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SOPHISTICATED VS. SIMPLE SYSTEMIC RISK MEASURES

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Sophisticated vs. Simple Systemic Risk Measures[*]

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Abstract: This paper evaluates whether sophisticated or simple systemic risk measures are more suitable in identifying which institutions contribute to systemic risk. In this investigation, *ΔCoVaR*, *Marginal Expected Shortfall* (*MES*), *SRISK* and *Granger-Causality Networks* are considered as sophisticated systemic risk measures. Market capitalization, total debt, leverage, the stock market returns of an institution, and the correlation between the stock market returns of an institution and the market, are considered as simple systemic risk measures. Systemic relevance is approximated by the receipt of financial support during the financial crisis and the classification, as a systemically important institution, by national or international regulators. The analyses are performed for all companies included in the S&P 500 composite index. The findings suggest that simple systemic risk measures have more explanatory power than sophisticated risk measures. In particular, total debt is found to be the most suitable indicator to detect institutions which contribute to systemic risk, according to the explanatory power and model fit. The most suitable sophisticated risk measure seems to be *SRISK*.

Keywords: Systemic Risk, ΔCoVaR, Marginal Expected Shortfall, SRISK, Granger-Causality Networks

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1. Introduction

In the aftermath of the financial crisis of 2008, a wholly new strand of literature emerged with the goal of measuring systemic risk.[1] These measures can broadly be divided into two categories: (1) macroprudential measures with the goal of measuring the systemic risk of the entire financial system, and (2) microprudential measures which have the goal of identifying the individual contribution of companies to the overall systemic risk of the financial system. The four most relevant sophisticated microprudential measures are: *ΔCoVaR* (Adrian and Brunnermeier, 2011), *Marginal Expected Shortfall* (*MES*) (Acharya et al., 2010; Corvasce, 2013), *SRISK* (Acharya et al., 2012),[2] and *Granger-Causality Networks* (Billio et al., 2012).[3]

Besides these attempts to develop systemic risk measures, there is also the contrasting view in in the literature that systemic risk measures, with an increasing degree of sophistication, have some shortfalls. More specifically, the application of sophisticated systemic risk measures is difficult; hence, they lack transparency (Drehmann and Tarashev, 2011). Therefore, sophisticated measures might not necessarily be the best choice for identifying and regulating systemically relevant institutions. Consequently, simple measures might be more suitable (see, for example, Pottier and Sommer, 2002; Drehmann and Tarashev, 2011; Haldane, 2012; Patro et al., 2013; Rodríguez-Moreno and Peña, 2013).

This paper evaluates whether sophisticated or simple systemic risk measures are more suitable in indicating which companies contribute to systemic risk. In a first approach, I examine the explanatory power of various measures with respect to governmental support received during the financial crisis of 2008. My analysis is based on U.S. companies listed in the S&P 500 composite index in 2007. In a second approach, I investigate which measures correctly predict companies that were recently labeled systemically important. The analysis is based on U.S. companies listed in the S&P 500 composite index in 2013.

The contribution of this paper is threefold. Firstly, this is the first empirical comparison of sophisticated and simple systemic risk measures by means of a benchmark approximating systemic risk. Other studies usually either only provide rankings (Rodríguez-Moreno and Peña, 2013; Huang et al., 2012) or only test sophisticated systemic risk measures (Idier et al.,

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1 An overview of the various measures is provided by Bisias et al. (2012).

2 *SRISK* is not an acronym, but the name of the systemic risk measure indicating how much capital a company needs in a future crisis.

3 According to Neale (2012), Benoit et al. (2013), Balla et al. (2014), Eling and Pankoke (2014) and Jobst (2014), *ΔCoVaR*, *MES*, *SRISK* and *Granger-Causality Networks* are the most widely used systemic risk measures; hence, this is why I focus on these measures in this paper.

2013).[4] Secondly, to the best of my knowledge, this is the first study using a heterogeneous and large sample in the context of systemic risk measures.[5] This carries the advantage that companies are included in the analyses, which are not banks, but which can still be systemically important (e.g., AIG).[6] Thirdly, this paper is the first using information about which companies received financial support during the financial crisis and information about the classification of institutions by regulators to evaluate the usefulness of systemic risk measures. So far, there have only been a few papers that tested systemic risk measures in a way other than by the measure's ability to forecast the company's stock market returns.[7]

There are two basic assumptions made in this paper. The first is that, during the financial crisis, as well as during the present time, regulators have been able to detect the institutions which are contributing to systemic risk. The second is that microprudential risk measures are independent of the general state of the system. The idea to use the regulator's point of view in a regression analysis as the dependent variable is first mentioned by Benoit et al. (2013), but has not yet been implemented.[8] The first study using the information about which institutions received financial support to approximate systemic risk is Weiß and Mühlnickel (2014). The second assumption is generally implicitly made in the literature. For example, none of the previously mentioned systemic risk measures are sensitive to the market context in the sense that it takes feedback effects into account. Whether the stock market is in a slump or booming it has no impact on the methodology of the measures.

The primary empirical findings are as follows. 1) Simple systemic risk measures have more explanatory power than sophisticated ones, in determining the institutions which received financial support during the financial crisis. In addition, they can better explain the amount of

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4 As additional examples, each paper introducing a new systemic risk measure can be named. Normally, each paper introduces a new concept for measuring systemic risk and presents a small empirical implementation, which should prove the superiority of the systemic risk measure at hand. Alternative sophisticated or simple systemic risk measures are usually ignored (see, e.g., Huang et al., 2009; Acharya et al., 2010; Adrian and Brunnermeier, 2011; Billio et al., 2012).

5 Recent studies only consider very small sample sizes. For example, Calice et al. (2012) focus on 16 banks form the U.S. and Europe, Patro et al. (2013) only consider 22 U.S. banks, Balla et al. (2014) consider 29 U.S. depositories and Papanikolaou and Wolff (2014) focus on 20 U.S. banks.

6 The financial crisis has been caused by institutions of the financial sector (see, e.g., Gorton and Metrick, 2012). Consequently, systemic risk measures should indicate companies belonging to this sector. However, one cannot only focus on the financial sector, since a few companies from other sectors, like General Electric (see, e.g., Katz, 2013), are also highly contributing to systemic risk.

7 An exception is the study by Duca and Peltonen (2013). They use a dependent variable in their regressions based on a financial stress index. As explanatory variables, they use macroprudential systemic risk indicators as GDP growth, inflation and the current account deficit of a country.

8 Furthermore, in a comment by DeYoung (2012) about the paper of Calice et al. (2012) he uses the receivement of TARP funds as a sanity check and asks: "Are these point estimates consistent with our knowledge of how these large banks fared during the financial crisis?"

financial support each company received. 2) Simple systemic risk measures have more explanatory power than sophisticated ones, in determining which institutions are currently considered systemically relevant by national or international regulators. 3) The size of a company and its total debt level are the most suitable indicators to determine the systemic risk contribution of an institution. The explanatory power of the size variables is higher than the one of leverage, stock market returns or correlation variables. 4) Among the sophisticated risk measures, *SRISK* seems to be the most suitable, since it has explanatory power in various model settings; in comparison to the other sophisticated risk measures, it is the most significant.

The rest of the paper is structured as follows. Section 2 explains the methodology, including the sophisticated and simple systemic risk measures. Section 3 describes the data. Section 4 discusses the results. Finally, Section 5 concludes and further research questions are discussed.

2. Methodology

This paper empirically evaluates whether sophisticated or simple systemic risk measures are more suitable to identify institutions which contribute to systemic risk. Therefore, I regress the systemic relevance of institutions on sophisticated and simple systemic risk measures. The suitability of measures is finally interpreted according to the significance of the results and the model fit.

The systemic relevance of companies is approximated via two different approaches. The first approach focuses on the receipt of financial support during the financial crisis and leads to two different dependent variables. A dichotomous variable is created by taking into account whether financial support is received, and a cardinal variable, by focusing on the amount of received financial support. The second approach takes into account the institutions which are classified as systemically important institutions (SII) in 2013 and leads to a dichotomous variable.[9] Consequently, there will be two dummy variables approximating systemic relevance: the reception of financial support and the classification as *SII* by national or international supervisors. The extent of the systemic relevance of an institution will be approximated by the amount of financial support the institution received. These three variables are used as dependent variables in the regression analyses. This approach follows Weiß and Mühlnickel (2014, p. 109), who "define the most systemically important insurers as those companies that required aid under TARP [Troubled Asset Relief Program]".[10]

For the first approach, the following programs are considered, all of which target individual institutions to ensure financial stability or to reduce systemic risk:[11] TARP, Temporary Liquidity Guarantee Program (TLGP), Maiden Lane I, II, III, AIG Revolving Credit Facility and Securities Borrowing Facility for AIG.

The second approach, and the selection of the *SIIs*, is based on the Financial Stability Board's (FSB) designations of global systemically important banks and global systemically important insurers, as well as on the U.S. Financial Stability Oversight Council's (FSOC) designations of Nonbank Financial Companies and Financial Market Utilities, which are systemically

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9 Two different samples are used in the analyses. The first approach is based on the companies included in the S&P 500 composite index as of January 2007. The second approach is based on S&P 500 companies as well, but in contrast, as a reference point, January 2013 is considered.

10 In addition, see Papanikolaou and Wolff (2014) who relate the participation in TARP of an institution to systemic risk as well.

11 See Congress of the U.S. (2008, Sec 2 [1]), Federal Deposit Insurance Corporation (2008) and Federal Reserve System (2014).

important.[12] The participation in the Comprehensive Capital Analysis and Review by the Federal Reserve Board is not considered an indicator for systemic relevance, because only the 50 largest banks are considered in the review. An inclusion would have led to problems of endogeneity.

As mentioned previously, there is a variety of microprudential sophisticated systemic risk measures. In this paper, *ΔCoVaR, MES, SRISK* and *Granger Causality Networks* are applied, since they are considered the most relevant by the literature. In addition, they cover a wide field of different approaches to systemic risk (Neale, 2012; Benoit et al., 2013; Balla et al., 2014; Eling and Pankoke, 2014; Jobst, 2014)

The simple systemic risk measures used in this paper are motivated by Haldane (2012), in the case of leverage, as well as by Drehmann and Tarashev (2011), in the case of size. Another reason why size has to be included in the analyses is provided by the too-big-to-fail (TBTF) literature. Brewer III and Jagtiani (2013) for example examine mergers of banks in the U.S. between 1991 and 2004 and define a TBTF institution as one with total book value assets in excess of \$100 billion. They find that between \$15 billion and \$23 billion premiums have been paid more for mergers which resulted in a TBTF institution than for mergers which resulted in smaller companies. Therefore, markets assume implicitly that size determines systemic risk, because TBTF institutions are only bailed out due to their impact on financial stability.[13] The motivation for using stock market returns as a simple systemic risk measure is based on the calculation of *MES* (Acharya et al., 2010). The *MES* of a company considers the stock market returns, but only considers the returns of a company when the entire market is in a slump. However, previous studies have not tested if the "tail returns" considered by *MES* do have more explanatory power ex ante than stock market returns. The same logic applies to the linear correlation between the stock market returns of a company and the returns of the entire market. Many researchers argue that correlation should play an important part in the design of any systemic risk measure. For example, Billio et al. (2012) and Chen et al. (2014) use *Granger-Causality Networks* to access systemic risk. In particular, Balla et al. (2014) argue that the tail correlations between different entities should be considered. The Pearson

[12] See FSB (2013a), FSB (2013b) and FSOC (2013). The FSB is an international organization that was established by the G-20 in April 2009. Its purpose is to monitor the finance industry and to make recommendations for addressing systemic risk. The FSOC is a committee chaired by the U.S. Secretary of the Treasury and an insurance expert appointed by the U.S. President. Its purpose is to identify threats to the stability of the financial system.

