareholders equity. Liquidity is calculated as the Total current assets divided by Total current liabilities. Firm size is calculated by the natural logarithm of the Total assets.

As can be seen in Table 5-1, SRISK stands out as the most correlated risk measure, which is expected due to its construction. For other systemic risk measures, the pattern is more varied. Liquidity stands out with a moderate negative relation to VaR, MES, and ΔCoVaR, at highly significant levels. The negative sign indicates that a higher portion of assets, compared to liabilities, lower the systemic risk, which is intuitive. Another observation is that the size factor seems to outperform the liquidity effect in SRISK.

	VaR	MES	ΔCoVaR	SRISK	Liquidity	M/B	LvG	Size
VaR	1.00							
MES	0.98***	1.00						
ΔCoVaR	0.98***	0.97***	1.00					
SRISK	-0.01	-0.02	0.06***	1.00				
Liquidity	-0.31***	-0.33***	-0.27***	0.28***	1.00			
M/B	-0.08***	-0.08***	-0.01	0.89***	0.38***	1.00		
LVG	-0.01	0.00	0.06***	0.77***	0.03*	0.83***	1.00	
Size	0.03*	-0.02	0.08*	0.88***	0.48***	0.78***	0.56***	1.00

Asterisks are used to denote significance at standard significance levels (* $p<0.10$, ** $p<0.05$, and *** $p<0.01$).

Table 5-1: Correlation of systemic risk measures and fundamentals
This table shows the correlations between the systemic risk measures and the fundamental values for the whole sample period. The correlations between SRISK and the fundamentals are significant, and very high (0.77 with leverage, 0.89 with market to book, and 0.88 with size). Liquidity, that can be seen as a measure for the banks ability to meet its short term obligations, is not found to be a driving factor of any of the systemic risk measures, even though a sharp decrease in liquidity followed the global financial crisis.

Further, we investigate the correlations of the systemic risk measures as can be seen in Table 5-2. There are a strong positive correlations, over all time periods, between VaR, MES, and ΔCoVaR, which confirm the common movements displayed in Figure 5-2 and 5-3. Note that VaR is not used as a systemic risk measure due to its simplicity and is, according to literature, not expected to identify such a risk. Instead, VaR is rather a measure of the systematic risk (i.e., market risk) and not the systemic risk. Although SRISK does not correlate with any of the risk measures during the whole period, there are periods of high correlation in times of lower size growth.

June 2006–June 2007

	VaR	MES	SRISK	ΔCoVaR
VaR	1.00			
MES	0.95***	1.00		
SRISK	0.05	-0.05	1.00	
ΔCoVaR	0.99***	0.96***	0.01	1.00

April 2009–April 2010

	VaR	MES	SRISK	ΔCoVaR
VaR	1.00			
MES	0.97***	1.00		
SRISK	0.54***	0.48***	1.00	
ΔCoVaR	0.99***	0.97***	0.57***	1.00

January 2019–December 2019

	VaR	MES	SRISK	ΔCoVaR
VaR	1.00			
MES	0.90***	1.00		
SRISK	-0.13**	-0.12**	1.00	
ΔCoVaR	0.99***	0.89***	-0.16**	1.00

2005–2019

	VaR	MES	SRISK	ΔCoVaR
VaR	1.00			
MES	0.98***	1.00		
SRISK	-0.01	-0.02	1.00	
ΔCoVaR	0.98***	0.97***	0.06***	1.00

Asterisks are used to denote significance at standard significance levels (* p<0.10, ** p<0.05, and *** p<0.01).

Table 5-2: Correlation of systemic risk measures
The correlations are being displayed in four time periods: (i) pre-global financial crisis, (ii) pre-European debt crisis, (iii) 2019, and (iv) the full sample period.

Lastly, due to the high correlation between the measures we apply a Principal Component Analysis (PCA) with rotation matrices to measure the commonality among the measures. Here, the main advantage of performing a PCA is that the principal components are uncorrelated. First, we compare the measures over the whole sample period and note that the first component (PC1) captures almost 74% of the variability across the four different measures. As can be seen in Table 5-3, VaR, MES, and ΔCoVar explain a similar proportion of PC1, which is expected. If we also load the second component (PC2), we note that 99% of the variability across the different measures can be explained, with PC2 almost exclusively consists of SRISK.

The remaining PCA outcomes are equivalent to the entire sample period, except for (ii) the period pre-European debt crisis. In this period, both the eigenvalue and the variance is at its peak in PC1 at 3.32 and 83.06% respectively. This is expected since we experience the highest correlations between the measures in this period too, as can be seen in Table 5-2. The first component consists, as previous, mainly of VAR (54%), MES (53%), and ΔCoVaR (54%), but, SRISK shows a (significantly) higher value (37%) than in other periods.

June 2006–June 2007				
	PC1	PC2	PC3	PC4
VaR	0.58	0.04	-0.45	-0.68
MES	0.57	-0.06	0.82	-0.05
SRISK	0.01	0.99	0.07	0.02
ΔCoVaR	0.58	0.01	-0.36	0.73
Eigenvalue	2.93	1.01	0.06	0.00
Variance %	73.34	25.14	1.47	0.06
Cumulative %	73.34	98.47	99.94	100

April 2009–April 2010				
	PC1	PC2	PC3	PC4
VaR	0.54	-0.19	-0.45	0.69
MES	0.53	-0.28	0.80	0.03
SRISK	0.37	0.93	0.09	0.03
ΔCoVaR	0.54	-0.15	-0.39	-0.73
Eigenvalue	3.32	0.65	0.03	0.00
Variance %	83.06	16.16	0.70	0.08
Cumulative %	83.06	99.22	99.92	100

January 2019–December 2019				
	PC1	PC2	PC3	PC4
VaR	0.58	0.08	-0.38	-0.71
MES	0.56	0.08	0.82	0.02
SRISK	-0.12	0.99	-0.01	0.02
ΔCoVaR	0.58	0.05	-0.42	0.70
Eigenvalue	2.89	0.97	0.13	0.00
Variance %	72.15	24.28	3.35	0.23
Cumulative %	72.15	96.42	99.77	100

2005-2019				
	PC1	PC2	PC3	PC4
VaR	0.58	-0.03	-0.48	0.66
MES	0.58	-0.04	0.81	0.09
SRISK	0.01	0.99	0.03	0.06
ΔCoVaR	0.58	0.05	-0.32	-0.75
Eigenvalue	2.96	1.00	0.03	0.01
Variance %	73.92	25.10	0.64	0.33
Cumulative %	73.92	99.02	99.67	100

Table 5-3: Principal Component Analysis (PCA)
The Principal Component Analysis (PCA) are being displayed in four time periods: (i) pre-global financial crisis, (ii) pre-European debt crisis, (iii) 2019, and (iv) the full sample period. The upper part of the tables shows the rotation matrices (eigenvectors) whilst the lower part shows the eigenvalue, variance (%) and cumulative variance (%).

5.2 Systemic Risk Rankings Evaluation

We have shown the systemic risk measures ability to measure and identify an aggregate systemic risk level in a way that is consistent with our ex-post knowledge. In this section we rank the banks based on their individual systemic risk contribution in pre-crisis periods. We provide ranking stability and investigate rank similarities to see whether systemic risk measures estimate the same systemically important banks. We add measures of interconnectedness and market concentration to measure the degree of systemic risk.

The first thing we identify is a low commonality between the systemic risk measures. We note that the dispersion across rankings is apparent, but the highly correlated measures of VaR, MES and ΔCoVaR are reflected to some extent. However, not a single bank is included in the top 10 risk rankings of all systemic measures pre-global financial crisis and pre-European debt crisis. We find that four banks (SEB, Credit Agricole, Nordea Bank and BNP Paribas) are included in all of the top 20 systemic risk rankings in advance of the global financial crisis. We can add one bank (Banco Santander) to that list if we exclude VaR.

Rank	VaR	MES	SRISK	ΔCoVaR
1	Banca Monte	Banca Monte	Barclays	Handelsbanken
2	National Bank of Greece	**SEB**	Deutsche Bank	**Nordea Bank**
3	Commerzbank	GAM Holding	**BNP Paribas**	**SEB**
4	Alpha Bank	Natixis	**Credit Agricole**	Close Brothers
5	Natixis	Commerzbank	UBS	Banco Santander
6	**SEB**	**Credit Agricole**	RBS Holdings	**BNP Paribas**
7	DNB	Societe Generale	Royal Bank of Scotland	Banco Bilbao
8	Swedbank	**BNP Paribas**	Commerzbank	Swedbank
9	AIB	Barclays	Credit Suisse	Credit Suisse
10	Piraeus Bank	Swedbank	Societe Generale	DNB
11	Erste Bank	Handelsbanken	Dexia	**Credit Agricole**
12	Close Brothers	DNB	UniCredit	Jyske Bank
13	Eurobank Ergasias	Erste Bank	Banco Santander	UBS AG
14	**Credit Agricole**	Capitalia	UniCredit Bank	Standard Chartered
15	Dexia	**Nordea Bank**	Danske Bank	Deutsche Bank
16	Handelsbanken	Close Brothers	DEPFA Bank	Erste Bank
17	**Nordea Bank**	AIB	Natixis	Mediobanca
18	Banca Popolare	Dexia	**Nordea Bank**	Danske Bank
19	KBC Group	Banco Santander	**SEB**	Societe Generale
20	**BNP Paribas**	Standard Chartered	Lloyds Banking	HSBC

Bold entries highlight the banks that are simultaneously in the four rankings.

