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Comparison and evaluation of systemic risk measures

Master's thesis

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Abstract

The consequences of the global financial crisis unveiled the shortcomings in the regulation and monitoring of systemic risk. The issue with regulating and measuring systemic risk is the fact there are many definitions and consequently many ways to quantify systemic risk. This thesis empirically compares four methods of measuring cross-sectional systemic risk in the European banking system (MES, ΔCoVaR, SRISK and DIP). Furthermore, relations between these measures and the underlying banks' characteristics are investigated using VAR method and panel models. The different measures are shown to be good indicators of systemic risk for the overall banking system, but show differences on individual bank level. The differences can be explained by the underlying inputs of measuring systemic risk. Market-to-book and leverage are found to be important bank variables to consider for regulation, as these ratios drive the systemic risk of one quarter ahead. Other bank characteristics show mixed results across different systemic risk measures, which makes the interpretation rather difficult.

Keywords: systemic risk, risk measures, MES, SRISK, CoVaR, distress insurance premium, financial crisis, banking system

Contents

1 Introduction

The credit crunch, which arose from the bursting U.S. housing bubble in 2006 eventually led to the global financial crisis, causing harm to financial institutions globally. This crisis in 2008, the most severe global crisis since the 1930s, was the cause of many (near-)failures of major financial institutions, including Bear Stearns, IndyMac, Fannie Mae, Freddie Mac and AIG. Governments were forced to intervene and bail out certain firms that they considered either "too big to fail" (TBTF) or "too interconnected to fail" (TITF). They feared that the failure of certain systemically important financial institutions would lead to serious consequences to other firms and the economy. These events renewed the general interest in the definition, measurement and regulation of systemic risk. Systemic risk can be seen as the possibility that an event at the company level can trigger strong instability or a collapse of an entire industry or economy. Governments can then use systemic risk as a reason to intervene in the economy. They can reduce or eliminate spillover effects from company-level events through regulatory measures or other actions.

The financial crisis led to the bailout of AIG. At the time, AIG was considered too big to fail, as many institutional investors were both invested in and also were insured by the company. The institution was bailed out by the Federal government with loans of over $180 billion. It was believed by analysts and regulators that a bankruptcy of AIG would lead to the collapse of numerous other financial institutions. Similar to AIG, Lehman Brothers was also in danger of insolvency. However, the government decided to not bailout Lehman Brothers resulting in the firm's collapse in 2008. The Federal Reserve did not have the funds to loan out money with the risk of losing it in accordance with U.S. regulations. Even though the size of Lehman Brothers was considered too big to fail, the Fed and the U.S. Treasury decided that a failure of Lehman Brothers would not pose large spillover effects. This led to the largest bankruptcy filing in history. Because of the firm's size as well as its integration into the U.S. economy, the negative impact of the collapse was spread throughout the financial system and the economy, leading to a systemic crisis. These events made clear that at the time systemic risk of certain institutions could be highly underestimated by regulators.

The consequences of the financial crisis unveiled the shortcomings in the regulation and monitoring of systemic risk. In response to this, The Basel Committee on Banking Supervision proposed a new regulatory framework, which is referred to as Basel III. The previous Basel Accords (Basel I and Basel II) were primarily focused on the level of loss reserves that banks are required to hold to be able to cover idiosyncratic risks that these banks face. Under Basel II, banks could either adopt a simple methodology that applies relatively high risk weights or invest in internal models that predict the probability of default (PD) and loss given default (LGD) of each loan or security. Since 2007, banks that use internal models have been rewarded with lower aggregate risk weights because regulators wanted to encourage them to invest in better risk management. Basel III introduces two additional capital buffers to cover systemic risk and the risk of a bank-run, requiring different levels of reserves for different forms of bank deposits. Next to Basel III, The Dodd-Frank Wall Street Reform and Consumer Protection Act (Dodd-Frank) and the Solvency II Directive are some of the other regulatory frameworks that intend to reduce systemic risks in the financial system. The Financial Stability Oversight Council (FSOC), which was established by Dodd-Frank, has the duty to identify and monitor risks to the U.S. financial system arising from the distress or failure of large, financial institutions, or from risks that could arise outside the financial system.

Systemic risk can be a threat to a complete economic system. Therefore it is critical for regulators to know in what way individual firms should contribute to managing systemic risk. It is important that the level of regulatory capital of banks are modeled accurately, because it can take away from a bank's efficiency if it holds too much capital. Furthermore, policymakers should look at systemic risks in a complete banking system, as only taking into account risks on individual level can lead to underestimation. To implement successful regulation and monitoring, it is important to know how to accurately measure systemic risk. However, because of its complexity, there is no clear general definition for systemic risk among regulators, academics, practitioners and policymakers. This makes it difficult to find a single appropriate way to accurately measure systemic risk. Any single definition will most likely fall short and consequently any single systemic risk measure will not be able to be the most accurate at all times as the financial system continues to evolve.

The research idea that follows from this is to empirically compare various methods of calculating cross-sectional systemic risk measures, meaning the co-dependence of institutions on each other. The models that regulators choose will implicitly decide their operational definition of systemic risk. Various systemic risk measures should be analysed to be able to work out problems from different directions. It is therefore important to know the commonalities and differences between different systemic risk measures. Benoit *et al.* (2013) conduct a similar research, theoretically and empirically comparing four major systemic risk measures that calculate the marginal contribution of individual firms to total systemic risk (MES, SES, SRISK and ΔCoVaR) for American banks. This thesis will add to their results by also taking into account an additional measure (DIP) and compare the different measures on a data set of European banks. The DIP differs from the previous measures as it is an *ex ante* systemic risk measure for the insurance premium against a systemic event. It is important to note that the most effective ways to measure systemic risk may be ones that use proprietary data that only regulators or central bankers have access to. Academia usually do not have this data, which is why only the measures that require analytics that can be estimated using public market data are considered.

From looking at the analytical expressions, one can look at how different models are calculated and see what the common factors are across these measures as shown by Benoit *et al.* (2013). The different components across these models can show that they have different aims or definitions for systemic risk. Looking at empirical results of different systemic risk measures, we can see whether the systemic risk rankings of financial institutions are similar. Here, we are particularly interested in the Systemically Important Financial Institutions (SIFI), which are identified by the Financial Stability Board (FSB). The globally systemically important banks (G-SIBs) are SIFI banks that contribute most to the financial system and who's collapse could trigger a financial crisis. Different ways to measure and look at systemic risk can lead to differences in ranking in terms of systemic risk contributions. In case of differences, the goal is to explain the ranking differences across the risk measures and look at the main factors that drive these systemic risk rankings. Furthermore, an analysis is done on time series of systemic risk measures and their dynamics for individual banks. Especially for banks that went through a bailout or bankruptcy, it will be interesting to see how different systemic risk measures (co-)move leading up to the event.

Even though there is a lot of literature on quantifying systemic risk and different systemic risk measures, there is not much research on whether these measures are feasible for regulation purposes. Since there is no benchmark to compare systemic risk measures against to check their viability, it is difficult to evaluate whether a measure is working well in practice. Acharya *et al.* (2012) argue that the systemic risk measures based on expected shortfall can be seen as a substitute of the stress tests performed by regulators. Benoit *et al.* (2013) conclude from discussions with central bankers and regulators that systemic risk measures such as MES, SRISK and CoVaR are being used for monitoring of individual firms' systemic risk. As the empirical analysis by Benoit *et al.* (2013) has shown, different systemic risk measures result in different SIFI rankings. This implies that there are fundamental differences between the different measures and that it should not be customary to decide on any individual measure as an input for regulation. Furthermore, a systemic risk measure is only useful for regulatory purposes if it is able to detect systemically important banks before they actually become a systemic threat. A serious downside of the current systemic risk measures is that they give an individual firm's contribution to systemic risk *post hoc*, which makes them not an effective tool for regulators and policy makers. These agents are responsible for identifying the systemically important banks to require additional capital buffers against systemic events. For them, it would be helpful to have leading indicators as a reliable warning for increasing systemic risk. For this reason, we test whether bank-specific variables can act as a leading indicator to the individual systemic risk measures. To the best of our knowledge, analyzing this relation between predictive bank characteristics and systemic risk measures is a novelty that has not been attempted in previous research. The results should show whether a bank's fundamental drivers of value have some predictive power in assessing a bank's systemic risk contribution, which in turn would mean that they should be used for micro-prudential regulation to prevent systemic events. This can also show whether the increased capital requirements, minimum leverage ratio, and the liquidity requirements of Basel III actually help to cover systemic risk.

This research shows that time series analysis of the four systemic risk measures, MES, ΔCoVaR, SRISK and DIP seem to capture systemic events well as their time dynamics show to move as expected compared to major systemic events, especially in crisis times. These measures appear to be good indicators for overall systemic risk in the banking system. Aggregated, these measures also show comparable dynamics over time. On individual level however, differences between the measures become more clear. The systemic risk rankings show varying results across measures, where it is clear that SRISK and DIP hold a bank's size as an important factor. This also leads to these two measures having similar rankings, while pairs with other systemic risk measures show a relatively low commonality in rankings over time. These results show that the systemic risk measures are important for regulators when monitoring systemic risk in the banking system as a whole, but less reliable in identifying the most systemically important institutions.

Afterwards, banks' systemic risk, as defined by the four measures MES, ΔCoVaR, SRISK and DIP, are found to be driven by their market-to-book and leverage ratios. A lower market-to-book ratio or a higher loan-to-deposit ratio of banks leads to an increase in systemic risk in the following quarter. Other bank variables considered, such as the banks' liquidity and performance are found to be not a consistently driving factor of all the systemic risk measures. These results are important novelties for research for regulators to take into account when identifying factors that trigger an increase in systemic risk. They can react on movements in market-to-book and leverage ratios of banks to prevent it from affecting the systemic risk in the banking system. Interestingly, relations between systemic risk measures and bank variables can be different for banks from the PIIGS (Portugal, Ireland, Italy, Greece and Spain) subgroup.

This thesis further consists of a literature review in section 2, which will examine different definitions and measures for systemic risk. Afterwards, the European bank data for the empirical analysis will be discussed in section 3. Section 4 follows with the methodology of calculating the four systemic risk measures and the methods used to analyze relations between these measures and bank variables. The results of the research are presented in section 5 and 6. Section 7 concludes and gives suggestions for further research.

2 Literature review

2.1 Definition of systemic risk

Because of the complexity of systemic risk, there is not one generalized definition for systemic risk and consequently there are many different methods in literature to quantify it. Therefore, it is important to first have a good understanding of the different existing interpretations that exist for systemic risk.

The G10 proposed a working definition of systemic risk in their Report on Consolidation in the Financial Sector (2001) as follows: "Systemic financial risk is the risk that an event will trigger a loss of economic value or confidence in, and attendant increases in uncertainly about, a substantial portion of the financial system that is serious enough to quite probably have significant adverse effects on the real economy." The abstract terms, such as 'a loss in confidence' and 'quite probably' make it difficult to interpret the definition analytically. The Bank for International Settlements (BIS) defines systemic risk as "the risk that the failure of a participant to meet its contractual obligations may in turn cause other participants to default with a chain reaction leading to broader financial difficulties." The definition proposed in the U.S. Commodity Futures Trading Commission Glossary is: "the risk that a default by one market participant will have repercussions on other participants due to the interlocking nature of financial markets." The European Central Bank (ECB) refers to systemic risk in their Financial Stability Review December 2009 as "the risk that financial instability becomes so widespread that it impairs the functioning of a financial system to the point where economic growth and welfare suffer materially." The International Monetary Fund (IMF), BIS and the FSB together (2009) give a definition of systemic risk as 'a risk of disruption to financial services that is caused by an impairment of all or parts of the financial system, which has the potential to have serious negative consequences for the real economy.'

Also in academia, different interpretations of systemic risk can be found. Kaufman and Scott (2003) refer to systemic risk as "the risk or probability of breakdowns in an entire system, as opposed to breakdowns in individual parts or components, evidenced by comovements (correlation) among most or all the parts." Kupiec and Nickerson (2004) define systemic risk as "the potential for a modest economic shock to induce substantial volatility in asset prices, significant reductions in corporate liquidity, potential bankruptcies and efficiency losses." Chan *et al.* (2005) see systemic risk as the possibility of a series of correlated defaults among financial institutions - typically banks - that occur over a short period of time, often caused by a single major event. A formal definition is given by Billio *et al.* (2011) as "any set of circumstances that threatens the stability of or public confidence in the financial system."

This partial collection of definitions for systemic risk is the cause of the many different methods to quantify systemic risk analytically. Various risk measures exist to be able to capture the complexity of the financial system and its risks. The common factor that is clear in each definition for systemic risk is that there is a risk of a trigger event, which led to negative consequences in the economy. However, these risks, trigger events and consequences are often defined differently, and sometimes contradicting. Therefore, one should decide on what exactly is measured, in what frequency and over what observation interval. It is important to know the distinction between triggering events to identify where the systemic risks stem from. A more detailed literature review on the causes of systemic risk and on why systemic risk is especially important in the financial sector can be found in the Appendix.

2.2 Systemic risk measures

Because systemic risk is a concept with various definitions, there are many methods and models proposed by researchers to approach systemic risk. These different methods and models are needed to be able to capture the complexity of the financial system and its risk. According to Brunnermeier *et al.* (2009), a good systemic risk measure should identify the risk on the system by individual systemic financial institutions. Largely, measuring the systemic risk contribution of individual financial institutions can be categorized in two approaches. First, and perhaps the most useful measures, are the ones using proprietary information on positions and risk exposures of the financial institutions. This data is provided by financial institutions to regulators and is therefore not easily accessible to academics. The second category focuses on market data, such as stock returns and CDS spreads, which is publicly available. These market prices are believed to reflect all of the publicly available information about the firms. The focus in this research will lie on the systemic risk measures using public market data.

One way to look at different systemic risk measures is to divide them in two dimensions: the time dimension and cross-sectional dimension (Bisias *et al.*, 2012). The time dimension looks at how the aggregate risk of the whole financial system changes over time, whereas the cross-sectional dimension looks at how systemic risk is allocated over the financial institutions at one given point in time. In the time dimension, the systemic risk stems from positive correlation of the financial system with the economy. This can be reduced by building buffers that are countercyclical. In the cross-sectional dimension, systemic risk arises from the interconnectedness of the financial system and the exposures that come with it. For this problem, one should look at the individual contribution of each financial institution to the overall systemic risk. This allocation of risk among the institution must then be balanced as efficient as possible, to ensure that each institution pays for the risk it imposes on the financial system. Up to this point, there has not been a systemic risk measure that is robust and works well for both dimensions simultaneously.

In this paper, cross-sectional systemic risk measures will be compared empirically. The measures for systemic risk commonly found in literature are:

1. Marginal expected shortfall (MES) (Acharya *et al.*, 2010)
2. ΔCoVaR (Adrian & Brunnermeier, 2011)
3. SRISK (Brownlees & Engle, 2012)
4. Distress insurance premium (DIP), (Huang *et al.*, 2009)

The current paper will be largely based on the methods and findings of Benoit et al. (2013), who compare different cross-sectional systemic risk measures, both theoretically and empirically using data on U.S. financial institutions. They find that the systemic risk measures (MES, SES, SRISK and ΔCoVaR) can be expressed as linear transformations of market risk measures, such as Expected Shortfall (ES), Value at Risk (VaR) and firm betas. They further show that most of the variability of the different measures can be explained by one market risk measure or firm characteristic, such as beta, leverage and liabilities. With their empirical analysis, they try to find concordant pairs between top 10 rankings by systemic risk measures and by firm characteristics at one time period. The systemic risk measures are all methods that measure the potential spillover effects onto other banks or the entire system in case of a systemic event. The disadvantage of these methods is that they lack the additive property, that allows the individual contributions to be consistently aggregated. For this reason, we extend the research with the DIP, which first calculates a systemic risk indicator and then allocates the risk across the individual firms. Furthermore, the DIP takes into account components of risk premium using CDS data, whereas the other three risk measures are based on stock return. Another difference between these methods is that the ΔCoVaR looks at the systemic distress, conditional on the individual institutions in distress, compared to the other three measures that focus on the individual systemic risk contribution conditional on the banking system's distress. The systemic risk measures will be explained in more detail in the methodology section.

Bisias *et al.* (2012) collect various quantitative systemic risk measures found in literature and divide them by data requirements. Some of the categories are macroeconomic measures, network measures, forward-looking risk measures, stress-test measures and the already discussed cross-sectional measures. What these different measures have in common in the way they look at systemic risk is that the financial sector is seen as a portfolio, which consists of financial institutions as individual assets. A more detailed description of other ways to approach systemic risk can again be found in the Appendix.

2.3 Predicting systemic risk

There is a recent development in literature on the predictive power of macroeconomic variables and firm characteristics on systemic risk measures. Varotto & Zhao (2014) introduce a standardised version of systemic risk measures and analyse whether bank balance sheet variables can act as early indicators to this new systemic risk measure. They find that indeed firm characteristics such as size, leverage and growth in assets have predictive power on banks. They find that these variables affect the standardised systemic risk measure differently between US banks and European banks. Adding to bank characteristics, Laina *et al.* (2015) also investigate whether macroeconomic variables can act as leading indicators of systemic banking crises in Europe, and in particular Finland. They find that loan-to-deposit ratios and house price growth rates are the best leading indicators for systemic risk. To our knowledge, there has not been a research on whether the most commonly known cross-sectional systemic risk measures MES, ΔCoVaR, SRISK and DIP can be predicted to some extent, using bank characteristics.