[13] See Brewer III and Jagtiani (2013) for additional evidence that TBTF institutions are only bailed out because of their impact on financial stability.

correlation should not be such a good indicator since the goal is to focus on spillover effects and not to focus on general co-movements in the market. Nevertheless, Patro et al. (2013) propose the Pearson correlation as a simple systemic risk measure. In an empirical application they show for 22 large U.S. banks that during times of crisis overall correlation spikes and seems to be a useful systemic risk measure.

An overview of the variables and their expected relationships can be found in Table 1. Detailed descriptions of the systemic risk measures can be found in Sections 2.1, 2.2, 2.3 and 2.4. The regression models are illustrated in Section 2.5.

	Explanation	Rationale
Dependent Variables		
First Approach		
Support	Dichotomous variable. One, if the company received financial support in 2008, otherwise zero.	Goal of financial support is to ensure financial stability (see, e.g, Congress of the U.S., 2008, Sec 2 [1]).
Amount	Continuous variable. Amount of received financial support in million USD in 2008.	Goal of financial support is to ensure financial stability (see, e.g, Congress of the U.S., 2008, Sec 2 [1]).
Second Approach		
SII	Dichotomous variable. One, if company is classified as systemically important in 2013, otherwise zero.	Goal of classification is to indicate institutions which can contribute to a systemic crisis (see, e.g., IAIS, 2013, p. 6).
Independent Variables - Sophisticated Systemic Risk Measures		
ΔCoVaR	Systemic risk measure which considers the entire contribution of a company to systemic risk (Section 2.1). The smaller the *ΔCoVaR*, the higher the systemic risk contribution.	For an institution to be in distress at the same time as the market is a sign of a high contribution to systemic risk (Adrian and Brunnermeier, 2011).
MES	Systemic risk measure which focuses on the stock market returns of an institution during a crisis (Section 2.2). The smaller the *MES* (*Marginal Expected Shortfall*), the higher the systemic risk contribution.	Does not focus on the contribution of an institution to the probability of a systemic crisis, but on its impact on the severity (see, e.g., Acharya et al., 2010).
SRISK	Systemic risk measure which determines how much capital in million USD an institution needs if a crisis occurs (Section 2.3).	Advancement of *MES* which takes debt into account and is supposed to be forward looking. Does not take the probability of a crisis into account (Acharya et al., 2012).
Granger-Out	Systemic risk measure which takes Granger-causality relationships between the stock market returns of institutions into account (Section 2.4). The more interconnections, the higher the systemic risk contribution.	The focus lies on the interconnections within a system. Institutions which are highly interconnected are considered to contribute strongly to systemic risk (Billio et al., 2012).
Independent Variables - Simple Systemic Risk Measures		
Size	Natural logarithm of market capitalization in million USD.	On the one hand, size increases impact in the case of bankruptcy (see, e.g., FSB, 2009; Drehmann and Tarashev, 2011). On the other hand, size as an indicator ignores aligned behavior (see, e.g. Adrian and Brunnermeier, 2011). *Debt* is an alternative measure for the size of a company.
Debt	Natural logarithm of total debt in million USD.	
Leverage	Market leverage: total debt / market capitalization.	Leverage (*Leverage* and *Book*) increases the vulnerability of a company in adverse market situations. Increased forecasting power of leverage for bank bankruptcies is assumed (Haldane, 2012).
Book	Book leverage: total debt / total assets.	
Return	One year stock market return of the company.	*MES* and *SRISK* approximate tail returns. The question is if simple stock market returns are sufficient to determine companies which contribute to systemic risk.
Cor-relation	Linear correlation between the stock market returns of a company and the market index.	*ΔCoVaR* and *Granger-Causality Networks* both approximate the interconnectedness between companies (see, e.g., Adrian and Brunnermeier, 2011; Billio et al., 2012). *Correlation* is a simpler approach to assess the interconnections. The question is if it is viable.

Table 1: Description of dependent and independent variables used in the regression analyses.

2.1. ΔCoVaR

ΔCoVaR is a risk measure based on Adrian and Brunnermeier (2011). Its general idea is to measure the value at risk (VaR) of a market, conditional on the state of a certain institution. Hence, it measures the contribution of an institution to systemic risk.

$\Delta CoVaR_q$ indicates the difference between the $VaR_{0.5}$ of a market, conditional on an institution at its $VaR_{0.5}$, and the VaR_q of a market, conditional on an institution at its VaR_q. Weekly stock market returns can be used to calculate the *ΔCoVaR* if the focus only lies on the risk of adverse asset price movements. If funding liquidity risk should also be captured, weekly market-valued total asset prices should be used.

As suggested by Adrian and Brunnermeier (2011), I use quantile regressions to derive *ΔCoVaR*. To calculate the CoVaR measure, I use the quantile regression:

$$\hat{X}^{system|i}{}_q = \hat{\alpha}^i{}_q + \hat{\beta}^i{}_q X^i \tag{1}$$

where: $\hat{X}^{system|i}{}_q$ is the estimated q quantile of returns of the entire market, conditional on institution *i*. X^i are the returns of institution *i*. $\hat{\alpha}^i{}_q$ is the estimated constant and $\hat{\beta}^i{}_q$ the estimated coefficient for institution *i*. Since the q quantile of the market is equivalent to the VaR_q level:

$$VaR^{system|X^i}{}_q = \hat{X}^{system|i}{}_q \tag{2}$$

$$VaR^{system|VaR^i{}_q}{}_q = CoVaR^{system|i}{}_q = \hat{\alpha}^i{}_q + \hat{\beta}^i{}_q VaR^i{}_q \tag{3}$$

$CoVaR_q$ is then generated by only considering the case where $X^i = VaR^i{}_q$, as in Equation (3). Finally, *ΔCoVaR* as applied in this paper, is the difference between the CoVaR of the system at a 1% level and the CoVaR of the system at a 50% level. I choose 1%, to replicate the measure *ΔCoVaR* by Adrian and Brunnermeier (2011) as close as possible.[14] Mathematically, *ΔCoVaR* is described in Equation (4).

$$\Delta CoVaR^{system|i}{}_{0.01} = \hat{\beta}^i{}_{0.01}(VaR^i{}_{0.01} - VaR^i{}_{0.5}) \tag{4}$$

[14] Robustness tests for 5% and 10% quantils are conducted as well. Results do not offer further insights and are displayed in Table 13 and Table 14 in the Appendix.

The growth rate of the market-valued total asset prices is generated as:

$$X^i{}_t = \frac{Equity^i{}_t + Debt^i{}_t}{Equity^i{}_{t-1} + Debt^i{}_{t-1}} - 1 \qquad (5)$$

where: $X^i{}_t$ indicates the growth rate of the market-valued total assets of company *i* at time *t*. $Equity^i{}_t$ denotes the market value of company *i*'s equity value at time *t* (measured by total market capitalization). $Debt^i{}_t$ denotes the book value of company *i*'s total debt.

2.2. MES

The *MES* is a systemic risk measure introduced by Acharya et al. (2010). The general idea is to measure the expected magnitude of a crisis. Therefore, the measure focuses on the expected contribution of an institution to the aggregated capital loss during a crisis but not on the probability of a systemic crisis to occur.[15]

The *MES* of a company is simply the weighted average of the company's historical stock market returns during the time when the entire market is in distress. The *MES* of a company is defined as:

$$MES^i{}_{5\%} = \mathrm{E}\left[\frac{\mathrm{Equity}^i{}_t}{\mathrm{Equity}^i{}_{t-1}} - 1 | \mathrm{I}_{5\%}\right] \qquad (6)$$

$MES^i{}_{5\%}$ indicates the *MES* of company *i*, conditional on the 5% worst trading days of the market in the last year.[16] I choose 5% to replicate the measure *MES* by Acharya et al. (2010) as close as possible. $Equity^i{}_t$ denotes the equity value of company *i* at time *t* and $I_{5\%}$ is an indicator function, denoting the 5% worst market outcomes. The time invariant MES, in this paper considers only the last year of the stock market movements. The applied calculation in this paper is:

$$MES(t)^i{}_{5\%} = \frac{1}{13}\sum\nolimits_{t-261}^{t}\left[\frac{\mathrm{w}^i{}_t}{\mathrm{w}^i{}_{t-1}} - 1 | \mathrm{I}_{5\%,261}\right] \qquad (7)$$

where: $MES(t)^i{}_{5\%}$ stands for the *MES* at time *t* and $I_{5\%,261}$ is an indicator function for the 5% worst market returns during the last 261 trading days.

[15] The fact that the *MES* focuses on the expected magnitude, and not on the probability of a crisis, is often neglected in the literature (Rodríguez-Moreno and Peña, 2013). For the analysis in this paper *MES* is fine since both aspects contribute to the systemic relevance of an institution. An institution can contribute to systemic risk by either increasing the probability or the magnitude of a crisis.

[16] Robustness tests for the 1% and 10% worst trading days are conducted as well. Results do not offer further insights and are displayed in Table 13 and Table 14 in the Appendix.

2.3. SRISK

SRISK is a systemic risk measure developed by Acharya et al. (2012) and is related to *MES*. It is a measure for the expected capital shortfall of a company, given a crisis, and indicates how much additional capital is needed by a company to stay solvent during the next crisis. *SRISK* can be seen as a substitute for stress tests.

The major advancement of *SRISK* over *MES* is that it takes the total debt of a company into account and is supposed to be forward looking. However, as *MES*, *SRISK* does not account for the probability of a crisis to occur. *SRISK* is defined as:

$$SRISK^{i}{}_{t} = E_{t-1}(Capital\ Shortfall^{i}|\text{Crisis}) \tag{8}$$

where: $SRISK^{i}{}_{t}$ indicates the expected capital shortfall of a company *i* at a time *t* given a crisis. *Crisis* is an indicator function, denoting the presence of a crisis. Acharya et al. (2012) suggests measuring the expected capital shortfall of a company via simulated equity returns and the crisis via a broad stock market index, which is simulated for six months in the future. Whenever it falls by more than 40%, this is viewed as a crisis. As Acharya et al. (2012), due to practical reasons, I employ a version of *SRISK* which can be derived directly from certain book and market based variables. The calculations are:

$$\begin{aligned} SRISK^{i}{}_{\mathrm{t}} &= E_{t-1}\big(\big(\mathrm{k}\big(Debt^{i} + \mathrm{Equity}^{i}\big) - \mathrm{Equity}^{i}\big)|\text{Crisis}\big) \\ &= kDebt^{i}{}_{t} - (1-k)\big(1 - LRMES^{i}{}_{t}\big) * Equity^{i}{}_{t} \end{aligned} \tag{9}$$

where: k stands for the capital ratio (equity as a fraction of total liabilities), which I assume to be 8%, as in Acharya et al. (2012). $Debt^{i}{}_{t}$ indicates the total book value of debt and $Equity^{i}{}_{t}$ is the market value of equity, whereas *i* stands for the company and *t* indicates the time. $LRMES^{i}{}_{t}$ indicates the Long Run *MES* and is approximated by $1 - e^{-18*-MES^{i}{}_{t}}$, whereas $-MES^{i}{}_{t}$ represents the *MES*, as in Section 2.2.[17]

[17] For the sake of consistency, I calculate *MES* as in Acharya et al. (2010). Therefore, I use a different threshold for indicating a crisis by using a market downfall of -5%, instead of -2%. In addition, I have to use a different algebraic sign in the approximation for *LRMES*, since in Acharya et al. (2010), *MES* is a negative number, whereas in Acharya et al. (2012), *MES* is considered positive. For a further discussion of *LRMES*, see Brownlees and Engle (2012). Robustness tests for *SRISK* considering different *MESs* are displayed in Table 13 and Table 14 in the Appendix.

