U.S. Systemically Important Financial Institutions and Their Contribution to Systemic Risk - A Quantile Regression Approach

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"Systemic risk refers to a risk of financial instability so widespread that it impairs the functioning of a financial system to the point where economic growth and welfare suffer materially."
(ECB, 2009)

I. Introduction

Systemic risk can arise when the distress of an individual institution generates negative externalities on others, which in the worst case then triggers a collapse of an entire industry or economy. Throughout history academics, practitioners and regulators have examined various factors that define and influence systemic risk events. Broad definitions, however, suggest that the roots of financial instability are deep, widespread and extremely complex. Common characteristics of these definitions show that the phases of systemic risk evolution follows sequences, vicious spirals and reinforcing patterns. Research has focused on the causing natures of such disruptive events, the fragile context of the unbalanced financial system, the dynamics of propagation channels throughout various sectors, and the direct and indirect, ultimate effects of systemic risk events on the real economy and on social welfare. During recent years, however, academics and regulators have shifted their emphasis toward predictive measures that potentially detect and assess the marginal risk contribution of systemically important institutions to the aggregate market. Whether it is the so-called *Systemic Expected Shortfall (SES)* by Archarya, Pedersen, Philippon and Richardson (2010), the *Conditional or Comoving value-at-risk (CoVaR* by Adrian and Brunnermeier (2011) or the *SRISK* by Brownlees and Engle (2017), research contributes strongly to the improvements and adaptions of international regulatory frameworks.

10 years after the financial crisis it remains arguable whether the predominance of the financial sector has changed due to intensified regulatory supervision and the introduction of predictive, enhanced risk measures. New regulations, e.g. Basel III, try to take better care of systemic risk by introducing additional capital buffers for systemically important financial institutions, liquidity requirements and countercyclical capital buffers. However, the percentage of total assets held by the 100 largest U.S. commercial banks is still concentrated toward the ten largest banks, now constituting for more than 60 % of total

assets, compared to a pre-crisis level of 55% (Fernholz & Koch, 2017). The finance and insurance sector still accounts for 7.5% of the U.S. GDP in 2016, thereby representing one of the three biggest contributors to U.S. GDP, besides real estate and manufacturing. This level is somehow comparable to pre-crisis levels of 7.6% as of 2006 and 2007 (U.S. Bureau of Economic Analysis). Furthermore, the Wall Street Journal (WSJ) highlights that regulatory authorities are mainly administered by former executives of financial institutions that contributed immensely to systemic risk during the financial crisis in 2008. The notorious credit-rating institutions, S&P, Moody's and Fitch, constitute for 94% of the credit-rating industry's revenue (as of 2016), and 96% of mortgage security issuance is still done by Fannie Mae, Ginnie Mae and Freddie Mac - three government-backed firms of which two were bailed out in 2008. Even though this is just an extract of the current situation, the intimation and assertion is clear: whether federal regulations try to reshape the financial industry or not, the level of risk contribution by the financial sector has probably remained unchanged. Hence, the development of predictive measurements is an appealing approach. Simulating stress tests with various input parameters based on current institution-specific data provides more valuable information than, for instance, measuring systemic risk by assessing the *expected shortfall (ES)* and/or *value-at-risk (VaR)* of an institution. Whereas the quantification of *ES* or *VaR* seems to be a powerful approach, the validity of these single measures is, however, limited as they only reflect risk of an institution in isolation. Moreover, *VaR* is commonly wrongly defined as the maximum expected loss of a portfolio over a given time horizon with a certain confidence interval, even though - and depending on the heaviness of the tail of the loss distribution - much more can be lost.

The above mentioned risk measures, *SES*, *CoVaR* and *SRISK* dismantle this conflict by introducing different conditionalities. The *SRISK*, for instance, measures the systemic risk contribution of a financial firm by assessing the capital shortfall of a firm conditional on a severe market decline and institution-specific variables such as size, leverage and risk (Brownlees & Engle, 2017).

According to these different approaches, the motivation of this paper is to contribute to recent findings by examining how sensitive the aggregate stock market in the U.S. responds to shocks to the returns – more precisely the value-at-risk – of the systemically most important financial institutions. Furthermore, we analyse how such sensitivities correspond to the systemic risk contribution of an individual institution and whether these sensitivities provide supporting or opposing power for already existing measures of systemic risk.

Based on the daily return series of all systemically important U.S. financial institutions that exhibit positive *SRISK*, and the aggregate S&P 500 as an indicator of overall market performance and stress, we will estimate the $1\% VaR$ of each institution and the $1\% VaR$ of the S&P 500, respectively. By fitting a GJR-GARCH model we will additionally capture the asymmetric effects of negative shocks, and the heteroskedasticity inherently incorporated in financial return series to extract the conditional volatility. Subsequently, a *quantile regression* approach will model the relationship between the dependent variable 1% $VaR_{S\&P500}$ and the explanatory variable 1% VaR_i. This approach enables us to derive the institution-specific sensitivities for each quantile of the S&P 500, denoted as the β-coefficients. By multiplying these β-coefficients (or sensitivities) with the difference between the 1% quantile of the 1% VaR_i and the 50% quantile of the 1% VaR_i, we are able to subsequently quantify the systemic risk contribution of an individual institution. In particular, we then multiply the product of β-coefficients and VaR_i [1] difference with the

[1] For simplicity and if not otherwise specified we always refer to the 1% *VaR* when mentioning the *VaR*

institution-specific market capitalization. We introduce this systemic risk measure as the *Shock Sensitivity Value-at-Risk (SSVaR)*, denoted in $ billion and as a percentage of aggregate systemic risk. In a robustness-check we will further evaluate the *SSVaR* for its supporting power as a complementary or alternative risk measure. The robustness-check will contrast *SSVaR* to *SRISK* as a recent, widely acknowledged and sophisticated measure of systemic risk. Hence, we contrast these measures by applying various periodicities to our return series, different computation methods and varying time horizons.

Therefore, we test for the following three main hypotheses:

i. The higher the difference between the *1% VaR*, representing a state of distress for an institution, and the *50% VaR*, representing the median or normal state of an institution, the higher the S&P 500's sensitivity. In other words, the higher the risk of a financial institution is under extreme market conditions in relation to its average risk the more sensitive is the S&P 500 toward this institution.

ii. In periods of overall market distress the S&P 500 exhibits higher β-coefficients, and therefore higher sensitivities, toward shocks to the *VaR* of financial institutions. This means, that the β-coefficients of the S&P 500 *VaR* distribution toward financial institutions will especially feature overproportional high values in the lower quantiles and lower values in the higher quantiles, thereby displaying an asymmetry factor.

iii. As a product of the 1% quantile and 50% quantile *VaR* difference, the β-coefficient and the institution-specific market capitalization, *SSVaR* can be used as an alternative measure of systemic risk that features characteristics of systemic risk that are not yet incorporated into risk measures like *SRISK*.

The paper is structured as follows: First, we will address how systemic risk can be measured according to the above introduced systemic risk measures, why the financial sector is an unbalanced, fragile system, what types of risk particular institutions (non-financial and financial institutions) have to bear during extreme market conditions, how dynamic contagion propagates insolvency and liquidity problems, and how the adverse consequences for the real economy and social welfare are characterized. Second, we will present the data used and the underlying methodology of our research approach. Afterwards we will thoroughly describe and interpret our empirical results. Lastly, we will conduct a detailed robustness check, give concluding remarks on our research approach and discuss actions and possibilities for further, advanced research.

II. **Systemic Risk**

Defining systemic risk theoretically and operationally implies setting boundaries that are either satisfied by a certain institution of a system or not. Hence, if a institution falls within the range of a particular systemic risk definition, the government would be committed to rescue such an institutions during financial distress in order to avoid the negative externalities of a bankruptcy of a systemically important institution. This consideration leaves behind extensive room for interpretation on how to define a systemic risk event – or so called *shock* –, how to efficiently measure the systemic risk contribution of an individual institution, or sector, to an entire system and how to appropriately set regulatory limits (e.g. capital ratios) according to this measure. Broad consensus among practitioners and academic is missing, causing an imbalance of understanding. As this paper examines the potential impact of a distressed financial institution to the overall stock market, we propose the following three considerations that shall offset the imbalance of understanding and give guidance in the literature review (following Taylor (2010) who operationally defined systemic risk): First, how can systemic risk be measured, secondly, how what are the implied changes individual institutions have to bear during financial distress, and thirdly, how does the risk of a financially distressed firm transmitted to other institutions, hence the system?

i. How can systemic risk be measured?

Proposing a measurement for regulation authorities that captures the risk an individual institution is contributing to the overall system, or marginally to its sector, has been considerably shaped by the work of Acharya, Pedersen, Philippon and Richardson (2010), Adrian and Brunnermeier (2011), as well as Brownlees and Engle (2017). While Acharya et al. (2010) introduced the *Systemic Expected Shortfall*, a measurement that focusses solely on the expected shortfall of a company, Adrian and Brunnermeier (2011) introduced the dynamic measurement *CoVaR*, a variable that predicts future systemic risk using a value-at-risk approach that integrates institutional-specific components such as size, leverage and maturity mismatch on the balance sheet. In contrast to all other measures, Brownlees and Engle (2017) used a similar but more complex (in terms of computation) evaluation tool for systemic risk, the so called *SRISK*, which measures the capital shortfall of a firm conditional on a pre-specified market decline which enables them to rank institutions according to their risk contribution. All measures aim to quantify the risk that an individual institution contributes to the overall financial sector when being in distress. While all, *Systemic Expected Shortfall*, *CoVaR* and *SRISK* stress test financial institutions, the difference between those three measurements is rather straightforward:

The first measure, *SES*, is a risk variable that is solely based on the expected shortfall of an institution and its contribution to a systemic crisis. While VaR examines the loss an institution is maximally exposed to at a certain confidence level, the expected shortfall is the expected loss conditional on the loss being greater than the *VaR*.

$$VaR = Pr(R < -VaR_\alpha) = \alpha$$
$$ES_\alpha = -E(R|R \leq -VaR_\alpha)$$

It follows that the expected shortfall of an institution and its contribution to the risk of the system is equal to the marginal expected shortfall of institution i.

$$\frac{\delta ES_\alpha}{\delta y_i} = -E(r_i|R \leq -VaR_\alpha) \equiv MES^i_\alpha$$

The systemic expected shortfall is therefore equal to the expected amount bank i is undercapitalized during a systemic event in which the financial system itself is undercapitalized. In other words, the *SES* is the expected amount of undercapitalization if the banks equity w^i_1 deceeds the prudential capital requirement during an extreme event. The prudential capital requirement is the product of the prudential capital ratio, z, and the banks assets, a^i. The extreme event is defined as the aggreagte capital of banks, W_1, being less than the aggregate prudential capital requirement, denoted as z times the sum of all banks' assets, A.

$$SES^i \equiv E[za^i - w^i|W_1 < zA]$$

Based on their proposed measure *SES* an optimal tax fee could be computed as the marginal contribution to systemic risk by an institution can be calculated accordingly. Hence, penalizing institution for their systemic risk component as well as their institution-specific risk component.