A large portion in literature has attempted to capture the predictability of the macroeconomy using various systemic risk measures, since systemic events on individual level can lead to spillover to the economy. A good systemic risk measure as an input for regulation and policy choices should therefore have some predictive power on the macroeconomy. Giglio *et al.* (2016) examine 19 different measures for systemic risk, as well as a common factor using dimension reduction techniques, on their predictability of macroeconomic shocks. They find that systemic risk measures have significant prediction power out-of-sample in the lower tail of future macroeconomic shocks. Allen *et al.* (2012) also propose an aggregate systemic risk measure, CATFIN, to forecast macroeconomic downturns using bank data. They find that CATFIN can forecast significant declines in economic conditions six months ahead.

3 Data

For this research, the focus will be on the European banking system. For data, public market and book data of European banks will be used. The sample will contain firms that are included in the Stoxx Europe Banks 600 index at some point in the time sample considered. This market capitalization weighted index is made up of a collection of banks across 18 countries in the European region. Next to banks from the Eurozone, this index also consists of systemically important banks in Switzerland and the United Kingdom. The sample data will cover the period between January 2001 until December 2015, which makes the sample exactly 15 years. This allows us to see how the European banks evolved before, during and after the financial crisis. Another criterion for the banks included in our data sample is the size of the firms. In 2013, the European Union decided to follow a single supervisory mechanism (SSM) for banks. The European Central Bank (ECB) leads this SSM by monitoring the financial stability of systemically important banks. The most significant criteria of systemic importance for direct supervision by the ECB is that the value of the bank's assets exceeds € 30 bn. For this reason, the data sample will only include banks with total assets that exceed this threshold at some point during the time sample. This sample further includes banks, which emerge and/or dissolve during the time period. The full sample that results from this consists of 86 banks from 19 European countries.

Daily stock returns of firms and the value-weighted market returns will be taken from Bloomberg. Quarterly bank balance sheet data are taken from Datastream. Table 8 shows the sample banks names and information, including their rank in the sample set by each characteristic. The sample banks have an average total assets over the sample period ranging from € 4.62 bn for Marfin Investment Group to € 169.98 bn for BNP Paribas. Note that the 19 European banks that are identified as a Global Systemically Important Bank (G-SIB) by the FSB are all present in the top 25 in total assets of currently active banks. This shows that indeed size is a very important measure for the FSB to determine systemically important banks. The average leverage ratios, calculated as the market value of total assets (book value of debt + market value of equity) divided by the market value of equity, range from 1.29 for GAM Holding to 465.71 for Dexia. The leverage ratio for Dexia is exceptionally high and results from their large sovereign government bond holdings, which resulted in Dexia becoming the first large casualty of the European sovereign debt crisis in 2011. The average market-to-book ratio (M/B) over the sample period ranges from 0.24 for Santander to 2.60 for Irish Bank Resolution Corporation, which was nationalized in 2009. The average liquidity of banks, for which the loan-to-deposit ratio is used as proxy, ranges from 72.70 for Deutsche Bank to 1724.20 for Bradford & Bingley, a British bank nationalised in 2008 due to the credit crisis. Finally, the average return on assets (RoA) of banks as profitability ranges from -0.69 for Bank of Greece to 9.85% for Almanij, a Belgian bank that merged with KBC Group in 2005. Furthermore, the average 5-year senior unsecured CDS spreads for the 56 available banks are included in the table as an indication of the probability of default, which is needed to calculate the Distress Insurance Premium. This ranges from 24.31 for Capitalia to 1021.31 for National Bank of Greece. The summary statistics of the banks are displayed in Table 1.

Table 1 Summary statistics

	Total assets	Leverage	M/B	Liquidity	Profitability
mean	315,763	15.47	1.32	225.83	0.38
median	117,258	8.08	1.24	156.35	0.13
max	1,699,803	465.71	2.60	1724.20	9.85
min	4,617	1.29	0.24	72.70	-0.69
std dev	423,168	49.41	0.47	242.50	1.46
skewness	1.87	8.96	0.52	4.12	5.53
kurtosis	2.71	81.96	3.08	19.51	31.10
observations	3324	3093	3121	1049	3337

Note This table shows the summary statistics of the averaged bank variables over the 86 European banks across the full sample period January 2001 to December 2015. The total assets are in €m. The leverage ratio is calculated as (book value of debt + market value of equity) divided by the market value of equity. Market-to-book is the ratio of market equity value over the book equity value. The liquidity ratio is calculated by total loans divided by total deposits. Finally, the profitability is defined as the return on assets, which is the net income divided by the average total assets as a percentage. The data is taken from Datastream. All data is on a quarterly frequency, except the liquidity ratio, which is yearly.

To construct the time-varying ΔCoVaR measure, the VSTOXX, German government bond yields and swap rates are taken from Bloomberg to construct macroeconomic state variables. For each systemic risk method, banks are excluded from the data set if the available public data needed to construct a systemic risk measure is less than a year.

4 Methodology

To see how the financial institutions are ranked in terms of systemic risk, we compare the ranking of the top systemically important financial institutions that are identified using each risk measure. For this analysis, the focus here will be on the top 20 financial institutions with the highest contribution to systemic risk, which is close to the number of global systemically important banks (G-SIBs) in Europe defined by the Financial Stability Board (FSB).

The methodology follows from the methods used to calculate the respective systemic risk measures as they are shortly explained below.

4.1 MES

The marginal expected shortfall (MES) is defined as the marginal contribution of one institution to the systemic risk. First proposed by Acharya *et al.* (2010), the MES can be measured by calculating the Expected Shortfall (ES) of the system. Formally, a financial institution's MES is its expected equity loss conditional on the whole financial system (market returns) taking a loss greater than its Value-at-Risk at their α% lowest quantile. The higher the MES of a firm, the higher its individual participation to the overall systemic risk.

Following the definition of ES, the ES of the overall banking system at time t is:

$$ES_{st}(C) = \mathbb{E}_{t-1}(r_{st}|r_{st} < C) = \sum_{i=1}^{N} w_{it}\mathbb{E}_{t-1}(r_{it}|r_{st} < C) \tag{1}$$

where r_{st} and r_{it} are the market return and the returns of firm i at time t. The market return, or the aggregate banking sector return, is the value-weighted average of all banks' returns, $r_{st} = \sum_{i=1}^{N} w_{it}r_{it}$, where w_{it} is the relative market capitalization weight of firm i. Here, the expected shortfall is conditional on the market return exceeding a predetermined threshold C. Then the MES is the partial derivative of the system's ES with respect to the weight of firm i in the system.

$$MES_{it}(C) = -\frac{\partial ES_{st}(C)}{\partial w_{it}} = -\mathbb{E}_{t-1}(r_{it}|r_{st} < C) \tag{2}$$

This partial derivative measures the increase in systemic risk as a cause of a marginal increase in the weight of bank i in the system. The sign is switched to make sure that a higher MES means a higher systemic risk to keep consistent with the other measures.

Acharya *et al.* (2010) then propose an extended concept of the systemic expected shortfall (SES), which measures one financial institution's contribution to systemic risk conditional on times of a systemic crisis. It can be seen as the institution's expected losses in the case that the system as a whole is undercapitalized. This measure is however similar to the SRISK measure in construction, which is why SES will not be included in our further analysis.

4.2 △ CoVaR

This method is based on the concept of VaR, which is the maximum loss within an α%-confidence interval, and was first proposed by Adrian & Brunnermeier (2011). The CoVaR is then the VaR of the financial system conditional on an institution-specific event $\mathbb{C}(r_{it})$.

$$\Pr\left(X_{st} \leq CoVaR_t^{s|\mathbb{C}(X_{it})} | \mathbb{C}(X_{it})\right) = \alpha \tag{3}$$

An institution's contribution to systemic risk is then defined as the difference between CoVaR conditional to the institution being under distress and the CoVaR conditional on the normal state of the institution. Again, the sign is changed for comparison reasons.

$$\Delta CoVaR_{it}(\alpha) = -\left(CoVaR_t^{s|X_{it}=VaR_{it}(\alpha)} - CoVaR_t^{s|X_{it}=Median(X_{it})}\right) \tag{4}$$

This model uses growth rates of market valued total assets as input for the returns of the system and individual institutions. This growth of market valued total assets for institution i is then calculated as:

$$X_t^i = \frac{ME_t^i \cdot LEV_t^i - ME_{t-1}^i \cdot LEV_{t-1}^i}{ME_{t-1}^i \cdot LEV_{t-1}^i} \tag{5}$$

where ME_t^i is the market value of equity of the institution at time t and LEV_t^i is a leverage ratio of book value of total assets over book value of equity. The returns on the market valued total assets of the system is then simply the returns on the average market valued total assets returns of banks.

CoVaR is estimated using quantile regressions. First, the predicted value of the systemic asset returns with an individual bank asset return as explanatory variable in a quantile regression gives:

$$\hat{X}_q^{system,i} = \hat{\alpha}_q^i + \hat{\beta}_q^i X^i \tag{6}$$

for the q^{th} quantile. This quantile q is 50% for the median level. The value at risk then follows by definition, because the value at risk, given X^i is the conditional quantile.

$$VaR_q^{system}|X^i = \hat{X}_q^{system,i} \tag{7}$$

Then, if we have a particular predicted value for $X^i = VaR_q^t$, then the CoVaR measure according to the definition by Adrian & Brunnermeier (2011) follows as:

$$CoVaR_q^{system|X^i=VaR_q^i} := VaR_q^{system}|VaR_q^i = \hat{\alpha}_q^i + \hat{\beta}_q^i VaR_q^i \tag{8}$$

The constant systemic risk measure of bank i for the q^{th} quantile is then:

$$\Delta CoVaR_q^{system|i} = \hat{\beta}_q^i (VaR_q^i - VaR_{50\%}^i) \tag{9}$$

However, the quantile regression gives a $\Delta CoVaR$ measure that is constant over time. To compare with the other systemic risk measures, we use a similar method to compute the time-varying $\Delta CoVaR$, which can be estimated with the use of lagged state variables M_t that contain a lot of information on time variation in asset returns. These state variables are included as conditioning variables. The time-varying $\Delta CoVaR$ metric is computed as follows:

$$X_t^i = \alpha^i + \gamma^i M_{t-1} + \varepsilon_t^i \tag{10}$$

$$X_t^{system} = \alpha^{system|i} + \beta^{system|i} X_t^i + \gamma^{system|i} M_{t-1} + \varepsilon_t^{system|i} \tag{11}$$

from which the estimated values are used to get:

$$VaR_t^i(q) = \hat{\alpha}_q^i + \hat{\gamma}_q^i M_{t-1} \tag{12}$$

$$CoVaR_t^i(q) = \hat{\alpha}^{system|i} + \hat{\beta}^{system|i} VaR_t^i(q) + \hat{\gamma}^{system|i} M_{t-1} \tag{13}$$

From this, the time-varying $\Delta CoVaR$ is given as

$$\Delta CoVaR_t^i(q) = CoVaR_t^i(q) - CoVaR_t^i(50\%) \tag{14}$$

$$= \hat{\beta}^{system|i}(VaR_t^i(q) - VaR_t^i(50\%)) \tag{15}$$

4.3 SRISK

SRISK is a systemic risk measure proposed by Acharya *et al.* (2012) and Brownlees & Engle (2012) who extend the MES to take into account both the liabilities and the size of the financial institution. Similar to the MES, the SRISK index is the expected capital shortfall of a financial institution in the case of a systemic event, which they define as a substantial market decline over a given time horizon. The SRISK of a financial institution depends on its leverage degree, size and its MES. The sum of the SRISKs of the whole financial system represents the potential capital shortfall that the government may be pressured to recapitalize in crisis periods. Brownlees & Engle argue that the calculation of the SRISK is similar to the stress tests that are often applied to financial institutions.

Acharya *et al.* (2012) define SRISK as follows:

$$SRISK_{it} = \mathbb{E}(k(D_{it} + E_{it}) - E_{it} | Crisis) \tag{16}$$
$$= kD_{it} - (1-k)(1 - LRMES_{i,t})E_{i,t} \tag{17}$$

where k is the prudential capital ratio. D_{it} is the book value of total liabilities and E_{it} is the market value of equity at time t. Equation (16) can be interpreted as a company needing enough equity to cover k times total assets to be able to prevent a failure in the case of a crisis period. The $LRMES$ is the Long Run Marginal Expected Shortfall. It is the expected loss of equity value of firm i in the case that the market drops more than a given threshold within the next six months. According to Acharya *et al.* (2012), the $LRMES$ can be approximated as $1 - \exp(-k * MES_{it})$ where MES_{it} is the one day expected loss if market returns are lower than -2%. Here, the parameter k is estimated by extreme value theory and has been found to be close to 18. Assuming the book value of debt will not change considerably in the next six months, the SRISK can be calculated using Equation 17. The higher the SRISK level of a bank, the higher its capital shortfall in times of crisis. A negative value of SRISK implies that the bank has a large enough equity buffer to protect itself against failures. Because we will look at measuring systemic risk, we look at positive values of SRISK as done by Brownlees & Engle (2012):

$$SRISK_{it} = \max(0, kD_{it} - (1-k)(1 - LRMES_{i,t})E_{i,t}) \tag{18}$$

4.4 DIP

The distress insurance premium is an *ex ante* systemic risk indicator proposed by Huang *et al.* (2009) that represents the price of insurance against financial distress. The financial distress is defined as when the financial system's total losses exceed a given threshold. The DIP gives the theoretical insurance premium to be charged to protect against these losses in the next 12 weeks. The marginal contribution of each financial institution to systemic risk is a function of its size, default probability (PD) and forecasted asset return correlations. The PD and asset correlations need to be estimated from CDS spreads and stock price co-movements.

The first step is to calculate the one-year risk-neutral PDs of each individual bank using CDS spreads as follows:

$$PD_{it} = \frac{a_t s_{it}}{a_t LGD_{it} + b_t s_{it}} \tag{19}$$

where $a_t = \int_t^{t+T} e^{-rx} dx$ and $b_t = \int_t^{t+T} xe^{-rx} dx$, LGD the loss given default, s_{it} the CDS spread of bank i at time t and r the risk-free rate.

The second step is to estimate the correlation between the banks' assets. This is done by using

Engle's dynamic conditional correlation (DCC) method (2004) using daily stock return correlation as a proxy for asset return correlation, assuming leverage remains constant in the short-term. This approach is also used by Huang *et al.* (2012). This correlation measure is estimated as follows:

1. Let r_{it} be the daily stock return of bank i at time t, n the number of banks in the sample, the conditional standard deviation is

$$h_{it} = E_{t-1}(r_{it}^2), \qquad r_{it} = \sqrt{h_{it}}\varepsilon_{it},\ i = 1, 2, ..., n$$

2. r_t is a vector of daily returns of all banks on time t, $r_t = (r_{1t}, r_{2t}, ..., r_{nt})'$. Then the conditional covariance matrix of returns is defined as $E_{t-1}(r_t r_t') \equiv H_t$

3. Then the DCC model is as follows:

$$H_t = D_t R_t D_t, \quad \text{with } D_t = diag\left\{\sqrt{h_{it}}\right\}$$

   where R_t is the conditional correlation matrix we need.

For this method, we assume that the conditional covariance matrix of ε's is Q_t. Then $q_{ij,t}$ is its i'th row, j'th column element following the GARCH(1,1) model:

$$q_{ij,t} = \bar{\rho}_{ij} + \alpha(\varepsilon_{i,t-1}\varepsilon_{j,t-1} - \bar{\rho}_{ij}) + \beta(q_{ij,t-1} - \bar{\rho}_{ij})$$

where $\bar{\rho}_{ij}$ is the unconditional correlation between ε_{it} and ε_{jt}. Then the i'th row, j'th column element in the R_t conditional correlation matrix is

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}}$$

R_t is a positive definite matrix, as it is the correlation matrix from the covariance matrix Q_t. Using these statistics, the DCC model is estimated by quasi-maximum likelihood estimation method for robustness to misspecification of the normal distribution. Then, we can model the time-varying conditional correlation matrix R_t using the DCC model and the estimated parameters.

Finally a portfolio is constructed consisting of debt instruments issued by the banks considered, weighted by the liability size of each bank. The risk indicator is then calculated as the risk-neutral expectation of portfolio credit losses that equal or exceed a certain threshold level of the total liabilities. Based on the inputs of risk-neutral PDs, correlations and liability weights, the systemic risk indicator can be calculated by Monte Carlo simulation. The simulation is based on Tarashev and Zhu (2008). The first part is to calculate the probability distribution of joint defaults, which is done as follows:

1. Obtain an $N \times 1$ vector of default thresholds using the $N \times 1$ PDs and the assumption that

asset returns are standard normally distributed.

2. Draw an $N \times 1$ vector from N standard normal variables of which the correlation matrix is equal to the asset return correlation matrix. The number of values in this vector that are smaller than the default thresholds are the number of simulated defaults for each draw.

3. Repeat this many times (500,000) to derive the probability distribution of the number of defaults. Shown as $\Pr(nd = k)$, where $k = 0, 1, ..., N$ and nd is the number of defaults.

The second simulation is to incorporate the LGD distribution to compute the probability distribution of portfolio losses.

1. For a given number of defaults k, draw LGDs for the default exposures 1,000 times and compute the conditional loss distribution, $\Pr(TL|k)$ with TL the total losses.

2. Do this for each $k = 1, ..., N$ and calculate the unconditional probability distribution of portfolio losses as

$$\Pr(TL) = \sum_k \Pr(TL|nd = k) \cdot \Pr(nd = k) \tag{20}$$

3. Using this unconditional distribution of losses, calculate the probability of an event that the total losses are higher than $\alpha\%$ of the total banking system liabilities. Here, we define that a distress as a default of $\alpha\%$ of total liabilities in the financial system, for which the authors use 15%. The DIP is calculated by multiplying the probability with the expected losses conditional on an event that the losses are above 15% of the total banking system liabilities.