Table 5-4: Systemic risk rankings pre-global financial crisis
This table shows the risk rankings of the top 20 systemically important banks as calculated per June 2006–June 2007. For a complete ranking list, see Appendix A-3.

The commonality increases a bit in advance of the Eurobank debt crisis. Now we find that seven banks (KBC, Royal Bank of Scotland, Lloyds Banking, Natixis, Barclays, Deutsche Bank and UBS) are included simultaneously in the top 20 risk rankings. We can add three banks (Credit Agricole, Nordea, and BNP Paribas) if we exclude VaR. Still not a single bank is included in the top 10 systemic risk rankings of all systemic risk measures.

Rank	VaR	MES	SRISK	ΔCoVaR
1	AIB Group	Bank of Ireland Group	**Royal Bank of Scotland**	**KBC Group**
2	Bank of Ireland Group	**KBC Group**	BNP Paribas	HSBC
3	**KBC Group**	AIB Group	**Barclays**	Nordea Bank
4	Eurobank	**Royal Bank of Scotland**	**Deutsche Bank**	Swedbank
5	**Royal Bank of Scotland**	**Natixis**	Credit Agricole	SEB
6	**Lloyds Banking**	**Barclays**	HSBC	**UBS**
7	Alpha Bank	**Lloyds Banking**	Societe Generale	Handelsbanken
8	**Natixis**	Erste Bank	Commerzbank	**Deutsche Bank**
9	National Bank of Greece	SEB	**Lloyds Banking**	Erste Bank
10	Piraeus Bank	Commerzbank	**UBS**	DNB
11	Erste Bank	Swedbank	UniCredit	BNP Paribas
12	**Barclays**	**Deutsche Bank**	Banco Santander	Credit Suisse
13	Swedbank	Credit Agricole	Dexia	Banco Santander
14	Commerzbank	DNB	Credit Suisse	**Natixis**
15	Dexia	**UBS**	**Natixis**	**Lloyds Banking**
16	SEB	Societe Generale	Intesa Sanpaolo	**Barclays**
17	DNB	Nordea Bank	Danske Bank	**Royal Bank of Scotland**
18	**Deutsche Bank**	UniCredit	Nordea Bank	Credit Agricole
19	**UBS**	BNP Paribas	**KBC Group**	Banco Bilbao
20	UniCredit	Eurobank	Banco Bilbao	Danske Bank

Bold entries highlight the banks that are simultaneously in the four rankings.

Table 5-5: Systemic risk rankings pre-European debt crisis
This table shows the risk rankings of the top 20 systemically important banks as calculated per April 2009–April 2010. For a complete ranking list, see Appendix A-4.

To proceed our analysis we compare the systemic risk contribution of each systemic risk measure with the pronounced systemically important banks, as stated by the Financial Stability Board (FSB). SRISK identifies all (11) of the European banks included in the G-SIB rankings of 2019, followed by ΔCoVaR (8), MES (7), and VaR (3), as shown in Table 5-6.

VaR is the only model that seems to be unable to capture systemic risk on an individual level. Again, based on the rankings, VaR seems to identify the systematic risk. Due to the vague definition of systemic risk, we should clarify that we cannot conclude that any risk measure is more accurate than any of the other. Nevertheless, our findings indicate that the models are able to point out systemically important banks if we use the G-SIB rankings as a proxy for a true indicator, and the ranking privileges input values that better corresponds to SRISK than the other measures.

Rank	VaR	MES	SRISK	ΔCoVaR
1	Dexia	Piraeus Bank	BNP Paribas*	Deutsche Bank*
2	Piraeus Bank	Natixis	Credit Agricole*	Banco Santander*
3	Alpha Bank	Commerzbank	Deutsche Bank*	Banco de Sabadell
4	National Bank of Greece	Royal Bank of Scotland	HSBC*	Swedbank
5	Eurobank	Bank of Ireland Group	Societe Generale*	Danske Bank
6	Bank of Ireland Group	Societe Generale*	Barclays*	Nordea Bank
7	Banco Monte dei Paschi	Deutsche Bank*	Banco Santander*	Banco Bilbao
8	AIB Group	National Bank of Greece	UniCredit*	BNP Paribas*
9	Commerzbank	Barclays*	Royal Bank of Scotland	Udi Banche Italiane
10	Deutsche Bank*	Alpha Bank	Lloyds Banking	Handelsbanken
11	Udi Banche Italiane	UniCredit*	UBS*	Credit Suisse*
12	Banco de Sabadell	Credit Agricole*	Intesa Sanpaolo	Societe Generale*
13	Natixis	BNP Paribas*	Credit Suisse*	Jyske Bank
14	Swedbank	Udi Banche Italiane	Banco Bilbao	UniCredit*
15	UniCredit*	Lloyds Banking	Standard Chartered*	HSBC*
16	Royal Bank of Scotland	Banco de Sabadell	Commerzbank	Commerzbank
17	Banco Portugues	Banco Santander*	Natixis	SEB
18	Societe Generale*	DNB	Danske Bank	Close Brothers
19	Danske Bank	Erste Bank	Nordea Bank	Natixis
20	Erste Bank	SEB	Banco de Sabadell	Credit Agricole*

Asterisk is used to denote the banks included in the G-SIB list from 2019, as in appendix A-5.

Table 5-6: Systemic risk rankings per 2019
This table shows the risk rankings of the top 20 systemically important banks as calculated per January 2019–December 2019. For a complete ranking list, see Appendix A-6.

We also perform a Kendall rank correlation analysis between the systemic risk measures to assess agreement among the rankings, as can be seen in Table 5-7. The similarity of the rank orders signals a coefficient of concordance in the range of 0.48 to 0.58, over the computed periods. This implies the agreements to be neither complete nor incomplete, which agrees fairly well with our previous remarks. However, to examine systemically important banks the differences in the order of the rankings make it difficult to fully determine which banks are the most prominent systemic risk contributors. The ranking stability show higher values, with SRISK well above the other measures, reaching 0.93 in the full sample period and values ranging from 0.82 to 0.88 in the other time periods. This is presumably a factor of size and leverage of the individual firms that not vary significantly over time. However, what really matters is the correct identification of the bucket of the e.g., first five or ten riskiest banks. Unfortunately, we did not have time do this because of the time constraint.

June 2006–June 2007				
	VaR	MES	SRISK	ΔCoVaR
VaR	1.00			
MES	0.53***	1.00		
SRISK	0.50**	0.51	1.00	
ΔCoVaR	0.51***	0.51***	0.51**	1.00
Ranking stability	0.59	0.59	0.82	0.60

April 2009–April 2010				
	VaR	MES	SRISK	ΔCoVaR
VaR	1.00			
MES	0.49***	1.00		
SRISK	0.52***	0.50**	1.00	
ΔCoVaR	0.54***	0.48***	0.49***	1.00
Ranking stability	0.66	0.63	0.88	0.66

January 2019–December 2019				
	VaR	MES	SRISK	ΔCoVaR
VaR	1.00			
MES	0.53***	1.00		
SRISK	0.50***	0.48***	1.00	
ΔCoVaR	0.50***	0.51***	0.48***	1.00
Ranking stability	0.71	0.61	0.83	0.64

2005–2019				
	VaR	MES	SRISK	ΔCoVaR
VaR	1.00			
MES	0.53***	1.00		
SRISK	0.58***	0.55	1.00	
ΔCoVaR	0.53***	0.55***	0.58	1.00
Ranking stability	0.77	0.75	0.93	0.78

Asterisks are used to denote significance at standard significance levels (* p<0.10, ** p<0.05, and *** p<0.01).

Table 5-7: Kendall's W

Kendall's W is measured daily, and averaged out for each observed time period. The ranking similarity assess agreement between the systemic risk measures, and is simply defined as the proportion of firms that are concurrently in the same rankings on a given date. The ranking stability shows the variance among the rankings over the environments within each measure. Kendall's W ranges from 0 (no agreement) and 1 (complete agreement), and are being displayed in four time periods: (i) pre-global financial crisis, (ii) pre-European debt crisis, (iii) 2019, and (iv) the full sample period.

To further test our results at firm level, we run another PCA where we instead use the individual firm's return as input. The time-series results for the cumulative risk fraction are presented in Table 5-6. The first component (PC1) is at its lowest level in the beginning of the sample period, but increases steadily over time. In the end of the sample period PC1, PC2 and PC3 amounted to 44.5%, 7.6%, and 5.1% respectively (57.2% cumulative), comparing to 26.9%, 3.0%, and 4.4% (34.3% cumulative) in the beginning, implying systemic risk has increased. This is intuitive since the banks in more recent years have been more and more similar, but also because the sample size has shrunk over time.

The time-series graph for all principal components (PC1, PC2, PC3, and PC4–PC69) shows that the first three principal components capture an extensive proportion of the variability during the whole sample period, but the relative importance varies across time. We also note that the PC1–PC3 increase heavily in times of financial distress, which corresponds to previous findings in related literature (see e.g., Billio et al. (2012)).