The second systemic risk measure, *CoVaR*, is defined as the difference between the *VaR* of the financial system j conditional on institution i being under distress and the *VaR* of the financial system conditional on the median state of the institution (note that X^i is the variable of institution i for which the VaR^i_q is defined). Hence, in terms of risk, it captures the marginal contribution of a particular institution to the entire system (*CoVar*, Adrian & Brunnermeier).

$$\Delta CoVaR_q^{j|i} = CoVaR_q^{j|X^i=VaR_q^i} - CoVaR_q^{j|X^i=Median^i}$$

In contrast to the *value-at-risk* approach, *CoVaR* examines the tail distribution, implying that it is more extrem than the unconditional *VaR* and that it is simply a *VaR* that is conditional on an extreme event. Thus, considering *VaR* as a systemic risk measure is not sufficient as it reflects the risk of an institution in isolation. Adrian and Brunnermeier suggested different estimation approaches for *CoVaR* - a time-invariant, a time-variant and a forward-looking method. While all estimation approaches make use of quantile regression the time-variant approach is an extension of the time-invariant approach. The conditional distribution is hereby estimated using a function with lagged state variables which in their case were defined by the VIX index, aggregate credit spread, and the slope of the yield curve. In order to construct a predictive risk measure that links regulatory guidelines to institution specific attributes, characteristics like leverage, size, market-to-book value or the maturity mismatch on a balance sheet, were integrated into their estimation approach.

The approach by Adams, Fuess and Gropp (2012) is, with regard to the methodology, highly interesting. The authors aim is to evolve a *state-dependent sensitivity value-at-risk (SDSVaR)* measure that captures the direction, extent and perpetuity of risk spillovers among commercial banks, investment banks, hedge funds and insurance companies as a function of the state of financial markets. In contrast to the measure *CoVaR*, which models the distribution of returns via quantile regression, *SDSVaR* first models and estimates the distribution of the *VaR* for each institution and then regresses the *VaR* measure of those four institutions on the dependent, previously estimated *VaR* in different states of financial markets (volatile, normal and tranquil) - meaning that the estimated *VaR* is regressed over the entire range of quantiles. Hence, the β coefficients quantify the direction of spillovers among financial institutions as a function of the state of financial markets - the so-called *state-dependent sensitivity value-at-risk*.

Lastly, and in contrast to *SES* and *CoVaR*, the most recent approach of systemic risk measures, *SRISK*, quantifies the capital shortfall (*CS*) of a company conditional on a certain market decline and time period. The *CS* is hereby defined as the difference between the value of quasi-assets kA, which is the product of the total assets A of an institution i and the prudential capital fraction k, and the market value of equity W.

$$CS_{i,t} = kA_{it} - W_{it} = k(D_{it} + W_{it}) - W_{it}$$

Brownlees and Engle (2017) *stress test* the capital shortfall for institution i during the time period *t+1* and *t+h* conditional on an extreme event within the market m. The extreme event is hereby denoted as the multiperiod arithmetic market return $R_{mt+1:t+h}$ deceeding a certain treshold C.

$$\begin{aligned} SRISK_{it} &= E_t(CS_{it+h}|R_{mt+1:t+h} < C) \\ &= W_{it}[kLVG_{it} + (1-k)LRMES_{it} - 1] \end{aligned}$$

Hence, *SRISK* is a function of the size of a company – based on the current market capitalization W_{it} – the degree of leverage (LVG_{it}) and the expected equity loss conditional on the market decline, which is denoted as the *Long-Run Marginal Expected Shortfall* estimator (*LRMES*).

$$LRMES_{it} = -E_t(R_{it+1:t+h}|R_{mt+1:t+h} < C)$$

One estimation approach for the *LRMES* is based on a static bivariate normal framework of a GARCH-DCC model. This approach shows how the *SRISK* combines relevant balance sheet information with market information – one distinguishable attribute other risk measures do not capture.

$$LRMES_{it}^{stat} = -\sqrt{h}\beta_i E(r_{mt+1}|r_{mt+1} < C)$$

The *LRMES* is equal to the product of the square of the forecast horizon h, the market beta b_i and the expected shortfall for one market period. By aggregating *SRISK* the *Volatility Laboratory* of the *NYU Stern School of Business* provides a list of the systemically most important financial institutions. The weekly published list gives an understanding of how an individual institution contributes to overall risk. Within the model parameters like the *geographic area*, the relevant *capital requirement ratio*, and dimension of the potential *market decline* can be simulated (Brownlees & Engle, 2017).

ii. What are the implied changes individual institutions have to bear during financial distress?

Prior to demonstrating how an adverse shock affects financial institutions it is helpful to categorize the major risk channels especially financial institutions are exposed to. Hence, we defined the following risk categories which will be further outlined in the following paragraphs:

- *Liquidity risk*: the risk that a surge in funding withdrawals will force a financial institution to liquidate assets at low prices.
- *Default risk*: the risk that promised cashflows from loans and fixed income securities may not be paid in full.
- *Interest rate risk*: the risk incurred by a financial institution when the maturity (duration) of their assets and liabilities are mismatched. This category further subdivides into i) *refinancing risk*: short funded financial institutions have to refinance at higher interest rates & ii) *reinvestment risk*: long funded financial institutions have to reinvest at lower interest rates.
- *Market value risk*: the present values of assets and liabilities are affected asymmetrically by changes in interest rates.

In recent years several academics have approached explaing the implications of systemic risk events and how intertwined major risk channels are. In order to consolidate the different approaches we will mainly discuss liquidity risk as it is the most comprehensive term for explaining systemic risk. Brunnermeier and Pedersen (2007) address liquidity risk by demonstrating the linkage of the liquidity of an asset (market liquidity) and the funding liquidity of a trader, thereby providing a first understanding on how liquidity correlates with systemic risk events and shocks to financial markets. Per definition, liquidity refers to how quickly and cheaply an asset can be converted into cash. The risk hereby incurred is that assets can be highly liquid or highly illiquid. Hence, liquidity tells us about how big the trade-off is between the speed of the sale and the price it can be sold for (Oxford University Press, 2008). Consider a security that is purchased on the market: besides the objective of generating returns for investment purposes, this security can be used as collateral for other trades such as short-selling, too. Borrowing against another stock requires the trader to finance a certain margin on that trade in order to cover a certain part of the credit risk the counterparty (e.g. broker or exchange) bears. The margin in such a trade is defined as the difference between the security's price and collateral value (Brunnermeier & Pedersen, 2007). Assuming that the funding liquidity of the trader is declining, the trader will start avoiding to take on positions that require higher-margin securities. The direct effect within the market is that liquidity drops further and volatility rises. This effect adds to the liquidity spiral, as the risk of financing a trade increases and margins rise correspondingly. Brunnermeier & Pedersen (2007) observed that margins increased during liquidity crisis. Financiers of trades adjusted margin requirements as they were in turn unsure about whether price changes were due to fundamental news or liquidity shocks. Volatility was classified as a time-variant process, meaning that a liquidity shock leads to price volatility and therefore, to increased margins. Furthermore, the destabilizing effect on margins forced speculators to de-lever their positions which lead to pro-cyclical market liquidity provision. This effect was highly vivid during the subprime crisis in 2008. Even though the crisis' loss carried only about 5% of the aggregate stock market capitalization the impact was immense as highly-levered financial institutions experienced a maturity mismatch on their balance sheet, which in turn lead to a loss of more than 8 trillion dollars (Brunnermeier & Pedersen, 2007). As long as traders margin cushion is large enough or do not fall below the margin requirement there is no risk in the market that within future trading days a margin call is required, hence market liquidity stays at its highest level and is insensitive to marginal changes in capital and margins. Therefore, market liquidity is only at risk if financiers are either required to make a margin call or expect a margin call to take place. Brunnermeier and Pedersen (2007) allude that during this stage prices movements are rather impelled by rectified liquidity consideration than by movements in fundamentals. Liquidity risk of a financial market is influenced by the overall instability of market liquidity as with high levels of investors capital, market must be in a liquid equilibrium, and, if investors capital is reduced enough, the market must eventually switch to a low-liquidity/high-margin equilibrium.

iii. How is the risk of a financially distressed firm transmitted to other institutions, hence to the system?

As our paper aims to measure the impact of a shock to the systemically most important financial institutions on to the aggregate U.S. stock market, it is necessary to understand the transmission channels through which a shock is forwarded to the aggregate (stock) market. The so-called credit contagion is thereby the proliferation of shocks or financial crisis of one company to other companies. According to Giesecke (2006) and Davis and Lo (2001) two credit contagion channels are existent. Firstly, the *counterparty* transmission channel which reflects the subsequent loss a firm can experience in case it is financially closely linked/has a high financial exposure to the firm in distress/failed firm. Secondly, the *information* transmission channel. Hereby, the failure of an institution causes investors to negatively rectify their market outlooks, hence triggering off distress to other institutions – without direct linkage – and boosting the spiral of misery (Giesecke, 2006). According to Chakrabarty and Zhang (2012) the distinction between those channels is applicable in theory, but empirically a difficult task as counterparty relationships of a failed institutions are seldom unveiled to public. Their findings, however, are straightforward and in line with the market and funding liquidity hypotheses of Brunnermeier and Pedersen (2007). Financial institutions that are closely linked to a failed institution suffer from a decline in liquidity due to changes in trading activities (e.g. negative order imbalance), higher transaction costs and negative returns. The empirical research shows that as soon as direct linkage between the institution being in distress and the counterparty institutions is revealed to the public, investors are more likely to sell the stock of this particular company. Kaufman (1994) addresses five factors that shall give answers to the question, why especially banks or financial institutions contribute the most to contagion in times of market distress, and not, for instance, non-financial firms.

i. *Contagion occurs faster within the financial sector*

   Looking at the balance sheet and multiple share-/stakeholders of financial firms compared to non-financial firms we observe a different level of construction. While short-term debt and large proportions of capital demand are main balance sheet items, (sudden) adverse shocks lead to withdrawals that exceed the banks' resources (= bank run). In order to satisfy the imbalance banks have to sell parts of their assets immediately, most commonly at lower prices. This effect describes nothing else than the market and funding liquidity risk explained earlier. As the bank-loan customer relationship, interbank funding and the overall payment system are suddenly disrupted, a liquidity problem can soon be followed by a solvency problem.