Huang *et al.* (2011) then propose a way to decompose the systemic risk into marginal risk contributions of individual banks. Each marginal risk contribution is then the bank's expected loss conditional on a large loss for the banking system. Here, the marginal contribution to the systemic risk indicator, the distress insurance premium is:

$$\frac{\partial DIP}{\partial L_i} = E(L_i | L \geq L_{min}) \tag{21}$$

where L is the loss of the whole system and L_i the loss of bank i. This method is similar in calculating the marginal expected shortfall as they both look at a bank's losses conditional on the system falling below a certain threshold level. The sum of these marginal contributions is again the total systemic risk, which allows for an easier risk allocation over individual banks for regulators. To be able to include the effect of size directly, we follow Black *et al.* (2015), using banks' total liabilities as weights to calculate the marginal contribution of the DIP.

4.5 Implementation

To calculate the different systemic risk measures, certain variables and settings must be decided on appropriately. To be able to compare these different systemic risk measures, a common framework is needed. For MES, we set the treshold C as the 5% quantile of the market returns. The losses of the banking system L, to calculate the marginal contributions of the DIP measure, will be set to 10% as done in Huang *et al.* (2011). To calculate the ΔCoVaR measure, 5%-quantile regressions are used. The state variables included for the quantile regressions are:

1. VSTOXX, an implied volatility index based on European option prices
2. Liquidity spread, difference between the 3-month repo rate and 3-month German government bond yield. Measures short-term liquidity risk
3. First differences of the 3-month German government bond yield
4. First differences of the slope of the yield curve, proxied by the yield spread between the 10-year and 3-month German government bond yield.
5. Simple returns on the market, STOXX Europe 600
6. The real estate sector returns in excess of the market returns

These variables should contain sufficient information on the time variation in asset returns. For the SRISK measure, a prudential capital ratio k of 8% is taken, which follows from the papers of Brownlees & Engle (2012) and Acharya *et al.* (2012). To calculate the DIP, the loss given default is set to 55% as recommended by the Basel Accord. The 10-year Germany government bond yield is taken as a proxy for the risk-free rate.

For this research, the rolling h-day horizon, which is needed to calculate the different systemic measures over time, is set to one quarter (or 65 days) for all four measures.

4.6 Systemic risk rankings

The commonalities between the different average systemic risk measures can be analyzed by looking at the correlations between the daily time series levels of the measures. Furthermore, a principal component analysis (PCA) on these time series gives more insight on the common variation across these four measures. One can also compare the systemic risk measures on the firm level, by looking at the commonalities between the systemic risk rankings of different measures. The differences in rankings can be displayed by calculating the concordant pair percentage between two measures. This percentage is calculated as

$$\frac{\#\text{concordant pairs}}{n(n-1)/2} \tag{22}$$

where a pair of two banks are concordant if the order of the two banks are the same in both systemic risk measures.

4.7 Evaluation with bank variables

To test whether bank balance sheet data have some forecasting power regarding the different systemic risk measures, we need a reasonable selection of bank-specific variables. The first bank variable that will be considered is the leverage ratio, calculated by the market value of total assets divided by the market value of equity. This leverage ratio, aggregated over all banks, can be seen as the banking system's financial strength against systemic events. A second variable to consider is the market-to-book (M/B) ratio, calculated as the market equity value over its book equity value. A high M/B-ratio typically means a high average return of the firm, whereas a low M/B-ratio signifies a firm in relative distress. Therefore, a relatively low average M/B-ratio should pair with the banking system's aggregate systemic risk. The last variable is the loan-to-deposit (L/D) ratio. This is a ratio often used to proxy the liquidity of a bank. Liquidity is an important factor for Basel III as it defines how much liquid assets should be held by financial institutions. Banks are required to hold sufficient highly-liquid assets to cover unforeseen short-term debt. Holding too much however, means that banks are less able to lend out short-term debt. At aggregate level, this means that a high L/D-ratio signifies a short of liquidity in a systemic crisis. Finally, return on assets (RoA) will also be considered as a measure of profitability to see whether a bank's performance is linked with its systemic risk.

For this analysis, we will look at the correlation and the vector autoregression (VAR) model to see whether the balance sheet variables have a relation and can to some extent forecast the systemic risk measures. Using the VAR model gives the possibility to see possible relations in both directions, which could give new insights. The p^{th} order VAR model, VAR(p), explains the evolution of z_t, which is a $k \times 1$ vector consisting of k variables, and can be written as

$$z_t = c + A_1 z_{t-1} + A_2 z_{t-2} + ... + A_p z_{t-p} + e_t, \tag{23}$$

where p is the number of lags, c is a vector of intercepts, A_i are time invariant $k \times k$ matrices containing coefficients of the lags and e_t a $k \times 1$ vector of error terms. To determine the optimal number of lags for the VAR, we look at the models with the lowest Akaike information criterion (AIC) and Schwarz information criterion (BIC). Because of the fact that the bank balance sheet data are reported quarterly for most banks, the regressions are performed on quarterly basis.

Yearly data for liquidity will be linearly interpolated, whereas quarterly averages are calculated for daily time series of the systemic risk measures. The time series first have to be tested for stationarity, using the Augmented Dickey-Fuller test.

A panel analysis using data on each individual firm information and over time is also used. This panel model is as follows:

$$y_{it} = \alpha_i + \beta' X_{i,t-1} + \varepsilon_{it}, \tag{24}$$

where y_{it} is the dependent variable, one of the four systemic risk measures, for bank i at time t, $X_{i,t-1}$ the explanatory variables lagged one quarter, α_i the time-invariant individual effects of each bank, and ε_{it} the error term. Because we allow for the errors to be possibly correlated with the bank variables (X_i), we have to use a fixed effects estimator to deal with this endogeneity. The fixed effect component α_i, which is a random unobserved variable, captures a time-invariant unobserved heterogeneity across banks. The fixed effects model is transformed to remove this fixed effects component to be able to consistently estimate the general relation between systemic risk and bank variables (β). This within-transformation is done as follows:

$$y_{it} - \bar{y}_i = (\alpha_i - \alpha_i) + \beta'(X_{i,t-1} - \bar{X}_i) + (\varepsilon_{it} - \bar{\varepsilon}_i) \tag{25}$$

$$y^*_{it} = \beta' X^*_{i,t-1} + \varepsilon^*_{it} \tag{26}$$

where $\bar{y}_i = \frac{1}{T}\sum_{t=1}^{T} y_{it}$ and likewise for $\bar{\alpha}_i$ and $\bar{\varepsilon}_i$. The model is then estimated by OLS of y^*_i on $X^*_{i,t-1}$. To account for the fact that not every bank has available data over the complete time period, we omit the time points with missing data in the panel data regression.

An important assumption of a fixed effects panel model is that the individual effect and the bank variables are possibly correlated. If this is the case, the OLS estimations are biased and inconsistent. Furthermore, the standard errors of the estimator are incorrect, which means that statistical inference on these standard errors are invalid. Bertrand *et al.* (2004) show that conventional standard errors are largely understated if there is indeed autocorrelation in the errors. To combat possible heteroskedasticity and autocorrelation in the error terms, Newey & West (1987) propose a non-parametric covariance matrix estimator which produces robust standard errors that are heteroskedasticity and autocorrelation consistent (HAC). Since we are using panel data, combining both cross-sectional and time series data, the residuals from cross-sectional firms can also be correlated with each other. Driscoll and Kraay (1998) build on the estimation technique by Newey & West, to also account for this so-called spatial correlation in panel data models. Therefore we use the Driscoll and Kraay standard errors for the estimated coefficients in our panel models to account for spatial (or cross-sectional) correlation and to make our statistical results more reliable. These standard errors are slightly adjusted for it to be able to be used on unbalanced panel data. The method to obtain these standard errors are explained in the Appendix. To test for joint significance on multiple parameters, the Wald test is used to see whether a (sub-)set of estimated parameters are jointly different from zero.

5 Empirical results - Comparing systemic risk measures

The results for the four systemic risk measures over the past fifteen years for European banks are shown in figure 2. The graphs show the DIP measure and the average ΔCoVaR, MES and SRISK over the sample banks to show the overall movement of systemic risk over time.

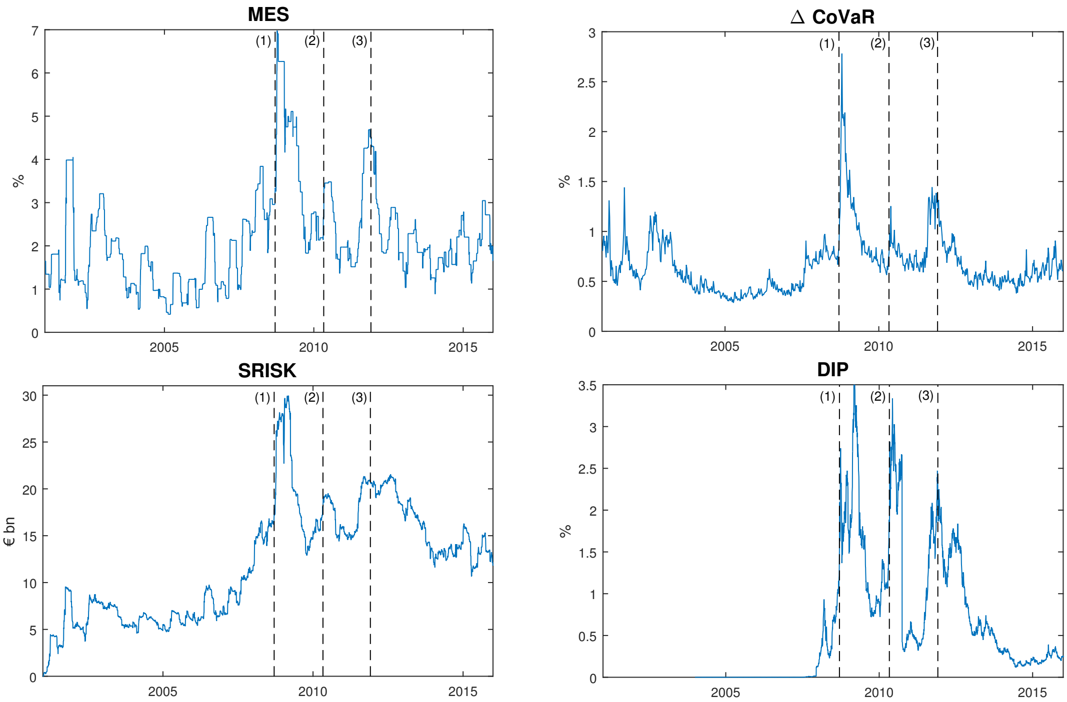

Figure 2: Time series of average systemic risk measures
This figure shows weekly time series of the systemic risk measures from January 2001 to December 2015. For MES, ΔCoVaR and SRISK, these are averages of the measures over the 86 sample banks and DIP shows the total Distress Insurance Premium. MES, ΔCoVaR and DIP are shown in percentages, whereas SRISK is shown in € bn. The vertical dashed lines are times of major events in the financial crisis and the European debt crisis. (1) September 15$^{\text{th}}$, 2008: Lehman Brothers bankruptcy. (2) May 2$^{\text{nd}}$, 2010: Greek government bailout (3) November 30$^{\text{th}}$, 2011: Federal Reserve, ECB and European central banks lower dollar swaps.

Before the comparison between the different systemic risk measures, it is good to confirm that they are each working appropriately to monitor how systemic risk have changed over the past fifteen years. This can be done by comparing the systemic risk time series results with systemic and economic events as well as results found in literature. Since European data is used, compared to U.S. data in most research papers on these systemic risk measures, differences can be a result of systemic events on a local level.

Note that the graph for the distress insurance premium has missing data until the start of 2004. This is due to a lack of availability in CDS data from Datastream for different banks. From 2004 on, the DIP remains relatively close to zero until the end of 2007 and the start of 2008. Overall, spikes in systemic risk are common across all four measures can be seen, most notably during the time of the global financial crisis of 2007 and 2008 and following the European sovereign debt crisis of 2010. This makes sense as the global financial crisis led to the collapse and spillover of many global systemically important financial institutions. The European sovereign debt crisis led to failures and bailouts of many European banks, namely in Portugal, Ireland, and Greece. The different systemic risk measures reach common peaks around the time of two systemic events with large impact on the European banking system, the Lehman Brothers bankruptcy and the Greek government bailout. The systemic risk starts to stabilize after the central banks lowered swap rates to increase liquidity in the banking system. The spikes at time of systemic events show that the systemic risk measures seem to be able to give a broad indication on the actual level of systemic risk. The most important result is that all four measures, which are constructed from very different methods using different input, generally show the same movements. The ΔCoVaR measure seems to be more sensitive to other factors, such as systematic risk, than solely systemic risk, compared to the other measures, as it is showing a lot of short-term movement.

Table 2 shows the correlation matrix between the different systemic risk measures over the complete time sample. Especially between MES and ΔCoVaR (81.9%) and SRISK and DIP (83.1%) are shown to have a strong positive relation. These high correlations confirm the common movements in these measures. Using a principal component analysis (PCA), one could summarize these risk indices to construct a measure to better capture systemic risk and reduce noise of other factors affecting the individual systemic risk measures. This PCA is performed on the correlation matrix of the systemic risk measures, since the scales of the measures are very different. The principal components of the standardized systemic risk measures are displayed in table 3 and show that the first principal component captures 84.02% of variability across the four underlying measures. The constructed index, the first principal component, is shown in the Appendix.

Table 2 Correlation matrix

	MES	ΔCoVaR	SRISK	DIP
MES	1.000***	0.819***	0.728***	0.750***
ΔCoVaR		1.000***	0.590***	0.743***
SRISK			1.000***	0.831***
DIP				1.000***

Note This table shows pairwise correlations between the daily time series of the systemic risk measures MES, ΔCoVaR, SRISK and DIP. For MES, ΔCoVaR, SRISK, the average over the 86 sample banks is taken. The time series run from Q1 2001 to Q4 2015, where the DIP only has observations available from Q1 2004.

Figure 3 zooms in on the great financial crisis period and shows the movement of the systemic risk measures. The plot also shows major events that happened during the crisis that are expected to have had an impact on the overall European banking systemic risk. The systemic risk measures generally seem stable before the crisis. Then they start increasing, where the measures reach a peak at the time of the Bear Stearns acquisition. The failure of Bear Stearns came with increased

Table 3 PCA eigenvalues and variance

Component	Eigenvalue	Variance %	Cumulative %
1	3.481	84.02	84.02
2	0.340	8.21	92.23
3	0.194	4.69	96.92
4	0.128	3.08	100.00

Note This table shows the eigenvalues, the explained variance and cumulative explained variance for each principal component. These components are calculated by PCA of the systemic risk measures MES, ΔCoVaR, SRISK and DIP. For MES, ΔCoVaR, SRISK, the average over the 86 sample banks is taken. The time series run from Q1 2001 to Q4 2015, where the DIP only has observations available from Q1 2004.

systemic risk since it would most likely affect the banking system and the real economy due to its high level of interconnectedness. This is also the reason why the Federal Reserve Bank decided to provide bailout loans. The effect of this can be seen in the four systemic risk measures as they seem to stabilize until the time of the failure of Lehman Brothers. The MES and ΔCoVaR start steadily declining shortly after the default, whereas the SRISK and DIP reach a second peak at the time of the 2009 G20 London summit. During this summit, it was agreed that systemically important firms would be subject to stricter regulation and oversight, which has helped to stabilize the market. Afterwards, it is clear that the bank systemic risk starts improving and show a downward movement.

The time series of the systemic risk measures during the European sovereign debt crisis are displayed in figure 4. After the decrease of systemic risk at the end of the great financial crisis, the systemic risk measures seem relatively low and stable. On May 2$^{\text{nd}}$, the day of the announcement that the Greek government would receive a bailout package worth € 110 bn in the following three years, the systemic risk reached a peak according to all four measures. The indicators start seeing sharp increases again in the middle of 2011, when the market had increased fear for potential spillovers to other European sovereigns, namely Spain and Italy. The results for the European Union bank stress tests were published in July 2011, in which five Spanish, two Greek and one Austrian banks had failed. This led to the second peak, for which the timing is also in line with the height of the European sovereign debt crisis. To combat this increasing systemic risk and the debt crisis, the ECB, Federal Reserve and other central banks decided to increase liquidity in the financial markets by lowering the swap rate between the dollar and other currencies by 50 basis points. The effects of this measure by the central banks can also be seen in the time series of systemic risk as they start decreasing afterwards. The increased liquidity of the central banks in its turn led to the commercial banks to stay healthy as their liquidity in other currencies were stable. Afterwards, the 'whatever it takes' speech of Mario Draghi returned the market trust in the eurozone economies and further stabilized the European banking system. This can be seen in the systemic risk measures as they start decreasing from this point on.

These results show that the overall movements of systemic risk is similar across measures. Compared to what we would expect of how economic events affect systemic risk in the banking system, the dynamics of the systemic risk measures seem to make sense and empirically prove that they are good indicators for monitoring systemic risk. However, zooming in, it can be seen that there are differences in the short-term movements, which makes sense as they are calculated differently and use different definitions and input data. The systemic risk measures and their differences in dynamics will be compared in more detail in this section.