2.4. Granger Causality Networks

Billio et al. (2012) propose *Granger-Causality Networks* to measure interconnectedness and systemic risk. The underlying idea is to measure the systemic risk of a market with *m* companies by evaluating the interconnection of all *m*(m-1)* pairs in the market. A pair is regarded as interconnected if a Granger-causality relationship between the stock market returns of the two companies cannot be rejected at a 5% significance level.[18] The systemic risk of the system is finally measured by the sum of pairs which are considered interconnected. The order of the pairs must be considered. Otherwise, the direction of the interconnection is ignored. Companies which Granger-cause stock market returns of many other companies contribute most to systemic risk. In addition, companies whose stock market returns are heavily influenced by the returns of other companies can be considered vulnerable. Mathematically, Granger-causality can be described as follows:

$$\mathrm{R^i}_{t+1} = \mathrm{a^i}\mathrm{R^i}_t + \mathrm{b^{ij}}\mathrm{R^j}_t + \varepsilon^{\mathrm{i}}_{t+1} \tag{10a}$$

$$\mathrm{R^j}_{t+1} = \mathrm{a^j}\mathrm{R^j}_t + \mathrm{b^{ji}}\mathrm{R^i}_t + \varepsilon^{\mathrm{j}}_{t+1} \tag{10b}$$

where: $R^i{}_t$ and $R^j{}_t$ represent the time series of the stock market returns, whereas *i* and *j* indicate the two companies of a given pair. *t* stands for the time and ε indicates an error term. $a^i, b^{ij}, a^b,\ b^{ji}$ are the coefficients of the model. If b^{ij} is different from zero, then $\mathrm{R^j}$ Granger-causes $\mathrm{R^i}$ and if b^{ji} is different from zero, then R^i Granger-causes R^j. Mathematically, the indicator of Granger-causality is:

$$(\mathrm{i} \rightarrow \mathrm{j}) = \begin{cases} 1 \text{ if } \mathrm{R^i} \text{ Granger} - \text{causes } \mathrm{R^j} \\ \qquad 0 \text{ otherwise} \end{cases} \tag{11}$$

Finally, the number of Granger-causality connections used as a measure for the systemic risk contribution of a company is derived as:

$$GrangerOut_i = \sum_{\mathrm{i=1,j\neq i}}^{\mathrm{m}} (\mathrm{i} \rightarrow \mathrm{j}) \tag{12}$$

where: $GrangerOut_i$ represents the number of companies whose stock market returns are influenced by the stock market returns of company i. The variable m indicates the sample size.[19]

[18] I conduct robustness tests in which 1% and 10% significance levels are considered as well. The results do not offer further insights and are displayed in Table 13 and Table 14 in the Appendix.

[19] In contrast to Billio et al. (2012), I do not adjust *GrangerOut* (the number of connections) to the sample size, since the sample size is rather stable and the focus of this paper does not lie in the comparison of the systemic risk contributions of companies over time.

2.5. Regression Models

For the logistic regressions regarding the dependent variables, *Support* (first approach, companies which received financial support during the financial crisis) and *SII* (second approach, companies lately classified as systemically important institutions by regulators), the respective models are:

$$logit(Support)_i = \alpha + \sum_{j=1}^{n}(\beta_j X_{ji}) + \varepsilon_i \tag{13a}$$

$$logit(SII)_i = \alpha + \sum_{j=1}^{n}(\beta_j X_{ji}) + \varepsilon_i \tag{13b}$$

where: $logit(Support)_i$ and $logit(SII)_i$, respectively stand for the natural logarithm of the odds ratios of the variables *Support* and *SII*. Note that α indicates the constant and ε_i the error term. β_j represents the regression coefficient of variable j. X_{ji} stands for the independent variable j. i displays the company. The total amount of variables is represented by n and is varying according to the different model specifications.

For the multivariate linear regressions regarding the first approach, the following model is used:

$$Amount_i = \alpha + \sum_{j=1}^{n}(\beta_j X_{ji}) + \varepsilon_i \tag{14}$$

The notation is the same as for the models in Equations (13a) and (13b). Again, the number of considered independent variables is varying according to the model specifications.

3. Data

The data used in this paper is entirely available from public sources. Table 2 provides an overview of the data used to derive the variables employed in the analyses. Moreover, the source of the data is listed.

	Necessary Data	Source
Dependent Variables		
First Approach		
Support	• Information about which institutions received financial support	• U.S. Department of the Treasury (website) • Federal Reserve System (website) • Federal Deposit Insurance Corporation (website)
Amount	• Information about the amount of support the concerning institutions received	
Second Approach		
SII	• Information about which institutions are designated as systemically important	• Financial Stability Oversight Council (FSOC) (website) • Financial Stability Board (FSB) (website)
Independent Variables - Sophisticated Systemic Risk Measures		
ΔCoVaR	• Market capitalization • Total debt • Returns of market index	• DataStream • Thomson One
MES	• Market capitalization • Returns of market index	• DataStream
SRISK	• *MES* • Total liabilities • Market capitalization	• DataStream • Thomson One
GrangerOut	• Market capitalization	• DataStream
Independent Variables - Simple Systemic Risk Measures		
Size	• Market capitalization	• DataStream
Debt	• Total debt	• Thomson One
Leverage	• Market capitalization • Total debt	• DataStream
Book	• Total debt • Total assets	• Thomson One
Return	• Market capitalization	• DataStream
Correlation	• Market capitalization	• DataStream

Table 2: Description of the data used to generate the dependent and independent variables.

The samples of my analyses are based on the S&P 500 composite index; therefore, my initial samples consist of 500 companies. The advantage of not only focusing on financial institutions is that financial institutions which are not labeled as such are included as well. The AIG case has proven that, from a systemic risk perspective, it is important to incorporate a very broad perspective, since it is not possible to conclude from the industry specification of a company that certain activities are not undertaken.[20]

Based on the S&P 500 composite index, I use two different samples for my analyses. For the first approach, regarding the variables *Support* and *Amount* as a reference point, the constituents list of the index is considered as of January 2007. The explanatory power, ex ante and ex post, of the sophisticated and simple systemic risk measures is evaluated. Companies going bankrupt after January 2007 are not excluded from the sample to avoid a survivorship bias. From the initial sample of 500 companies, 26 companies are excluded, due to missing data, so that the final sample consists of 474 institutions. For the second approach, regarding the variable *SII* as a reference point, the constituents list of the index is considered as of January 2013. The final sample consists of 470 companies. Overall, 30 companies are excluded again due to missing data.

In order to calculate the *MES* risk measure of the individual companies, returns of a reference stock market are necessary. I use the S&P 500 composite index as an approximation for the U.S. market. For the calculation of the *MES* risk measure, daily stock market returns are used. All information are taken from DataStream.

ΔCoVaR is calculated for the companies in the S&P 500 composite index. In order to generate the weekly growth rate of the market-valued asset prices, information on the total market capitalization of the companies are obtained from DataStream on a weekly basis. Book-valued total debt data is obtained from Thomson One on a quarterly basis. Linear interpolation is used to compute the weekly book-valued total debt information for each company in the sample. In total, the *ΔCoVaR* calculations consider data from January 2000 to January 2009 in the case of the first approach and data from January 2003 to January 2014 in the case of the second approach. Following Adrian and Brunnermeier (2011), I only consider companies for which at least 260 weeks of data are available. The growth rate of the market-valued total assets of the system is derived by taking the weighted average of institutions' growth rate.

SRISK is based on the *MES* measure and requires further information. Figures about the market capitalization of each company are obtained from DataStream and information about the total liabilities from Thomson One.[21] The variable *SRISK* indicates the capital (in million

[20] See, e.g., Harrington (2009) and Katz (2013).

[21] Acharya at al. (2012) mention total debt instead of total liabilities. Though, their results can only be replicated with the total liabilities from DataStream and not with total debt. Therefore, I decided to use total liabilities from DataStream.

USD) a company needs for surviving the next crisis. If it is negative, no additional capital is necessary.

The *Granger-Causality Networks* are based on the Granger-causality relationships within a system. Therefore, the market capitalizations of all institutions in the samples are obtained from DataStream. In the case of the first approach, there are 224,202 possible interconnections. In the second approach, there are 220,430.

For the cross sectional analyses regarding the first approach (*Support* and *Amount* as dependent variables), the following points in time are chosen: January 2007, January 2008 and January 2009. Since all of the financial support programs during the financial crisis were introduced in 2008, the analyses for January 2007 have an ex ante character and the ones for January 2009 an ex post character.

Regarding the second approach (*SII* as dependent variable), the analyses focus on January 2013 and January 2014. Institutions have been designated as systemically important in 2013; therefore, the analyses for January 2013 have an ex ante character and the ones for January 2014 an ex post character.

For the logistic regressions regarding the first approach, further adjustments to the dependent variable *Support* are made. I consider the insurers Allstate, Principal Financial and Prudential Financial as participants in the TARP, although they received no financial support. The reason is that they were considered systemically important and were offered financial support, which they declined (Harrington, 2009). In addition, I treat Fannie Mae, Lehman Brothers and Washington Mutual as if they had received financial support. Fannie Mae did not participate in a government / FED program, but nevertheless received support (see, e.g., Federal Reserve System, 2008), not supporting Lehman Brothers was considered a mistake (see, e.g., Palank, 2013) and Washington Mutual was only taken over by JPMorgan Chase due to pressure by federal agencies (see, e.g., Isidore, 2013).

4. Results

4.1. Results of the First Approach (Financial Support in 2008)

The first approach takes into account the financial support programs initiated during the financial crisis in 2008. It is evaluated whether sophisticated or simple systemic risk measures are more suitable to explain which institutions received financial support, as well as how much support these institutions received.

Table 3 illustrates the results regarding the variable *Support* for January 2007 (Panel A) and 2009 (Panel C); the results for January 2008 (Panel B) can be found in Table 6 in the Appendix. In these cases, the evaluation involved determining if the systemically risky companies can be indicated correctly. Models one to five show the results of the regressions regarding the sophisticated systemic risk measures. Models six to thirteen illustrate the results regarding the simple systemic risk measures. The results in Table 3 (Panel A) suggest that sophisticated systemic risk measures do not have any explanatory power ex ante. The fit of all models regarding these measures (models one to five) is poor. Only *ΔCoVaR* has a significant impact at a 5% level.[22]

Regarding the simple systemic risk measures (models six to thirteen), *Debt* and *Leverage* are found to have a decent explanatory power. Both variables are significant at a 1% level and, at least in the case of *Debt*, the model fit seems to be good with a pseudo R^2 of 0.45. In model twelve, both variables *Size* and *Book* have a negative and significant impact at a 1% level. This is against economic intuition, since this means that institutions with low market capitalization and low leverage received financial support. A more likely interpretation is that this result is due to the multicollinearity issues between the two leverage variables, *Leverage* and *Book*, and both size variables, *Size* and *Debt*. In models six and thirteen, *Size* has a positive and significant impact at a level of 1%, but the fit of the models is worse than the one of the model regarding the variable *Debt* (model seven). Therefore, one can conclude that, ex ante, mainly the amount of debt seems to have explanatory power whether an institution is contributing to systemic risk.

Furthermore, market capitalization and leverage might be helpful indicators. According to the results presented in Panel A of Table 3, sophisticated systemic risk measures seem, ex ante, not be useful in determining the institutions contributing to systemic risk.

[22] In order to evaluate the goodness of fit of a model, I apply the Nagelkerke information criterion (pseudo R^2). The values below 0.2 indicate a very poor model fit, the values above 0.2 indicate a decent fit and the values above 0.4 indicate a good fit (Backhaus et al., 2006, p. 456).