ii. *Bank contagion is broader within industry*

Investors and individuals often view banks as one homogeneous mass that is characterized by similar elements such as size, location and types of products. Hence, new information about one bank can affect all banks even though similar characteristics and/or a direct linkage (e.g. through interbank loans) are non-existent.

iii. *Bank contagion results in a larger number of failures*

Due to banks having substantially lower capital ratios than their non-financial counterparts, a shock can much quicker result in a crisis. Nowadays, and after experiencing the aftermath of several financial crises, the implementation of prudential regulations, as Basel III, is gradually proceeding. Before the financial crisis in 2007, for instance, capital ratios of financial institutions have been lower than of non-financial institutions due to a reduced market discipline by depositors, as federal deposit insurances were in place.

iv. *Bank contagion results in larger loss to creditors*

Looking at the creditors of financial institutions, it becomes clear why especially bank contagion is harmful to the economy. It is the combination of i) financial institutions having considerably lower capital ratios, hence creating losses that can potentially exceed available capital whenever a systemic risk event occurs, and ii) private individuals bearing that excess loss. A direct effect on the less protected depositors leads to an aggregate shock within the economy and reduced purchasing power of individuals.

v. *Bank contagion extends beyond the banking industry*

As banks are considered being the largest and most efficient providers of financial intermediation services, Kaufman (1994) observed three channels a shock can possibly spill over from a financial firm to a non-financial firm: I) creditors (depositors) of banks. As bank deposits are the largest component of money supply and the largest transmitter of capital within an economy, a failure of a bank can foremost lead to major losses on the depositors side (especially if depositors keep more than the guaranteed governmental bailout sum on their bank account). II) bank failures interrupt ongoing loan relationships. Firms with long-term investment projects/horizons are directly affected when banks cannot further feed their loans. Furthermore, banks that still could extend loans will become more reluctant in extending risky loans. III) bank insolvencies disrupt the payment system.

III. Data

This section shall shortly outline which data sets we used for computation and how this data was transformed.

Even though regions like Asia and Europe momentarily have countries with higher aggregated *SRISK* than the U.S. – e.g. China, Japan and France – we concentrate on U.S. financial institutions in order to establish comparability with a large number of similar studies.

More precisely, we focus on all U.S. financial institutions with positive *SRISK* as of the 29th of December 2017. Due to the fact that *SRISK* itself can either be a positive value or 0 U.S. financial institutions with positive *SRISK* correspond to firms that contribute to systemic risk. We identified the systemically most important financial institutions of the U.S. from the data of the interactive systemic risk analysis tool provided by the Volatility Laboratory (V-Lab) of the N.Y.U. Stern School of Business (Quelle). The computation of *SRISK* for our data set is based on a dynamic marginal expected shortfall (MES) model with simulation, a capital requirement ratio of 8% and a predicted system capital shortfall of 40%. These settings match the default of the V-Lab.

Out of these 37 we excluded a total of five institutions of which two, namely CNO Financial Group Inc and CIT Group Inc, went bankrupt during our sample period, and the other three U.S. financial institutions, namely Ally Financial Inc, Voya Financial Inc and Brighthouse Financial Inc, as they have not been listed for more than 5 years. Hence, full sample period is not covered.

For the remaining 32 institutions we obtained the daily adjusted simple returns, the market capitalization on the last day of our sample period and the SIC industry classification code from CRSP. In line with other papers our sample period extends from the beginning of 1990 to the end of 2017 [01.01.1990 – 29.12.2017], thereby including the three recessions of 1991, 2001, and 2007-09 and multiple financial crisis (1987, 1998, 2000, and 2008). Additionally, we also obtained the daily S&P 500 simple returns for the same period and the total S&P market capitalization for the last day of our sample from CRSP. We transform those simple returns into log returns utilizing the normal distribution of log returns for the purpose of GARCH fitting and VaR calculations.

Due to the long sample period, we cannot obtain the same number of observations for all U.S. financial institutions. However, for 23 out of these 32 institutions full data sets are available; additional six institutions provide data sets at least from 2000 onwards, whereas two data sets start before 2002 and the remaining one in 2004. Thus, our data set comprises between 3424 and 7056 observations per institution. This guarantees that our sample includes data points for the financial crisis in 2008 and all institutions. Since we calculate the shock sensitivity VaR in relation to the S&P 500 for each institute respectively, the different sample lengths do not pose a problem.

In addition to the institution-specific *SRISK* denoted in $, we include further firm specific data from the V-Lab in our analysis. These additions include the LRMES estimator defined above, the beta coefficient of a CAPM model including the financial institutions and the S&P 500, the conditional return correlation with the S&P 500 calculated via a DCC-GARCH model, the annualized equity volatility calculated with a GJR-GARCH model and the quasi-leverage of the firm, defined as 1 + the book value of liabilities divided by the market value of equity. All those measures refer to the 29th of December 2017, too.

IV. Methodology

The aim of this paper is to examine how sensitive the aggregate stock market in the U.S. responds to shocks to the returns – more precisely the value-at-risk – of the systemically most important financial institutions. Furthermore, we want to analyse how such sensitivities correspond to the systemic risk contribution of an individual institution and whether these sensitivities provide supporting or opposing power for already existing measures on systemic risk.

The general outline of our methodology can be describes as follows: First, we will transform the simple returns to continuously compounded returns in order to receive instantaneous, normally distributed rates of return for the specific financial institutions. Second, the institution-specific *VaR* is estimated using an GJR-GARCH model which captures the asymmetric effects of negative shocks besides heteroskedasticity and the conditional volatility. The *VaR* offers an intuitive, adequate measure of risk that is widely used among regulations and corporations. Thirdly, a quantile regression is conducted which enables us to examine the quantile-dependent β coefficients - a sensitivity measure for the risk a financially distressed institution is contributing to the aggregate systemic risk. In a final step, these sensitivity coefficients are tested for their supporting power by regressing them on the risk measure *SRISK* – a sophisticated measure that captures the risk a financial institutions is contributing to the aggregate market.

In order to derive the continuously compounded returns from the simple, adjusted returns of the 32 systemically most important U.S. financial institutions we apply the natural logarithm function.

$$r_{t,i} = ln(\frac{P_{t,i}}{P_{t-1,i}} + 1).$$

In order to define the loss in market value of an institution over a given time horizon that is exceeded with probability τ we will estimate the *VaR* at the 1% quantile (Koenker, 2017, p. 578):

$$VaR = Pr(r_t < -VaR_t|\mathscr{F}_{t-1}) = \tau$$

whereas $\mathscr{F}_{t-1}$ is the information set at time $t-1$. This approach, however, misses that financial time series are subject to a changing, conditional volatility, meaning that the distribution of returns is time-varying. One common model that captures this fact is the ARCH (autoregressive conditionally heteroskedastic) model by Engle, which makes the "conditional variance of the time *t* prediction error a function of time, system parameters, exogenous and lagged endogenous variables, and past prediction errors" (Nelson, 1991, p. 347). In contrast, the generalized ARCH model (GARCH (p,q)) has only three variables that allow for a boundless number of squared roots to influence the conditional variance. This condition enables GARCH to be a better fit for modeling time series data that exhibit heteroskedasticity and volatility clustering. Certain dynamics of particular time series are, however, also not captured by a GARCH model, hence, requiring a further model extension. In our approach, the GARCH (1,1) model does not capture asymmetric leverage effects, meaning that shocks do affect conditional volatility asymmetrically in a sense that negative shocks (bad news) are inclined to influence volatility more than positive shocks (good news). A GARCH (1,1) model would not capture higher volatility during extreme negative events and lower volatility in rising market conditions. The effect of negative shocks to the market and their transmission were already reflected in section II. (Zivot, 2008). The Glosten-Jagannathan-Runkle GARCH (GJR-GARCH) model captures this asymmetry and denotes as follows:

$$\sigma_t^2 = \omega + (\alpha + \gamma I_{t-1})\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2$$

where

$$I_{t-1} := \begin{cases} 0 & \text{if } r_{t-1} \geq \mu \\ 1 & \text{if } r_{t-1} < \mu \end{cases}$$

The formula shows that if r_{t-1} is positive or there is positive news, the effective coefficient associated with a positive shock is α, whereas the effective coefficient associated with a negative shock is $\alpha + \gamma$. This shall hereby incorporate empirical observations, namely that negative shocks at time $t-1$ influence the variance at time t more strongly than positive shocks. In fomer times, the implied asymmetry was related to the so-called leverage effect as the increase in risk originated from the increased leverage induced by a negative shock. Nowadays, however, this effect is considered as being too small.

Based on the GJR-GARCH fitted volatility we derive the *1% VaR* of each financial institution. Next, we substract the 50% quantile of the *1% VaR* - hereby representing the median or normal state - from the 1% quantile of the *1% VaR* - representing an extreme state.

$$\Delta VaR_q^{1\%}, i = VaR_{0.01,i}^{1\%} - VaR_{0.5,i}^{1\%}$$

This approach is founded on the idea of *CoVaR* by Adrian and Brunnermeier (2011), except that the *VaR* is not estimated by an GJR-GARCH model but via quantile regression – which does not capture the previously mentioned asymmetry. After having estimated the *VaR* with conditional, underlying volatility and calculated the institution-specific ΔVaR_i^Y at the 1% level, *quantile regression* is used to provide a sensitivity measure that quantifies the risk contribution of a financially distressed institution to the aggregate S&P 500.