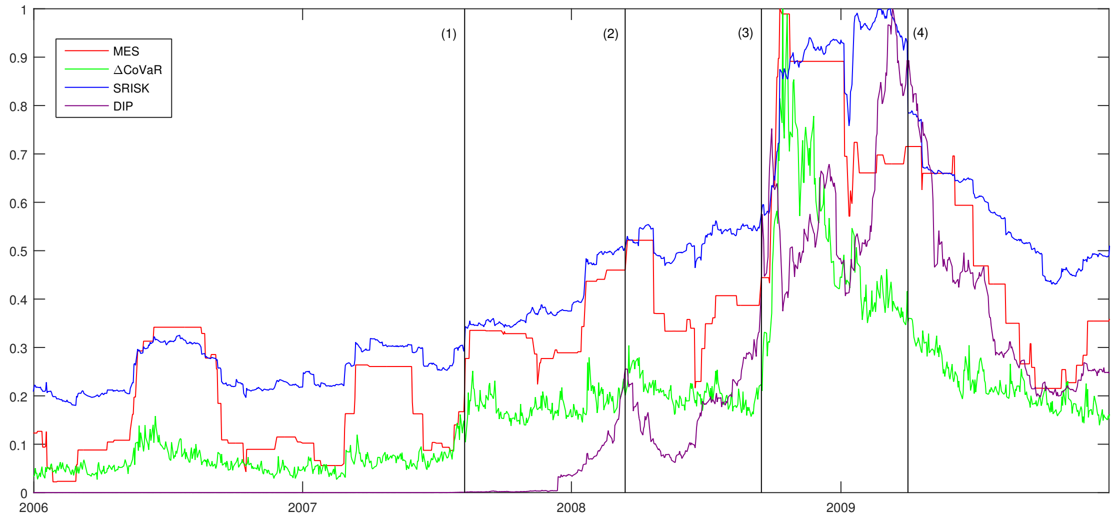

Figure 3: Time series of average systemic risk measures during the great financial crisis
This figure shows weekly time series of the systemic risk measures from January 2006 to December 2009. For MES, ΔCoVaR and SRISK, these are averages of the measures over the 86 sample banks and DIP shows the total Distress Insurance Premium. The observations are normalized over the complete time sample to adjust the scaling for comparison reasons. The vertical black lines are times of major events in the financial crisis. (1) August 9th, 2007: BNP Paribas freezes funds for three hedge funds. (2) March 14th, 2008: Bear Stearns bailout and merger. (3) September 15th, 2008: Lehman Brothers bankruptcy. (4) April 2nd, 2009: G20 London summit.

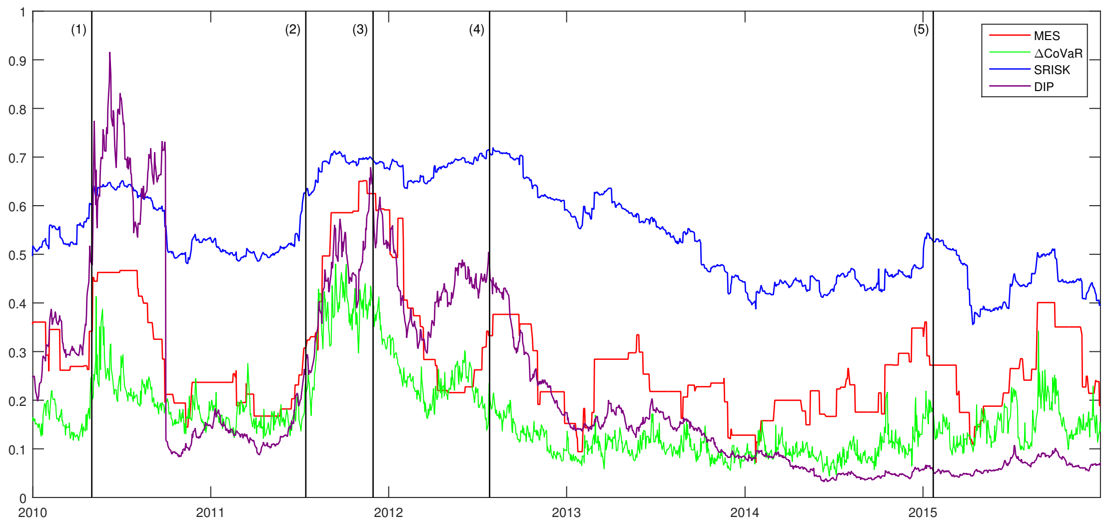

Figure 4: Time series of average systemic risk measures during the Euro sovereign debt crisis
This figure shows weekly time series of the systemic risk measures from January 2010 to December 2015. For MES, ΔCoVaR and SRISK, these are averages of the measures over the 86 sample banks and DIP shows the total Distress Insurance Premium. The observations are normalized over the complete time sample to adjust the scaling for comparison reasons. The vertical black lines are times of major events in the Euro sovereign debt crisis. (1) May 2nd, 2010: Greek government bail-out. (2) July 15th, 2011: European Banking Authority releases EU bank stress test results. (3) November 30th, 2011: Federal Reserve, ECB and European central banks lower dollar swaps. (4) July 26th, 2012: Mario Draghi's 'whatever it takes'. (5) January 22nd, 2015: ECB announces government bond-buying program of at least € 1.1 tn total.

5.1 Comparison of systemic risk rankings

To see whether different systemic risk measures result in similar results, one can look at the systemic risk rankings of banks at one point in time. Table 8 shows the top 20 results of the systemic risk rankings for each risk measure on the last time point in our sample, December 31st, 2015. The first thing we note is that there seems to be no clear pattern across the different risk measures. Each ranking contains different banks and it is not possible to infer which banks carry more systemic risk than others due to the differences across rankings. There is not a single bank that is present in the top 5 ranking of all four systemic risk measures simultaneously at this time point. Furthermore, we see in the rankings for SRISK and DIP, the banks identified as containing the highest systemic risk tend to be the larger banks of the sample, such as BNP Paribas, Deutsche Bank and Credit Agricole. This makes sense as many definitions of systemic risk, as well as the Basel Committee, consider the size of a financial institution as one of the most important factors of systemic risk. The SRISK and DIP also take the size of the bank as an important factor in calculating the measures. Size seems to be of less importance in the rankings of the other two risk measures. The MES shows two Greek banks (National Bank of Greece and Piraeus) as the ones with the highest systemic risk. Greek banks at this time are under high pressure of default as a result of the bank-runs in Greece following the Greek government debt crisis.

To clarify that the ranking differences between measures is not only the case at one specific time point, Table D in the Appendix shows the rankings for a different time point (December 31st, 2010), from which we can draw the same conclusions. The different rankings especially become clear from figure 5, which shows the percentage of concordant pairs of banks between two systemic risk measures. The average concordant pair percentage over time for each pair of measures, apart from the pair SRISK and DIP, are respectively 53.7%, 62.9%, 60.0%, 55.9%, 57.3%. This means that about 40% of the banks are ranked in an opposite order in one systemic risk measure compared to another. For regulators using these measures, it is therefore hard to determine which banks carry more systemic risk based on one method. Only the SRISK and DIP seem to return very similar rankings, with an average of concordant pair percentage of 93.5%, as banks' size is an important influence for both methods. This is due to the fact that both of these measures hold banks' size as an important input in measuring its systemic risk contribution. The MES and SRISK show a relatively high concordant pair percentage. This can be explained by the fact that the SRISK is an extension of the MES, for which MES is used to approximate the long run marginal expected shortfall (LRMES). This LRMES is used as an input for SRISK, which leads to more similar rankings between these two measures.

To check whether the systemic risk measures individually are stable over time, one can look at the Kendall rank correlation coefficient, taking observations at of all banks at time t and of time $t-1$

as a pair for each systemic risk measure. This coefficient is calculated as

$$\tau = \frac{(\#\text{concordant pairs}) - (\#\text{disconcordant pairs})}{n(n-1)/2}. \tag{27}$$

where a pair is called concordant if the order of the two banks are the same at both time t and $t-1$ and disconcordant if one bank is higher (lower) in the ranking at time t but lower (higher) in the ranking at time $t-1$. The correlations are all significant over time according to the Student's t-test. The correlations seem to be very high, with averages of 96.7%, 95.8%, 99.3% and 99.8% for the MES, ΔCoVaR, SRISK and DIP measures. These high levels of Kendall rank correlations mean that the rankings of the individual systemic risk measures do not change much on a day-to-day basis. This proves that the individual measures are stable over time and that therefore the differences in ranking across measures are the result of the underlying differences in the definitions or inputs of the systemic risk measures. This is a desired result, as the systemically important banks identified by each individual measure should not change drastically on a day-to-day basis.

The result that there is no clear pattern across different systemic risk measures is in line with the systemic risk rankings of American banks, found by Benoit *et al.* (2013). This paper takes a different approach to look at commonalities of the rankings between pairs of measures, by looking at the top 10 SIFI rankings identified by each systemic risk measure and analyzing whether these institutions are present in both rankings. They find that there is indeed a low commonality between the top 10 systemic risk rankings of MES, ΔCoVaR and SRISK. For MES and SRISK, they find that on average, roughly two institutions are commonly present in the top 10 rankings for pairs of these measures. The conclusion that follows from their results is consistent with our results, since in both analyses, the differences in the order of the rankings makes it difficult to fully determine which banks are responsible for the most systemic risk.

This raises the question whether the existing systemic risk measures can explain the actual individual contributions to systemic risk in the banking sector, since they all yield different results. It is especially difficult since there is no true indicator of systemic risk and therefore no 'real' systemic risk to compare the different methods with. It is possible that a combination of these different results, that approach systemic risk in different ways, can complement each other in monitoring the real systemic risk in the banking system. Perhaps even completely new methods are needed for regulators to give a better indication of which banks carry more systemic risk than others.

Table 4 Systemic risk rankings

Ranking	MES	ΔCoVaR	SRISK	DIP
1	National Bank Of Greece	ING	BNP Paribas	HSBC
2	Piraeus Bank	Raiffeisen Bank Intl.	Deutsche Bank	BNP Paribas
3	Allied Irish Banks	Credit Suisse	Credit Agricole	Deutsche Bank
4	Investec	Banco Santander	Banco Santander	Credit Agricole
5	Banco Portugues Invest.	Deutsche Bank	Commerzbank	Banco Santander
6	Banca Monte Dei P.S	Caixabank	ING	Royal Bank of Scotland
7	Banca Carige	Nordea Bank	Credit Suisse	Lloyds Banking Group
8	Banca Popol Emilia Rom.	UBS	Natixis Banques Popul.	UBS
9	Deutsche Bank	Skandinaviska Enskilda	UBS	Unicredit
10	Banco Popol. Soc.Coop.	Erste Group Bank	Intesa Sanpaolo	ING
11	Ubi Banca	Ubi Banca	Banca Monte Dei P.S.	Credit Suisse
12	Banco Comercial Portug.	DNB	Caixabank	Intesa Sanpaolo
13	Commerzbank	Jyske Bank	Banco De Sabadell	Nordea Bank
14	Societe Generale	Swedbank	National Bank Of Greece	Standard Chartered
15	Banco Santander	Svenska Handelsbanken	Bankia	Commerzbank
16	Banca Bilbao Viz.Arg	Commerzbank	Banco Popular Espanol	Natixis Banques Popul.
17	Barclays	GAM Holding	Raiffeisen Bank Intl.	Danske Bank
18	Svenska Handelsbanken	Banco Portugues Invest.	Piraeus Bank	Santander
19	Julius Baer	Banco Popular Espanol	Ubi Banca	Caixabank
20	Skandinaviska Enskilda	Banco Comercial Portug.	Erste Group Bank	Svenska Handelsbanken

Note This table shows the top 20 systemic risk rankings for each of the systemic risk measures MES, ΔCoVaR, SRISK and DIP at December 31st, 2015. A total of 86 European banks are considered.

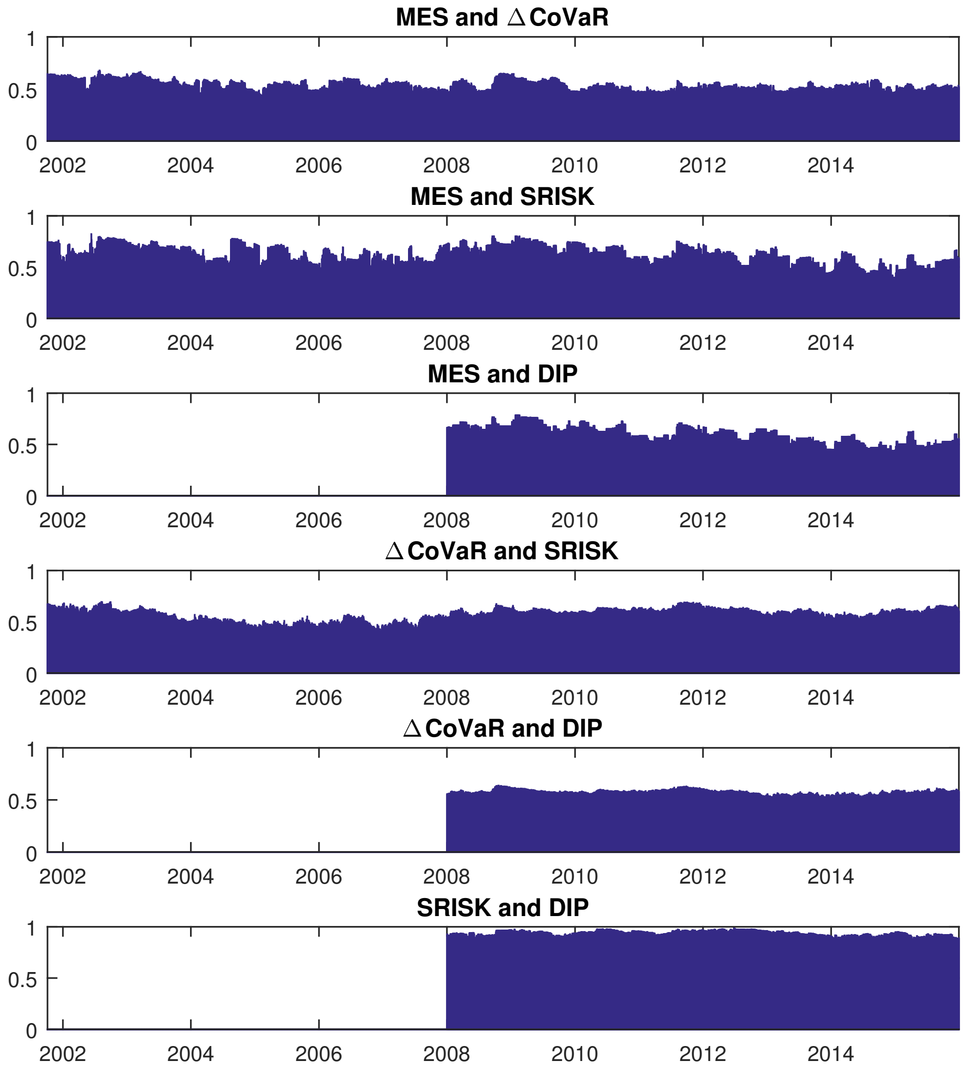

Figure 5: Percentage of concordant pairs between two systemic risk measures
This figure shows the percentage of concordant pairs of banks between two systemic risk measures from October 2001 to December 2015. Pairs of banks at a point of time are only taken into account if they are both active and have available data. A pair of banks is considered concordant if the order of the two banks are the same in the rankings of both measures. Then the percentage of concordant pairs is calculated as $\frac{\#\text{concordant pairs}}{n(n-1)/2}$, where n is the number of banks with available data.

5.2 Systemic risk measures for UBS and Greek banks

The different results between the systemic risk measures are evident. It is however still unclear whether these are the cause of different underlying definitions and interpretations of systemic risk, different data inputs, or something else. Looking at individual cases could help in seeing and understanding these differences more clearly.

Since our data covers the financial crisis of 2007/2008, it is interesting to see the dynamics of the systemic risk measures leading up to this time. One European bank that was severe distressed in these times is UBS. It is the bank that suffered one of the worst losses as a result of the subprime mortgage crisis, leading to their bailout by the Swiss National Bank with funds of close to $60 billion in October 2008. Figure 6 shows the time series of the systemic risk measures for UBS from January 2004 to December 2010. In what seems to be a calm period until the subprime mortgage crisis in 2007, we see that the SRISK measure for UBS has large up and down movements, while MES and ΔCoVaR stay relatively stable. This is mostly driven by the size factor, which is incorporated in SRISK and not in the other two measures. This period saw a large growth in size as well as earnings. As the crisis developed further, the systemic risk in the banking system started increasing, as can also be seen in the four systemic risk measures for UBS. All four indicators see two peak points: one at the time that UBS announced losses of $ 37 bn, the largest losses of any other bank at that time and afterwards at the time of the government bailout by the Swiss National Bank. This shows that the four systemic risk measures peak similarly and can be used to monitor systemic risk *ex post*. This is a good property to have for the systemic risk measures. At the time of the bailout, UBS was in high distress and the chances of its default were high, which is why the peaks in the systemic risk measures give a good indication of the health of the bank. This also explains the Swiss National Bank deciding to bailout UBS, because the failure of large systemically important bank can lead to instability in the whole banking system and/or the economy. Furthermore, the MES, SRISK and DIP see an increase already starting from early 2007 leading up to the bailout, whereas ΔCoVaR sees a sharp increase only at the time of the event. This could be caused by the different interpretations of systemic risk, since Δ CoVaR calculates the banking system's losses conditional on the institution in distress in distress, while the other measures look at an institution's losses conditional on systemic distress.