Panel A: January 2007													
Model	1	2	3	4	5	6	7	8	9	10	11	12	13
ΔCoVaR	-40.89** (4.33)	-	-	-	-47.73** (5.33)	-	-	-	-	-	-	-	-
MES	-	6.70 (0.07)	-	-	24.42 (0.82)	-	-	-	-	-	-	-	-
SRISK	-	-	0.00 (0.08)	-	0.00 (0.17)	-	-	-	-	-	-	-	-
GrangerOut	-	-	-	0.02 (2.48)	0.02 (2.67)	-	-	-	-	-	-	-	-
Size	-	-	-	-	-	0.77*** (26.51)	-	-	-	-	-	-2.17*** (22.10)	0.71*** (19.00)
Debt	-	-	-	-	-	-	1.24*** (55.01)	-	-	-	-	3.26*** (44.63)	-
Leverage	-	-	-	-	-	-	-	1.11*** (22.96)	-	-	-	-0.05 (0.05)	0.98*** (18.23)
Book	-	-	-	-	-	-	-	-	0.47 (0.24)	-	-	-15.62*** (33.84)	-
Return	-	-	-	-	-	-	-	-	-	0.80* (3.21)	-	0.79 (0.88)	0.80 (2.27)
Correlation	-	-	-	-	-	-	-	-	-	-	-0.02 (0.00)	2.04 (1.95)	0.22 (0.05)
Pseudo R^2	0.02	0.00	0.00	0.01	0.04	0.12	0.45	0.19	0.00	0.01	0.00	0.71	0.28

Panel C: January 2009													
Model	1	2	3	4	5	6	7	8	9	10	11	12	13
ΔCoVaR	14.24 (0.99)	-	-	-	21.66 (0.51)	-	-	-	-	-	-	-	-
MES	-	-37.87*** (49.47)	-	-	-11.26 (0.98)	-	-	-	-	-	-	-	-
SRISK	-	-	0.61*** (41.41)	-	0.54*** (27.00)	-	-	-	-	-	-	-	-
GrangerOut	-	-	-	0.01*** (17.47)	0.01 (1.92)	-	-	-	-	-	-	-	-
Size	-	-	-	-	-	0.02 (0.03)	-	-	-	-	-	-1.86*** (14.35)	0.64*** (16.42)
Debt	-	-	-	-	-	-	1.36*** (47.54)	-	-	-	-	3.69*** (34.18)	-
Leverage	-	-	-	-	-	-	-	0.13*** (12.79)	-	-	-	0.01 (0.03)	0.11*** (9.83)
Book	-	-	-	-	-	-	-	-	-0.41 (0.19)	-	-	-17.69*** (25.91)	-
Return	-	-	-	-	-	-	-	-	-	-2.90*** (16.48)	-	0.86 (0.15)	-3.84*** (11.30)
Correlation	-	-	-	-	-	-	-	-	-	-	-1.08 2.61	1.13 (0.34)	-1.62 (2.35)
Pseudo R^2	0.01	0.27	0.75	0.07	0.75	0.00	0.47	0.15	0.00	0.08	0.01	0.78	0.25

Table 3: Logistic regression results, based on the full sample (n = 474) for January 2007 and January 2009. Results for January 2008 are shown in Table 6 in the Appendix. The dependent variable is *Support* in all models, indicating whether a company received financial support during the financial crisis. Wald statistics are shown in brackets. ***, ** and * indicate a 1%, 5% and 10% significance level. Results regarding the constants are omitted.

In contrast, Panel C of Table 3 suggests that, ex post, sophisticated systemic risk measures can indeed explain which companies received financial support. *MES*, *SRISK* and *GrangerOut* have a significant impact at a 1% level. In addition, the goodness of fit for *SRISK* (model three) is high and the one for *MES* (model two) is decent. If all sophisticated risk measures are combined into one model (model five), only *SRISK* has a significant impact at a 1% level and the pseudo R^2 figure is not higher, as in model three, in which only *SRISK* is considered. Consequently, ex post, the application of *MES* on its own might be useful, but as soon as *SRISK* is employed, *ΔCoVaR*, *MES* and *GrangerOut* provide no further information.

The simple systemic risk measures reveal that *Debt* (model seven), *Leverage* (model eight) and *Return* (model ten) all have significant explanatory power at a 1% level. Though, only the model for *Debt* has a good model fit. Interestingly, in model twelve, which considers all simple systemic risk measures, *Size* and *Book* both have a negative and significant impact at a 1% level. This is against economic intuition, since this would imply that the lower the market capitalization of the company and the lower the book leverage ratio, the more likely it is that the company is systemically risky. The results can be explained by multicollinearity issues, since *Size* and *Debt*, as well as *Leverage* and *Debt*, are variables which measure the size and leverage of an institution. Results for model thirteen, which only considers one size variable and one leverage variable, reveal that, ex post, the size and leverage of an institution are helpful in determining which institutions are contributing to systemic risk.

In model thirteen, as in model ten, *Return* is significant and negative. This could be expected and is in line with economic intuition. More specifically, during a crisis, the most systemically contributing companies have the most adverse stock market returns. All in all, Panel C of Table 3 indicates that *SRISK* is, ex post, able to identify the institutions which are contributing to systemic risk. In addition, the amount of debt and leverage ratios of an institution can be helpful as well.

I conduct a robustness test for a subsample, only considering financial services companies, to check if the sophisticated systemic risk measures might only be applicable in the context of the financial sector. Table 8 (Panels A and C) and Table 10 (Panel B) in the Appendix illustrate the results for institutions which, according to the FTSE International Limited (2012) Industry Classification Benchmark, belong to the following sectors: banks, insurance, real estate and financial services. The subsample size is 84. Again, the results presented are for January 2007, January 2008 and January 2009.

The results for the full sample are supported. For financial services companies, ex ante, sophisticated systemic risk measures have no explanatory power. Among the simple systemic risk measures, *Debt* has the highest explanatory power and is, in all relevant models, significant at a 1% level. Interestingly, in contrast to the results for the full sample, *Correlation* has explanatory power in all relevant models at a 1% level. In the case of financial services companies, the institutions whose stock returns are negatively correlated with the S&P 500 composite index seem to have a higher likelihood of contributing to systemic risk.

From the ex post perspective (Panel C of Table 8), the results for the full sample are similar to the ones for the subsample. *SRISK* seems to be the most suitable sophisticated systemic risk measure for indicating the institutions contributing to systemic risk, and *Debt*, in the case of simple measures. In contrast to the results of the full sample, though, *Correlation* still has explanatory power and the leverage variables seem to have no impact at all. One explanation for that could be that financial services companies, which are contributing to systemic risk, had to deleverage after the financial crisis, and therefore, ex post, contributing and non-contributing institutions had similar leverage ratios (Papanikolaou and Wolff, 2014).

Table 4 illustrates the results regarding the variable *Amount* for January 2007 (Panel A) and January 2009 (Panel C). In Table 7 in the Appendix, the results for January 2008 (Panel B) are presented. It is analyzed whether the sophisticated and simple measures can correctly explain the volume of financial support that systemically risky institutions received. The results for the sophisticated systemic risk measures are shown in models one to five. The results for the simple systemic risk measures are shown in models six to thirteen.

Panel A: January 2007													
Model	1	2	3	4	5	6	7	8	9	10	11	12	13
ΔCoVaR	-0.44***	-	-	-	-0.12	-	-	-	-	-	-	-	-
	(-2.96)				(-0.68)								
MES	-	-0.15	-	-	-0.28	-	-	-	-	-	-	-	-
		(-0.93)			(-1.64)								
SRISK	-	-	-0.57***	-	-0.62***	-	-	-	-	-	-	-	-
			(-4.17)		(-3.84)								
GrangerOut	-	-	-	-0.02	0.02	-	-	-	-	-	-	-	-
				(-0.13)	(0.13)								
Size	-	-	-	-	-	0.73***	-	-	-	-	-	0.73***	-
						(6.42)						(6.10)	
Debt	-	-	-	-	-	-	0.65***	-	-	-	-	-	0.84***
							(5.12)						(5.33)
Leverage	-	-	-	-	-	-	-	0.19	-	-	-	0.05	-0.31*
								(1.15)				(0.39)	(-1.94)
Book	-	-	-	-	-	-	-	-	0.28*	-	-	-	-
									(1.78)				
Return	-	-	-	-	-	-	-	-	-	-0.12	-	-0.12	-0.06
										(-0.74)		(-1.02)	(-0.49)
Correlation	-	-	-	-	-	-	-	-	-	-	-0.02	-0.11	-0.04
											(-0.11)	(-0.92)	(-0.30)
Adjusted R^2	0.17	0.00	0.31	-0.03	0.38	0.52	0.41	0.01	0.06	-0.01	-0.03	0.50	0.43

Panel C: January 2009													
Model	1	2	3	4	5	6	7	8	9	10	11	12	13
ΔCoVaR	-0.15	-	-	-	-0.21*	-	-	-	-	-	-	-	-
	(-0.89)				(-1.85)								
MES	-	-0.26	-	-	-0.07	-	-	-	-	-	-	-	-
		(-1.64)			(-0.56)								
SRISK	-	-	0.70***	-	0.67***	-	-	-	-	-	-	-	-
			(5.68)		(5.91)								
GrangerOut	-	-	-	0.37**	0.34***	-	-	-	-	-	-	-	-
				(2.38)	(2.99)								
Size	-	-	-	-	-	0.37**	-	-	-	-	-	0.79***	-
						(2.41)						(5.81)	
Debt	-	-	-	-	-	-	0.69***	-	-	-	-	-	0.75***
							(5.46)						(5.56)
Leverage	-	-	-	-	-	-	-	0.47***	-	-	-	0.47***	0.05
								(3.05)				(3.82)	(0.32)
Book	-	-	-	-	-	-	-	-	0.27	-	-	-	-
									(0.12)				
Return	-	-	-	-	-	-	-	-	-	-0.35**	-	-0.55***	-0.43***
										(-2.25)		(-3.65)	(-2.92)
Correlation	-	-	-	-	-	-	-	-	-	-	0.25	-0.34**	-0.22
											(1.55)	(-2.41)	(-1.60)
Adjusted R^2	-0.01	0.04	0.48	0.11	0.59	0.12	0.47	0.20	0.05	0.10	0.04	0.61	0.59

Table 4: Least square regression results for January 2007 and January 2009. Results for January 2008 are shown in Table 7 in the Appendix. The sample (n = 37) only includes institutions which received financial support. The dependent variable is *Amount* in all models, indicating the amount of support a certain company received during the financial crisis. T-statistics are shown in brackets. ***, ** and * indicate a 1%, 5% and 10% significance level. Results regarding the constants are omitted.

Panel A of Table 4 illustrates that sophisticated systemic risk measures (model one to five) have only limited explanatory power ex ante on the volume of received financial support. *ΔCoVaR* (model one) and *SRISK* (model two) seem to have a significant impact at a 1% level. However, the adjusted R^2 figure in the case of *ΔCoVaR* is small. Only 17% of the variation of the dependent variable can be explained by the measure. The coefficient of *SRISK* is negative, which implies that its usefulness is very limited, because *SRISK* indicates how much additional capital a company needs to stay solvent during the next crisis.

Regarding the simple systemic risk measures (models six to thirteen), the size variables *Size* (model six) and *Debt* (model seven) have explanatory power. Both are significant at a 1% level and the adjusted R^2 statistics are high, at 0.52 and 0.41, respectively. Including other variables in the models (model twelve and thirteen) does not increase their explanatory power much. Adjusted R^2 statistics are 0.50 for model twelve and 0.43 for model thirteen. Due to multicollinearity issues, *Size, Debt, Leverage* and *Book* are not included in the same models.

Panel C of Table 4 indicates that, ex post, sophisticated systemic risk measures have much more explanatory power than ex ante to indicate the volume of financial support systemically relevant institutions received. The results for model five combine all sophisticated measures and indicate that *ΔCoVaR*, *SRISK* and *GrangerOut* are useful in determining the amount of support, ex post. The adjusted R^2 statistic for the entire model is 0.59; the mentioned measures are significant at a 10% and 1% level. *SRISK* seems to be the most powerful variable, because, for the model only including *SRISK* (model three), the adjusted R^2 statistic is already 0.48.

The simple systemic risk measures, *Size* (model six), *Debt* (model seven), *Leverage* (model eight) and *Return* (model ten) are all found to have explanatory power. All of these variables are significant at least at a 5% level. The highest adjusted R^2 of 0.61 is reported for model twelve. It can be seen that *Size* and *Leverage* have a significant impact at a 1% level, while *Return* and *Correlation* have a significant impact at least at a 5% level. For model thirteen, the adjusted R^2 figure with 0.59 can still be regarded as high, but only *Debt* and *Return* have a significant impact.