The majority of research is conducted on a linear regression approach where the OLS method estimates unknown parameters. Whereas linear regression describes the entire distribution of a particular information set at once, some academics have applied the so called *quantile regression* in order to examine particular parts of a distribution, which are prone to be differently distributed. Hence, *quantile regression* is able to identify asymmetry (inequality) within an information set as well as the average, represented as the median state. The conditional quantile function (*CQF*) is defined as follows:

$$Q_\tau(y_i|X_i) = F_y^{-1}(\tau|X_i)$$

τ describes the applicable quantile, y_i the dependent variable, X_i the vector of regressors and F_y^{-1} the distribution function of y_i conditional on the independent variable X_i. The *CQF* is similar to the conditional expectation function *CEF* – except that it takes quantiles into consideration. Recall, that the derivation of the *CEF* is accomplished by solving a mean-squared error prediction problem:

$$E[y_i|X_i] = \underset{m(X_i)}{\arg\min}\, E[(y_i - m(X_i))^2]$$

Equally, the *CQF* solves the following minimization problem:

$$Q_\tau(y_i|X_i) = \underset{q(X_i)}{\arg\min}\, E[\rho_\tau(y_i - q(X_i))]$$

The ρ_τ hereby represents the *check function*, which asymmetrically weights positive and negative terms within our information set. This means that positive residuals are weighted with τ while neagtive residuals are weighted with $(1-\tau)$. The objective check-function (more commonly known as the loss/cost-function) supports the quantile regression model by fitting a linear model to y_i and estimating the parameter β_τ:

$$\rho_\tau(u) = 1(u > 0)\tau u + 1(u \leq 0)(1-\tau)u$$

If this information set contains, for instance, financial data such as *log returns* of individual companies and the 70^{th} quantile shall be observed, the check function puts much higher weigths on positive residuals than on negative residuals. This means that underestimating the true parameter in the 70^{th} quantile is more *expensive* than overestimating. This asymmetric

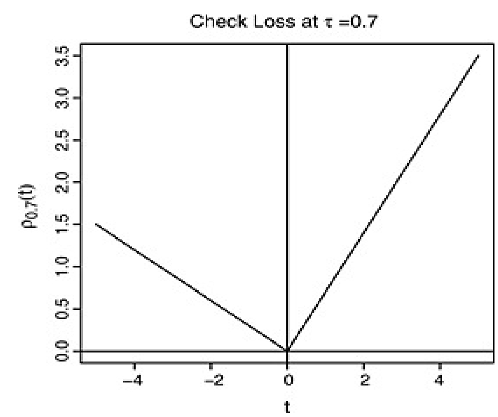

Figure 1: *Check function of a quantile regression model*

weighting generates a *minimand* that picks out conditional quantiles. The *CQF* bears, however, the same drawbacks as the *CEF*. Continuous or high-dimensional data X_i may be difficult to estimate and summarize. Hence, the term $q(X_i)$ is substituted by a linear model.

$$\beta_r = \underset{b\in\mathbb{R}^d}{\arg\min}\, E[\rho_\tau(y_i - X_i'b)]$$

Instead of receiving a general understanding of the information's set tendency, *quantile regression* can examine the distribution of data points close to the upper or lower extremes within a population (Koenker, 2017, p. 578). The *quantile regression* supplies a useful method for completely assessing and describing the conditional distribution. Overall, this approach is very similar to *OLS* as it cannot include the same independent variable twice, or have two possible intercepts. The arguments for the *OLS* and *quantile regression* are equal, except that the *check function* and not the squared differences are considered.

Our *quantile regression* will apply the 1% *VaR* of the S&P 500 as the dependent variable, whereas the 1% *VaR* of the particular institutions will serve as the independent variable. As a result, we will receive a vector of β-coefficients that quantifies the sensitivity of the *VaR* of the S&P 500 toward the *VaR* of individual institutions conditional on different market states, represented by the different quantiles of the *VaR* of the S&P 500. It is important to understand that the β-coefficients represent the respective quantiles of the *VaR* of the S&P 500, thus imparting how a shock to the *VaR* of a financial institution contributes to the aggregated *VaR* during different market periods.

Based on the product of the β_i-coefficient and the $\Delta VaR^{1\%}_{iq,i}$ we simply compute the *SSVaR* for institution i by multiplying this product with the current market capitalization of the respective institution.

$$\begin{aligned} SSVaR^{\tau}_{i,m} &= \beta^{\tau}_{i,m} * \Delta VaR^{1\%}_{q}, i * MC_i \\ &= \beta^{\tau}_{i,m} * (VaR^{1\%}_{0.01,i} - VaR^{1\%}_{0.5,i}) * MC_i \end{aligned}$$

Since we calculated the *VaR* based on *log* returns it is, however, very important to reverse the log transformation on the $\Delta VaR^{1\%}_{i}$ to, in order to accomplish the above stated multiplication.

In a robustness-check the *SSVaR* will be further evaluated for its supporting power as a complementary or alternative risk measure. On one side, the robustness-check will contrast *SSVaR* to *SRISK*. On the other side, the robustness-check will examine whether parameter adjustments to our *default* model will reveal tremendous, significant deviations. Hereby, we consider to adjust for the following model parameters:

i. Periodicities of return series: instead of using daily return series, we also consider weekly and monthly return series of the respective institutions.

ii. Computation method for estimating *VaR*: Besides the GJR-GARCH model the EGARCH model also incorporates the asymmetric leverage effect of financial return series. The literature is divided over the question which of the two is better. Thus we test for the e-GARCH(1,1) model, too.

iii. *VaR* distribution: in order to derive the *SSVaR* from the return series of individual institutions we derive the *1% VaR* from a scaled normal distribution, whereas the *1% VaR* can also be derived from a scaled student-t distribution, hence considering the fatter tails. We estimate the shape of the best fitting student-t distribution for each return series using a maximum likelihood approach. This technique is often used by practitioners and results in higher VaR estimations.

iv. Underlying time horizon: by altering the time horizon, we examine how the *SSVaR* deviates. In contrast to the initial time horizon between 02.01.1990 and 29.12.2017, we further consider the starting dates 02.01.2000, 02.01.2004, 02.01.2010 and 02.01.2015.

V. Empirical Results

In this section, we first provide an overview over the institutions included in our sample and then inspect certain characteristics of the simple returns to get an understanding of their distribution. Subsequently, we will describe and analyse the GJR-GARCH fitted conditional volatility and the 1% *VaR* measure we derive from the volatility. In a next step, we present and interpret the quantile regression results and therefore the connection between the *VaR* of a single institution and the *VaR* of the S&P 500. Finally, we will compare our

SSVaR measure with the *SRISK* measure by Brownlees and Engle (2017).

Out of 32 U.S. financial institutions, 24 firms are classified as either commercial or investment banks, 14 as insurance companies, and one firm as a financial services provider. The market capitalizations of these institutions range from $670 million for MBIA Inc to $371 billion for J.P. Morgan Chase & Co, whereas the median accounts for $12 billion. The aggregate market capitalization amounts to $1.758 trillion, which represents roughly 7.3% of the S&P's total market capitalization of around $23.8 trillion as of 29th of December 2017. Table 3 in the appendix provides an overview over the included institutions.

Table 4 in the appendix displays selected moments of the simple returns. All U.S. financial institutions have a rather high annualized volatility compared to the 18% annualized volatility of the S&P 500, as 16 of 32 institutions have an annualized volatility exceeding 40%. When looking at the yearly mean return, it is noticeable that specific institutions have compensated their shareholders for bearing such high risk levels by outperforming the S&P 500, whereas other institutions yielded low or even negative average returns over their respective sample periods. The high volatility also affects the tails of the return distributions. While the maximum one-day loss of the S&P 500 aggregates to 9%, most of the U.S. financial institutions display a maximum daily loss of more than 20%. These daily minimum returns mainly cluster around the three crises of 1991, 2000 and 2008, with the vast majority being observable around the financial crisis in 2008. Worth mentioning is also the high excess kurtosis of many institutions, which is a sign of fat tails - meaning the probability of extreme tail events is higher compared to a normal distribution. While the S&P 500 itself demonstrates a high excess kurtosis, it is, however, significantly smaller than for many of the financial institutions. A summary of the log returns derived from the simple returns can be found in table 5 in the appendix.

The conditional volatility calculated with a GJR-GARCH model fitted to the log returns for American International Group Inc (AIG), J.P. Morgan Chase & Co (J.P. Morgan) and the S&P 500 is displayed in Figure 2. While we will discuss the results for all 32 institutions below, we first want to illustrate the different steps of the methodology and the stylized results derived from the analysis using AIG and J.P. Morgan, as well as the S&P 500 as a comparison. We choose AIG and J.P. Morgan as examples as they represent the largest insurance company and bank – as of market capitalization – in our sample.

Figure 2 clearly demonstrates that conditional volatility clusters over time and that systemic risk events, such as the financial crisis of 2008, seem to affect all market participants. We can, however, also observe volatility shocks that seem to be firm- or industry-specific, such as the two spikes between 2004 and 2006 in the data sample of AIG. In general, it appears as if volatility accumulates in relatively calm market phases and spontaneously erupts during crises, hence forming spikes. These spikes of volatility in turn lead to an increased average level of volatility in the following periods which is only slowly degrading again. The different magnitudes of the shocks, however, indicate that a common shock seems to affect all market participants in some way, whereas shock to individual institutions are probably determined by other, firm specific characteristics such as risk exposure and capital buffer.

In the next step, we calculate the 1% *VaR* for each institution utilizing the above described conditional volatility as well as the mean and the 1% quantile of a normal distribution fitted to the returns of the respective company. Figure 3 shows how the *VaR*, due to its construction, naturally follows the conditional volatility. It therefore displays similar properties and characteristics as the volatility. Furthermore, we observe that the *VaR* as of December 2017 is relatively low compared to

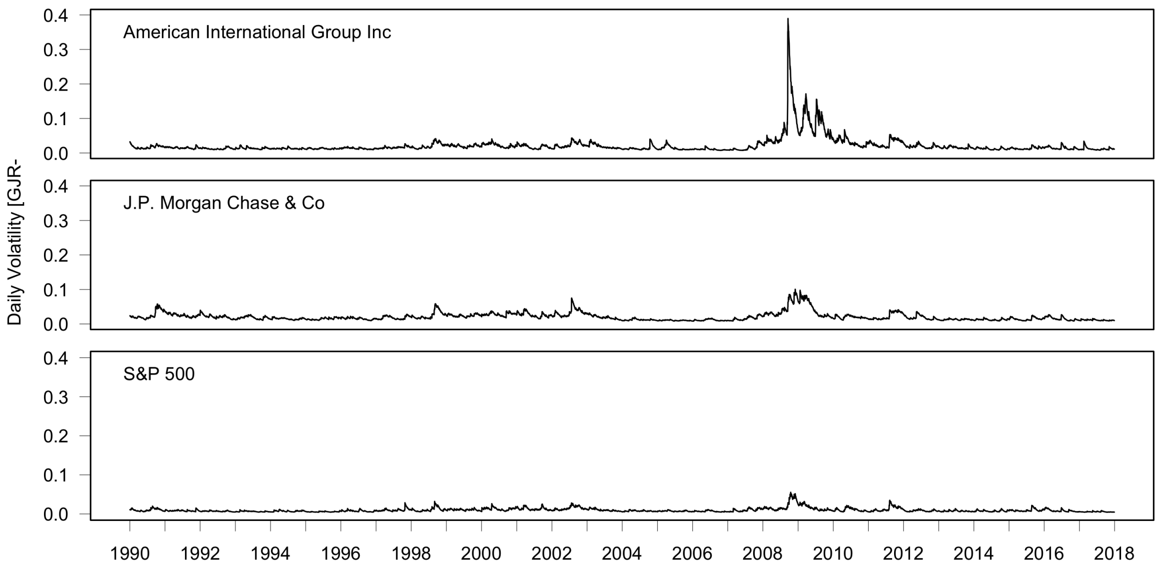

Figure 2: *Conditional Daily Volatility [GJR-GARCH] of AIG Inc, JP Morgan Chase & Co. and S&P 500*