Another interesting case to look at are the Greek banks during the still continuing Greek government-debt crisis, which followed from the 2007/2008 financial crisis. We highlight Piraeus Bank and Alpha Bank, which are the largest Greek banks in total assets and market capitalization respectively. The time series of the systemic risk measures are shown in figure 7. The first thing we note is that both banks show very similar movements for each individual method of systemic risk measures. The movements between different measures are however very different. The MES sees a sharp negative peak in April 2012 and at the end of 2015, but seems to be stable on a relatively high level otherwise. SRISK shows a lot of large movements in both ways, peaking in April 2013,

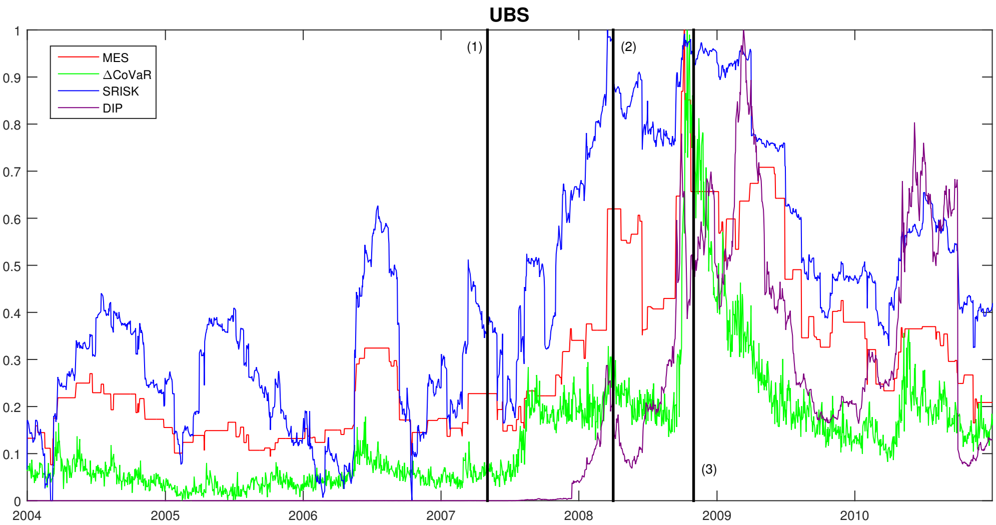

Figure 6: Time series of systemic risk measures for UBS
This figure shows the daily time series of the MES, ΔCoVaR, SRISK and the marginal contribution to DIP for UBS from January 2001 to December 2010. The observations are normalized over the complete time sample to adjust the scaling for comparison reasons. The vertical black lines are times of major events in the Euro sovereign debt crisis. (1) May 4$^{\text{th}}$, 2007: UBS closes hedge fund. (2) May 1$^{\text{st}}$, 2008: UBS doubles subprime writedowns (3) October 31$^{\text{st}}$, 2008: government bailout of UBS by the Swiss National Bank.

after which it slowly decreased until Q1 2014 and has increased again towards the end of the sample. The ΔCoVaR sees a small peak in the end of 2011, but seems very stable over the rest of the time sample. The DIP as well peaks in the end of 2011, after which it slowly decreases and shows a stable and relatively low systemic risk.

In the case of the Greek banks, the fundamental differences between the systemic risk measures become more clear in the time series. It is difficult to determine whether the movements of the different measures are the cause of purely systemic risk. Since each measure gives very different results, it becomes unclear which systemic risk measure gives the best indication of the actual systemic risk of Greek banks. This is another finding that supports the claim that regulators cannot identify systemically important financial institutions based on one of these measures. The recent developments in the Greek banking sector, which led to pressure of a Greek exit from the Eurozone, brings along unknown risks. There are many uncertainties that follow a potential 'Grexit'. Some of the uncertainties include investors' reactions, the contagion effects on the Eurozone banks and other political issues. Other countries such as countries in Southern Europe could also take Greece's example and leave the Eurozone, which would lead to bank-runs in these countries and consequently a banking crisis. All these concerns and unknown risks of the future are difficult to quantify. This could be the reason that the individual systemic risk contributions in the global financial crisis is well captured, whereas the systemic risk for Greek banks show varying results in the four measures.

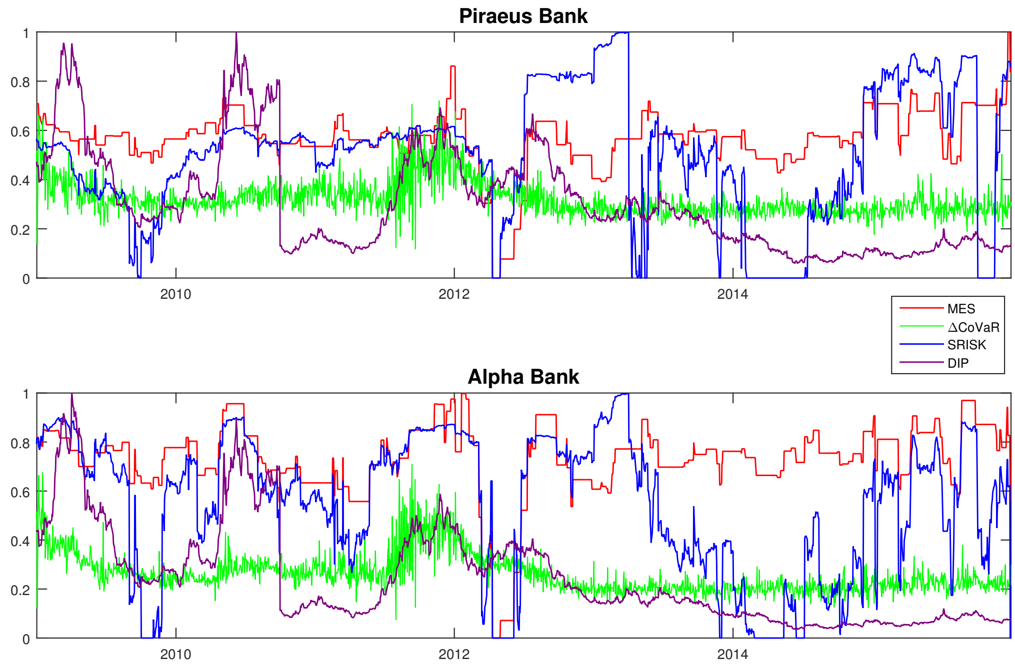

Figure 7: Time series of systemic risk measures for Greek banks
This figure shows the daily time series of the MES, ΔCoVaR, SRISK and the marginal contribution to DIP for Pireaus Bank and Alpha Bank from January 2009 to December 2015. The observations are normalized over the complete time sample to adjust the scaling for comparison reasons.

6 Empirical results - Financial ratio's and Systemic risk measures

As was shown in the example case for UBS, all four of the systemic risk measures reached their peak precisely at the time of default. This implies that these measures are viable to be used for monitoring systemic risk. However, for regulators to react before systemic risks can reach their highest point, it is preferable to be able to predict increases beforehand. This section focuses on potential leading indicators of systemic risk measures for regulators to use in identifying increases in systemic risk.

To be able to determine the effects of bank variables on the systemic risk measures, we first need an understanding of these explanatory variables. Figure 8 displays the average time series of the explanatory balance sheet variables of banks. This should help in understanding in what way these variables developed over time, before, during and after the global financial crisis and European Sovereign debt crisis. The variables' data is transformed using a 90% winsorization, setting the lowest and highest 5% percentile, to the 5% and 95% percentile. This is done to reduce the effect of outliers, since we are looking for a general effect of the bank variables on systemic risk. Outliers are often extreme observations for individual banks, such as the extreme levels of leverage ratio for Dexia (table 1), and could give distorted interpretation of results for the general banking system.

The figure shows that before the time of the 2008 global financial crisis, the leverage ratio of banks increased, which could mean that the leverage ratio of the banking system can give an early indication of its systemic risk. Furthermore, the average market-to-book ratio of European banks has seen a significant early decrease, which is a sign of tough financial times. This happens because the market lost faith in the assets of banks, leading to the market value to fall below the book value. The increase in the banking system's loan-to-deposit ratio for liquidity is also the cause of this, as the loss in faith in the banks led to bank customers withdrawing their deposits. In the banks' performance, we see a strong decline in the return on assets of banks in crisis times. This becomes especially clear following the European sovereign debt crisis in 2011 where the performance sees a sharp negative spike.

Figure 9 shows the standardized average bank variables together with one of the systemic risk measures, ΔCoVaR. On first look, it seems that systemic risk has a positive relation with leverage and liquidity and a negatively relation with market-to-book and performance. These relations make sense and expected as explained in section 4.7. To make sure that we work with stationary data, logarithmic differences are taken for SRISK and simple first differences are taken for the time series that are given in percentages (MES, ΔCoVaR, DIP, Leverage, Market-to-book and liquidity). This is to correct for seasonality and trends in the data. Table 5 shows the correlation matrix between the quarterly time series of the different aggregated systemic risk measures and the bank variables. The results again confirm the positive relations between systemic risk measures and leverage and liquidity and the negative relations between systemic risk and market-to-book and

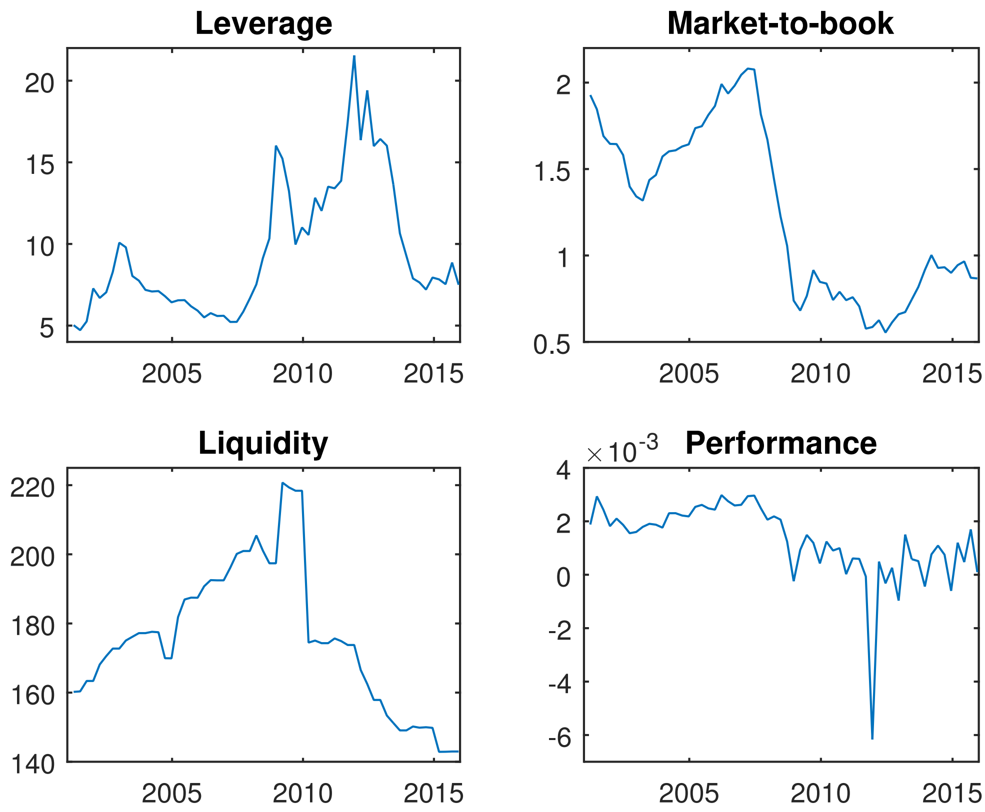

Figure 8: Time series of average systemic risk measures
This figure shows the average time series of the different bank variables over the 86 sample banks from January 2001 to December 2015. For Leverage, Market-to-Book, and Performance, quarterly reported data is used, whereas yearly reported data for the liquidity ratio is linearly interpolated to quarterly data. Leverage is calculated as the market value of total assets divided by market value of equity. Market-to-Book is the book equity value divided by market equity value. Liquidity is calculated as the total loans divided by total deposits. Performance is the return on assets.

performance. The table also shows the results of the Augmented Dickey-Fuller test for a unit root for each of the quarterly time series. The test shows that for all the series, the null hypothesis is rejected, which means that the data series are stationary after adjustment.

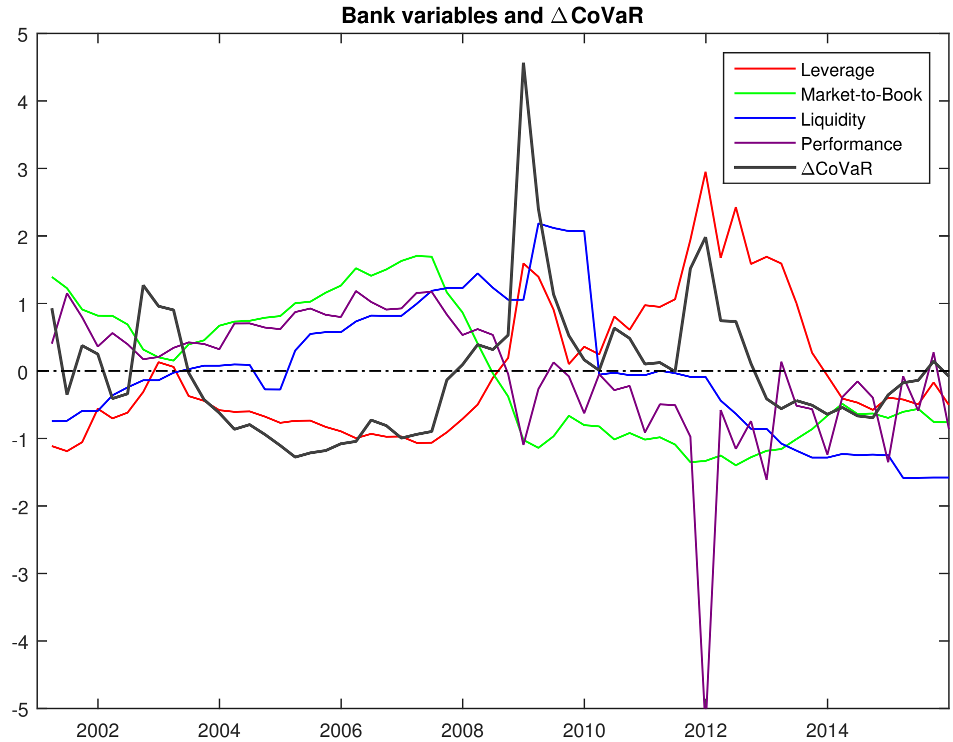

Figure 9: Time series of average systemic risk measures and ΔCoVaR
This figure shows the average time series of the different bank variables and the ΔCoVaR measure over the 86 sample banks from January 2001 to December 2015. For Leverage, Market-to-Book, and Performance, quarterly reported data is used, whereas yearly reported data for the liquidity ratio is linearly interpolated to quarterly data. Leverage is calculated as the market value of total assets divided by market value of equity. Market-to-Book is the book equity value divided by market equity value. Liquidity is calculated as the total loans divided by total deposits. Performance is the return on assets. The observations are normalized over the complete time sample to adjust the scaling for comparison reasons.

Table 5 Correlation matrix

	MES	ΔCoVaR	SRISK	DIP	Leverage	M/B	Liquidity	Perf.
MES	1.000***	0.667***	0.595***	0.596***	0.515***	-0.442***	-0.076	-0.104
ΔCoVaR		1.000***	0.186	0.473***	0.647***	-0.550***	-0.087	-0.138
SRISK			1.000***	0.587***	0.297**	-0.389**	-0.010	-0.134
DIP				1.000***	0.445***	-0.401**	0.028	-0.057
Leverage					1.000***	-0.648***	0.072	-0.252
M/B						1.000***	-0.032	-0.003
Liquidity							1.000***	0.109
Perf.								1.000***
ADF-test	-9.023***	-8.739***	-12.019***	-5.692***	-8.002***	-4.463***	-7.290***	-4.356***

Note This table shows pairwise correlations between the quarterly time series of the systemic risk measures MES, ΔCoVaR, SRISK and DIP, and explanatory bank variables leverage, market-to-book, liquidity, and performance. For MES, ΔCoVaR, SRISK and bank variables, the average over the 86 sample banks is taken. The time series run from Q1 2001 to Q4 2015, where the DIP only has observations available from Q1 2004. The Augmented Dickey-Fuller test statistic for each time series is also shown. The asterisks show the rejection of the null hypothesis of a unit root on a confidence level of 1%(***), 5%(**) and 10%(*).

6.1 VAR model results

Based on the AIC and the BIC, the number of lags for the VAR model is set to 1. The results of the VAR models are shown in table 6. We focus first on the lagged bank variables driving the future level of systemic risk, for which we see that most of the results with the systemic risk measures as dependent variable are insignificant. However, the F-test for the MES, SRISK and DIP regression do show that the coefficients are jointly different from zero (MES and SRISK on 5% level and DIP on 1% level), which means that the lagged systemic risk measure and bank variables jointly do contain some explanatory power for the change in systemic risk one quarter forward. The F-test for the ΔCoVaR regression does not reject the null hypothesis, implying that there is no way to identify the coming changes in systemic risk measured by this method with the information of the bank variables. Each covariate for ΔCoVaR is also non-significant on the 5% level.

The market-to-book ratio of banks is shown to be one of the covariates that is significant for the other systemic risk measures, SRISK on a 5% confidence level, and MES and DIP on a 10% level. The results show that a decreasing market-to-book ratio leads to a decrease in the systemic risk in the following quarter. A 1% decrease in the average market-to-book ratio of the 86 sample banks leads to a positive change in the MES level of the following quarter of 0.304%. Similar effects are present for the SRISK and DIP, where a 1% decrease in the market-to-book ratio leads to a positive effect in the following quarter of 0.299% and 0.315% respectively. This negative relation makes sense as firms in high distress have low M/B-ratios. The leading aspect of the M/B on systemic risk can also be seen in figure 9, where the average M/B ratio sees a sharp decline already starting in June 2007, before the systemic risk measure sees the sharp increase. This strong decline was a sign of the European banks' stocks decreasing and consequently increasing the banks' systemic risk. The M/B ratio of banks, which basically says how the market views the health of the banks, can be seen as an early warning indicator for increasing systemic risk in the European banking sector. This is a valuable result that can be used by regulators in monitoring and predicting systemic risk. After the crisis, the average M/B-ratio seems to be volatile on a relatively low level of below 1 until the end of the time sample. This means that the banks are still in high distress and therefore a high systemic risk in the European banking sector. A low M/B-ratio often means high uncertainty in a firm's earnings. Regulators could react to this low and volatile market-to-book ratio by encouraging banks to focus on business models with higher certainty of earnings. This leads to these banks being less sensitive to shocks and consequently a lower systemic risk.