All in all, sophisticated risk measures are more useful, ex post, in explaining the volume of financial support, than ex ante, but the simple systemic risk measures still have more explanatory power. A model which combines size and leverage variables is most suitable.

As a robustness test, I conduct the same analyses for a subsample, only considering financial services companies. The results are presented in the Appendix (Table 9). The sample size, in these cases, is reduced to 35 observations, since I only consider financial companies according to the Industry Classification Benchmark. The analyses are performed for January 2007 (Panel A), January 2008 (Panel B) and January 2009 (Panel C).

The results of the robustness test corroborate the full sample results. For financial services companies, ex ante, sophisticated systemic risk measures only have little explanatory power. *SRISK* is significant at a 1% level and has an adjusted R^2 statistic of 0.37, but it has a negative coefficient and can be interpreted as misleading. The results suggest that institutions which do not need additional capital, according to *SRISK*, are contributing to systemic risk.

ΔCoVaR seems to be more suitable. The results are significant at a 5% level and the adjusted R^2 statistic is 0.11 in model one. However, in model five, which combines all sophisticated systemic risk measures, *ΔCoVaR* has no significant impact anymore. In contrast, as for the full sample, the simple systemic risk measures have a stronger explanatory power ex ante, if only financial services companies are considered. *Size* and *Debt* in models six and seven are significant at a 1% level and the adjusted R^2 statistics are at 0.47 and 0.36, respectively.

Regarding the ex post perspective, the results for the analyses, based on the full sample and the subsample, are the same on the level of individual variables. *SRISK, GrangerOut, Size, Debt, Leverage, Return* and *Correlation* have a significant impact at least at a 5% level. An important observation is that the sophisticated systemic risk measures seem to have more explanatory power than the simple systemic risk measures. For example, the adjusted R^2 for the model, including all sophisticated measures, is 0.69 (model five); the adjusted R^2 for each model, including most of the simple measures (model twelve and thirteen), is 0.57.

4.2. Results of the Second Approach (Classification as SII in 2013)

The second approach focuses on the information about which institutions have been labeled as systemically important in 2013 by national and international regulators. It is evaluated if sophisticated or simple systemic risk measures are more suitable to explain which institutions are designated as contributing to systemic risk. The results regarding the variable *SII* are presented in Table 5. Panel A illustrates the results for January 2013, and therefore, can be considered the ex ante perspective. In contrast, Panel B illustrates the results for January 2014 and represents the ex post perspective. Models one to five show the results of the regressions regarding the sophisticated systemic risk measures. Models six to thirteen illustrate the results regarding the simple systemic risk measures.

It seems that sophisticated systemic risk measures have explanatory power to indicate which institutions are deemed systemically important, ex ante (Panel A of Table 5). In particular, the results for *MES* (model two) and *SRISK* (model three) are significant at a 1% level. The best goodness of fit is achieved in model five, which includes all sophisticated risk measures. In this model, only *SRISK* is significant at a 1% level. In comparison with the results of the first approach in Table 3 (Panel A), the results at hand provide stronger evidence that systemic risk measures might be able to detect institutions contributing to systemic risk.

Regarding the simple systemic risk measures (models six to thirteen), *Size* (model six), *Debt* (model seven), *Return* (model ten) and *Correlation* (model eleven) are significant at least at a 10% level. The results for *Size* and *Debt* are robust in the way that these variables are significant, even when controlling for other simple systemic risk measures (models twelve and thirteen).

It is interesting that if *Debt* is included in the model, *Size* and *Leverage* are no longer significant (model twelve). However, if *Debt* is not included, *Size* and *Leverage* are significant (model thirteen). The pseudo R^2 figures are high for *Debt* in model seven (0.56) and in model twelve, which includes *Debt* and other simple measures (0.78). Models without *Debt* have a pseudo R^2 statistic at the most of 0.35 (model thirteen). This pattern suggests that the total amount of debt is suitable for indicating ex ante institutions contributing to systemic risk. In addition, *Debt* seems to be a better indicator than *SRISK*, since the pseudo R^2 statistic is higher (0.56 vs. 0.35). In general, the results seem to be in line with the results of the first approach. In Table 3 (Panel A) and Table 5 (Panel A) *Debt* has the highest explanatory power.

Panel A: January 2013													
Model	1	2	3	4	5	6	7	8	9	10	11	12	13
ΔCoVaR	19.57	-	-	-	21.36	-	-	-	-	-	-	-	-
	(0.59)				(0.46)								
MES	-	-129.11***	-	-	-53.46	-	-	-	-	-	-	-	-
		(13.41)			(1.39)								
SRISK	-	-	0.10***	-	0.09***	-	-	-	-	-	-	-	-
			(19.83)		(13.06)								
GrangerOut	-	-	-	-0.03	-0.04	-	-	-	-	-	-	-	-
				(1.14)	(0.76)								
Size	-	-	-	-	-	1.15***	-	-	-	-	-	-0.96	1.30***
						(20.18)						(1.20)	(19.68)
Debt	-	-	-	-	-	-	1.68***	-	-	-	-	3.55***	-
							(29.77)					(11.67)	
Leverage	-	-	-	-	-	-	-	0.29	-	-	-	0.05	0.32***
								(6.27)				(0.01)	(9.48)
Book	-	-	-	-	-	-	-	-	-2.05	-	-	-16.30***	-
									(1.21)			(9.57)	
Return	-	-	-	-	-	-	-	-	-	1.22*	-	-5.02*	0.60
										(2.97)		(2.88)	(0.27)
Correlation	-	-	-	-	-	-	-	-	-	-	6.52**	13.53*	5.42
											(6.09)	(2.97)	(2.29)
Pseudo R^2	0.01	0.13	0.35	0.02	0.38	0.20	0.56	0.08	0.01	0.02	0.07	0.78	0.35

Panel B: January 2014													
Model	1	2	3	4	5	6	7	8	9	10	11	12	13
ΔCoVaR	16.46	-	-	-	13.17	-	-	-	-	-	-	-	-
	(0.40)				(0.23)								
MES	-	-60.27	-	-	-24.82	-	-	-	-	-	-	-	-
		(0.19)			(0.23)								
SRISK	-	-	0.06***	-	0.05***	-	-	-	-	-	-	-	-
			(8.57)		(7.02)								
GrangerOut	-	-	-	-0.11*	-0.12*	-	-	-	-	-	-	-	-
				(3.46)	(3.54)								
Size	-	-	-	-	-	1.30***	-	-	-	-	-	-0.58	1.59***
						(21.90)						(0.48)	(19.74)
Debt	-	-	-	-	-	-	1.67***	-	-	-	-	2.84***	-
							(30.79)					(11.06)	
Leverage	-	-	-	-	-	-	-	0.54***	-	-	-	0.37	0.52***
								(7.18)				(0.46)	(12.14)
Book	-	-	-	-	-	-	-	-	-2.65	-	-	-14.92***	-
									(1.84)			(9.80)	
Return	-	-	-	-	-	-	-	-	-	0.29	-	0.67	0.85
										(0.52)		(1.10)	(2.40)
Correlation	-	-	-	-	-	-	-	-	-	-	6.41***	0.07	6.00**
											(6.94)	(0.00)	(5.39)
Pseudo R^2	0.00	0.02	0.09	0.07	0.16	0.24	0.55	0.10	0.02	0.00	0.10	0.75	0.43

Table 5: Logistic regression results, based on the full sample (n = 470), for January 2013 and January 2014. The dependent variable is *SII* in all models, indicating whether a company is designated as systemically important. Wald statistics are shown in brackets. ***, ** and * indicate a 1%, 5% and 10% significance level. Results regarding the constant are omitted.

Sophisticated systemic risk measures cannot explain, ex post, which companies are designated to be systemically important, as illustrated in Panel B of Table 5. *ΔCoVaR* and *MES* are not significant in any model (model one, two and five). *GrangerOut* is significant at 5% and 10% levels in models four and five, respectively, but the algebraic signs of the coefficients are negative. This implies that the companies are systemically contributing to systemic risk, which are deemed by *Granger-Causality Networks* not to be systemically relevant.

Lastly, *SRISK* is significant at a 1% level in models three and five. However, this cannot be interpreted as evidence for the suitability of *SRISK*, since the pseudo R^2 statistics of models three and five are very low (0.09 and 0.16). These results are in contrast to the ones of the first approach in Table 3 (Panel C), since, in the first approach, *SRISK* seems to be suitable for the ex post perspective.

Considering the simple systemic risk measures in Panel C of Table 5, the results reveal that *Size* (model six), *Debt* (model seven), *Leverage* (model eight) and *Correlation* (model ten) all have significant explanatory power at a 1% level. However, taking several simple systemic risk measures together into account leads to similar results, as presented in Panel A of Table 5.

In all models in which *Debt* is included, the variable is strongly significant and the pseudo R^2 statistics are high (0.55 in model seven and 0.75 in model twelve). Models without *Debt* have much lower pseudo R^2 results and other variables are only significant in certain model specifications. For example, *Correlation* is significant at a 1% and 5% level in models eleven and thirteen, respectively, but not significant in model twelve. In contrast to the first approach (Panel C of Table 3) where, ex post, sophisticated risk measures had comparable explanatory power as simple systemic risk measures, the results at hand show that *Debt* has clearly the most explanatory power.

I again perform a robustness test for a subsample of only financial services companies. Table 12 in the Appendix illustrates the results which are for January 2013 (Panel A) and January 2014 (Panel B). The subsample size is 82. This time, the results for the full sample are only partially supported. For financial services companies, ex ante, sophisticated systemic risk measures are found to have much more explanatory power. *SRISK* is significant at a 1% level in all relevant models and the pseudo R^2 statistics are high, with 0.56 (model three) and 0.61 (model five). Regarding the simple systemic risk measures, ex ante, a combined model of all variables still has the highest pseudo R^2 figure with 0.80 (model twelve), but, in this model, no variable is significant.

For the ex post perspective in Panel B, the same pattern can be found. *SRISK* is significant at a 1% level in models three and five. Furthermore, the pseudo R^2 figures of these models are rather high, with 0.30 and 0.43. In contrast, the variable *Debt* is only significant in model seven at a 1% level, but the highest pseudo R^2 figure is still achieved by a combined simple systemic measures model with 0.82.

All in all, the results for the sophisticated systemic risk measures are much better for the subsample, than in the case of the full sample. This is not astonishing, since the measures have been developed mainly with the banking industry in mind, and therefore, are calibrated to deliver the best results in the case of banks. Other industries were not considered in the development, even though non-financial companies can also contribute to systemic risk.

4.3. Discussion

The results suggest that *ΔCoVaR* is not able to correctly identify institutions which contribute to systemic risk ex ante or ex post, neither at the moment, nor during the financial crisis. Besides its popularity, this result could be expected, since major shortcomings of this sophisticated risk measure are already pointed out in the literature. For example, Benoit et al. (2013) illustrate that an institution's *ΔCoVaR* is proportional to its Value at Risk, and therefore, an institution's contribution to systemic risk is seen in isolation from the system. In addition, Löffler and Raupach (2013) dispute the usefulness of *ΔCoVaR*, since an increase of an institution's idiosyncratic risk decreases its contribution to systemic risk, according to the risk measure.

For *MES* the results are nearly as poor as for *ΔCoVaR*. Only from the ex ante perspective of 2013 does it seem to correctly identify institutions which contribute to systemic risk. However, these results could be driven by the fact that some institutions have been already labeled as systemically relevant in 2012, and therefore, their share prices dropped substantially at the announcement date. My findings are in line with Idier et al. (2013, p. 18), who analyze whether *MES* would have been suitable, in advance, to identify the banks impaired the most by the financial crisis. According to their analysis, *MES* is not. They "thus strongly doubt that the *MES* can really help regulators identify systematically important banks on the eve of a future severe systemic crisis."