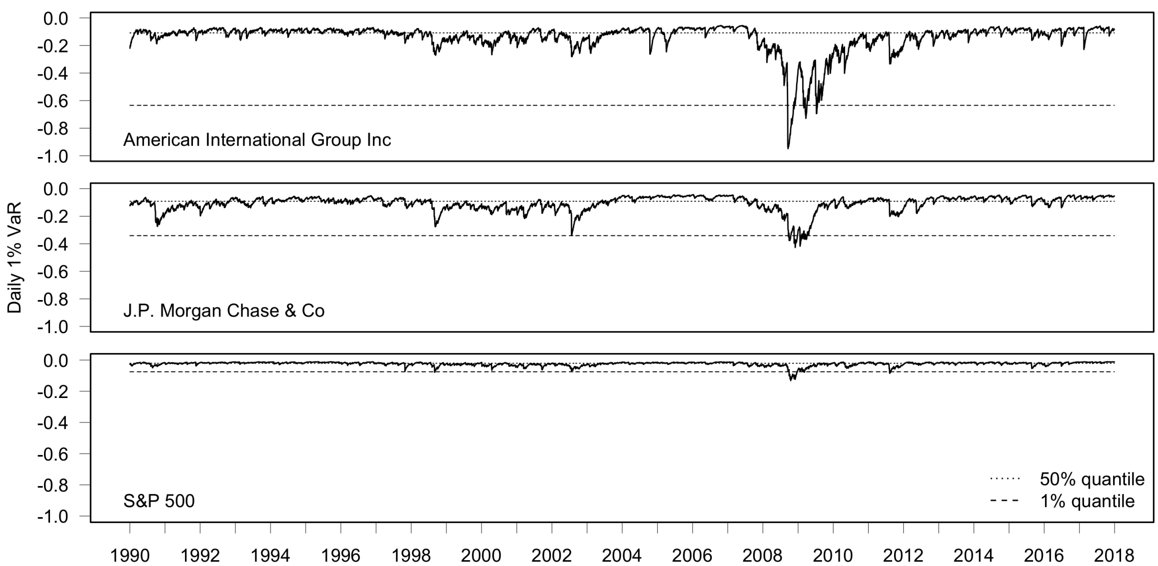

Figure 3: *Daily 1% VaR of AIG Inc, JP Morgan Chase & Co. and S&P 500*

historic values which will conversely influence the calculation of the *SSVaR* below. Table 6 and 7 in the appendix provide further details about the volatility and *VaR* of the 32 U.S. financial institutions. Especially relevant for the calculation of the *SSVaR* is the 1% and 50% quantile of the 1% *VaR* distribution. According to these numbers investors can expect that the median 1% *VaR* of the S&P 500 is around -2%, while the 1% *VaR* of the S&P 500 will - on average - not drop below -7.5% in 99% of the cases. A relatively small absolute 50%

quantile in combination with a high absolute 1% quantile of the *VaR* can be a sign that during phases of market decline the 1% *VaR* of an institution increases disproportionately. Hence, this institution's risk contribution seems to be higher compared to counterparties that demonstrate contrary behaviour. By comparing J.P. Morgan to AIG this effect becomes more coherent: while J.P. Morgan and AIG have a similar median 1% *VaR* (AIG: -9%, J.P. Morgan: -11%) the 1% quantile of the 1% *VaR* distribution of AIG is nearly twice as low as the respective measure for J.P. Morgan (AIG: -64%, J.P. Morgan: -34%).

The relationship between the *VaR* of individual institutions and the *VaR* of the S&P 500 as the market is analysed more formally in figure 4; again, on the examples from above.

Panel A of figure 4 displays scatterplots of AIG and J.P. Morgan respectively. Both scatterplots include a OLS regression line, illustrated by the black line, and several quantile regression lines, illustrated by dashed lines, that refer to the upper and lower quantiles. The OLS regression lines indicate the sensitivity of the *VaR* of the S&P 500 to the *VaR* of the individual institution. It is noticeable that the slope of this line, hence the sensitivity of the S&P 500, is higher for J.P. Morgan. Thus, the market in general seems to be more sensitive to the *VaR* of J.P. Morgan. The OLS regression line, however, only indicates the average sensitivity across all market states – whether good or bad – and does not provide specific information about the sensitivities under extreme positive or negative market conditions. OLS regressions contain little to no information about the sensitivity conditional on a general market decline or shock. In contrast, quantile regression can estimate the sensitivity of the S&P 500 conditional on different states of the market. The different states of the market are defined as different quantiles of the S&P 500 *VaR* distribution. The sensitivity, denoted as the β-coefficient, at the 1% quantile therefore indicates how sensitive the market is to an individual institution conditional on the market being in distress. Both J.P. Morgan and AIG demonstrate a sensitivity that increases with respect to lower quantiles. Thus, in periods of high volatility and therefore high *VaR*, the sensitivity of the S&P 500 regarding J.P. Morgan and AIG increases.

The alteration of the β-coefficients, or sensitivities, over the different quantiles is illustrated in more detail in panel B of figure 4. The grey area indicates the 95% confidence interval around the point estimations. Note, that the difference between various sensitivities appear to be highly significant. Additionally, both examples display a disproportional increase in sensitivity towards the lower end of the *VaR* distribution of the S&P 500. This observation supports our first hypothesis that the sensitivities between the *VaR* of the market and financial institutions increases substantially in times of financial distress. Table 8 in the appendix displays the β-coefficients for all 32 U.S. financial institutions – thereby confirming that the sensitivity increases in times of extreme negative market conditions.

Lastly, we can compute the Shock Sensitivity Value-at-Risk (*SSVaR*) by first multiplying the difference of the 1% and 50% quantile of the *VaR* distribution of an institution with the lower quantile β-coefficient of the S&P 500 (thereby referring to an extreme market situation). In case of J.P Morgan *SSVaR* amounts to

$$0.71 * (-0.16 - 0.04) = -0.11$$

whereas for AIG it is equal to:

$$0.66 * (-0.26 - 0.03) = -0.15.$$

Therefore, according to *SSVaR* 11% of J.P. Morgan's market capitalization and 15% of AIG's market capitalization can be considered as systemic risk. In US$ ($) this amounts to $34 billion for J.P. Morgan and $7.1 billion for AIG.

The *SSVaR* expressed in $ billion calculated for all 32 systemically relevant U.S. financial

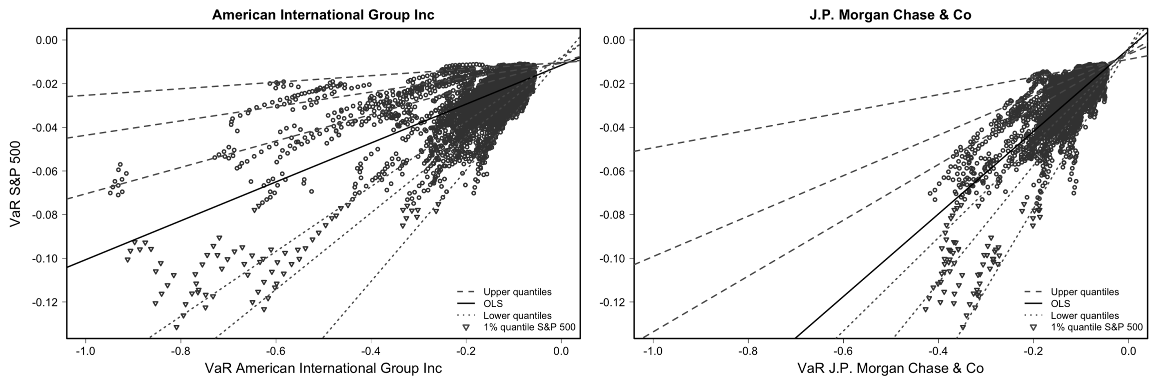

Figure 4: *Scatterplot of AIG Inc [Panel A] and JP Morgan Chase & Co. [Panel B]*

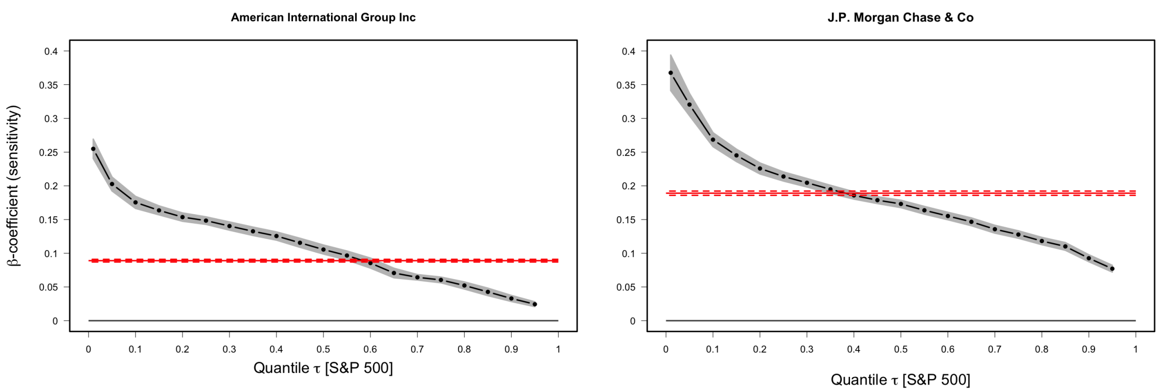

Figure 5: *Scatterplot of AIG Inc [Panel A] and JP Morgan Chase & Co. [Panel B]*

institutions is displayed in figure 6. While the *SSVaR* is displayed on the x-axis the corresponding systemic risk measure *SRISK* for each individual institution is displayed on the y-axis. The comparison with *SRISK* therefore does not only provide a frame of reference to broadly asses the validity of *SSVaR*, but also makes the two different systemic risk measures comparable. This comparison allows us to highlight certain characteristics of *SSVaR*. Note, that the scale of the y- and x-axes decrease subsequently from left to right to provide a detailed overview of not only relatively large, but also medium and small U.S. systemic risk contributors. By comparing *SRISK* and *SSVaR* on level of individual institutions we can see on the one hand that *SSVaR* assigns – compared to *SRISK* – rather high levels of systemic risk to Wells Fargo & Co, J.P. Morgan and Bank of America Corp. On the other hand, the systemic risk of Citigroup Inc. according to *SSVaR* is smaller compared to *SRISK*. *SSVaR* therefore seems to put more emphasis on other aspects of systemic risk than *SRISK*.