The VAR results also show a significant negative effect of liquidity to the ΔCoVaR and DIP in the next quarter. This is unexpected as we would expect an opposite effect, since high average loan-to-deposit ratios means the banking system is less liquid, which increases the banks' vulnerability to shocks and therefore leads to higher systemic risk. The other bank variables generally do not show a significant effect on the future level of systemic risk in any method. An increase in performance seems to have a positive effect on the average ΔCoVaR, even though an opposite relation was expected. This positive relation could be caused by banks taking excessive risks to improve their short-term performance, which in its turn also leads to higher systemic risk.

The VAR model also allows us to check relations with a reversed direction. In general, there is no effect of the systemic risk measures on the bank variables one quarter ahead that is consistently significant across all four measures. Only the ΔCoVaR seems to have a positive effect on the European banking system's liquidity in the following quarter. A 1% increase in the banks' systemic risk according to the ΔCoVaR definition leads to an increase of 0.480% in the average loan-to-deposit ratio of European banks. Intuitively, again an opposite relation makes more sense.

Table 6 (a) VAR model results

	MES	Leverage	M/B	Liquidity	Perf.
MES	-0.389**	-0.020	0.077	0.278	-0.093
	(0.147)	(0.140)	(0.137)	(0.155)	(0.133)
Leverage	0.184	-0.296	0.185	0.086	0.289**
	(0.186)	(0.177)	(0.173)	(0.195)	(0.168)
M/B	-0.304*	-0.499***	0.643***	0.112	0.278**
	(0.170)	(0.161)	(0.158)	(0.178)	(0.153)
Liquidity	-0.091	-0.218*	0.130	0.024	0.128
	(0.126)	(0.120)	(0.136)	(0.133)	(0.114)
Performance	0.204	0.253*	-0.117**	0.271***	0.560***
	(0.134)	(0.128)	(0.137)	(0.141)	(0.121)
c	-0.012	0.003	0.012	-0.007	-0.031
	(0.123)	(0.117)	(0.129)	(0.130)	(0.111)
Adjusted R^2	0.129	0.215	0.244	0.042	0.276
F-test	2.690**	4.124***	4.678	1.505	5.338***
	[0.030]	[0.003]	[0.001]	[0.204]	[0.000]
	ΔCoVaR				
ΔCoVaR	-0.227	0.119	0.084	0.480***	-0.148
	(0.171)	(0.166)	(0.156)	(0.170)	(0.152)
Leverage	0.002	-0.366	0.173	-0.049	0.328*
	(0.199)	(0.141)	(0.132)	(0.198)	(0.177)
M/B	-0.208	-0.470	0.648***	0.166	0.262*
	(0.174)	(0.166)	(0.156)	(0.173)	(0.154)
Liquidity	-0.239*	-0.200	0.133	0.056	0.119
	(0.129)	(0.145)	(0.136)	(0.128)	(0.114)
Performance	0.231*	0.251	-0.117	0.270*	0.560***
	(0.136)	(0.146)	(0.137)	(0.135)	(0.121)
c	0.025	0.003	0.012	-0.006	-0.031
	(0.125)	(0.136)	(0.128)	(0.124)	(0.111)
Adjusted R^2	0.067	0.223	0.244	0.118	0.282
F-test	1.824	4.272	4.669	2.524**	5.476***
	[0.124]	[0.002]	[0.001]	[0.040]	[0.000]

Table 6 (b) VAR model results

	SRISK				
SRISK	-0.257**	-0.019	-0.078	0.175	-0.008
	(0.093)	(0.130)	(0.127)	(0.147)	(0.124)
Leverage	0.046	-0.301*	0.229	0.179	0.252
	(0.121)	(0.168)	(0.165)	(0.190)	(0.161)
M/B	-0.299**	-0.501***	0.608***	0.102	0.292*
	(0.118)	(0.164)	(0.160)	(0.185)	(0.156)
Liquidity	-0.069	-0.217*	0.118	-0.001	0.138
	(0.086)	(0.119)	(0.116)	(0.134)	(0.114)
Performance	0.143	0.256*	-0.102**	0.250*	0.560***
	(0.093)	(0.130)	(0.127)	(0.146)	(0.124)
c	-0.095	0.003	0.012	-0.008	-0.031
	(0.084)	(0.117)	(0.115)	(0.133)	(0.112)
Adjusted R^2	0.165	0.215	0.245	0.000	0.269
F-test	3.257**	4.124***	4.693***	0.999	5.193***
	[0.012]	[0.003]	[0.001]	[0.428]	[0.001]

	DIP				
DIP	-0.029	0.065	0.031	0.173	-0.187
	(0.146)	(0.165)	(0.152)	(0.191)	(0.158)
Leverage	0.177	-0.314	0.209	0.132	0.306
	(0.178)	(0.201)	(0.186)	(0.233)	(0.193)
M/B	-0.315*	-0.467**	0.648***	0.083	0.279
	(0.173)	(0.196)	(0.181)	(0.227)	(0.188)
Liquidity	-0.333***	-0.220	0.118	-0.012	0.129
	(0.117)	(0.133)	(0.123)	(0.154)	(0.127)
Performance	0.200	0.256*	-0.109**	0.251***	0.538***
	(0.130)	(0.147)	(0.135)	(0.170)	(0.141)
c	0.008	0.004	0.001	-0.039	-0.081
	(0.129)	(0.147)	(0.135)	(0.170)	(0.140)
Adjusted R^2	0.258	0.182	0.228	0.037	0.240
F-test	4.126***	3.001**	3.659*	0.681	3.834***
	[0.004]	[0.022]	[0.080]	[0.641]	[0.006]

Note This table shows the results of the four Vector Autoregressive (VAR) models, using five standardized variables with quarterly time series: one systemic risk measure for each model (MES, ΔCoVaR, SRISK or DIP) and the four explanatory bank variables leverage, market-to-book, liquidity and performance. The estimated VAR model is $y_t = c + Ay_{t-1} + \varepsilon_t$, where y_t consists of one of the systemic risk measures or the bank variables, c is a constant term, A is the matrix of coefficients of the lagged variables y_{t-1} and ε_t is a vector of error terms. The columns show the dependent variables and the rows show the one-lagged explanatory variables. The asterisks show the statistical significance of the regression coefficients on a confidence level of 1%(***), 5%(**) and 10%(*). Finally, the adjusted R^2 as well as the F-test statistic and its p-value (in square brackets) are reported for each regression. The F-test tests the null hypothesis of the regression coefficients being jointly zero. The asterisks show the rejection of this F-test on a confidence level of 1%(***), 5%(**) and 10%(*).

6.2 Panel data regression

The fact that the VAR results do not return many significant results could mean that there is simply no relation between the bank variables, apart from market-to-book ratio, and the systemic risk measures one quarter ahead. These results can also be caused by a lack of data, since we use quarterly data over fifteen years equaling 60 data points. This could also be the reason for some counterintuitive results. It could be possible that we lose a lot of information by simply taking the average of systemic risk measures and bank variables across banks. One way to overcome this problem is to use the panel data regression, using quarterly data of each individual bank instead of averages to increase the number of observations.

The results for this lagged regression on the fixed effects model are shown in table 7. Also the VAR results with the systemic risk measures as dependent variables are again reported for comparison, with the coefficient of the intercept omitted from the table. Going from the VAR results to the panel data regression result, the (robust) standard errors of the coefficients are considerably lower and the Wald test shows that the coefficients are jointly nonzero with high confidence for all measures. Furthermore in the panel analysis, the market-to-book ratio return significant results in explaining systemic risk for each measure one quarter ahead. Surprising is that the MES and SRISK have a significant negative relation with their respective lagged measures, while the DIP shows a positive coefficient. A reason for this could be that the DIP takes probability of systemic risk into account with CDS spreads input, while the other methods measure the systemic risk 'after the event'. Therefore, an increase in DIP means an increase in the chance of a systemic event, which in its turn increases again the systemic risk. A 1% change in the MES and SRISK leads to a negative change of 0.261% and 0.324%, improving the systemic risk in the following quarter. The coefficients for market-to-book become significant for all systemic risk measures on a 1% confidence level, apart from ΔCoVaR which shows significance on a 10% level, and negatively related to the measures in the following quarter. This is similar to the results of the VAR model with average variables, however the effect seems to be weaker. A 1% decrease in a bank's market-to-book ratio leads to an increase in its systemic risk contribution of 0.119%, 0.072%, 0.142% and 0.091% for MES, ΔCoVaR, SRISK and DIP. The most interesting result is that the leverage ratio becomes significant in explaining systemic risk according to all methods, compared to the VAR model results. A 1% increase in leverage leads to a 0.133%, 0.018%, 0.044% and 0.036% change in MES, ΔCoVaR, SRISK and DIP. The leverage ratios of banks are significantly correlated and have a lag effect on all the systemic risk measures. The positive relation can be explained by the fact that both average leverage ratio across banks and systemic risk proxy the distress in the banking system. They both give an indication of the banking system's distress. Leverage can therefore be seen as a leading indicator of systemic risk, which is also the reason that the Basel III Accord focused on leverage ratio requirements to reduce systemic risk.

None of the other bank variables are consistently significant across all measures. However, some bank variables do become significant in explaining the future levels of systemic risk for certain measures. The average performance of the banking system is also shown to have significant predicting power for MES, ΔCoVaR and DIP. A 1% increase in the average RoA leads to a 0.094% increase in MES, 0.055% increase in ΔCoVaR and a 0.017% increase in DIP in the following quarter. Again, here the explanation is that banks take high risks to achieve higher returns, which eventually increases the banks' systemic risk. Furthermore, the counterintuitive result from the VAR model using average data that showed that liquidity has a significant negative relation with the future ΔCoVaR and DIP is now corrected in the panel model. The relation with ΔCoVaR becomes insignificant, whereas MES, SRISK and DIP now have a positive relation between the liquidity ratio and the risk measures in the following quarter. A 1% increase in the loan-to-deposit ratio for liquidity leads to a increase of 0.022%, 0.023% and 0.011% in the respective measures next quarter. This relation makes sense as times where banks have a relatively high loan-to-deposit means that the banking system has low liquidity, increasing the systemic risk.

Afterwards, the individual fixed effects panel analysis is done again by adding a dummy variable dividing the full sample. This is to check whether it makes sense to use a full sample panel model or whether banks in different regions have different relations between bank variables and systemic risk. The panels are divided by banks in the PIIGS countries (Portugal, Ireland, Italy, Greece and Spain) and banks in other European countries. PIIGS is a term used for countries in which governments have have failed to bailout banks that were highly in debt. Banks in these countries have been highly distressed as a cause of the financial turbulence and the European sovereign debt crisis over the last years. This has implications on their systemic risk contributions and therefore could lead to a significantly different relation with lagged bank variables for banks in these countries. The PIIGS banks in the sample consist of 39 banks, which is slightly less than half of the total 86 banks. The new dummy panel model looks as follows:

$$y_{it} = \beta' X_{i,t-1} + \gamma' X_{i,t-1} D_{PIIGS} + \varepsilon_{it} \tag{28}$$

$$y_{it} = (\beta' + \gamma' D_{PIIGS}) X_{i,t-1} + \varepsilon_{it}, \tag{29}$$

where $D_p = \begin{cases} 1, \text{if PIIGS} \\ 0, \text{other} \end{cases}$, β is the general effect coefficient of the explanatory variables on systemic risk and γ the additional effect coefficient for the PIIGS banks. From this point on, this model will be referred to as the dummy model.

Going back to table 7, the Wald test in the dummy model shows that the null hypothesis that the γ coefficients are jointly zero gets rejected, implying that overall there are significant differences in the effect of the lagged explanatory variables on systemic risk for PIIGS banks compared to other European banks. This is true for all four measures of systemic risk. Looking at the individual variables, there is no single bank variable that shows a significantly different effect on PIIGS banks compared to non-PIIGS banks consistently across different measures. For the SRISK measure, liquidity seems to have a significantly larger effect on systemic risk for PIIGS banks compared to other banks. The performance of banks seem to have a large positive effect on the SRISK measure for non-PIIGS banks, whereas in PIIGS the effect seems to be eliminated to an extent. A 1% change in the Return on Assets leads to a change of 0.232% in SRISK for non-PIIGS banks, compared to a 0.005% change for PIIGS banks. Market-to-book has a significantly weaker effect on PIIGS banks and other PIIGS banks according to the DIP measure. A 1% change in the market-to-book ratio of a PIIGS bank leads to a change of -0.040% for DIP in the next quarter, compared to -0.162% in non-PIIGS banks. For the other measure this difference appears to be non-significant. The joint differences and the fact that some variables show a different effect according to certain measures confirm that dividing the full sample to PIIGS banks and other banks make sense. It is shown that bank variables have different implications on the future level of the systemic risk of banks in countries in which governments have not been able to bailout their government debt or their failing banks.

Based on quarterly bank ratios, the market-to-book and the leverage ratios is found to be a early indicator for systemic risk across the four measures MES, ΔCoVaR, SRISK and DIP. This means that it is important for regulators to monitor these ratios of banks to be able to predict future changes in systemic risk and act before extreme levels of systemic risk are reached. Other bank ratios such as liquidity and performance do contain some predictive power for some systemic risk measures but none of them consistent across all measures. Depending on what regulators define as systemic risk and how they construct the measure, these other bank ratios could also help to predict future changes in systemic risk. These bank ratios could then be incorporated in the measurement of systemic risk to include an *ex ante* factor.

Table 7 (a) Fixed effects model results 2

MES				
	VAR	Panel	Dummy model	
			β	γ
MES	-0.389**	-0.261***	-0.203***	-0.130
	(0.147)	(0.059)	(0.057)	(0.100)
Leverage	0.184	0.133**	0.104*	0.035
	(0.186)	(0.074)	(0.055)	(0.112)
M/B	-0.304*	-0.119***	-0.161***	0.077
	(0.170)	(0.039)	(0.056)	(0.052)
Liquidity	-0.091	0.022***	0.019**	0.048
	(0.126)	(0.009)	(0.008)	(0.058)
Performance	0.204	0.094***	-0.023	0.134*
	(0.134)	(0.025)	(0.076)	(0.081)
Observations	58	3486		
Adjusted R^2	0.129	0.099		
F-test	2.690**	76.676***	57.459***	14.120**
	[0.030]	[0.000]	[0.000]	[0.015]

ΔCoVaR				
	VAR	Panel	Dummy model	
			β	γ
ΔCoVaR	-0.227	-0.130	-0.145	0.015
	(0.171)	(0.138)	(0.143)	(0.018)
Leverage	0.002	0.018*	0.049	-0.047
	(0.199)	(0.013)	(0.052)	(0.065)
M/B	-0.208	-0.072*	-0.132*	0.095
	(0.174)	(0.048)	(0.078)	(0.061)
Liquidity	-0.239*	-0.008	-0.015	0.082
	(0.129)	(0.011)	(0.013)	(0.060)
Performance	0.231*	0.055**	0.158	-0.120
	(0.136)	(0.024)	(0.105)	(0.102)
Observations	58	3486		
Adjusted R^2	0.067	0.021		
F-test	1.824	11.689***	11.649**	10.837*
	[0.124]	[0.000]	[0.040]	[0.055]

Table 7 (b) Fixed effects model results

SRISK				
	VAR	Panel	Dummy model	
			β	γ
SRISK	-0.257**	-0.324***	-0.177***	-0.189***
	(0.093)	(0.065)	(0.069)	(0.079)
Leverage	0.046	0.044***	0.074*	-0.049
	(0.121)	(0.019)	(0.042)	(0.055)
M/B	-0.299**	-0.142***	-0.120***	-0.038
	(0.118)	(0.039)	(0.029)	(0.062)
Liquidity	-0.069	0.023*	0.009	0.185***
	(0.086)	(0.018)	(0.013)	(0.064)
Performance	0.143	0.030	0.232***	-0.227***
	(0.093)	(0.026)	(0.064)	(0.066)
Observations	58	2047		
Adjusted R^2	0.165	0.096		
F-test	3.257**	79.232***	73.270***	27.009***
	[0.012]	[0.000]	[0.000]	[0.000]

DIP				
	VAR	Panel	Dummy model	
			β	γ
DIP	-0.029	0.145	0.132	-0.008
	(0.146)	(0.123)	(0.122)	(0.019)
Leverage	0.177	0.036*	0.127**	-0.124**
	(0.178)	(0.026)	(0.055)	(0.051)
M/B	-0.315*	-0.091***	-0.162**	0.121*
	(0.173)	(0.039)	(0.072)	(0.063)
Liquidity	-0.333***	0.011***	0.008*	0.032
	(0.117)	(0.004)	(0.004)	(0.021)
Performance	0.200	0.017*	0.052	-0.043
	(0.130)	(0.013)	(0.087)	(0.088)
Observations	46	2941		
Adjusted R^2	0.258	0.037		
F-test	4.126**	19.300***	30.444***	12.488**
	[0.004]	[0.000]	[0.000]	[0.029]

Note This table shows the coefficients results of the fixed effects panel model analysis described by $y^*_{it} = \beta' X^*_{i,t-1} + \varepsilon^*_{it}$, where y^*_{it} consists of one of the four systemic risk measures, $X^*_{i,t-1}$ are the systemic risk measure of the dependent variable and the explanatory bank variables leverage, market-to-book, liquidity and performance, and ε^*_{it} the error terms. The rows show the one-lagged explanatory variables. The Driscoll & Kraay standard errors are reported in round brackets. The asterisks show the statistical significance of the regression coefficients on a confidence level of 1%(***), 5%(**) and 10%(*). The results for the same analysis with an added dummy for PIIGS banks are also reported, described as $y_{it} = (\beta' + \gamma' D_{PIIGS}) X_{i,t-1} + \varepsilon_{it}$. Furthermore, the number of observations, adjusted R^2 as well as the F- or Wald test statistic and its p-value (in square brackets) are given for each regression. The Wald test (F-test) tests the null hypothesis of the regression coefficients being jointly zero. The asterisks show the rejection of this F-test on a confidence level of 1%(***), 5%(**) and 10%(*).