According to Benoit et al. (2013), *SRISK* is a compromise of the too-big-to-fail and the too-interconnected-to-fail paradigm. The "interconnectedness" is considered via *MES* and its proportionality to its firm beta. At the same time, "size" is considered by the equity and debt levels of a company. However, this promising approach is only partially supported by my results. On the one hand, most of the time, *SRISK* can correctly identify the institutions which contribute to systemic risk. Out of 32 models which include *SRISK* as an independent variable, in 22 models, *SRISK* is significant and the models have at least a decent fit. On the other hand, in six models, *SRISK* is not significant, and what is much more important, in two models, it is misleading. In addition, the question remains if the results are mainly driven by one of the constituents of *SRISK* – equity, debt and *MES* – or indeed are the outcome of the composition.

The last sophisticated systemic risk measure I evaluate is the *Granger-Causality Network*. In general, the key statement of Billio et al. (2012) is supported by my analyses: the overall interconnectedness in the market is increasing during the financial crisis. In January 2007, there are 10’911 (4.91% of all possible connections) Granger-causality connections between the S&P 500 companies; in January 2008, there are 12’503 (5.62%); and in January 2009, there are 22’225 (10.00%) connections. The results about whether the Granger-causality relationships can successfully indicate the companies which contribute to systemic risk are mixed. Out of the 32 models, *GrangerOut* is significant in twelve models; in 16, it is not significant, and in four, it is misleading (significant, but with a negative algebraic sign).

The robustness tests show that the results are generally the same for financial services institutions. Only in the case of the second approach, do the sophisticated systemic risk measures fare better for the subsample (only financial services companies) than for the full sample (all companies). Therefore, one cannot argue that the sophisticated risk measures are suitable conditional on the limitation that they are only relevant for the context of financial institutions.

Regarding the simple systemic risk measures, three results are worth discussing. First, the size variables, *Size* and *Debt*, are most suitable for indicating companies contributing to systemic risk. This could be expected, since the size of an institution is considered by regulators in determining the contribution of an institution to systemic risk (see, for example, IAIS, 2013). It is interesting that the market capitalization of a company is not the best indicator, but the total debt level of a company is. One explanation could be that the severity of spillover effects (i.e., interconnections in extreme conditions between institutions), are primarily driven by counterparty credit risk and not by market risks (e.g., equity and interest rate risks). The volatility of stock prices is even high in normal times.[25] Therefore, extreme stock price movements are expected by the market and the financial system is robust towards them. In contrast, default rates are extremely low and the financial system never had to prove that it is stable, even when debt cannot be paid on a large scale.[26] This puts the results for *SRISK* into perspective. As Benoit et al. (2013) suggest, *SRISK* is highly correlated to leverage and total liabilities. The goodness of fit of the models, including *Debt*, always exceeds the *SRISK* models. Consequently, the explanatory power of *SRISK* might be simply driven by debt. However, total debt as reported in the balance sheets, as an indicator for systemic relevance, does have some shortcomings. For example, all off-balance sheet exposures are not considered.

[25] E.g., between 1970 and 2005, the maximal loss within one week of the S&P 500 composite index was 22%.
[26] E.g., according to Vazza and Kraemer (2013), the S&P investment-grade default rates between 1981 and 2012 never exceeded 0.42%.

Second, the results for the leverage variables (*Leverage* and *Book*) are very mixed. In models without the variable *Debt, Leverage* often has explanatory power. However, in models controlling for *Debt*, the explanatory power of *Leverage* is often not significant. Furthermore, *Book* has a negative algebraic sign in all models in which the variable is significant. This means that, on the one hand, leverage ratios are not very well suited to detect companies contributing to systemic risk and, on the other hand, low leverage ratios can be an indicator of systemic risk. These results are in sharp contrast to the majority view of regulators and academics who emphasize that leverage ratios are at least a good indicator for companies which are vulnerable to systemic risk (see, e.g., FSB, 2009; Baluch et al., 2011; Haldane, 2012; IAIS, 2013). An explanation for this result could be that the vulnerability and the contribution to systemic risk are indeed two different concepts: an institution vulnerable to systemic risk needs not necessarily contribute to it and vice versa. For example, a very small, highly leveraged bank is intuitively not very robust towards adverse market situations. However, the leverage itself is not a good indicator, in this case, for a contribution to systemic risk, since the total debt level of the institution is small. Therefore, its impact on other institutions, in the case of a bankruptcy, is very limited. Another argument which can explain why the results for leverage variables are mixed is presented by Papanikolaou and Wolff (2014). After the financial crisis of 2008 financial services institutions had to deleverage and put asset prices under pressure. As a consequence the amount of available credit shrank and systemic risk in the overall market went up. Therefore, according to the literature, it is possible that not so much the leverage of institutions contributes to systemic risk but a sudden deleveraging.

Third, comparing the fit of the models combining the sophisticated systemic risk measures with models combining the simple measures illustrates that simple measures are more powerful. Consequently, simple systemic risk measures can be regarded as more suitable to detect companies contributing to systemic risk than sophisticated systemic risk measures. One has to keep in mind, though, that this result is primarily due to *Debt*; other simple measures do not fare much better as their sophisticated counterparts.

As mentioned in Section 1, two main assumptions are made. First, regulators successfully supported the institutions contributing most to systemic risk during the financial crisis in 2008, as well as designated correctly the *SIIs* in 2013. Second, the contribution to the systemic risk of a company is independent from the general state of the system. If the first assumption is violated, the results of this paper would suggest that the wrong institutions have been supported during the financial crisis, since the sophisticated risk measures and the decisions of regulators are obviously not in line. Consequently, billions of USD could have been wasted for institutions which did not need the financial support. The vice versa situation, that some institutions needed financial support and received none, is unlikely, since the financial system did not break down. If the second assumption is violated and the contribution of an institution to systemic risk is dependent on the state of the system, the usefulness of all current microprudential sophisticated risk measures has to be doubted, since none takes the state of the system into account.

5. Conclusion

In this paper, I empirically evaluate whether sophisticated risk measures or simple systemic risk measures are more suitable to detect institutions which contribute most to systemic risk. I use two approaches, which use different variables approximating the systemic relevance of an institution. In the first approach, I use information about which institutions received financial support during the financial crisis and what amount they received. In the second approach, the systemic relevance is approximated by the fact of whether or not an institution is currently regarded as systemically important by national or international supervisors. Finally, I regress the systemic relevance variables on the various sophisticated and simple systemic risk measures.

The results of the paper suggest that simple systemic risk measures are more suitable to detect institutions contributing to systemic risk than sophisticated ones. This finding holds true for an ex ante and ex post perspective, regarding the point in time when the dependent and independent variables are calculated. In addition, this finding is valid for a broad sample of diverse companies (companies included in the S&P 500 composite index), as well as for a sample only considering financial institutions (all S&P 500 composite index companies labeled as banks, insurers, real estate or financial services companies).

In particular, the total amount of debt of a company is the strongest indicator for systemic relevance, followed by its market capitalization. Interestingly, the results for the leverage variables are rather mixed. *Leverage* seems not to have such a strong impact, as currently assumed (see, e.g., FSB, 2009).

Among the sophisticated systemic risk measures, the best results are achieved for *SRISK*. Most of the time, it can successfully indicate companies which received financial support during the financial crisis and companies which are regarded currently as contributing to systemic risk. However, in the case of explaining, ex ante, the amount of financial support each institution received in 2008, it is misleading. This is a meaningful finding, since *SRISK* combines market based information (via *MES* and market capitalization), as well as balance sheet information (debt), and shows that combining sophisticated and simple systemic risk measures might be a viable attempt to measure the systemic risk of institutions.

The results are of importance to academics and their choice of an adequate risk measure. Each sophisticated measure should at least have more explanatory power than the total amount of debt in determining companies contributing to systemic risk. Furthermore, the results can be of use for regulators assessing if an indicator based approach to identify systemically important institutions is sufficient or other measures should be considered as well. In my opinion, the regulatory discussion should focus more on the robustness of the financial system towards a systemic crisis, instead of focusing on institutions contributing to systemic risk. Labeling institutions as systemically relevant might create the false impression that regulators or academics are able to do so correctly, and therefore, might create a risk of its own.

Despite the vast number of studies on measuring systemic risk and the last financial crisis, there is still a need for further research. Firstly, in this paper, the assumption is made that during the financial crisis, financial support was given to the institutions which were contributing most to systemic risk. This assumption is commonly made, but it has not been evaluated yet whether it is true in all regards. More importantly, there is no discussion if the billions of dollars for the bailout programs were spent effectively and whether the institutions really needed the financial support for keeping the financial system stable. Secondly, sophisticated risk measures currently under discussion, try to achieve additivity (i.e., the sum of the systemic risk contributions of each company within a system equals the systemic risk of the system). However, it is not clear whether feedback effects can be ruled out. Maybe the state of the system influences the systemic risk contribution of an institution as well. Finally, as illustrated in this paper, and by the discussion in the literature about systemic risk measures, there is still no commonly acceptable measure, approach or framework which can properly determine systemic risk.

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Appendix

Panel B: January 2008													
Model	1	2	3	4	5	6	7	8	9	10	11	12	13
ΔCoVaR	-39.49* (3.80	-	-	-	13.29 (0.25)	-	-	-	-	-	-	-	-
MES	-	-124.81*** (47.02)	-	-	-93.59*** (17.42)	-	-	-	-	-	-	-	-
SRISK	-	-	0.09*** (24.82)	-	0.05*** (6.78)	-	-	-	-	-	-	-	-
GrangerOut	-	-	-	0.05 (28.57)	0.04*** (11.31)	-	-	-	-	-	-	-	-
Size	-	-	-	-	-	0.51*** (13.51)	-	-	-	-	-	-1.44*** (15.08)	0.81*** (24.64)
Debt	-	-	-	-	-	-	1.26*** (54.29)	-	-	-	-	2.63*** (44.59)	-
Leverage	-	-	-	-	-	-	-	0.35*** (14.66)	-	-	-	-0.72 (0.36)	0.25*** (8.55)
Book	-	-	-	-	-	-	-	-	0.01 (0.00)	-	-	-12.06*** (27.35)	-
Return	-	-	-	-	-	-	-	-	-	-1.86*** (11.63)	-	0.61 (0.76)	-2.37** (9.34)
Correlation	-	-	-	-	-	-	-	-	-	-	2.11** (4.76)	1.91 (1.40)	1.36 (1.48)
Pseudo R^2	0.02	0.26	0.22	0.13	0.38	0.06	0.46	0.14	0.00	0.06	0.02	0.67	0.28

Table 6: Logistic regression results, based on the full sample (n = 474) for January 2008. The dependent variable is *Support* in all of the models, indicating whether a company received financial support during the financial crisis. Wald statistics are shown in brackets. ***, ** and * indicate a 1%, 5% and 10% significance level. Results regarding the constants are omitted.

Panel B: January 2008													
Model	1	2	3	4	5	6	7	8	9	10	11	12	13
ΔCoVaR	-0.33** (-2.11)	-	-	-	-0.33** (-2.15)	-	-	-	-	-	-	-	-
MES	-	0.15 (0.93)	-	-	0.36** (2.13)	-	-	-	-	-	-	-	-
SRISK	-	-	0.03 (0.17)	-	0.13 (0.73)	-	-	-	-	-	-	-	-
GrangerOut	-	-	-	0.36** (2.33)	0.31* (1.95)	-	-	-	-	-	-	-	-
Size	-	-	-	-	-	0.66*** (5.20)	-	-	-	-	-	0.81*** (5.95)	-
Debt	-	-	-	-	-	-	0.61*** (4.54)	-	-	-	-	-	0.68*** (4.30)
Leverage	-	-	-	-	-	-	-	0.13 (0.79)	-	-	-	0.10 (0.67)	-0.22 (-1.27)
Book	-	-	-	-	-	-	-	-	0.26 (1.61)	-	-	-	-
Return	-	-	-	-	-	-	-	-	-	-0.13 (-0.77)	-	-0.36** (-2.53)	-0.11 (-0.69)
Correlation	-	-	-	-	-	-	-	-	-	-	0.25 (1.52)	-0.12 (-0.86)	0.03 (0.20)
Adjusted R^2	0.09	0.00	-0.03	0.11	0.22	0.41	0.35	-0.01	0.04	-0.01	0.03	0.50	0.33

Table 7: Least square regression results for January 2008. The sample (n = 37) only includes institutions which received financial support. The dependent variable is *Amount* in all models, indicating the amount of support a certain company received during the financial crisis. T-statistics are shown in brackets. ***, ** and * indicate a 1%, 5% and 10% significance level. Results regarding the constants are omitted.