A more formal way of analysing the relationship between the two measures of systemic risk is through an OLS regression. The black line in figure 5 depicts the slope and intercept of such a regression with *SRISK* as the dependent and *SSVaR* as the independent variable. The slope of the regression line and therefore the coefficient of the regression is 0.5 indicating that a 1% increase in *SSVaR* is on average accompanied by a 0.5% increase in *SRISK*. Our newly introduced measure of systemic risk

SSVaR therefore seems to be more conservative than *SRISK* meaning that it predicts higher amounts of systemic risk. However, since the intercept of the regression amounts to -3.5 this picture is slightly distorted. This can also be seen when looking at the total value of estimated systemic risk in the financial system of the United States according to the two measures for the 29th of December, 2017. *SRISK* estimates a total systemic risk of \$211 billion, whereas *SSVaR* estimates \$ 190 billion which represents a deviation of -9%. The total amount of systemic risk in the U.S. financial system at this specific point is therefore slightly lower according to *SSVaR*.

The adjusted R^2 of the regression between *SRISK* and *SSVaR* amounts to 0.28, indicating that the *SSVaR* explains around 28% of the total variation in *SRISK*. This number is rather small compared to e.g. the market capitalization of the individual institutions which also explains around 29% of the total variation in *SRISK*. Note, however, that *SRISK* itself is not a definitive measure of the systemic risk associated with a specific financial institution and is – like all other systemic risk measures – purely an approximation that depends on its own model assumptions and calculation methods. The exact systemic risk measures per institution according to *SRISK* and *SSVaR*, including a summary of the regression analysis, can be found in table 9 of the appendix.

The correlation matrix in Table 1 provides further insights into the firm level determinants of the level of *SSVaR* that a specific institution bears. We can see that the leverage and volatility of financial institutions are relatively strongly correlated with different *VaR* quantiles and, hence, also the *VaR* difference which is a determinant of the *SSVaR*. The 1% sensitivities derived by quantile regression are also highly correlated the *VaR* in general and in the 1% *VaR* quantile particularly. Hence, institutions with an above average 1% *VaR* quantile seem to also exhibit an above average 1% *VaR* sensitivity with regard to the *VaR* of the S&P 500. Note also that *SSVaR* is strongly negatively correlated with the market capitalization of an institution and strongly positively correlated with the *VaR* difference. The level of *SSVaR* that a financial institution exhibits is therefore strongly connected to its size determined by its market capitalization and the amount by which its *VaR* increases in periods of stress. However, since both factors are main determinants of *SSVaR* this result is not unexpected.

VI. Robustness Test

In this section, we present the results of a robustness test covering three main aspects of our methodology. First, by calculating the

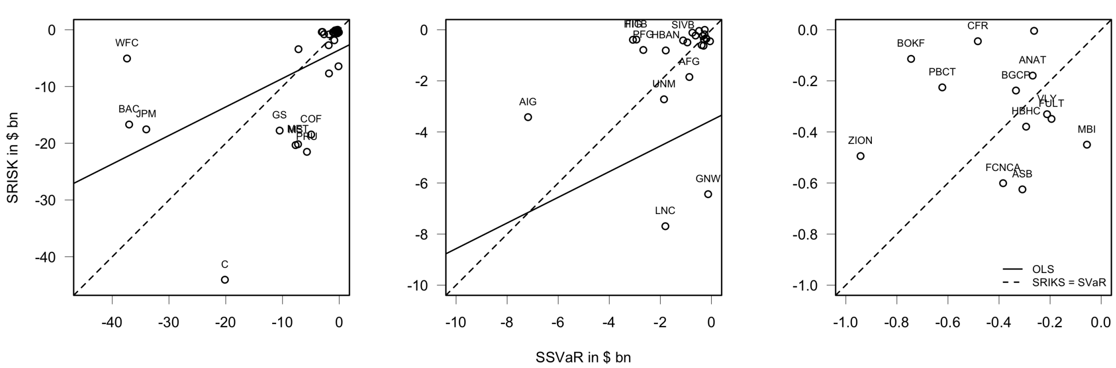

Figure 6: *SRISK vs SSVaR*

Variable	SRISK in $ bn	LRMES	Beta	CAPM Correlation	Volatility	Leverage	Marketcap in $ bn	1% VaR quantile in %	5% VaR quantile in %	50% VaR quantile in %	VaR Diff in %	1% sensitivity	5% sensitivity	50% sensitivity	SSVaR in %	VaR Diff in $ bn	SSVaR in $ bn
SRISK in $ bn	1.00																
LRMES	0.20	1.00															
CAPM-beta	-0.20	0.33	1.00														
Correlation	-0.54	-0.38	0.39	1.00													
Volatility	0.21	0.56	0.59	-0.47	1.00												
Quasi-leverage	-0.12	0.09	0.04	-0.30	0.44	1.00											
Marketcap in $ bn	-0.56	-0.29	0.06	0.52	-0.30	-0.07	1.00										
1% VaR quantile in %	0.19	-0.15	-0.25	0.02	-0.36	-0.52	-0.01	1.00									
5% VaR quantile in %	0.04	-0.47	-0.47	0.17	-0.67	-0.58	0.12	0.86	1.00								
50% VaR quantile in %	0.12	-0.51	-0.51	0.09	-0.62	-0.56	0.08	0.81	0.97	1.00							
VaR Diff in %	0.20	-0.04	-0.17	-0.00	-0.27	-0.48	-0.03	0.99	0.78	0.71	1.00						
1% sensitivity	0.26	-0.15	-0.36	-0.13	-0.32	-0.34	-0.08	0.87	0.75	0.71	0.85	1.00					
5% sensitivity	0.25	-0.12	-0.39	-0.15	-0.32	-0.34	-0.10	0.92	0.78	0.74	0.91	0.97	1.00				
50% sensitivity	-0.05	-0.27	-0.42	-0.08	-0.36	-0.18	0.05	0.65	0.69	0.64	0.61	0.64	0.69	1.00			
SSVaR in %	0.14	0.25	0.24	-0.19	0.34	0.09	-0.19	0.50	0.11	0.06	0.58	0.28	0.41	0.24	1.00		
VaR Diff in $ bn	0.63	0.31	-0.06	-0.52	0.30	0.06	-0.97	0.10	-0.08	-0.04	0.13	0.15	0.18	0.00	0.25	1.00	
SSVaR in $ bn	0.53	0.30	-0.02	-0.47	0.30	0.07	-0.99	0.03	-0.12	-0.09	0.06	0.07	0.10	-0.04	0.25	0.97	1.00

Table 1: *Correlation matrix*

SSVaR for the same sample basis on weekly and monthly returns we test the impact of different return frequencies. We extract the weekly and monthly returns from the daily returns and use exactly the same approach as described above. Secondly, we test for the impact of different calculation methods by using an EGARCH instead of an GJR-GARCH for the calculation of the volatility, and by using a fitted student-t distribution instead of a normal distribution for the calculation of the textitVaR. Lastly, we analyse whether a change to the sample period has an impact on the *SSVaR* measures and their correlation to *SRISK*. We assess the different models with four different methods. We compare the total amount of *SSVaR* that each model estimates, the adjusted R^2 of a linear regression whereas *SRISK* represents the dependent variable and *SSVaR* represents the independent variable, as well as the Pearson and Spearman correlation coefficients between *SRISK* and the respective *SSVaR* measures. Besides from the above mentioned adjustments all models resemble the standard model described above. The results from this robustness test are displayed in table 10 of the appendix and are described below:

Return frequency: Instead of using daily return frequencies, weekly return frequencies and monthly return frequencies lead to significantly higher total systemic risk levels. Since, however, the results of the OLS regression and the two different correlations stay qualitatively the same, this seems to be a mere scaling effect.

Calculation methodology: While the use of an EGARCH for the volatility estimation leads to lower aggregated levels of *SSVaR* compared to the use of an GJR-GARCH model, the use of a student-t distribution in the calculation of the textitVaR leads to higher aggregated levels of systemic risk. Again, the R^2 measures and the correlation measures stay qualitatively the same. Since the aggregated level of systemic risk of the above mentioned methodology is most closely in line with the absolute value estimated with the established *SRISK* measure, we see no reason to adjust the model.

Sample period: The various subsample periods were specifically chosen to cover different states of the market to a varying extent. For example, the subsample beginning in 2010 was selected to test whether calculating the *SSVaR* for a period without a major financial crisis changes the results. Interestingly, the methodology based on a sample period starting in 2010 seems to more closely resemble the systemic risk measures obtained with *SRISK*. The adjusted R^2 and correlation results for the model starting in 2015 cannot be compared to the other models since two companies, namely Fulton Financial Inc and Genworth Financial Inc, had to be dropped from the sample since their GARCH did not converge due to high volatility.

In summary, our proposed *SSVaR* measure of systemic risk seems to be rather robust over different frequencies, different calculation methodologies and different sample periods. However, it seems like there might be some advantages – at least concerning the correlation with *SRISK* – regarding shorter sample periods. Presumably, shorter sample periods place more emphasis on recent data and therefore provide more important information.

VII. Conclusion

In this research paper, we propose the risk measure *Shock Sensitivity Value-at-Risk (SSVaR)* – a complementary systemic risk measure that combines particular risk characteristics of systemically important financial institution and the stock market, as well as a sensitivity coefficient and the market capitalization of the respective institution. Hereby, the β-coefficient measures the sensitivity of a stock index – in this case the S&P 500 – toward systemically important financial institution conditional on the overall market being in distress.

Based on the 1% quantile of the *VaR* of the S&P 500, we ascertain that the sensitivities alter substantially, meaning the higher the difference between the extreme state and the median state of the 1% *VaR*, the higher the S&P 500's sensitivity. Hence, the respective stock market is more sensitive toward systemically important financial institutions that carry high risk during extreme negative events than toward financial institutions that bear low risk during extreme negative events.