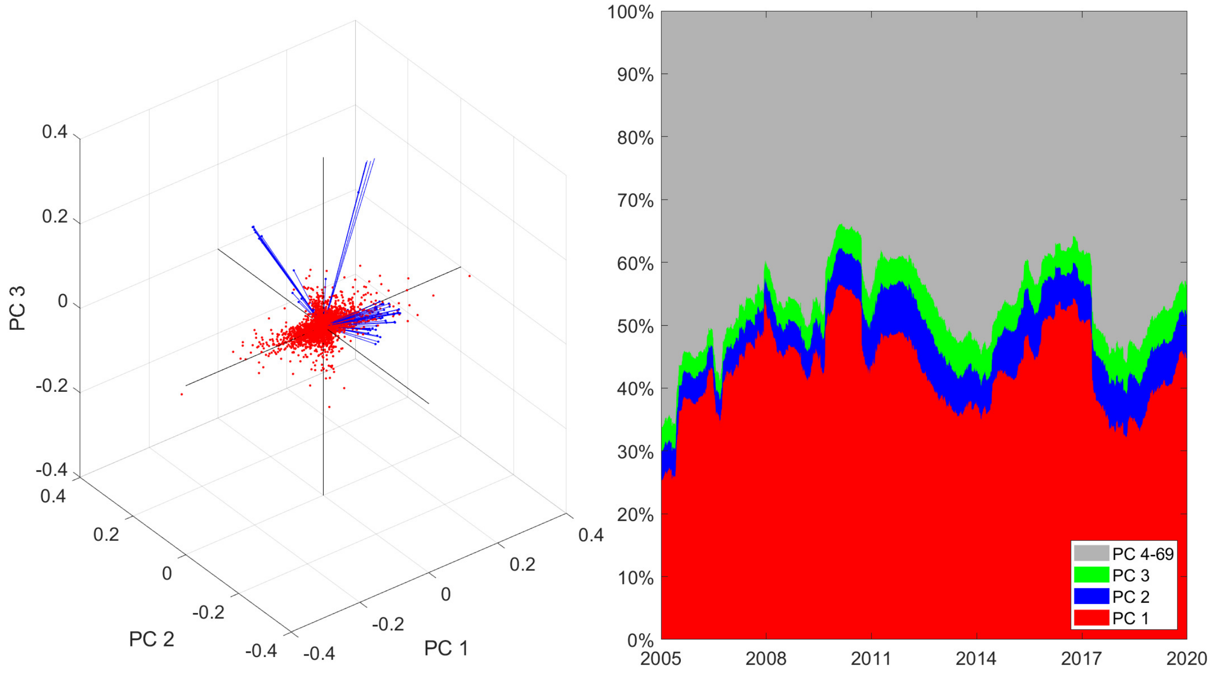

Figure 5-6: Principal component analysis (PCA) - institution level
These both plots visualize the characteristics of the principal components on firm level for the whole sample. In the left three dimensional (3D) plot we can see how the observations can be projected (dots). The straight lines goes through the average point in order to get a coordinate value along the PC-line. The right plot is showing the development of the principal components over time where PC1, PC2 and PC3 amounted to 44.5%, 7.6%, and 5.1% respectively in the end of our sample period (57.2% cumulative), comparing to 26.9%, 3.0%, and 4.4% (34.3% cumulative) in the beginning.

We then apply a Granger-causality test, the Dynamic Causality Index (DCI), to measure the degree of systemic risk. It is defined in the way that an increase in the DCI indicates a higher level of system interconnectedness, as stated by Billio et al. (2012). Moreover, in times when few principal components explain a large part of total variation these can be associated with an increased interconnectedness between the banks. Our findings reveal that the DCI tends to increase in pre-crisis times, suggesting that the asset returns are more interconnected in advance of a turmoil period, as can be seen in Figure 5-7. We find steep increases to occur in, e.g., (i) June 2007, only a couple of months before BNP Paribas froze its investment funds and less than a year before the global financial crisis and (ii) October 2009, less than a year before the Greek government bailout. The fragility in the market increases at the occurrence of crises, which indicates that the sensitivity of the asset return is ascending, as can be seen in Figure 5-7.

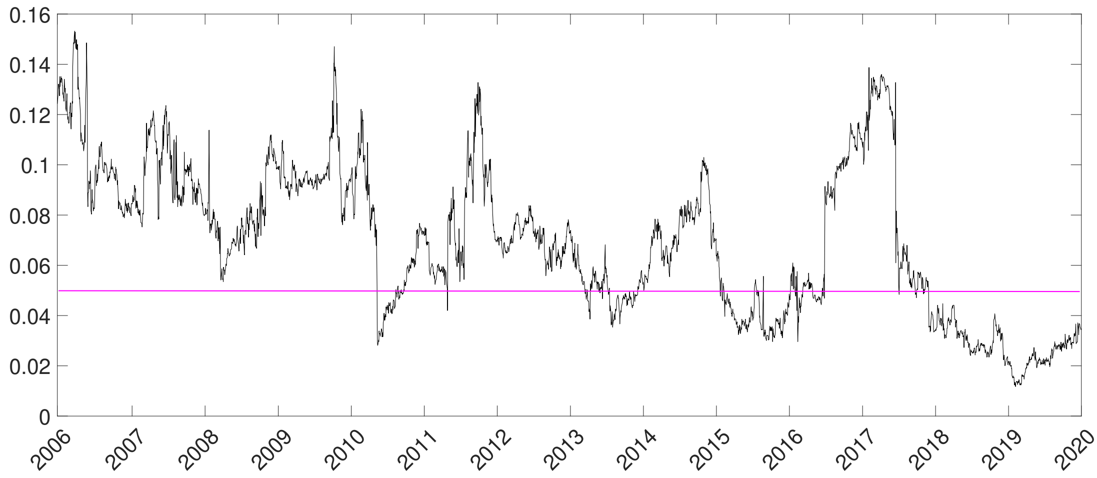

Figure 5-7: Dynamic Causality Index
The DCI states the number of connections as a percentage of the total amount of possible connections, at the at the 5% level of statistical significance. This time series of linear Granger causality contain the full sample size from 2005—2019. The straight line works as a threshold of no casual relationships, as in Billio et al. (2012).

Further, we compute the Herfindahl-Hirschman index (HHI), as can be seen in Appendix B-1, to measure the degree of systemic risk in terms of concentration in the system. The closer the HHI-score is to one, the closer a market is to a monopoly and vice versa. Findings reveal a low market concentration, indicating a highly competitive market, with a HHI-score close to 0.05 on average[16]. This is the value the index would take if the top-twenty firms each held one-twentieth of the total systemic risk. This works as an indicator for a smaller share of the banks' in our sample to explain a great share of the results, which corresponds to the findings in the principal component analysis.

The systemic risk measures presented earlier in this paper measure the systemic risk embedded in the financial markets across time. We stated that tightly coupled financial markets are more fragile to systemic risk events. It is important to clarify that systemic risk does not prove, unconditionally, that a financial crisis will arise, but that the financial market is especially vulnerable in case of a systemic risk event. However, highly interconnected and concentrated markets could be especially plagued by credit and counterparty risks in case of a systemic risk event. This implies that the effects and consequences of a systemic risk event spread a lot quicker and broader in a financial market that is closely linked, which was evidenced in both the global financial crisis and the European debt crisis.

[16]The HHI-score in our sample is 0.049 on average. The minimum and maximum values are 0.032 and 0.066 respectively. HHI is calculated by summing up all of the squared daily market share percentages of each bank.

5.3 Forecasting and Impulse Response Analysis

We complete this section by focusing on forecasts. First, we fit a VAR(1) model with estimated systemic risk measures and fundamentals to examine their relationships and predictive power. We determined the number of lags by considering the models with the lowest value in the Final Prediction Error (FPE), the Akaike's Information Criterion (AIC), the Hannan and Quinn Information Criterion (HQIC), and the Bayesian Information Criterion (BIC).