Panel A: January 2007													
Model	1	2	3	4	5	6	7	8	9	10	11	12	13
ΔCoVaR	-0.54	-	-	-	-31.52	-	-	-	-	-	-	-	-
	(1.36)				(0.75)								
MES	-	7.74	-	-	19.19	-	-	-	-	-	-	-	-
		(0.03)			(0.11)								
SRISK	-	-	-0.02	-	-0.01	-	-	-	-	-	-	-	-
			(1.01)		(0.45)								
GrangerOut	-	-	-	0.03	0.03	-	-	-	-	-	-	-	-
				(2.55)	(2.35)								
Size	-	-	-	-	-	0.85***	-	-	-	-	-	-1.66**	0.83**
						(8.46)						(5.68)	(6.03)
Debt	-	-	-	-	-	-	0.68***	-	-	-	-	2.06***	-
							(15.54)					(16.57)	
Leverage	-	-	-	-	-	-	-	0.24	-	-	-	-0.33	0.10
								(2.33)				(1.50)	(0.42)
Book	-	-	-	-	-	-	-	-	-0.41	-	-	-6.33***	-
									(0.15)			(7.12)	
Return	-	-	-	-	-	-	-	-	-	0.88	-	1.30	0.81
										(0.66)		(0.69)	(0.48)
Correlation	-	-	-	-	-	-	-	-	-	-	-4.12***	-2.46	-4.47***
											(7.13)	(1.59)	(6.87)
Pseudo R^2	0.01	0.00	0.02	0.05	0.07	0.15	0.33	0.05	0.00	0.01	0.13	0.59	0.27

Panel C: January 2009													
Model	1	2	3	4	5	6	7	8	9	10	11	12	13
ΔCoVaR	-11.66	-	-	-	-24.71	-	-	-	-	-	-	-	-
	(0.28)				(0.70)								
MES	-	-8.89	-	-	-5.51	-	-	-	-	-	-	-	-
		(2.48)			(0.31)								
SRISK	-	-	0.06***	-	0.06**	-	-	-	-	-	-	-	-
			(7.00)		(5.01)								
GrangerOut	-	-	-	0.00	0.00	-	-	-	-	-	-	-	-
				(1.30)	(0.34)								
Size	-	-	-	-	-	0.43**	-	-	-	-	-	-0.62	1.48***
						(4.92)						(0.87)	(12.24)
Debt	-	-	-	-	-	-	1.01***	-	-	-	-	2.77***	-
							(16.02)					(12.90)	
Leverage	-	-	-	-	-	-	-	-0.00	-	-	-	-0.01	-0.00
								(0.37)				(0.12)	(0.36)
Book	-	-	-	-	-	-	-	-	-1.02	-	-	-10.47***	-
									(1.01)			(7.91)	
Return	-	-	-	-	-	-	-	-	-	-0.78	-	0.02	-7.11***
										(0.85)		(0.00)	(11.16)
Correlation	-	-	-	-	-	-	-	-	-	-	-2.64**	-3.42	-7.71***
											(6.40)	(1.56)	(10.03)
Pseudo R^2	0.01	0.04	0.29	0.02	0.31	0.09	0.47	0.01	0.02	0.01	0.11	0.80	0.48

Table 8: Logistic regression results, based on the subsample (n = 84) of financial services companies for January 2007 and January 2009. The dependent variable is *Support* in all models, indicating whether a company received financial support during the financial crisis. Wald statistics are shown in brackets. ***, ** and * indicate a 1%, 5% and 10% significance level. Results regarding the constants are omitted.

Panel A: January 2007													
Model	1	2	3	4	5	6	7	8	9	10	11	12	13
ΔCoVaR	-0.36**	-	-	-	-0.19	-	-	-	-	-	-	-	-
	(-2.26)				(-1.50)								
MES	-	-0.23	-	-	-0.44***	-	-	-	-	-	-	-	-
		(-1.37)			(-3.27)								
SRISK	-	-	-0.62***	-	-0.84***	-	-	-	-	-	-	-	-
			(-4.62)		(-7.44)								
GrangerOut	-	-	-	-0.01	-0.08	-	-	-	-	-	-	-	-
				(-0.03)	(-0.80)								
Size	-	-	-	-	-	0.70***	-	-	-	-	-	0.70***	-
						(5.63)						(5.32)	
Debt	-	-	-	-	-	-	0.62***	-	-	-	-	-	0.82***
							(4.58)						(4.64)
Leverage	-	-	-	-	-	-	-	0.21	-	-	-	0.06	-0.30
								(1.25)				(0.45)	(-1.68)
Book	-	-	-	-	-	-	-	-	0.23	-	-	-	-
									(1.36)				
Return	-	-	-	-	-	-	-	-	-	-0.07	-	-0.12	-0.05
										(-0.43)		(-0.94)	(-0.35)
Correlation	-	-	-	-	-	-	-	-	-	-	-0.01	-0.12	-0.03
											(-0.03)	(-0.89)	(-0.19)
Adjusted R^2	0.11	0.02	0.37	-0.03	0.65	0.47	0.36	0.02	0.02	-0.02	-0.03	0.44	0.37

Panel C: January 2009													
Model	1	2	3	4	5	6	7	8	9	10	11	12	13
ΔCoVaR	-0.10	-	-	-	-0.14	-	-	-	-	-	-	-	-
	(-0.57)				(-1.39)								
MES	-	-0.31*	-	-	-0.14	-	-	-	-	-	-	-	-
		(-1.87)			(-1.35)								
SRISK	-	-	0.76***	-	0.71***	-	-	-	-	-	-	-	-
			(6.49)		(7.00)								
GrangerOut	-	-	-	0.39**	0.34***	-	-	-	-	-	-	-	-
				(2.43)	(3.36)								
Size	-	-	-	-	-	0.30*	-	-	-	-	-	0.73***	-
						(1.80)						(4.95)	
Debt	-	-	-	-	-	-	0.66***	-	-	-	-	-	0.70***
							(4.85)						(4.82)
Leverage	-	-	-	-	-	-	-	0.52***	-	-	-	0.49***	0.09
								(3.33)				(3.69)	(0.59)
Book	-	-	-	-	-	-	-	-	0.21	-	-	-	-
									(1.19)				
Return	-	-	-	-	-	-	-	-	-	-0.36**	-	-0.55***	-0.43**
										(-2.27)		(-3.36)	(2.72)
Correlation	-	-	-	-	-	-	-	-	-	-	0.23	-0.33**	-0.22
											(1.38)	(2.20)	(-1.56)
Adjusted R^2	-0.02	0.07	0.56	0.12	0.69	0.06	0.42	0.25	0.13	0.11	0.03	0.57	0.57

Table 9: Least square regression results, based on a subsample (n = 35) of financial services companies for January 2007 and January 2009. The sample only includes institutions which received financial support. The dependent variable is *Amount* in all models, indicating the amount of support a certain company received during the financial crisis. T-statistics are shown in brackets. ***, ** and * indicate a 1%, 5% and 10% significance level. Results regarding the constants are omitted.

Panel B: January 2008													
Model	1	2	3	4	5	6	7	8	9	10	11	12	13
ΔCoVaR	-5.18	-	-	-	23.08	-	-	-	-	-	-	-	-
	(0.03)				(0.32)								
MES	-	-25.67	-	-	35.59	-	-	-	-	-	-	-	-
		(1.61)			(1.22)								
SRISK	-	-	0.04**	-	0.05**	-	-	-	-	-	-	-	-
			(5.87)		(4.48)								
GrangerOut	-	-	-	0.06***	0.06***	-	-	-	-	-	-	-	-
				(12.22)	(9.77)								
Size	-	-	-	-	-	0.68***	-	-	-	-	-	-1.01	1.18***
						(7.29)						(2.43)	(11.34)
Debt	-	-	-	-	-	-	0.65***	-	-	-	-	1.67***	-
							(15.40)					(14.38)	
Leverage	-	-	-	-	-	-	-	0.04	-	-	-	-0.19*	-0.00
								(0.53)				(2.82)	(0.00)
Book	-	-	-	-	-	-	-	-	-0.53	-	-	-3.64*	-
									(0.26)			(3.06)	
Return	-	-	-	-	-	-	-	-	-	-0.36	-	2.00	-2.64**
										(0.27)		(1.17)	(5.27)
Correlation	-	-	-	-	-	-	-	-	-	-	-2.61*	-3.46	-4.96**
											(2.91)	(1.85)	(5.96)
Pseudo R^2	0.00	0.03	0.14	0.23	0.33	0.13	0.33	0.01	0.00	0.00	0.05	0.55	0.28

Table 10: Logistic regression results, based on a subsample (n = 84) of financial services companies for January 2008. The dependent variable is *Support* in all models, indicating whether a company received financial support during the financial crisis. Wald statistics are shown in brackets. ***, ** and * indicate a 1%, 5% and 10% significance level. Results regarding the constants are omitted.

Panel B: January 2008													
Model	1	2	3	4	5	6	7	8	9	10	11	12	13
ΔCoVaR	-0.25	-	-	-	-0.02	-	-	-	-	-	-	-	-
	(1.52)				(-0.14)								
MES	-	0.07	-	-	0.27*	-	-	-	-	-	-	-	-
		(0.40)			(1.86)								
SRISK	-	-	0.51***	-	0.50***	-	-	-	-	-	-	-	-
			(3.39)		(3.27)								
GrangerOut	-	-	-	0.46***	0.35**	-	-	-	-	-	-	-	-
				(3.02)	(2.50)								
Size	-	-	-	-	-	0.62***	-	-	-	-	-	0.79***	-
						(4.58)						(5.24)	
Debt	-	-	-	-	-	-	0.58***	-	-	-	-	-	0.63***
							(4.05)						(3.69)
Leverage	-	-	-	-	-	-	-	0.16	-	-	-	0.10	-0.20
								(0.91)				(0.64)	(-1.07)
Book	-	-	-	-	-	-	-	-	0.20	-	-	-	-
									(1.14)				
Return	-	-	-	-	-	-	-	-	-	-0.15	-	-0.41**	-0.10
										(-0.85)		(-2.45)	(-0.56)
Correlation	-	-	-	-	-	-	-	-	-	-	0.27	-0.17	0.05
											(1.61)	(-1.02)	(0.25)
Adjusted R^2	0.04	-0.03	0.24	0.19	0.38	0.36	0.31	-0.01	0.01	-0.01	0.04	0.45	0.27

Table 11: Least square regression results, based on a subsample (n = 35) of financial services companies for January 2008. The sample only includes institutions which received financial support. The dependent variable is *Amount* in all models, indicating the amount of support a certain company received during the financial crisis. T-statistics are shown in brackets. ***, ** and * indicate a 1%, 5% and 10% significance level. Results regarding the constants are omitted.