7 Concluding remarks

This paper compares four measures for cross-sectional systemic risk, MES, ΔCoVaR, SRISK and DIP on individual European bank-level. Furthermore, bank balance sheet ratios are evaluated on their prediction power on these measures to see if these ratios affect the future levels of overall systemic risk in the banking system. This is done on a sample of 86 sample banks from 19 European countries, representative for the European banking system. The time sample period of 15 years, which is from January 2001 until December 2015, covers the global financial crisis of 2007 and 2008 as well as the European sovereign debt crisis of around 2010.

When aggregated, the four different systemic risk measures overall show similar movements and seem to determine the level of systemic risk in the banking system well. The differences in these measures, however, are significant, especially on the individual bank contribution level. The first main finding is that the systemic risk rankings are different for each measure, which makes it difficult for regulators to determine which banks are responsible for the most systemic risk and consequently should be assigned the highest risk weights. Since there is not one general definition of systemic risk, there is no clear 'truth' to see which measure presents the most accurate rankings. Results for each method give an interpretation for systemic risk in different ways and these can all provide information in capturing the complexity of banking systemic risk.

Looking at individual cases also gives meaningful insights on the current systemic risk measures. Since the measures considered are all proposed after the global financial crisis, these methods are made to correctly describe the systemic events and the banking system's risk *ex post*, even though the DIP contains predictive elements with default probabilities as input. Therefore, these systemic risk measures do seem to be good monitoring instruments, as is shown for UBS where each measure peaked at the time of its bail-out. However, it is not likely that these measures are able to capture unknown risk to the banking system. Similar to how the risks of the CDOs were underestimated before the global financial crisis, it could be possible that there are determinants of significant unknown risks that are not (yet) taken into account in the current systemic risk measures. This becomes clear in the case of the Greek banks, where the different measures are not able to show a clear pattern that can describe the uncertainties of the Greek banking system. This also means that it is impossible to find a risk measure that perfectly and completely describes the known and the unknown risks in the banking system.

Another main finding is that there are fundamentals in bank's balance sheets that can to a certain extent predict the level of systemic risk in the future. The only bank ratios that shows to be driving the bank systemic risk consistently according to all measures are the market-to-book and loan-to-deposit ratios. These bank ratios can therefore be seen as leading indicators for systemic risk monitoring tools. This becomes most clear during the time of the global financial crisis, where the market-to-book ratio already sees a sharp decline from mid 2007 before the systemic risk indices start to increase and the loan-to-deposit ratio sees a constant increase (decrease in liquidity) from 2001 until the crisis period. These ratios should be used to make predictions on banking systemic risk or it could be integrated in the measurement of systemic risk for regulatory purposes. A decreasing market-to-book ratio and increasing loan-to-deposit ratio is followed by higher systemic risk. To combat an increase systemic risk, regulators should react to a decreasing market-to-book ratio by stimulating banks to set up business plans with higher certainty of earnings, to make sure they become less sensitive to shocks in the banking system. High levels of leverage can be combated by using leverage caps for banks as was introduced by the leverage requirements in Basel III. Banks' liquidity ratio and performance show varying results in driving the systemic risk measures, and not consistent across all four methods. These results are inconsistent with the response of the Basel Committee in developing Basel III to introduce new capital requirements for liquidity to decrease an individual bank's contribution to systemic risk.

When discussing the results of this research, it is important to note that regulators often do have access to proprietary data that can improve measures of systemic risk. According to surveys, the public market measures are used as one of many inputs by regulators in calculating systemic risk. Furthermore, the current measures are not purely measures for systemic risk as they are influenced by systematic risk as well. During this research many assumptions have been made for settings according to the papers on which the methods are based, to be able to calculate the different systemic risk measures. These settings, such as the loss threshold of the market returns to calculate MES, can be modified to other definitions of systemic risk, which will then naturally yield different results for this research. Since there are many definitions and many methods in calculating systemic risk, it is still an ongoing search to find one method that collects all the relevant information from the current systemic risk measures and can correctly identify which banks are responsible for the highest systemic risk.

The research in this paper can also be conducted on other financial institutions, such as insurance companies and investment management companies. Another interesting proposal is to do a similar research on systemic risk in other sectors than the financial sector, and see how that influences the banking sector. An example of this could be to see how the systemic risk in the real estate sector affects the returns of banks.

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Appendix

A Literature review - systemic risk

Types of systemic risk

In academic literature, often the distinction within systemic events is made between an event in a 'narrow' and a 'broad' sense (de Bandt and Hartmann, 2000). Systemic risk in the narrow sense as an event is similar to contagion and can be seen as the release of negative news about a financial institution or its default, or the crash of a financial market leading to considerable adverse effects on one or several other financial institutions or markets. The broad sense of systemic risk is traditionally seen as macroeconomic risks, such as common shocks or recessions. This means that the trigger of the event could be a shock from outside or from within the financial system. Systemic risk is largely categorized in three sources: contagion, common shocks and informational spillovers (Kaufman, 2000).

Contagion effects in the 'narrow' sense emerge when firms within a system are interconnected and have economic exposure to each other. Allen and Gale (2000) find that interconnectedness in interbank markets leads to a better allocation of risk-sharing and liquidity allocation. They find that especially in a complete interbank market, where each node is connected to every other node, initial idiosyncratic shocks can be absorbed. On the other hand, they find that when the network is incomplete, contagion effects will occur more strictly. This is consistent with Gai and Kapadia (2010), who find that increased interconnectedness and risk-sharing leads to a lower probability of contagious default. However, conditional on the failure of one firm triggering contagious defaults, high interconnectedness increases the chance of contagion spreading more widely. An example of systemic risk as cause of this contagion is a bank run (Mundy, 2004). In a bank run, many depositors of a financial institution withdraw their cash at the same time, because of insecurity about the institution's solvency. This increases the chances of default for the financial institution as they become unable to satisfy these withdrawals. The banking sector is very interconnected thrugh interbank deposits, loans and clearings (Kaufman, 2000). One failure therefore causes other banks or financial institutions to default as a consequence.

Another type of systemic risk are common shocks, which arises from indirect connections between firms. Common shocks can be seen as systemic risk in the 'broad' sense, focusing on contagion from an initially exogenous external shock. This risk depends on correlation between firms rather than direct causation. Systemic risk is then present when there are strong similarities between firms' risk exposures (Kaufman and Scott, 2003). Especially in the banking system, banks may strategically choose to invest in similar assets as a reaction to negative externalities. Effects of the 2008 financial crisis were stronger due to the fact that many financial institutions had invested in similar assets (subprime mortgages), exposing them to risk from a common shock. Georg and

Poschmann (2010) find that common shocks carry a greater threat to the stability of a system than contagion effects.

Another source of systemic risk is informational contagion, also known as information spillovers. Acharya and Yorulmazer (2003) suggest that this is an important type of systemic risk that should also be taken into account. To illustrate information spillover effects, we consider two banks in a banking system. If one bank fails to pay its depositors their interest, it gives a bad sign of the overall state of the economy. Depositors of the other bank then quickly update their rates and require a higher interest rate on their deposits. If both banks show good performance, then it is taken as good news about the state of the economy, which is why depositors are willing to lend to banks at lower interest rates. This implies that the borrowing cost of banks are lower if both banks survive together than when one fails. This is an example of information spillover of one bank's failure on the other bank's borrowing cost. An information contagion then follows if the surviving bank cannot afford the revised borrowing rate and fails as well. The greater the correlation between loan returns of banks, the higher the chance that these banks will survive together. To increase this interbank correlation, banks tend to lend to similar industries, which is also referred to as bank herding. Intuitively, banks prefer to survive together, rather than surviving individually as they want to avoid information spillover risk. The overall concept of information spillovers is based on the fact that the insolvency of one bank can lead to an increase in refinancing cost of the surviving banks. The financial crisis has made clear that banks show herding behavior (Acharya and Yorulmazer, 2003). The authors show that banks attempt to counter this information contagion risk by herding ex-ante and undertaking correlated investments to increase the likelihood of joint survival.

Systemic risk in the financial sector

The term systemic risk is mostly used to denote the risk of a collapse of an entire financial system. However, systemic risk is not a unique concept for only the financial sector. A default of a large retailer for example, may have severe consequences to the firm's suppliers and the local economy. The recent bankruptcy of V&D in the Netherlands is an example for this, as the default of this department store chain led to serious damage to their suppliers. Still, the failure of a nonfinancial firm rarely leads to a threat to a competitor or the entire economic system. Compared to other sectors, the financial system especially is vulnerable to systemic risk. For this reason, there is a returning discussion on government regulation and supervision for large financial institutions to reduce the negative consequences of systemic risk. Schwarcz (2008) argues that the financial sector is vulnerable to systemic risk, because of the fact that financial institutions are important sources of capital. Their failures can therefore lead to a decreased availability of capital in society, especially when there are failures in a large number of institutions, and an increase of the cost of capital. These are serious consequences that result from systemic failure. Gavin and Hausmann

(1996) mention several reasons why the banking system is more vulnerable than other industries. Bullard *et al.* (2009) summarize three reasons, which fall in line with Gavin and Hausmann, why especially the financial system contains systemic risks that other sectors do not hold.

The first reason is the interconnectedness of the financial sector. The banking sector is highly interconnected due to bilateral transactions and relationships, such as interbank loans, trades and other transactions. A big danger for financial institutions is settlement risk, which is the risk that one party fails defaults on the terms of a contract with another party at the settlement date, especially since financial institutions have large daily exposures that run into the billions in dollars. It is difficult for a bank to have a clear overview of its counterparties, because of the lightning-fast speed in which banks and market makers trade and the complexity of banks' balance sheets and securities. Therefore, a default of a large financial institution may lead to enormous losses for other counterparty firms, as well as third parties that are again connected with these firms. Lagunoff and Schreft (2001) construct a game theory model for what they refer to as financial fragility. The model incorporates interrelated portfolios and payment commitments between firms as linkages of financial institutions. They show that indeed an economy becomes more fragile and a financial crisis occurs as defaults spread across the system, causing links to break.

Another reason why systemic risk is more of an issue for the financial sector than other sectors is the leverage of financial institutions. As financial institution have a higher debt-to-equity ratio compared to firms in other sectors, their return on equity will have a higher rate in good times, but also a higher risk of default when the markets are turning against them. Because of this, financial institutions as well as non-financial firms have the incentive to identify an optimal debt-to-equity ratio. Compared to other sectors, financial firms have a significantly higher leverage ratio, meaning that they fund their assets with debt rather than equity. The average leverage ratio of financial institutions is 15.85 to 1 compared to 2.83 to 1 in the second highest leveraged sector, services (as of April 2016). When there is a small drop in value of a highly leveraged institution, it may have a severe effect on its equity, causing the firm to raise additional capital or sell their assets. During the financial crisis, large investment banks such as Fannie Mae and Freddie Mac had financial difficulties because of their high leverage (Acharya *et al.*, 2011).

The third and last reason mentioned by Bullard *et al.* (2009) for why the financial sector is more vulnerable to systemic risk than other sectors is the fact that financial firms tend to deal with their holding of long-term assets with short-term liabilities. This mismatch of maturities in their assets and liabilities makes financial institutions exposed to interest rate risks and liquidity shocks. Financial intermediaries generally employ a gap strategy, where they borrow short and lend long. This strategy is profitable as short rates are commonly lower than long rates. This can have adverse effects as commercial banks rely on demand deposits, which means that depositors can withdraw their funds at any time. If depositors suddenly decide to take out their funds because of times of uncertainty, the bank can be forced into bankruptcy.

Also within the financial sector, different industry groups, such as banks, real estate, diversified financials and insurance companies, have varying vulnerability to systemic risk. An empirical comparison of the degree of systemic risk across various sectors is conducted by Bühler and Prokopczuk (2010). They find a significantly larger systemic risk in banks than in all other industries of the economy. Billio *et al.* (2011) find an asymmetry in the degree of interconnectedness among various financial industries. They show that banks and insurance companies have a larger impact on hedge funds, brokers and dealers than the other way around, suggesting that banks and insurance companies carry more systemic risk. They explain the asymmetry of the banks carrying more systemic risk by the fact that banks lend capital to the other financial institutions. Chen *et al.* (2014) examine the interconnectedness between banks and insurance companies using Granger causality tests. They find that the impact banks have on insurance companies is stronger and of longer duration than vice versa. Furthermore they find that banks carry significant systemic risk for insurers but not the other way around. Cummins and Weiss (2014) evaluate U.S. insurance companies on their systemic risk and did not find significant results, implying that the default of insurance companies will generally not cause significant systemic risk events affecting the economy.

Other systemic risk approaches

Macroeconomic measures for systemic risk lean on the aggregate imbalances in cases of financial instability in the system. These imbalances are then seen as leading indicators for systemic risks. Therefore, macroeconomic time series and statistics are used for systemic risk measures. For example, Alessi and Detken (2009) test macroeconomic variables as early warning indicators for costly aggregate asset price boom/bust cycles. In the same trend, Borio and Drehmann (2009) look for simultaneous financial imbalances in equity prices, property prices and credit gaps as indicators.

Another way to look at quantifying system risk in a financial system is to focus on the financial sector as a whole instead of individual contributions of institutions (Giesecke and Kim, 2011). One way to do this is by using a network model. In this framework, nodes represent legal entities and edges stand for contractual financial agreements between them. For this network to represent the financial system, the contracts can be seen as cash-flow obligations where the contractual relationships show the interconnectedness of the system. Using the network approach to assess financial linkages was first proposed by Chan-Lau *et al.* (2009) in the IMF Global Financial Stability Review, for which they primarily use institutional data to look at network externalities. Their network model can track the consequences of a credit event or liquidity squeeze throughout the entire system. Similarly, Tarashev *et al.* (2010) use the Shapley Value for risk allocation (Shapley, 1953) in a game theory network model to give a measure for institution's risk contribution as well as systemic-wide risk. Billio *et al.* (2010) use stock market data to create estimates of a latent network structure for different industries within the financial sector: banks, brokers, hedge funds and insurance companies. They use Granger-causality tests to identify the network of statistically significant Granger-causal relations among these institutions. The drawbacks of a network approach is that it requires data on the exposures between financial institutions. Many studies have tried to model the interconnections within the system without directly observing these exposures. Chan-Lau *et al.* (2009) proposed the default intensity model, using default data, which captures effects of direct and indirect linkages among financial institutions. This method then provides a risk metric of potential failures due to these linkages.

Forward-looking risk measures have the goal of capturing the implied cash-flows of each of the financial institutions for each contract that they hold. They can be useful for regulators in stress testing financial institutions. To calculate these measures, (forward-looking) asset prices are used, since movements in these prices reflect the changes in market anticipation on the future performance of their underlyings (Huang *et al.*, 2009). An example of this is the application of the Contingent Claims Analysis (CCA), also known as the Merton (1973) model, to measure systemic risk (Lehar, 2005; Gray and Jobst, 2010). Here, the contribution of each financial institution to the total liability of the regulator is measured, using the Merton model for bank liabilities. Capuano (2008) proposes a framework, using option prices, to derive the probability of default of financial institutions. He then extends this framework to detect early signals for systemic risk. Finally, Segoviano and Goodhart (2009) use CDS prices to see how individual institutions add to the potential distress of the system.

Another forward-looking approach to look at systemic risk is stress testing. This is a form of scenario-analysis, where the stability of the financial system is tested under possible, but extreme circumstances. Stress testing is often used in regulation and standards, such as the European Banking Authority or in Basel III, to calculate regulatory capital requirements for financial institutions. An example of a stress testing model for systemic risk is the macroeconomic stress test by Alfaro and Drehmann (2009). They use an auto-regressive model of GDP growth as they assume that typically the GDP growth decreases prior to crisis periods. Another approach is the 10-by-10-by-10 approach by Duffie (2011), where he tests ten systemically important financial institutions in different scenarios, such as the default of one of the institutions.