	VaR_{t-1}	MES_{t-1}	$\Delta CoVaR_{t-1}$	$SRISK_{t-1}$	$Liquidity_{t-1}$	M/B_{t-1}	LVG_{t-1}	$Size_{t-1}$
VaR_t	1.74**	-0.04	-1.30**	0.14	0.75	-0.13	0.00	0.15
	(0.65)	(0.37)	(0.67)	(0.37)	(2.6)	(0.19)	(0.00)	(0.66)
MES_t	1.86**	0.05	-1.47*	0.10	-0.28	0.01	0.00	0.36
	(0.86)	(0.49)	(0.88)	(0.49)	(3.47)	(0.26)	(0.01)	(0.87)
$\Delta CoVaRt_t$	1.05	-0.11	-0.53	0.20	0.28	-0.14	0.00	0.08
	(0.66)	(0.37)	(0.67)	(0.38)	(2.65)	(0.20)	(0.00)	0.67
$SRISKt_t$	-0.57*	0.40**	0.22*	0.78***	0.20	0.28**	-0.00	-0.39
	(0.31)	(0.18)	(0.32)	(0.18)	(1.27)	(0.09)	(0.00)	(0.32)
$Liquidity_t$	-0.02	-0.03*	0.05*	-0.02	0.15	0.00	-0.00*	-0.01
	(0.03)	(0.02)	(0.03)	(0.02)	(0.12)	(0.01)	(0.00)	(0.03)
M/B_t	0.67	-0.13	-0.33	0.69*	1.42	1.16***	-0.01	-1.99**
	(0.73)	(0.41)	(0.75)	(0.42)	(2.93)	(0.22)	(0.00)	(0.74)
LVG_t	21.87	12.67	-19.09	15.92	-30.76	20.93**	0.38**	-79.96**
	(31.18)	(17.56)	(31.90)	(17.81)	(125.58)	(9.34)	(0.18)	(31.63)
$Size_t$	-0.07	-0.10	0.25	0 .02	0.37	0.12**	-0.00	0.70***
	(0.15)	(0.07)	(0.16)	(0.09)	(0.62)	(0.05)	(0.00)	(0.16)

Asterisks are used to denote significance at standard significance levels (* p<0.10, ** p<0.05, and *** p<0.01).

Table 5-8: Vector Autoregressive model - VAR(1)
The table reports the average parameter estimates for VAR(1) model with estimated systemic risk measures and a subset of fundamental values. The time series are quarterly. Standard errors appear in parentheses.

Based on the VAR(1) model, we focus solely on the dynamics of the significant observations estimated in Table 5-8. First, we analyze and discuss the impulses to the systemic risk measures along with fundamentals and factor responses. (i) VaR is significantly moving with MES on a 5% significant level and on a 10% significant level with SRISK, which means that the lagged VaR seems to contain explanatory power for both MES and SRISK one quarter forward. This implies that a positive change in VAR, on average, correlate positively with MES, but negatively with SRISK in the following quarter. (ii) A positive change in MES appears to correlate positively with SRISK in the next quarter, on a 5% significant level. (iii) A positive change in ΔCoVaR is correlating negatively with both VaR and MES, but positively with SRISK in the following quarter. (iv) SRISK affects itself positively in the next quarter on a 1% significant level.

Further, when evaluating the fundamentals we can see that (v) liquidity does not have any significant lagged relationship with any systemic risk measures. However, the signs are positive, for VAR, MES, and SRISK, which is expected since high asset to liability ratio means that the bank has more muscles to operate in case of a shock. (vi) A positive change in M/B correlates positively with SRISK in the next quarter, on a 5% significant level.

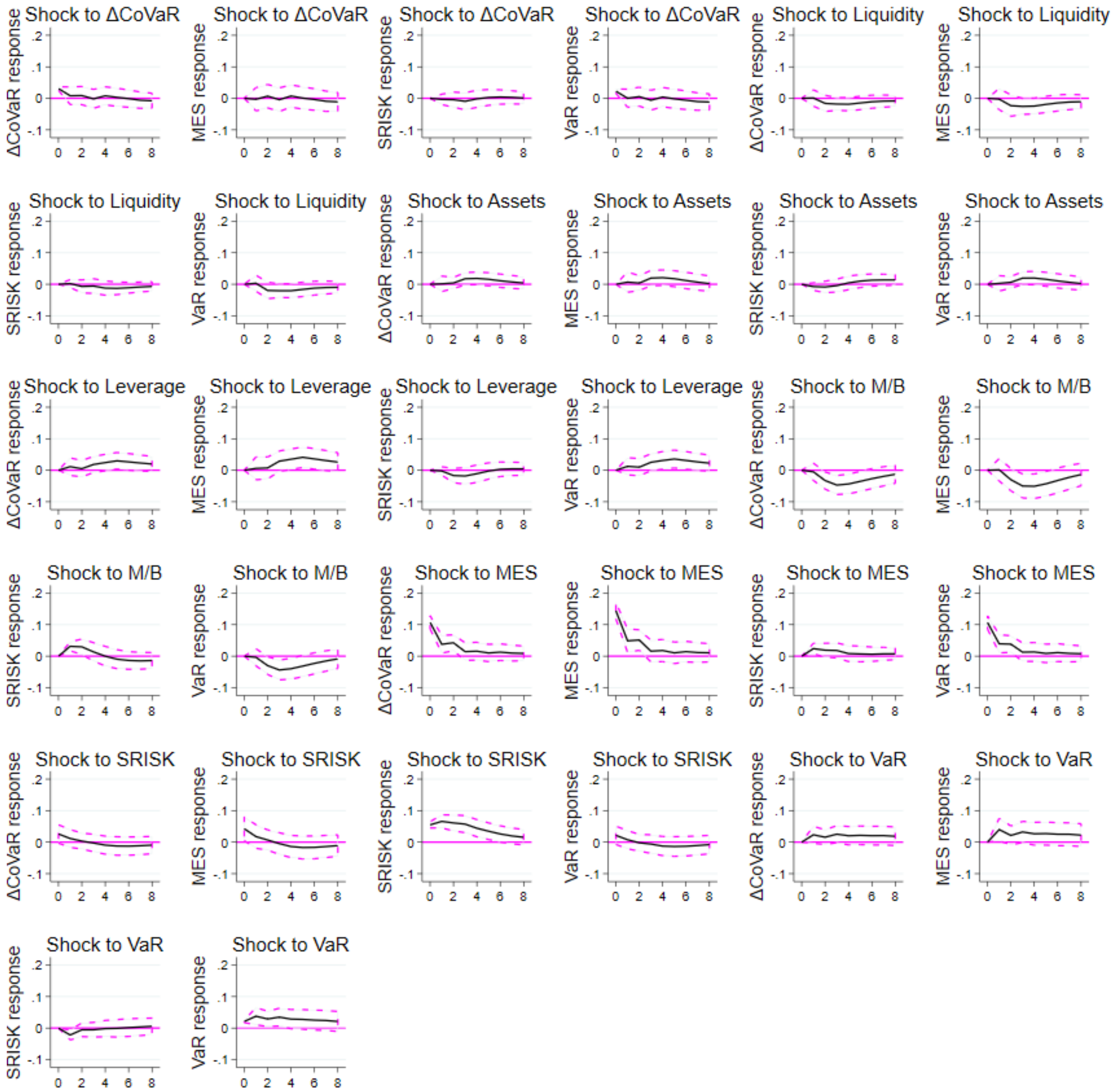

Figure 5-8: Impulse response functions based on the VAR(1)
This figure is based on the VAR(1) model (Table 5-8) with systemic risk measures and fundamentals. The impulse response functions visualise the dynamics and are calculated with 95% confidence level.

The low impact of the fundamentals are quite interesting and at the same time surprising, which could be for various reasons (c.f., Table 5-1). In especially SRISK, the fundamental values play a huge role. In that sense, the relationship seems to work as a direct response, rather than on a lagged relationship. It is difficult to determine how the measures are acting in relation to each other within a quarterly time frame.

To compare the systemic risk measures with each other, fundamental measures are excluded and daily data is being used instead. We fit a VAR(3) model based on FPE, AIC, HQIC, and BIC (i.e., 3 lags correspond to 3 trading days). This Vector Autoregressive model is presented in restricted form in Table 5-9 and is followed by an impulse response function analysis in Figure 5-9.

	VaR_{t-3}	MES_{t-3}	$\Delta CoVaR_{t-3}$	$SRISK_{t-3}$
VaR_t	1.01***	0.05*	-0.36***	0.00
	(0.03)	(0.02)	(0.11)	(0.00)
MES_t	0.10***	0.94***	-0.29**	0.00
	(0.04)	(0.03)	(0.12)	(0.00)
$\Delta CoVaR_t$	0.02**	0.01*	0.83***	0.00
	(0.01)	(0.01)	(0.04)	(0.00)
$SRISK_t$	-0.09***	-0.03	0.45***	0.98***
	(0.02)	(0.02)	(0.07)	(0.00)

Asterisks are used to denote significance at standard significance levels (* p<0.10, ** p<0.05, and *** p<0.01).

Table 5-9: Vector Autoregressive model - VAR(3)
The table reports the average parameter estimates for the VAR(3) model with estimated systemic risk measures. The time series are daily. Standard errors appear in parentheses.

As previously presented, the significant values will be processed and discussed. (i) A positive change in VaR appears to correlate positively with VaR, MES, and ΔCoVaR. However, the model also appears to correlate negatively with SRISK. (ii) A positive change in MES appears to correlate positively with VaR and ΔCoVaR. The model also appears to correlate positively with MES during the next three days, at a 1% significance level. (iii) A positive change in ΔCoVaR appears to correlate negatively with both VaR and MES, whereas it appears to correlate positively with both ΔCoVaR and SRISK.