Depending on the observed quantile, we further observe, that during periods of market distress the S&P 500 exhibits higher overall sensitivities toward shocks to the *VaR* of financial institutions than during periods of normal market states. In other words, the β-coefficients of the S&P 500 *VaR* distribution feature overproportional higher values in the lower quantiles and lower values in the higher quantiles, hence displaying the suggested asymmetry factor. The question why different financial institutions demonstrate different sensitivity profiles could be of possible interest for further research.

The empirical results of the institution-specific calculated *SSVaR* further demonstrate that the *SSVaR* can be used as an complementary measure of systemic risk as it reveals high robustness throughout different parameter settings. As opposed to the widely acknowledged, highly sophisticated measure *SRISK* the aggregate *SSVaR* deviates only by $18 billion ($210 aggregated *SRISK* vs. $192 aggregated *SSVaR*). Even though the deviation appears to be significant on an aggregate level, it has to be considered, that our proposed systemic risk measure differentiates substantially with regard to computation complexity and computational methodology. Additionally, both institution-specific characteristics such as for example leverage, and a prediction model are not integrated into the *SSVaR* approach.

SSVaR, however, has several limitations. First, we only concentrate on *SRISK* as a reference measure of systemic risk. Although *SRISK* is a well-established, both theoretical and empirical solid measure of systemic risk, it is by no means a definitive answer to how much systemic risk a financial institution inhibits. The reason why our proposed measure reveals much less systemic risk in some individual institutions could simply be that *SRISK* overestimates their systemic risk or emphasises different aspects of systemic risk more strongly than we do. A comparison with other risk measures and a larger sample to make statistical inference easier could help answer this question.

Second, we only looked at one specific point in time, the 29th of December, 2017. A more thorough or detailed analysis would also look at how the *SSVaR* develops over time and, particularly, how it then performs before, during and after periods of systemic shock. In other words, a more sophisticated approach for the *VaR* calculation would include the rolling calculation of volatility, mean and standard deviation to better capture the time variation of these measures.

Thirdly, our empirical analysis does not incorporate non-financial institutions. Non-financial institutions often exhibit higher capital ratios, different balance-sheet items and other institution-specific characteristics. Hence, the degree of information of our results could be improved as we are only examining the sensitivities of systemically important financial institutions. Additionally, it would also be important to analyse whether non-financials exhibit similar characteristics regarding the their *VaR* sensitivity.

Fourth, we only concentrate on institutions that exhibit positive *SRISK*. The list including the 32 systemically most important financial institutions does not guarantee that every institution that could contribute substantially to systemic risk is reflected.

Fifth, *SSVaR* does not have forecasting capabilities. However, they could be implemented in a similar way as in the case of *SRISK* and simulations could help to test and improve on the results. Furthermore, we only incorporate market data and no balance sheet data.

Lastly, instead of only examining the 1% *VaR*, the *5% VaR* and *10% VaR* levels can be considered, too. This comes along with the idea of also estimating and looking at the *VaR's* complementary risk measure, the *expected shortfall*.

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Appendix

Institution	SRISK %	RNK	SRISK ($ m)	LRMES	Beta	Correlation	Volatility	Leverage
Citigroup Inc	19.22	1	44052	51.78	1.51	0.63	17.59	9.30
Prudential Financial Inc	9.38	2	21513	43.85	1.31	0.57	16.91	12.87
Morgan Stanley	8.87	3	20326	54.64	1.60	0.67	17.57	8.77
MetLife Inc	8.80	4	20174	52.71	0.76	0.30	18.27	11.18
Capital One Financial Corp	8.05	5	18457	85.67	1.62	0.56	21.03	7.37
Goldman Sachs Group Inc/The	7.75	6	17765	44.85	1.55	0.62	18.45	9.61
JPMorgan Chase & Co	7.66	7	17552	51.85	1.32	0.63	15.42	7.12
Bank of America Corp	7.28	8	16698	49.09	1.26	0.54	17.00	7.53
Lincoln National Corp	3.36	9	7694	58.37	1.07	0.42	18.44	11.50
Brighthouse Financial Inc	3.13	10	7170	38.46	0.84	0.26	23.59	20.84
Genworth Financial Inc	2.81	11	6438	73.64	1.34	0.22	43.60	55.87
Voya Financial Inc	2.72	12	6241	29.25	1.28	0.32	29.53	17.91
Wells Fargo & Co	2.21	13	5063	53.63	1.07	0.49	15.80	6.54
American International Group Inc	1.49	14	3422	45.82	1.02	0.42	17.62	8.03
Ally Financial Inc	1.47	15	3372	26.97	1.29	0.47	19.97	12.67
Unum Group	1.19	16	2723	85.65	1.28	0.46	20.49	5.41
American Financial Group Inc/OH	0.81	17	1850	71.53	0.34	0.17	14.65	6.69
CNO Financial Group Inc	0.77	18	1768	87.98	1.17	0.41	20.87	7.72
Huntington Bancshares Inc/OH	0.35	19	810	56.84	1.15	0.43	19.48	6.58
Principal Financial Group Inc	0.35	20	791	43.07	1.04	0.56	13.72	8.03
Associated Banc-Corp	0.27	21	625	58.74	1.00	0.36	20.46	7.69
First Citizens BancShares Inc/NC	0.26	22	601	56.87	1.28	0.39	23.67	7.53
Zions Bancorporation	0.22	23	495	55.79	1.26	0.41	22.47	6.69
MBIA Inc	0.20	24	450	79.24	2.16	0.27	57.63	9.50
SVB Financial Group	0.18	25	418	70.85	1.97	0.54	26.87	4.78
Hartford Financial Services Group Inc/The	0.17	26	392	42.52	1.07	0.42	18.62	7.85
Fifth Third Bancorp	0.17	27	383	50.81	1.05	0.45	17.30	6.88
Hancock Holding Co	0.17	28	379	60.38	1.41	0.44	23.37	6.68
Fulton Financial Corp	0.15	29	349	62.59	1.34	0.42	23.33	6.70
Valley National Bancorp	0.14	30	331	49.81	1.09	0.43	18.67	8.17
BGC Partners Inc	0.10	31	238	93.33	1.44	0.33	31.52	2.45
People's United Financial Inc	0.10	32	226	54.41	1.08	0.45	17.64	6.66
American National Insurance Co	0.08	33	179	54.07	0.92	0.31	21.74	6.93
CIT Group Inc	0.05	34	119	45.64	1.48	0.48	22.40	7.48
BOK Financial Corp	0.05	35	114	59.61	1.27	0.49	18.97	5.88
Cullen/Frost Bankers Inc	0.02	36	45	60.38	1.07	0.43	18.06	5.65
UMB Financial Corp	0.00	37	4	56.05	1.20	0.41	21.24	6.07

Table 2: *SRISK Table as of the 29th of December, 2017*

Institution	Ticker	Industry	Marketcap in $ bn	Start of sample	End of Sample
American Financial Group Inc New	AFG	Insurance	9.56	1990-01-02	2017-12-29
American International Group Inc	AIG	Insurance	53.56	1990-01-02	2017-12-29
American National Ins Co	ANAT	Insurance	3.45	1990-01-02	2017-12-29
Associated Banc Corp	ASB	Commercial Bank	3.84	1990-01-02	2017-12-29
BGC Partners Inc	BGCP	Services	3.84	1999-12-13	2017-12-29
BOK Financial Corp	BOKF	Commercial Bank	6.04	1991-09-06	2017-12-29
Bank Of America Corp	BAC	Investment Bank	307.91	1990-01-02	2017-12-29
Capital One Financial Corp	COF	Commercial Bank	48.27	1994-11-17	2017-12-29
Citigroup Inc	C	Investment Bank	196.74	1990-01-02	2017-12-29
Cullen Frost Bankers Inc	CFR	Commercial Bank	5.98	1990-01-02	2017-12-29
Fifth Third Bancorp	FITB	Commercial Bank	21.41	1990-01-02	2017-12-29
First Citizens Bancshares Inc Nc	FCNCA	Commercial Bank	4.44	1990-01-02	2017-12-29
Fulton Financial Corp	FULT	Commercial Bank	3.13	1990-01-02	2017-12-29
Genworth Financial Inc	GNW	Insurance	1.55	2004-05-26	2017-12-29
Goldman Sachs Group Inc	GS	Investment Bank	96.10	1999-05-05	2017-12-29
Hancock Holding Co	HBHC	Commercial Bank	4.22	1991-06-05	2017-12-29
Hartford Financial Svcs Grp Inc	HIG	Insurance	20.08	1995-12-21	2017-12-29
Huntington Bancshares Inc	HBAN	Commercial Bank	15.74	1990-01-02	2017-12-29
J.P. Morgan Chase & Co	JPM	Investment Bank	371.05	1990-01-02	2017-12-29
Lincoln National Corp	LNC	Insurance	16.82	1990-01-02	2017-12-29
MBIA Inc	MBI	Insurance	0.67	1990-01-02	2017-12-29
Metlife Inc	MET	Insurance	53.20	2000-04-06	2017-12-29
Morgan Stanley Group Inc	MS	Investment Bank	94.86	1990-01-02	2017-12-29
Peoples United Financial Inc	PBCT	Commercial Bank	6.47	1990-01-02	2017-12-29
Principal Financial Group Inc	PFG	Insurance	20.37	2001-10-24	2017-12-29
Prudential Financial Inc	PRU	Insurance	48.75	2001-12-14	2017-12-29
S V B Financial Group	SIVB	Commercial Bank	12.33	1990-01-02	2017-12-29
S&P 500			23814.81	1990-01-02	2017-12-29
UMB Financial Corp	UMBF	Commercial Bank	3.59	1990-01-02	2017-12-29
Unum Group	UNM	Insurance	12.32	1990-01-02	2017-12-29
Valley National Bancorp	VLY	Commercial Bank	2.97	1990-01-02	2017-12-29
Wells Fargo & Co New	WFC	Investment Bank	298.75	1990-01-02	2017-12-29
Zions Bancorporation	ZION	Commercial Bank	10.15	1990-01-02	2017-12-29