Panel A: January 2013													
Model	1	2	3	4	5	6	7	8	9	10	11	12	13
ΔCoVaR	5.72	-	-	-	45.01	-	-	-	-	-	-	-	-
	(0.05)				(0.83)								
MES	-	-148.38***	-	-	51.60	-	-	-	-	-	-	-	-
		(9.17)			(0.31)								
SRISK	-	-	0.12***	-	0.14**	-	-	-	-	-	-	-	-
			(10.20)		(6.41)								
GrangerOut	-	-	-	-0.09	-0.08	-	-	-	-	-	-	-	-
				(2.29)	(0.77)								
Size	-	-	-	-	-	1.94***	-	-	-	-	-	1.32	2.45***
						(14.16)						(0.56)	(11.31)
Debt	-	-	-	-	-	-	1.17***	-	-	-	-	1.70	-
							(15.52)					(2.10)	
Leverage	-	-	-	-	-	-	-	0.12	-	-	-	1.17	0.19*
								(1.91)				(1.49)	(3.21)
Book	-	-	-	-	-	-	-	-	-1.87	-	-	-33.77	-
									(1.24)			(2.38)	
Return	-	-	-	-	-	-	-	-	-	1.37	-	-5.64	-3.79
										(1.03)		(1.95)	(2.32)
Correlation	-	-	-	-	-	-	-	-	-	-	6.22*	14.42	4.81
											(3.32)	(2.03)	(1.61)
Pseudo R^2	0.00	0.21	0.56	0.14	0.61	0.45	0.51	0.04	0.03	0.02	0.08	0.80	0.53

Panel B: January 2014													
Model	1	2	3	4	5	6	7	8	9	10	11	12	13
ΔCoVaR	5.48	-	-	-	3.56	-	-	-	-	-	-	-	-
	(0.04)				(0.01)								
MES	-	-77.24	-	-	19.99	-	-	-	-	-	-	-	-
		(1.48)			(0.03)								
SRISK	-	-	0.08***	-	0.07***	-	-	-	-	-	-	-	-
			(10.75)		(6.77)								
GrangerOut	-	-	-	-0.15**	-0.15*	-	-	-	-	-	-	-	-
				(5.19)	(3.45)								
Size	-	-	-	-	-	2.10***	-	-	-	-	-	2.09	2.12***
						(15.21)						(1.42)	(14.56)
Debt	-	-	-	-	-	-	1.19***	-	-	-	-	1.732	-
							(15.66)					(2.11)	
Leverage	-	-	-	-	-	-	-	0.22	-	-	-	5.48**	0.26
								(2.37)				(3.88)	(2.43)
Book	-	-	-	-	-	-	-	-	-1.92	-	-	-84.02**	-
									(1.23)			(4.21)	
Return	-	-	-	-	-	-	-	-	-	0.95	-	-1.07	1.53
										(0.93)		(0.15)	(1.14)
Correlation	-	-	-	-	-	-	-	-	-	-	1.50	-11.23	0.86
											(0.49)	(1.64)	(0.12)
Pseudo R^2	0.00	0.03	0.30	0.23	0.43	0.50	0.51	0.05	0.03	0.02	0.01	0.82	0.54

Table 12: Logistic regression results, based on a subsample (n = 82) of financial services companies for January 2013. The dependent variable is *SII* in all models, indicating whether a company is designated as systemically important. Wald statistics are shown in brackets. ***, ** and * indicate a 1%, 5% and 10% significance level. Results regarding the constants are omitted.

Dependent Variable:	Support						Amount						SII			
Model	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Date	2007	2008	2009	2007	2008	2009	2007	2008	2009	2007	2008	2009	2013	2014	2013	2014
Panel A:																
$\Delta CoVaR_{5\%}$	-211.98***	-206.85***	-78.75**	-	-	-	-0.21	-0.21	-0.24	-	-	-	23.63	12.00	-	-
	(25.30)	(22.35)	(4.69)				(-1.26)	(-1.27)	(-1.45)				(0.21)	(0.05)		
$\Delta CoVaR_{10\%}$	-	-	-	-448.78***	-467.40***	-227.90***	-	-	-	-0.16	-0.22	-0.26	-	-	12.29	23.77
				(37.05)	(33.89)	(11.35)				(-0.99)	(-1.34)	(-1.61)			(0.03)	-0.09
Pseudo R^2	0.13	0.12	0.02	0.22	0.20	0.06	-	-	-	-	-	-	0.00	0.00	0.00	0.00
Adjusted R^2	-	-	-	-	-	-	0.02	0.02	0.03	0.00	0.02	0.04	-	-	-	-
Sample Size	472	471	472	472	471	472	37	36	37	37	36	37	470	470	470	470
Panel B:																
$MES_{1\%}$	-21.96	-110.06***	-24.39***	-	-	-	-0.16	0.04	0.04	-	-	-	-81.74***	5.00	-	-
	(1.56)	(46.01)	(43.48)				(-0.96)	(0.24)	(0.26)				(14.40)	(0.03)		
$MES_{10\%}$	-	-	-	28.99	-133.07***	-46.83***	-	-	-	-0.04	0.07	-0.28*	-	-	-177.49***	-129.33**
				(1.03)	(32.56)	(42.74)				(-0.21)	(0.44)	(-1.73)			(14.44)	(4.54)
Pseudo R^2	0.01	0.28	0.27	0.01	0.17	0.22	-	-	-	-	-	-	0.14	0.00	0.14	0.04
Adjusted R^2	-	-	-	-	-	-	0.00	-0.03	-0.03	-0.03	-0.02	0.05	-	-	-	-
Sample Size	472	472	472	472	472	472	37	37	37	37	37	37	470	470	470	470
Panel C:																
$SRISK_{1\%}$	0.01	0.11***	0.55***	-	-	-	-0.51***	0.16	0.70***	-	-	-	0.12***	0.08***	-	-
	(1.20)	(26.72)	(43.56)				(-3.57)	(0.95)	(5.63)	-0.62***			(20.27)	(18.14)		
$SRISK_{10\%}$	-		-	0.00	0.07***	0.58***	-	-	-	(-4.76)	-0.05	0.69***	-		0.09***	0.04***
				(0.02)	(22.00)	(39.22)					(-0.29)	(5.48)			(19.85)	(3.31)
Pseudo R^2	0.01	0.27	0.68	0.00	0.16	0.65	-	-	-	-	-	-	0.45	0.18	0.31	0.05
Adjusted R^2	-	-	-	-	-	-	0.24	0.00	0.47	0.37	-0.03	0.46	-	-	-	
Sample Size	472	472	472	472	472	472	37	36	34	37	36	34	470	470	470	470
Panel D:																
$GrangerOut_{1\%}$	0.06*	0.12***	0.02***	-	-	-	0.14	0.33**	0.45***	-	-	-	-0.18	-0.51*	-	-
	(3.46)	(23.58)	(17.05)				(0.85)	(2.06)	(3.01)				(1.21)	(3.65)		
$GrangerOut_{10\%}$	-	-	-	0.01*	0.04***	0.01***	-	-		0.01	0.34**	0.33**	-		-0.02	-0.06*
				(3.35)	(29.60)	(15.86)				(0.08)	(2.14)	(2.07)			(1.52)	(3.76)
Pseudo R^2	0.01	0.10	0.08	0.01	0.13	0.07	-	-	-	-	-	-	0.02	0.07	0.03	0.07
Adjusted R^2	-	-	-	-	-	-	-0.01	0.08	0.18	-0.03	0.09	0.08	-	-	-	-
Sample Size	472	472	472	472	472	472	37	37	37	37	37	37	470	470	470	470

Table 13: Robustness tests for sophisticated systemic risk measures (partial models). Panel A refers to *ΔCoVaR* whereas $\Delta CoVaR_{5\%}$ takes into account the 5% quantil and $\Delta CoVaR_{10\%}$ the 10% quantil. Panel B refers to the *Marginal Expected Shortfall* whereas $MES_{1\%}$ and $MES_{10\%}$ focus on the 1% respectively 10% days with the most negative stock market returns within the last year. Panel C refers to *SRISK* using $MES_{1\%}$ and $MES_{10\%}$. Finally, Panel D shows the results for *GrangerOut*. $GrangerOut_{1\%}$ and $GrangerOut_{10\%}$ consider Granger-causality relationships at a significance level of 1% and 10%. In the cases of the dependent variables *Support* and *SII*, logistic regression models are used. Models regarding the dependent variable *Amount* employ least square regressions. Wald statistics are shown in brackets for models one to six and thirteen to sixteen. In models seven to twelve t-statistics are displayed instead. ***, ** and * indicate a 1%, 5% and 10% significance level. Results regarding the constants are omitted.

Dependent Variable:	Support						Amount						SII			
Model	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Date	2007	2008	2009	2007	2008	2009	2007	2008	2009	2007	2008	2009	2013	2014	2013	2014
$\Delta CoVaR_{5\%}$	-226.62***	-105.53**	-17.96	-	-	-	-0.15	-0.21	-0.28***	-	-	-	74.70	30.55	-	-
	(25.79)	(4.04)	(0.09)				(-1.04)	(-1.24)	(-2.82)				(1.31)	(0.25)		
$\Delta CoVaR_{10\%}$	-	-	-	-523.36***	-367.02***	-206.41*	-	-	-	-0.02	-0.19	-0.25**	-	-	52.36	65.48
				(41.28)	(16.62)	(3.54)				(-0.14)	(-1.14)	(-2.12)			(0.32)	(0.65)
$MES_{1\%}$	10.18	-67.57***	2.52	-	-	-	-0.22	0.13	0.12	-	-	-	-17.95	23.99	-	-
	(0.26)	(14.88)	(0.17)				(-1.53)	(0.72)	(1.25)				(0.31)	(0.59)		
$MES_{10\%}$	-	-	-	124.60***	-59.94**	13.36	-	-	-	-0.23	0.15	-0.03	-	-	-91.23	-116.99*
				(8.98)	(4.50)	(1.33)				(-1.61)	(0.77)	(-0.25)			(2.47)	(3.19)
$SRISK_{1\%}$	0.01	0.06***	0.57***	-	-	-	-0.50***	0.13	0.64***	-	-	-	0.11***	0.08***	-	-
	(0.45)	(9.24)	(28.99)				(-3.45)	(0.72)	(6.61)				(15.55)	(14.25)		
$SRISK_{10\%}$	-	-	-	0.00	0.04**	0.62***	-	-	-	-0.69***	-0.06	0.65***	-	-	0.07***	0.03
				(0.19)	(5.61)	(34.72)				(-4.91)	(-0.33)	(5.43)			(11.96)	(1.86)
$GrangerOut_{1\%}$	0.09**	0.09***	0.02**	-	-	-	0.17	0.25	0.43***	-	-	-	-0.12	-0.39	-	-
	(6.19)	(9.53)	(6.36)		0.03***		(1.17)	(1.39)	(4.36)				(0.38)	(2.25)		
$GrangerOut_{10\%}$		-	-	0.02*	(18.72)	0.01	-	-	-	0.00	0.32*	0.32***	-	-	-0.02	-0.07**
				(2.91)		(2.61)				(-0.02)	(1.81)	(2.77)			(1.16)	(4.50)
Pseudo R^2	0.16	0.42	0.70	0.27	0.38	0.68	-	-	-	-	-	-	0.47	0.23	0.35	0.15
Adjusted R^2	-	-	-	-	-	-	0.26	0.05	0.68	0.37	0.07	0.57	-	-	-	-
Sample Size	472	471	472	472	471	472	37	35	34	37	35	34	470	470	470	470

Table 14: Robustness tests for sophisticated systemic risk measures (full models). $\Delta CoVaR_{5\%}$ takes into account the 5% quantil and $\Delta CoVaR_{10\%}$ the 10% quantil. $MES_{1\%}$ and $MES_{10\%}$ focus on the 1% respectively 10% days with the most negative stock market returns within the last year. $SRISK_{1\%}$ and $SRISK_{10\%}$ indicate that for the calculation of *SRISK*, $MES_{1\%}$ and $MES_{10\%}$ are used. $GrangerOut_{1\%}$ and $GrangerOut_{10\%}$ consider granger-causality relationships at a significance level of 1% and 10%. In the cases of the dependent variables *Support* and *SII*, logistic regression models are used. Models regarding the dependent variable *Amount* employ least square regressions. Wald statistics are shown in brackets for models one to six and thirteen to sixteen. In models seven to twelve t-statistics are displayed instead. ***, ** and * indicate a 1%, 5% and 10% significance level. Results regarding the constants are omitted.