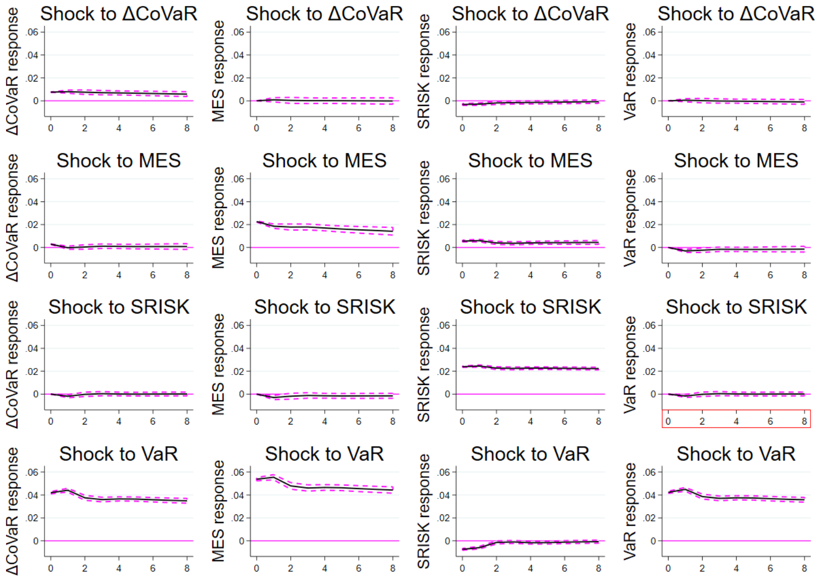

Figure 5-9: Impulse response functions based on the VAR(3)
This figure is based on the VAR(3) model, (Table 5-9), with systemic risk measures on daily basis. The impulse response functions visualise the dynamics of the systemic risk measurses and are calculated with 95% confidence level.

Further, to investigate the relationships and predictive power of the measures we perform a Granger causality Wald test, as can be seen in Table 5-10, which build on the VAR(3) model above. In the Wald test we can see how the excluded variables affect the whole equation for the specific variable. We note that (i) VaR appears to be affected by the previous movement of ΔCoVaR. (ii) MES appears to be affected by the previous movement of both VaR and ΔCoVaR. (iii) ΔCoVaR appears to be affected by the previous movement of VaR. (iv) SRISK appears to be affected by the previous movement of both VaR and ΔCoVaR.

It seems that SRISK does not influence any other measure in their future movement. However, we can see that SRISK is being affected by the previous movement of other measures. This is interesting as we have seen earlier, in Figure 5-1, Figure 5-2, and Figure 5-3, that the movement of SRISK in particular seemed rather independent of the other measures.

Equation	Excluded	Chi^2	df	Prob >Chi^2
VaR	MES	3.78*	1	0.052
	ΔCoVaR	11.03***	1	0.001
	SRISK	0.23	1	0.634
	All	12.82***	3	0.005
MES	VaR	7.12***	1	0.008
	ΔCoVaR	5.51**	1	0.019
	SRISK	0.39	1	0.534
	All	10.97**	3	0.012
ΔCoVaR	VaR	3.88**	1	0.049
	MES	3.37*	1	0.067
	SRISK	0.78	1	0.378
	All	11.23**	3	0.011
SRISK	VaR	14.96***	1	0.000
	MES	2.62	1	0.106
	ΔCoVaR	36.23***	1	0.000
	All	88.90***	3	0.000

Asterisks are used to denote significance at standard significance levels (* p<0.10, ** p<0.05, and *** p<0.01).

Table 5-10: Wald test for Granger causality
This table reports a Wald test for Granger causality based on the VAR(3) for the systemic risk measures.

Based on our results above and that we experience high autocorrelation, the VAR models may not be optimal. To address this, we perform a multivariate linear regression of the systemic risk measures on lagged principal components, by making use of previously calculated values. Again we include 3 lags of the PCs (on daily data), based on AIC, BIC, FPE, and HQIQ, in an attempt to estimate a leading indicator.

	$PC1_{t-3}$	$PC2_{t-3}$	$PC3_{t-3}$	$PC4_{t-3}$	R^2	$AdjR^2$
VaR	5125.58*** (48.88)	-294.23*** (39.98)	-3851.85*** (361.14)	7063.48*** (462.01)	0.90	0.90
MES	5500.33*** (53.19)	-479.17*** (46.34)	7517.56*** (406.15)	2118.28*** (480.95)	0.89	0.89
ΔCoVaR	1639.87*** (16.03)	121.24*** (12.87)	-786.70*** (116.40)	-1720.87*** (147.69)	0.90	0.90
SRISK	307.09*** (19.55)	14750.44*** (27.37)	248.86 (222.68)	-734.08** (285.53)	0.98	0.98

Asterisks are used to denote significance at standard significance levels (* p<0.10, ** p<0.05, and *** p<0.01).

Table 5-11: Lagged principal components on systemic risk measures
This table reports the multivariate linear regression of the systemic risk measures on 3 day lagged PCs, based on the PCA in Table 5-3. Standard errors appear in parentheses.

As presented in Table 5-3, the first and second principal component capture almost all of the variability across the four different measures. Therefore, we are focusing on $PC1_{t-3}$ and $PC2_{t-3}$. We note that there is strong significance and that the R^2 values are high above all systemic risk measures. This is intuitive since the principal components are based solely on the systemic risk measures. SRISK is the systemic risk measure that stands out with an R^2 as high as 0.98, whilst VaR, MES, and ΔCoVaR exhibit values around 0.89–0.90. If SRISK is leading, then the second principal component (PC2) should load positively on the other risk measures sooner than the first principal component (PC1) loads on SRISK. This is not the case, and we can therefore not conclude on a leading indicator.

6 Robustness

Findings from principal component analysis, Herfindahl-Hirschman, and dynamic causality all indicate a smaller fraction of the sample to explain a great share of the results. To test if the results persist despite the assumptions being changed, we will provide a robustness test.

We examine whether a restricted sample can also have an explanatory factor to be compared with the full sample. We run the global measures MES, ΔCoVaR, and SRISK with the original sample and a sample of the 10 largest banks from 2005.

Variable	N	Mean	Std. Dev.	Min	Max	R^2	Correlation
MES small***	3849	14988.5	5443.475	6331.644	47968.45	0.92	0.96
MES original	3849	27693.01	10124.44	12122.38	86978.43		
SRISK small***	3849	69137.57	19687.35	22528.03	109933.6	0.97	0.98
SRISK original	3849	49641.53	14941.26	15957.43	77566.73		
ΔCoVaR small***	3849	6209.016	1851.002	3118.102	17621.65	0.94	0.97
ΔCoVaR original	3849	10597.97	2989.464	5673.198	29174.78		

Asterisks are used to denote significance at standard significance levels (* p<0.10, ** p<0.05, and *** p<0.01).

Table 6-1: Test for robustness
This table shows a comparison of descriptive statistics, R-squared (R^2), and correlations of the two samples. The small sample contains the 10 largest banks as of 2005 (see Appendix A-1). The original sample contains all 69 banks as in the original sample. We report daily, average data over the full sample period, 2005–2019.

As can be seen in Table 6-1, the correlation is very high with values in the range from 0.96–0.98, which consequently also applies to the coefficient of determination (R^2) with values from 0.92–0.97. We interpret the coefficients as plausible and robust, which means that the results from our original sample can be well explained by the smaller sample. We can thus show that the results are similar after the assumptions have changed, and that the systemic risk measures are not particularly sensitive to the sample size.

The models of MES and ΔCoVaR generally generate lower estimates in terms of actual value when compared to the original sample. This is expected due to their low influence on balance sheet data. SRISK incorporates fundamentals and is therefore able to identify a higher extent of the larger firms, leading to higher values in the samples. We can therefore assume that the small sample is generating the results that it is expected to estimate.

There are several directions to extend this work such as changing threshold values (e.g., prudential capital ratio), splitting the sample, evaluate region-based risk (e.g., ranking in geographical areas) etc. However, due to the time constraints, we focus on what is the most important, as a smaller sample would be beneficial as opposed to monitoring the entire STOXX Europe 600 Index.

7 Conclusion

In this paper, we examine systemic risk on the European banking sector with a variety of measures. We find that the systemic risk measures respond to the same economic events. In addition, the indicators show that it was a build-up of systemic risk in the years before the global financial crisis, followed by turbulent times post-crisis. Subsequently, the banks' systemic risk remained at an elevated level, but increased further during the most intense period of the European debt crisis. Although the various systemic risk measures correlate and exhibit similar patterns in the overall systemic risk, they rank banks differently on an individual level. The ranking stability tends to be relatively constant over time for all measures. SRISK exhibits the most persistent ranking, which is expected due to its construction.

The results indicate that quantitative indicators can be used to distinguish systemically important banks from non-systemically important banks, and to rank banks according to their systemic risk. However, identifying systemically important banks with only one indicator is at risk and could lead to premature or incorrect conclusions. The results show that systemic risk is highly dependent on which definitions and criteria used to calculate each indicator. As pointed out in our impulse response analysis we cannot conclude any significant results from the fundamental values for predicting future movements in the cross-sectional measures. We interpret this as it could be explained by direct effects rather than lagged effects. When comparing the systemic risk measures separately, neither VAR nor PCA could identify any leading indicator.

A formalized identification process involves a number of difficult choices regarding which indicators to be used and the relative weight of the various indicators to be given. One risk is that alternative important indicators are omitted in the analysis. Another risk is an over-reliance on that system risk can be measured correctly, even in the perspective of FSB. Systemic risk has a vague definition and, in practice, systemic risk is a complicated and multifaceted concept that is affected by both bank-specific variables, interconnection in different parts of the financial system as well as policy responses.