Table 8 (a) Bank information and characteristics

Bank name	Country	Total assets	Rank	Leverage	Rank	M/B	Rank	Liquidity	Rank	Profitability	Rank	G-SIB	CDS	Rank
ABN AMRO NV	NE	741,602	13	9.21	33	1.69	14	145.52	53	0.12	44			
Ageas	BE	373,269	24	5.85	70	1.22	43	146.00	52	0.13	42		149.63	26
Alliance & Leicester PLC	GB	80,384	53	8.28	41	2.06	8	156.20	44	0.33	12		119.53	34
Allied Irish Banks PLC	IR	126,084	43	17.50	10	1.98	9	147.64	51	-0.18	83		750.52	6
Almanij NV	BE	240,410	29	10.96	23	0.58	85	111.26	72	9.85	1			
Alpha Bank AE	GR	53,803	58	11.20	22	1.55	24	149.17	50	0.04	64		985.53	3
Banca Antonveneta SpA	IT	46,204	64	6.63	59	1.41	33	209.19	22	-0.05	79		172.91	21
Banca Carige SpA	IT	30,251	75	8.04	44	1.13	58	171.24	35	0.00	75			
Banca Lombarda E Piemontese	IT	35,562	71	5.01	76	1.42	32	195.37	24	0.14	40			
Banca Monte Dei Paschi Di Siena	IT	182,159	37	15.00	13	0.83	71	191.75	25	-0.02	77			
Banca Nazionale Del Lavoro	IT	83,338	51	8.14	42	1.24	41	210.29	21	0.04	66		37.07	51
Banca Popol Dell'Emilia Romagna	IT	52,459	60	8.87	37	0.73	79	156.49	43	0.10	49			
Banca Popolare Di Lodi SpA	IT	42,930	67	10.16	26	0.93	66	236.96	18	-0.04	78			
Banca Popolare Di Milano	IT	44,738	65	10.88	24	0.70	80	155.46	45	0.04	63		248.55	14
Banca Popolare Di Sondrio	IT	24,326	79	4.02	80	1.22	45	123.27	70	0.16	33			
Banco Bilbao Vizcaya Argenta	SP	459,762	20	5.24	74	1.63	20	138.33	59	0.19	25	Yes	53.99	48
Banco Comercial Portugues SA	PO	80,498	52	11.54	21	1.13	57	162.45	39	0.04	65			
Banco De Sabadell SA	SP	92,350	48	6.57	61	1.22	42	160.49	40	0.14	39		196.43	16
Banco Espirito Santo SA	PO	63,656	54	9.02	35	1.05	61	167.07	36	0.02	73		81.51	42
Banco Pastor SA	SP	22,184	81	6.53	62	1.53	26	155.21	46	0.15	37		124.19	29
Banco Popolare Societa Cooperativa	IT	97,522	46	16.23	12	0.86	69	198.85	23	0.07	55			
Banco Popular Espanol SA	SP	101,220	45	6.67	58	1.65	18	171.38	34	0.19	26		356.83	9
Banco Portugues de Investimento SA	PO	36,727	70	8.11	43	1.22	46	143.95	56	0.11	46		68.15	46
Banco Santander SA	SP	891,133	10	5.62	73	1.21	48	143.98	55	0.17	30	Yes	179.18	17
Bank Of Greece	GR	55,127	57	17.35	11	1.53	27	1,141.33	2	-0.69	86			
Bank Of Ireland	IR	131,976	41	12.33	18	1.52	28	150.19	49	0.21	20		113.40	35
Bankia SA	SP	249,067	28	9.42	29	1.02	63	139.82	57	0.07	54			
Bankinter	SP	42,795	68	7.26	53	1.83	12	215.14	20	0.13	43		292.06	11
Banque Cantonale Vaudoise	SZ	26,466	77	4.40	78	1.62	21	136.41	60	0.26	17			

Table 8 (b) Bank information and characteristics

Bank name	Country	Total assets	Rank	Leverage	Rank	M/B	Rank	Liquidity	Rank	Profitability	Rank	G-SIB	CDS	Rank
Barclays Plc	GB	1,380,452	6	12.60	16	1.14	55	134.15	63	0.18	28	Yes	122.27	30
BNP Paribas	FR	1,699,803	1	6.25	63	0.92	67	103.97	74	0.10	50	Yes	36.76	52
Bradford & Bingley PLC	GB	53,784	59	21.59	9	1.45	30	1,724.20	1	0.26	16		166.71	23
Caisse Regionale de Cr.Agr.	FR	28,335	76	9.14	34	0.74	78	245.30	15	0.44	8			
Caixabank SA	SP	195,638	33	4.26	79	0.82	74	133.32	64	0.44	7			
Capitalia SpA	IT	131,520	42	8.29	40	1.33	36	191.27	26	0.13	41		24.31	54
Commerzbank AG	GE	592,598	16	31.71	5	0.61	82	180.39	31	0.00	74	Yes	49.34	49
Credit Agricole SA	FR	1,455,346	4	14.76	15	0.60	84	123.51	69	0.02	72	Yes	131.03	28
Credit Suisse Group AG	SZ	768,570	12	9.36	31	1.14	56	90.71	83	0.05	61	Yes	101.15	39
Creditansalt	AS	172,697	39	6.05	67	1.67	16	185.43	29	0.26	18			
Credito Valtellinese Scarl	IT	20,717	82	8.72	38	0.61	83	153.15	47	0.02	70			
Danske Bank AS	DE	384,830	23	14.79	14	1.17	52	237.67	17	0.08	53		120.72	33
Depfa Bank PLC	IR	186,897	35	38.22	3	2.06	7	921.95	4	0.06	58		860.68	4
Deutsche Bank AG	GE	1,505,880	3	12.18	19	0.80	75	72.70	86	0.03	68	Yes	111.06	36
Deutsche Postbank AG	GE	186,068	36	9.42	30	1.27	39	102.53	76	0.04	62			
Dexia SA	BE	450,381	21	465.71	1	0.86	70	303.83	11	0.02	71	Yes	341.49	10
DNB ASA	NO	189,334	34	7.78	49	1.21	47	182.09	30	0.20	23		60.22	47
Emporiki Bank Of Greece SA	GR	23,302	80	6.12	65	2.42	2	124.30	68	-0.36	84			
Erste Group Bank AG	AS	175,628	38	7.85	47	0.82	73	124.36	67	0.06	59		178.41	19
Eurobank Ergasias SA	GR	59,531	56	23.55	6	1.55	25	135.12	62	8.47	2		995.09	2
GAM Holding AG	SZ	10,679	85	1.29	86	1.84	11	961.56	3	4.88	3			
Glitnir EHF	IC	14,927	83	6.03	69	2.31	3	345.51	8	0.38	10		367.29	8
HBOS PLC	GB	707,693	14	7.78	48	1.61	22	174.25	33	0.20	22		71.22	45
HSBC Holdings PLC	GB	1,675,773	2	2.76	83	1.30	37	99.24	79	0.25	19	Yes	83.53	41
Hypovereinsbank AG	GE	519,281	17	23.43	7	1.00	65	231.17	19	-0.01	76			
IKB Deutsche Industriebank AG	GE	38,442	69	44.59	2	1.02	64	689.18	5	-0.09	80		204.47	15
ING Groep NV	NE	1,082,024	7	6.10	66	1.15	54	121.86	71	0.10	48	Yes	27.75	53
Intesa Sanpaolo SpA	IT	493,799	18	6.58	60	0.91	68	187.18	28	0.10	47		176.27	20
Investec PLC	SA	43,883	66	3.48	81	1.19	50	124.80	66	0.32	13			

Table 8 (c) Bank information and characteristics

Bank name	Country	Total assets	Rank	Leverage	Rank	M/B	Rank	Liquidity	Rank	Profitability	Rank	G-SIB	CDS	Rank
Irish Bank Resolution Corporation	IR	49,244	62	4.94	77	2.49	1	159.24	42	0.49	4		822.84	5
Julius Baer Group Ltd	SZ	46,353	63	2.15	84	1.78	13	75.97	85	0.27	14			
Jyske Bank	DE	31,907	74	7.08	56	1.25	40	159.84	41	0.17	32			
Kaupthing Bank EHF	IC	32,396	73	5.14	75	2.09	6	340.58	9	0.46	6		281.00	12
KBC Groep NV	BE	299,489	27	6.04	68	1.09	59	102.05	77	0.08	52		75.62	43
Komercni Banka AS	CZ	24,949	78	1.40	85	2.15	5	98.64	80	0.46	5			
Landsbanki HF	IC	14,683	84	5.85	71	1.96	10	245.07	16	0.41	9		256.88	13
Lloyds Banking Group PLC	GB	831,337	11	7.08	57	1.43	31	145.22	54	0.17	31	Yes	147.56	27
Marfin Investment Group Holdings	GR	4,617	86	6.21	64	1.08	60	98.55	81	-0.67	85			
Mediobanca SpA	IT	62,426	55	7.24	54	1.19	51	593.07	6	0.20	21		172.90	22
National Bank Of Greece	GR	90,733	49	7.69	50	1.20	49	103.47	75	-0.11	81		1021.31	1
Natixis Banques Populaires	FR	385,520	22	21.96	8	0.75	77	299.96	12	0.07	56	Yes	158.90	25
Nordea Bank AB	SW	467,607	19	7.14	55	1.37	35	163.78	38	0.14	38	Yes	84.54	40
NRAM PLC	GB	87,850	50	10.54	25	2.19	4	323.86	10	0.27	15			
OP Financial Group	FI	32,505	72	9.57	27	1.30	38	377.86	7	0.19	24			
Piraeus Bank SA	GR	50,316	61	12.40	17	1.16	53	135.46	61	-0.17	82		511.09	7
Raiffeisen Bank International AG	AS	96,716	47	7.30	52	1.22	44	139.63	58	0.19	27			
Royal Bank Of Scotland Group	GB	1,436,305	5	9.21	32	0.83	72	128.13	65	0.02	69	Yes	163.60	24
Sanpaolo IMI SpA	IT	225,990	30	5.63	72	1.67	15	176.30	32	0.15	34			
Santander UK PLC	GB	319,921	25	33.85	4	0.24	86	109.44	73	0.18	29		179.18	17
Skandinaviska Enskilda Banken AB	SW	221,699	31	7.66	51	1.40	34	164.37	37	0.12	45		105.18	38
Societe Generale SA	FR	1,026,358	9	8.47	39	0.80	76	98.27	82	0.06	57	Yes	46.70	50
Standard Chartered PLC	GB	303,642	26	3.25	82	1.59	23	99.91	78	0.35	11	Yes	122.17	31
Svenska Handelsbanken AB	SW	219,199	32	9.50	28	1.66	17	266.45	13	0.15	35		72.56	44
Swedbank AB	SW	168,409	40	7.90	46	1.47	29	263.19	14	0.15	36		121.22	32
Ubi Banca SpA	IT	108,431	44	12.12	20	0.67	81	188.48	27	0.03	67			
UBS Group AG	SZ	1,081,380	8	7.99	45	1.63	19	77.82	84	0.05	60	Yes	110.92	37
Unicredit SpA	IT	679,855	15	8.97	36	1.03	62	151.93	48	0.09	51	Yes		

Note This table displays the the bank characteristics for each of the 86 European banks taken as an average of quarterly data across the full sample period January 2001 to December 2015. Because of availability, the data for the liquidity ratio, which is the loan-to-deposit ratio, is in yearly frequency. Furthermore the CDS spread data is in daily frequency and is only shown for the 56 banks, for which CDS data is available in Datastream. The total assets are in €*m*. The leverage ratio is calculated as (book value of debt + market value of equity) divided by the market value of equity. Market-to-book is the ratio of market equity value over the book equity value. To assess liquidity, the loan-to-deposit ratio is taken, which is the total loans divided by the total deposits of a bank. Finally, the profitability is defined as the return on assets, which is the net income divided by the average total assets as a percentage. The table further shows how each bank ranks in each bank characteristic separately. Finally, the table shows whether the bank is considered a Global Systemically Important Bank (G-SIB) by the FSB. The data is taken from Datastream.

B Driscoll and Kraay standard errors

Consider the within-transformed fixed effects regression model:

$$y_{it}^{*} = \beta' X_{it}^{*} + \varepsilon_{it}^{*} \qquad i = 1, ..., N, \quad t = 1, ...T$$

where y_{it} is the dependent variable, X_{it} a $K \times 1$ vector of dependent variables, The observations across firms are stacked as one variable for the panel model as follows:

$$\begin{aligned} y_{it} &= (y_{1t_{11}}, y_{1t_{12}}, ..., y_{1T_1}, y_{2t_{21}}, ..., y_{NT_N})' \\ X &= (x_{1t_{11}}, x_{1t_{12}}, ..., x_{1T_1}, x_{2t_{21}}, ..., x_{NT_N})' \end{aligned}$$

which means that the panel data is allowed to be unbalanced. The error terms ε_{it} can be heteroskedastic, autocorrelated and correlated in the cross-section. Then the parameter β is consistently estimated by OLS as $\hat{\beta} = (X'X)^{-1}X'y$.

The Driscoll and Kraay covariance matrix is as follows:

$$V(\hat{\beta}) = (X'X)^{-1}\hat{S}_T(X'X)^{-1} \tag{30}$$

of which the square roots of the diagonal terms are the robust standard errors. Here the $\hat{S}_T$ is defined by Newey and West (1987) as:

$$\hat{S}_T = \hat{\Omega}_0 + \sum_{j=1}^{m(T)} w(j,m)(\hat{\Omega}_j + \hat{\Omega}_j') \tag{31}$$

Here $m(T)$ is the number of lags up to which the errors may be autocorrelated. For simplicity, we take $m(T) = \text{floor}(4(T/100)^{2/9})$ following Newey and West (1994), which is a rule of thumb, but not necessarily optimal. The so-called Bartlett weights make sure that $\hat{S}_T$ is positive semi-definite and that high order lags are assigned lower weights:

$$w(j, m(T)) = 1 - j/(m(T) + 1) \tag{32}$$

The $K \times K$ matrix $\hat{\Omega}_j$ is defined as

$$\hat{\Omega}_j = \sum_{t=j+1}^{T} h_t(\hat{\theta}) h_{t-j}(\hat{\theta})' \quad \text{with} \quad h_t(\hat{\theta}) = \sum_{i=1}^{N(t)} h_{it}(\hat{\theta}) \tag{33}$$

where in case of panel OLS estimation, the $h_{it}(\hat{\theta})$ is a vector of moment conditions of the linear regression model as shown

$$h_{it}(\hat{\theta}) = x_{it}\hat{\varepsilon}_{it} = x_{it}(y_{it} - x'_{it}\hat{\theta}) \tag{34}$$

C PCA

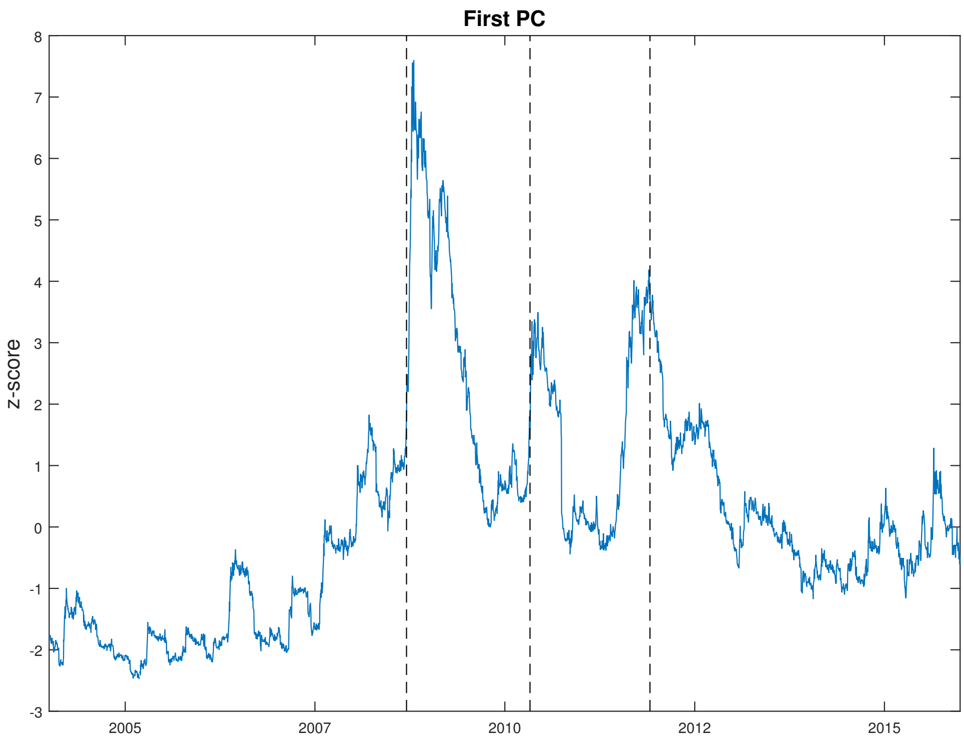

Figure 10: First component PCA systemic risk measures
This figure shows the first principal component, which accounts for the largest variance over the four systemic risk measures, MES, ΔCoVaR, SRISK and DIP from January 1st, 2004 until December 31st, 2015. The principal component is reported as z-scores, which means the number of standard deviations away from the historical mean taken over the complete time sample. The vertical dashed lines indicate major events in the crises periods. (1) September 15th, 2008: Lehman Brothers bankruptcy. (2) May 2nd, 2010: Greek government bailout (3) November 30th, 2011: Federal Reserve, ECB and European central banks lower dollar swaps.

D Systemic risk ranking

Table 9 Systemic risk rankings

Ranking	MES	△CoVaR	SRISK	DIP
1	Bank Of Ireland	UBS	Deutsche Bank	BNP Paribas
2	Allied Irish Banks	ING	BNP Paribas	Deutsche Bank
3	Credit Agricole	Credit Suisse	Credit Agricole	HSBC
4	Marfin Investment Group	Unicredit	ING	Barclays
5	Societe Generale	Erste Group Bank	Societe Generale	Royal Bank of Scotland
6	Banco Santander	Banco Bilbao Viz.Arg.	Commerzbank	Credit Agricole
7	Emporiki Bank Of Greece	Deutsche Bank	Unicredit	ING
8	Ageas	Banco Santander	Banco Santander	Banco Santander
9	Banco Bilbao Viz.Arg.	Skandinaviska Enskilda	Dexia	Lloyds Banking Group
10	ING	Nordea Bank	UBS	Societe Generale
11	Mediobanca	DNB	Intesa Sanpaolo	UBS
12	Banca Popol Di Milano	Raiffeisen Bank Intl.	Credit Suisse	Unicredit
13	National Bank Of Greece	Caixabank	Natixis Banques Popul.	Credit Suisse
14	Lloyds Banking Group	Swedbank	Banco Bilbao Viz.Arg.	Commerzbank
15	BNP Paribas	Jyske Bank	KBC Groep	Intesa Sanpaolo
16	Raiffeisen Bank Intl	Ubi Banca	Banca Monte Dei P.S.	Dexia
17	Natixis Banques Popul.	KBC Group	Deutsche Postbank	Nordea Bank
18	Bankinter	Svenska Handelsbanken	Bank Of Ireland	Banco Bilbao Viz.Arg.
19	Banco Espirito Santo	Banco Portugues Invest.	Allied Irish Banks	Natixis Banques Popul.
20	Dexia	Commerzbank	Banco Popol. Soc.Coop.	Danske Bank

Note This table shows the top 20 systemic risk rankings for each of the systemic risk measures MES, △CoVaR, SRISK and DIP at December 31^{st}, 2010. A total of 86 European banks are considered.