Many extensions can further increase the understanding of systemic risk and a future area of research may be to develop a method that weave together the information content of various cross-sectional measure into a combined systemic risk measure.

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A Appendix Tables

Bank	Ticker	Country	Weight	MCap (€ Bil.)
HSBC Holdings PLC	HSBA LN	Great Britain	11.58%	141.62
Royal Bank of Scotland Group PLC	RBS LN	Great Britain	6.49%	79.38
UBS AG	UBSN SW	Switzerland	5.77%	70.51
Banco Santander SA	SAN SM	Spain	4.71%	57.54
Barclays PLC	BARC LN	Great Britain	4.45%	54.37
BNP Paribas SA	BNP FP	France	3.91%	47.82
Banco Bilbao Vizcaya Argentaria SA	BBVA SM	Spain	3.64%	44.52
Credit Suisse Group AG	CSGN SW	Switzerland	3.15%	38.51
Lloyds Banking Group PLC	LLOY LN	Great Britain	3.14%	38.39
Deutsche Bank AG	DBK GR	Germany	2.91%	35.54
Societe Generale SA	GLE FP	France	2.75%	33.58
RBS Holdings NV	3577044Z NA	Netherlands	2.74%	33.55
HBOS PLC	HBOS LN	Great Britain	2.72%	33.30
Credit Agricole SA	ACA FP	France	2.69%	32.86
Ageas	AGS BB	Belgium	2.27%	27.69
UniCredit SpA	UCG IM	Italy	2.20%	26.87
Intesa Sanpaolo SpA	ISP IM	Italy	1.95%	23.80
Nordea Bank Abp	NDA SS	Sweden	1.79%	21.90
SanPaolo IMI SpA	SPI IM	Italy	1.64%	19.99
Dexia SA	DXBA GR	Belgium	1.60%	19.62
KBC Group NV	KBC BB	Belgium	1.42%	17.40
Standard Chartered PLC	STAN LN	Great Britain	1.34%	16.33
Danske Bank A/S	DANSKE DC	Denmark	1.26%	15.39
Almanij NV	AMVVP BB	Belgium	1.21%	14.76
AIB Group PLC	AIBD ID	Ireland	1.09%	13.30
Svenska Handelsbanken AB	SHBA SS	Sweden	1.09%	13.27
Bank of Ireland Group PLC	BIRG ID	Ireland	0.97%	11.92
Banco Popular Espanol SA	POP SQ	Spain	0.91%	11.10
UniCredit Bank Austria AG	BACA AV	Austria	0.83%	10.14
Skandinaviska Enskilda Banken AB	SEBA SS	Sweden	0.83%	10.14
DNB ASA	DNB NO	Norway	0.79%	9.70
Erste Group Bank AG	EBS AV	Austria	0.79%	9.63
Swedbank AB	SWEDA SS	Sweden	0.78%	9.52
Mediobanca Banca di Credito Finanziario	MB IM	Italy	0.77%	9.39
Commerzbank AG	CBK GR	Germany	0.75%	9.22
UniCredit Bank AG	HVM GY	Germany	0.74%	9.05
National Bank of Greece SA	ETE GA	Greece	0.68%	8.34
Bank of Greece	TELL GA	Greece	0.68%	8.34
Eurobank Ergasias SA	EUROB GA	Greece	0.65%	8.01
Capitalia SpA	CAP IM	Italy	0.61%	7.48
Banca Monte dei Paschi di Siena SpA	BMPS IM	Italy	0.56%	6.83
Banca Nazionale del Lavoro SpA	BNL IM	Italy	0.54%	6.62
Alpha Bank AE	ALPHA GA	Greece	0.51%	6.23
Banco Comercial Portugues SA	BCP PL	Portugal	0.51%	6.22
Irish Bank Resolution Corp Ltd/Old	ANGL ID	Ireland	0.50%	6.11
Alliance and Leicester Ltd	AL/ LN	Great Britain	0.48%	5.92
Banca Antonveneta SpA/Old	NTV IM	Italy	0.47%	5.75
Banca Popolare di Verona - S.Geminiano e	BPVN IM	Italy	0.45%	5.49
Deutsche Postbank AG	DPB GY	Germany	0.44%	5.37
Banco de Sabadell SA	SAB SM	Spain	0.43%	5.32
Unione di Banche Italiane SpA	UBI IM	Italy	0.43%	5.23
Natixis SA	KN FP	France	0.40%	4.90
Landmark Mortgages Ltd	NRK LN	Great Britain	0.38%	4.69
DEPFA Bank PLC	1340426 D GY	Ireland	0.37%	4.52
Investec PLC	INVP LN	Great Britain	0.33%	4.03
Banco Espirito Santo SA	BES PL	Portugal	0.33%	3.99
GAM Holding AG	GAM SW	Switzerland	0.29%	3.53
Banca Lombarda e Piemontese SpA	BL IM	Italy	0.26%	3.18
Bankinter SA	BKT SM	Spain	0.25%	3.00
Caisse Regionale de Credit Agricole Mutu	CAF FP	France	0.24%	2.99
Piraeus Bank SA	TPEIR GA	Greece	0.22%	2.66
Banca Popolare di Milano Scarl	PMI IM	Italy	0.21%	2.58
Banca Popolare di Lodi SpA	BPI IM	Italy	0.20%	2.41
Banco de Valencia SA	BVA SQ	Spain	0.19%	2.38
Banco BPI SA	BPI PL	Portugal	0.19%	2.30
Emporiki Bank SA	TEMP GA	Greece	0.17%	2.10
Jyske Bank A/S	JYSK DC	Denmark	0.15%	1.88
Close Brothers Group PLC	CBG LN	Great Britain	0.12%	1.52
Valiant Holding AG	VATN SE	Switzerland	0.09%	1.13

Table A-1: STOXX Europe 600 Banks Index
This table consist of the financial institutions included in the STOXX Europe 600 Banks Index as of 2005. The sorting is based on market capitalization in descending order.

Date	Bank	Company event
2005-03-02	Almanij NV	Merge with KBC
2005-12-30	Investec PLC	Headcourter moved to South Africa
2006-04-05	Banca Antonveneta SpA/Old	Delisted
2006-07-25	Banca Nazionale del Lavoro SpA	Merge with BNP Paribas
2006-12-29	SanPaolo IMI SpA	Merge with Banca Intesa
2007-03-29	Banca Lombarda e Piemontese SpA	Merge with Banche Popolare
2007-06-29	Banca Popolare di Lodi SpA	Merge with Banca Popolare
2007-06-29	Banca Popolare di Verona - S.Geminiano e	Merge with Banca Popolare
2007-09-28	Capitalia SpA	Merge with Unicredit
2007-10-02	DEPFA Bank PLC	Merge with Hypo Real Estate
2008-02-15	Landmark Mortgages Ltd	Default
2008-04-24	RBS Holdings NV	Merge into Banco Santander and Fortis
2008-05-19	UniCredit Bank Austria AG	Merge with Unicredit Hypoveiren
2008-09-15	UniCredit Bank AG	Merge with Unicredit Hypoveiren
2008-10-09	Alliance and Leicester Ltd	Merge Banco Santander
2008-12-30	GAM Holding AG	Dropped banking activity
2009-01-14	HBOS PLC	Merge into Lloyds Banks
2009-01-15	Irish Bank Resolution Corp Ltd/Old	Default
2009-05-12	Ageas	Dropped banking activity
2011-08-29	Emporiki Bank SA	Delisted
2013-03-01	Banco de Valencia SA	Merge with Caixa Bank
2014-08-01	Banco Espirito Santo SA	Divided into "bad" and "good" bank
2015-12-21	Deutsche Postbank AG	Merge with Deutsche Bank
2016-12-30	Banca Popolare di Milano Scarl	Merge with Banco Popolare
2017-06-06	Banco Popular Espanol SA	Merge with Banco Santander
2018-12-12	Banco BPI SA	Merge with Caixa Bank
2019-12-02	Dexia SA	State owned

Table A-2: Company events

This table consists of company events that have happened during the sample period(2005-2019). The events are recognized and investigated further when the data for some reason are suddenly disappearing. The main reason in the investigation was due to merger and its typically happening during times of distress.

Bank	VaR	Rank	MES	Rank	SRISK$_{\%}$	Rank	ΔCoVaR	Rank
AGEAS	1.10%	56	0.85%	55	0.00%	54	0.19%	59
AIB Group	2.71%	9	2.12%	17	0.28%	33	0.22%	56
Alliance and Leicester	1.01%	58	0.05%	66	0.29%	32	0.13%	63
Alpha Bank	2.95%	4	1.69%	35	0.00%	52	0.29%	48
Banca Monte dei Paschi di Siena	3.52%	1	2.93%	1	0.91%	23	0.54%	32
Banca Popolare di Milano	2.43%	18	1.58%	40	0.04%	40	0.57%	30
Banco Bilbao Vizcaya	2.09%	36	1.95%	27	0.24%	34	0.88%	7
Banco BPI	1.37%	49	0.54%	59	0.00%	57	0.29%	47
Banco Comercial Portugues	2.23%	28	1.30%	49	0.02%	44	0.42%	43
Banco de Sabadell	1.80%	42	1.46%	45	0.01%	47	0.57%	29
Banco de Valencia	2.03%	37	0.85%	56	0.00%	58	0.13%	62
Banco Espirito Santo	1.08%	57	0.39%	60	0.00%	49	0.23%	54
Banco Lombarda e Piemontese	1.01%	59	1.43%	46	0.00%	48	0.41%	44
Banco Nazionale del Lavoro	0.18%	66	0.16%	62	0.00%	56	0.01%	66
Banco Popolare di Lodi	1.19%	51	1.75%	32	0.03%	43	0.37%	45
Banco Popolare di Verona	1.19%	53	1.78%	31	0.01%	46	0.45%	39
Banco Popular Espanol	1.59%	44	1.28%	51	0.00%	66	0.47%	36
Banco Santander	2.18%	30	2.05%	19	2.87%	13	0.92%	5
Bank of Greece	2.21%	29	1.06%	53	0.00%	67	0.51%	35
Bank of Ireland Group	2.33%	23	1.63%	38	0.57%	28	0.28%	49
Bankinter	2.34%	22	2.00%	22	0.14%	36	0.70%	23
Barclays	2.32%	25	2.20%	9	9.94%	1	0.62%	27
BNP Paribas	2.39%	20	2.22%	8	8.42%	3	0.92%	6
Caisse Regionale de Credit Agricole	1.38%	48	0.61%	57	0.00%	53	0.42%	42
Capitalia	1.30%	50	2.14%	14	0.04%	42	0.45%	38
Close Brothers Group	2.59%	12	2.13%	16	0.00%	59	0.94%	4
Commerzbank	2.97%	3	2.48%	5	4.77%	8	0.72%	21
Credit Agricole	2.56%	14	2.39%	6	8.42%	4	0.84%	11
Credit Suisse	2.17%	32	1.96%	26	4.31%	9	0.86%	9
Danske Bank	2.00%	38	1.53%	43	1.86%	15	0.74%	18
DEPFA Bank	0.99%	60	1.62%	39	1.79%	16	0.24%	53
Deutsche Bank	2.16%	35	1.99%	24	9.73%	2	0.76%	15
Deutsche Postbank	1.96%	39	1.58%	42	0.74%	25	0.57%	31
Dexia	2.55%	15	2.08%	18	3.78%	11	0.13%	61
DNB	2.77%	7	2.17%	12	0.62%	26	0.86%	10
Emporiki Bank	1.42%	47	0.10%	65	0.00%	68	0.25%	51
Erste Group Bank	2.65%	11	2.15%	13	0.56%	29	0.74%	16
Eurobank	2.59%	13	1.29%	50	0.00%	60	0.19%	58
GAM Holding	1.46%	45	2.53%	3	0.00%	61	0.58%	28
HBOS	0.91%	62	0.61%	58	0.00%	62	0.17%	60
HSBC	1.42%	46	1.35%	47	0.49%	30	0.73%	20
Intesa Sanpaolo	2.18%	31	1.65%	36	0.30%	31	0.68%	24
Irish Bank Resolution Corp	1.14%	55	0.35%	61	0.01%	45	0.10%	64
Jyske Bank	2.25%	26	1.72%	33	0.00%	51	0.83%	12
KBC Group	2.42%	19	2.00%	23	0.97%	22	0.62%	26
Landmark Mortgages	0.82%	64	0.15%	64	0.76%	24	0.04%	65
Lloyds Banking Group	1.78%	43	1.52%	44	1.21%	20	0.43%	41
Mediobanca	2.17%	33	1.64%	37	0.00%	64	0.74%	17
National Bank of Greece	3.23%	2	1.97%	25	0.00%	50	0.35%	46
Natixis	2.89%	5	2.50%	4	1.77%	17	0.71%	22
Nordea Bank	2.46%	17	2.13%	15	1.43%	18	0.99%	2
Piraeus Bank	2.66%	10	1.58%	41	0.00%	69	0.23%	55
RBS Holdings	1.19%	52	2.02%	21	5.94%	6	0.44%	40
Royal Bank of Scotland	1.96%	40	1.71%	34	5.21%	7	0.46%	37
SanPaolo IMI	0.63%	65	1.03%	54	0.12%	37	0.25%	52
SEB	2.86%	6	2.54%	2	1.24%	19	0.96%	3
Societe Generale	2.36%	21	2.30%	7	4.18%	10	0.74%	19
Standard Chartered	2.33%	24	2.04%	20	0.08%	38	0.77%	14
Swedbank	2.74%	8	2.20%	10	0.61%	27	0.88%	8
Handelsbanken	2.51%	16	2.17%	11	1.00%	21	1.08%	1
UBS	2.16%	34	1.94%	28	8.14%	5	0.79%	13
UniCredit Bank	1.16%	54	1.81%	29	2.63%	14	0.54%	34
UniCredit Bank Austria	0.98%	61	1.26%	52	0.04%	41	0.27%	50
UniCredit	2.23%	27	1.80%	30	3.25%	12	0.63%	25
Unione di Banche Italiane	1.90%	41	1.34%	48	0.17%	35	0.54%	33
Valiant Holding	0.88%	63	0.16%	63	0.08%	39	0.21%	57

Table A-3: Bank characteristics pre-global financial crisis

This table include results of VaR, MES, SRISK, and ΔCoVaR. The banks is presented in alphabetic order and consists of 66 banks from June 2006 to June 2007.

Banks	VaR	Rank	MES	Rank	SRISK	Rank	ΔCoVaR	Rank
AIB Group	10.80%	1	5.67%	3	0.84%	24	0.86%	35
Alpha Bank	6.03%	7	3.28%	29	0.21%	36	0.59%	42
Banca Monte dei Paschi	3.81%	28	3.23%	32	0.81%	25	0.59%	43
Banca Popolare di Milano	3.77%	30	2.73%	37	0.14%	41	0.88%	34
Banco Bilbao Vizcaya	3.38%	39	3.22%	33	1.47%	20	1.44%	19
Banco BPI	3.37%	40	2.38%	41	0.15%	40	0.73%	37
Banco Comercial Portugues	3.44%	38	2.19%	42	0.30%	33	0.64%	38
Banco de Sabadell	2.67%	47	2.17%	43	0.20%	37	0.84%	36
Banco de Valencia	2.29%	48	1.56%	46	0.02%	48	0.15%	49
Banco Espirito Santo	2.82%	43	1.59%	45	0.17%	39	0.59%	41
Banco Popular Espanol	3.49%	37	3.06%	34	0.35%	32	1.00%	31
Banco Santander	3.54%	36	3.36%	28	3.15%	12	1.50%	13
Bank of Greece	2.71%	45	1.33%	47	0.09%	45	0.62%	40
Bank of Ireland Group	10.48%	2	6.99%	1	0.92%	22	1.24%	26
Bankinter	3.28%	41	2.53%	39	0.14%	42	0.98%	32
Barclays	5.45%	12	4.97%	6	8.37%	3	1.47%	16
BNP Paribas	4.04%	24	3.83%	19	9.39%	2	1.56%	11
Caisse Regionale de Credit Agricole	1.84%	49	0.84%	48	0.06%	47	0.57%	44
Close Brothers Group	2.71%	46	2.01%	44	0.00%	50	0.98%	33
Commerzbank	5.37%	14	4.50%	10	4.42%	8	1.30%	24
Credit Agricole	4.36%	21	4.24%	13	7.46%	5	1.45%	18
Credit Suisse	3.85%	26	3.49%	24	2.45%	14	1.52%	12
Danske Bank	3.77%	29	3.01%	35	1.83%	17	1.40%	20
Deutsche Bank	4.67%	18	4.29%	12	8.16%	4	1.63%	8
Deutsche Postbank	3.68%	32	3.23%	31	1.01%	21	1.07%	29
Dexia	5.32%	15	3.69%	21	2.80%	13	0.28%	48
DNB	5.02%	17	4.21%	14	0.78%	26	1.58%	10
Emporiki Bank	2.74%	44	0.27%	49	0.08%	46	0.48%	45
Erste Bank	5.65%	11	4.89%	8	0.77%	27	1.60%	9
Eurobank	6.29%	4	3.76%	20	0.28%	34	0.45%	47
Handelsbanken	3.84%	27	3.40%	27	0.72%	28	1.66%	7
HSBC	3.55%	34	3.48%	25	4.67%	6	1.84%	2
Intesa Sanpaolo	3.71%	31	3.51%	23	2.03%	16	1.17%	27
Jyske Bank	3.54%	35	2.63%	38	0.09%	44	1.32%	22
KBC Group	7.48%	3	6.12%	2	1.49%	19	1.94%	1
Lloyds Banking	6.12%	6	4.92%	7	4.36%	9	1.48%	15
Mediobanca	3.20%	42	2.46%	40	0.11%	43	1.09%	28
National Bank of Greece	5.87%	9	3.69%	22	0.24%	35	0.63%	39
Natixis	5.97%	8	5.03%	5	2.43%	15	1.48%	14
Nordea Bank	4.30%	22	3.89%	17	1.75%	18	1.74%	3
Piraeus Bank	5.72%	10	3.28%	30	0.17%	38	0.48%	46
Royal Bank of Scotland	6.16%	5	5.24%	4	9.96%	1	1.47%	17
SEB	5.07%	16	4.56%	9	0.90%	23	1.72%	5
Societe Generale	4.25%	23	4.05%	16	4.54%	7	1.33%	21
Standard Chartered	3.96%	25	3.45%	26	0.61%	30	1.31%	23
Swedbank	5.40%	13	4.44%	11	0.71%	29	1.74%	4
UBS	4.53%	19	4.08%	15	4.26%	10	1.67%	6
UniCredit	4.47%	20	3.87%	18	3.77%	11	1.27%	25
Unione di Banche Italiane	3.60%	33	2.94%	36	0.36%	31	1.02%	30
Valiant Holding	0.60%	50	0.08%	50	0.01%	49	0.15%	50

Table A-4: Bank characteristics pre-European debt crisis

This table include results of VaR, MES, SRISK, and ΔCoVaR. The banks is presented in alphabetic order and consists of 50 banks from April 2009 to April 2010.

Bank	Location
Agricultural Bank of China	Asia
Bank of America	United States
Bank of China	Asia
Bank of New York Mellon	United States
Barclays	**Europe**
BNP Paribas	**Europe**
China Construction Bank	Asia
Citigroup	United States
Credit Suisse	**Europe**
Deutsche Bank	**Europe**
Goldman Sachs	United States
Groupe BPCE	**Europe**
Groupe Crédit Agricole	**Europe**
HSBC	**Europe**
Industrial and Commercial Bank of China	Asia
ING Bank	**Europe**
JP Morgan Chase	United States
Mitsubishi UFJ FG	Asia
Mizuho FG	Asia
Morgan Stanley	United States
Royal Bank of Canada	Canada
Santander	**Europe**
Société Générale	**Europe**
Standard Chartered	**Europe**
State Street	United States
Sumitomo Mitsui FG	Asia
Toronto Dominion	Canada
UBS	**Europe**
UniCredit	**Europe**
Wells Fargo	United States

Source: FSB (Financial Stability Board, 2020)

Table A-5: G-SIB list from 2019
Globally Systemically Important Banks (G-SIB) of 2019 in alphabetic order. The list is based on end-2018 data and has been updated yearly since July 2013. The calculation on which firm that is assumed to be systemically important are build on many factors, where size, interconnectedness, and complexity play an extensive part. The method is described further in detail in BCBS (2014).

Bank	VaR	Rank	MES	Rank	SRISK	Rank	ΔCoVaR	Rank
AIB Group	4.09%	8	2.14%	23	0.16%	39	0.33%	41
Alpha Bank	5.12%	3	2.42%	10	0.23%	36	0.50%	38
Banca Monte dei Paschi	4.13%	7	1.91%	34	0.67%	27	0.63%	32
Banco Bilbao Vizcaya	2.56%	31	2.08%	25	2.65%	14	1.08%	7
Banco Comercial Portugues	3.10%	17	1.92%	32	0.29%	32	0.58%	33
Banco de Sabadell	3.61%	12	2.28%	16	1.06%	20	1.13%	3
Banco Santander	2.71%	27	2.26%	17	6.07%	7	1.14%	2
Bank of Greece	2.18%	40	0.93%	40	0.24%	35	0.50%	36
Bank of Ireland Group	4.22%	6	2.77%	5	0.52%	30	0.50%	37
Bankinter	2.71%	28	1.90%	35	0.23%	37	0.81%	24
Barclays	2.79%	22	2.43%	9	6.63%	6	0.74%	29
BNP Paribas	2.72%	26	2.40%	13	11.08%	1	1.04%	8
Caisse Regionale	1.50%	42	0.69%	42	0.11%	40	0.46%	39
Close Brothers Group	2.45%	36	2.02%	27	0.00%	43	0.89%	18
Commerzbank	3.91%	9	3.01%	3	2.53%	16	0.94%	16
Credit Agricole	2.65%	29	2.42%	12	8.48%	2	0.87%	20
Credit Suisse	2.49%	34	2.20%	21	2.96%	13	0.98%	11
Danske Bank	2.97%	19	1.87%	36	2.31%	18	1.10%	5
Deutsche Bank	3.67%	10	2.61%	7	7.53%	3	1.28%	1
Dexia	8.05%	1	0.83%	41	0.88%	22	0.41%	40
DNB	2.77%	23	2.25%	18	0.63%	28	0.86%	21
Erste Bank	2.83%	20	2.25%	19	0.84%	24	0.79%	25
Eurobank	4.34%	5	1.94%	31	0.22%	38	0.32%	43
Handelsbanken	2.34%	37	1.91%	33	0.96%	21	1.00%	10
HSBC	1.84%	41	1.77%	38	7.26%	4	0.94%	15
Intesa Sanpaolo	2.45%	35	2.00%	30	3.14%	12	0.77%	28
Jyske Bank	2.57%	30	1.81%	37	0.36%	31	0.95%	13
KBC Group	2.55%	33	2.06%	26	0.69%	26	0.65%	31
Lloyds Banking	2.75%	24	2.34%	15	3.54%	10	0.66%	30
Mediobanca	2.29%	39	1.55%	39	0.08%	41	0.78%	26
National Bank of Greece	4.97%	4	2.55%	8	0.28%	33	0.54%	35
Natixis	3.54%	13	3.03%	2	2.47%	17	0.87%	19
Nordea Bank	2.73%	25	2.01%	29	2.17%	19	1.10%	6
Piraeus Bank	6.81%	2	3.13%	1	0.28%	34	0.56%	34
Royal Bank of Scotland	3.27%	16	2.77%	4	3.60%	9	0.78%	27
SEB	2.80%	21	2.24%	20	0.86%	23	0.94%	17
Societe Generale	3.07%	18	2.77%	6	6.97%	5	0.96%	12
Standard Chartered	2.55%	32	2.12%	24	2.61%	15	0.84%	23
Swedbank	3.49%	14	2.15%	22	0.69%	25	1.12%	4
UBS	2.33%	38	2.02%	28	3.27%	11	0.85%	22
UniCredit	3.37%	15	2.42%	11	3.83%	8	0.95%	14
Unione di Banche Italiane	3.64%	11	2.38%	14	0.60%	29	1.03%	9
Valiant Holding	1.34%	43	0.46%	43	0.05%	42	0.33%	42

Table A-6: Bank characteristics per 2019

This table include results of VaR and the systemic risk measures MES, SRISK, and ΔCoVaR. The banks is presented in alphabetic order and consists of 43 banks from January 2019 to December 2019.

B Appendix Figures

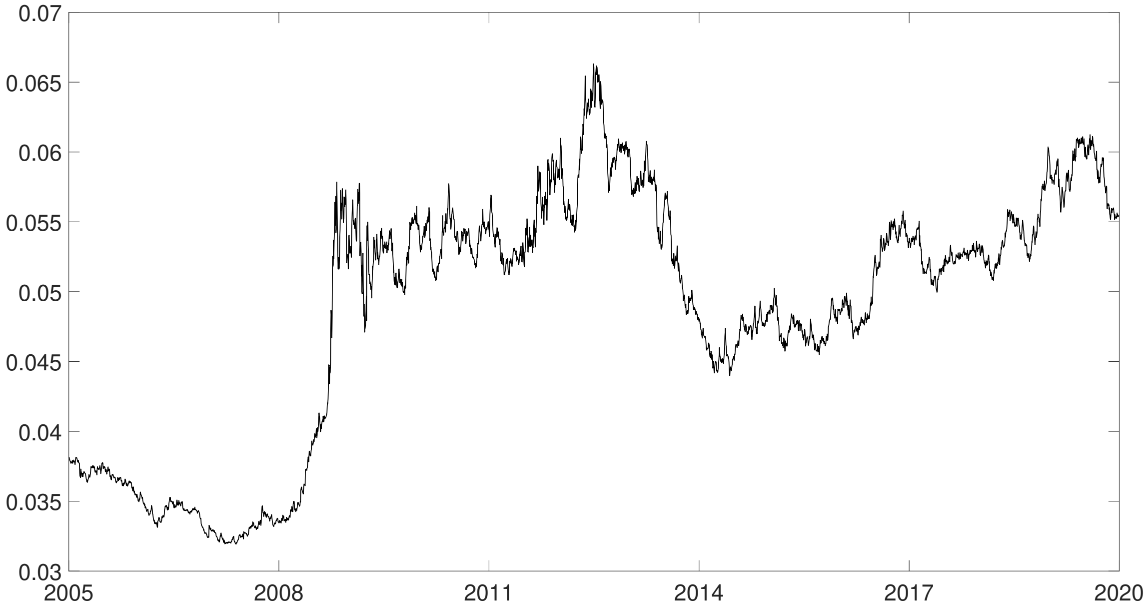

Figure B-1: Herfindahl-Hirschman Index

Herfindahl-Hirschman Index (HHI) is measuring the market concentration and is calculated by summing up all of the squared daily market share percentages of each bank. The closer the HHI-score is to one, the closer a market is to a monopoly and vice versa.