Table 3: *Overview of included institutions*

Institution	Yearly mean return	Annualized volatility	Min	1% quantile	5% quantile	Max	Skewness	Kurtosis
American Financial Group Inc New	9.70	29.41	-22.71	-4.81	-2.50	45.37	2.13	61.85
American International Group Inc	-2.54	51.88	-60.79	-7.85	-3.18	66.00	1.73	97.74
American National Ins Co	8.63	30.32	-21.84	-5.74	-2.60	28.48	0.17	18.00
Associated Banc Corp	8.74	32.59	-17.30	-5.38	-3.00	21.35	0.24	10.59
BGC Partners Inc	0.46	59.96	-28.22	-10.86	-5.29	48.57	1.22	15.24
BOK Financial Corp	8.41	50.76	-64.29	-8.29	-3.98	60.00	-0.41	70.02
Bank Of America Corp	6.41	42.33	-28.97	-7.02	-3.36	35.27	0.80	27.37
Capital One Financial Corp	14.59	48.05	-39.76	-7.81	-3.99	26.43	-0.19	15.09
Citigroup Inc	6.11	45.27	-39.02	-7.02	-3.61	57.82	1.35	47.34
Cullen Frost Bankers Inc	16.59	31.45	-19.31	-5.28	-2.86	21.88	0.67	10.69
Fifth Third Bancorp	9.24	44.73	-43.63	-6.69	-3.14	60.37	2.72	86.53
First Citizens Bancshares Inc Nc	11.31	31.83	-11.36	-4.95	-3.03	21.39	0.57	6.17
Fulton Financial Corp	9.19	34.02	-18.26	-5.43	-3.19	18.76	0.14	9.40
Genworth Financial Inc	-12.20	78.56	-54.41	-13.96	-5.41	88.89	3.94	79.04
Goldman Sachs Group Inc	8.24	37.75	-18.96	-6.24	-3.40	26.47	0.80	13.48
Hancock Holding Co	12.40	34.38	-18.02	-5.48	-3.27	20.00	0.13	6.86
Hartford Financial Svcs Grp Inc	5.99	53.16	-51.56	-8.40	-3.49	102.36	5.09	177.20
Huntington Bancshares Inc	6.76	46.12	-30.59	-7.43	-3.32	50.07	2.13	45.43
J.P. Morgan Chase & Co	12.47	38.10	-20.73	-6.06	-3.42	25.10	0.72	12.24
Lincoln National Corp	9.01	45.50	-39.88	-7.61	-3.25	43.67	0.92	47.58
MBIA Inc	-0.31	54.44	-33.81	-8.93	-4.11	46.55	1.57	28.53
Metlife Inc	9.86	41.87	-26.77	-7.38	-3.31	28.00	0.59	21.78
Morgan Stanley Group Inc	11.32	45.21	-25.89	-7.80	-3.71	86.98	3.94	120.19
Peoples United Financial Inc	15.20	35.55	-19.05	-6.06	-3.10	26.67	0.80	13.53
Principal Financial Group Inc	10.08	46.59	-29.59	-8.12	-3.40	40.76	0.90	30.11
Prudential Financial Inc	11.35	45.03	-24.72	-8.63	-3.20	38.25	1.19	30.85
S V B Financial Group	18.11	48.66	-42.27	-8.12	-4.20	26.77	-0.39	14.85
S&P 500	7.49	17.60	-9.04	-3.03	-1.69	11.58	-0.07	9.09
UMB Financial Corp	9.79	29.85	-24.65	-4.82	-2.65	17.80	0.10	12.04
Unum Group	7.53	39.81	-39.17	-6.58	-3.08	22.15	-1.40	36.89
Valley National Bancorp	8.86	31.48	-16.04	-5.46	-2.91	24.25	0.68	11.46
Wells Fargo & Co New	14.71	35.38	-23.82	-5.54	-2.94	32.76	1.66	31.05
Zions Bancorporation	11.98	41.07	-24.54	-7.24	-3.38	27.56	0.62	19.15

Table 4: *Summary statistics for simple returns*

Institution	Annualized mean	Annualized std. dev.	Min	1% quantile	5% quantile	Max	Skewness	Kurtosis
American Financial Group Inc New	9.26	29.41	-25.76	-4.93	-2.53	37.41	0.83	38.99
American International Group Inc	-2.58	51.88	-93.63	-8.17	-3.23	50.68	-3.68	149.42
American National Ins Co	8.28	30.32	-24.64	-5.91	-2.64	25.06	-0.38	17.43
Associated Banc Corp	8.38	32.59	-19.00	-5.53	-3.04	19.35	-0.14	10.56
BGC Partners Inc	0.45	59.96	-33.16	-11.49	-5.44	39.59	0.42	11.61
BOK Financial Corp	8.07	50.76	-102.96	-8.65	-4.06	47.00	-5.69	194.88
Bank Of America Corp	6.21	42.33	-34.21	-7.28	-3.41	30.21	-0.34	27.07
Capital One Financial Corp	13.62	48.05	-50.69	-8.13	-4.08	23.45	-1.12	23.44
Citigroup Inc	5.93	45.27	-49.47	-7.28	-3.68	45.63	-0.46	39.77
Cullen Frost Bankers Inc	15.35	31.45	-21.46	-5.42	-2.90	19.78	0.31	9.96
Fifth Third Bancorp	8.84	44.73	-57.32	-6.92	-3.19	47.23	-0.37	71.21
First Citizens Bancshares Inc Nc	10.71	31.83	-12.06	-5.08	-3.08	19.38	0.34	5.33
Fulton Financial Corp	8.79	34.02	-20.16	-5.58	-3.24	17.20	-0.24	9.99
Genworth Financial Inc	-13.01	78.56	-78.55	-15.03	-5.56	63.60	-0.34	55.89
Goldman Sachs Group Inc	7.92	37.75	-21.02	-6.44	-3.46	23.48	0.30	11.60
Hancock Holding Co	11.69	34.38	-19.87	-5.63	-3.32	18.23	-0.16	7.30
Hartford Financial Svcs Grp Inc	5.81	53.16	-72.49	-8.77	-3.55	70.49	-0.46	97.73
Huntington Bancshares Inc	6.54	46.12	-36.51	-7.72	-3.38	40.60	0.39	37.19
J.P. Morgan Chase & Co	11.75	38.10	-23.23	-6.25	-3.48	22.39	0.24	11.29
Lincoln National Corp	8.63	45.50	-50.89	-7.91	-3.31	36.23	-1.29	55.80
MBIA Inc	-0.31	54.44	-41.26	-9.36	-4.20	38.22	0.21	24.17
Metlife Inc	9.41	41.87	-31.16	-7.67	-3.37	24.69	-0.34	21.96
Morgan Stanley Group Inc	10.73	45.21	-29.97	-8.12	-3.78	62.59	1.15	46.22
Peoples United Financial Inc	14.15	35.55	-21.13	-6.25	-3.15	23.64	0.32	11.76
Principal Financial Group Inc	9.60	46.59	-35.09	-8.47	-3.46	34.19	-0.43	28.71
Prudential Financial Inc	10.75	45.03	-28.39	-9.02	-3.26	32.39	-0.05	26.05
S V B Financial Group	16.65	48.66	-54.93	-8.47	-4.29	23.72	-1.38	26.73
S&P 500	7.23	17.60	-9.47	-3.08	-1.70	10.96	-0.25	8.98
UMB Financial Corp	9.34	29.85	-28.30	-4.94	-2.68	16.38	-0.33	14.74
Unum Group	7.26	39.81	-49.71	-6.81	-3.13	20.01	-3.14	62.55
Valley National Bancorp	8.49	31.48	-17.48	-5.62	-2.95	21.71	0.32	10.04
Wells Fargo & Co New	13.73	35.38	-27.21	-5.70	-2.99	28.34	0.74	25.08
Zions Bancorporation	11.31	41.07	-28.16	-7.52	-3.43	24.34	-0.16	18.22

Table 5: *Summary statistics for log returns*

Institution	Mean	Std. dev.	Min	1% quantile	5% quantile	50% quantile	Max
American Financial Group Inc New	162.19	96.67	69.74	76.72	85.76	137.66	1199.31
American International Group Inc	216.23	251.62	75.18	82.20	96.50	150.97	3896.77
American National Ins Co	166.63	81.47	92.35	98.07	104.20	143.05	1028.76
Associated Banc Corp	181.39	100.82	63.45	73.99	88.90	156.32	916.27
BGC Partners Inc	334.84	201.93	134.65	147.06	163.83	257.98	1396.51
BOK Financial Corp	235.22	221.38	67.64	77.03	88.85	170.51	3441.61
Bank Of America Corp	209.93	159.98	81.68	88.26	98.16	169.30	1472.31
Capital One Financial Corp	264.20	174.30	107.05	114.79	125.91	213.61	1969.25
Citigroup Inc	228.96	179.59	71.54	81.64	98.20	189.79	1963.94
Cullen Frost Bankers Inc	179.19	90.80	71.31	82.35	93.08	149.98	762.49
Fifth Third Bancorp	203.85	191.39	80.52	89.16	98.26	154.53	2286.43
First Citizens Bancshares Inc Nc	184.04	70.32	95.39	104.07	113.67	166.07	790.76
Fulton Financial Corp	187.59	104.22	71.95	80.44	91.41	164.45	956.22
Genworth Financial Inc	328.34	335.57	85.38	97.07	109.13	226.17	3457.00
Goldman Sachs Group Inc	207.18	109.35	93.18	102.45	114.35	169.46	872.51
Hancock Holding Co	200.39	67.08	126.59	132.27	139.98	181.54	779.51
Hartford Financial Svcs Grp Inc	229.34	242.63	76.69	90.66	102.22	167.09	2722.51
Huntington Bancshares Inc	211.42	190.63	83.18	91.69	102.69	158.78	2005.86
J.P. Morgan Chase & Co	207.33	121.03	83.20	90.61	98.30	174.65	1006.37
Lincoln National Corp	213.67	188.33	87.16	97.63	107.95	163.60	2298.60
MBIA Inc	268.68	212.85	85.75	98.61	110.81	198.46	1552.85
Metlife Inc	208.26	155.67	91.84	100.51	108.69	162.74	1580.06
Morgan Stanley Group Inc	236.53	147.74	113.56	120.28	128.73	194.60	1995.18
Peoples United Financial Inc	195.07	111.73	72.89	86.25	98.02	156.73	975.00
Principal Financial Group Inc	214.52	196.96	76.59	83.56	96.27	154.11	1652.55
Prudential Financial Inc	206.99	178.66	90.57	96.20	106.12	153.55	1381.51
S V B Financial Group	275.50	155.90	102.23	116.61	132.11	226.90	1631.88
S&P 500	97.20	52.57	44.14	47.36	51.78	82.17	553.81
UMB Financial Corp	166.30	74.79	89.94	98.89	106.22	145.29	988.93
Unum Group	225.34	173.50	100.18	110.44	118.57	173.76	2229.45
Valley National Bancorp	171.39	95.40	72.26	80.94	89.79	140.52	803.36
Wells Fargo & Co New	180.58	127.92	62.46	71.06	82.11	152.14	1186.81
Zions Bancorporation	213.24	146.74	80.65	94.88	107.39	171.22	1158.71

Table 6: *Summary statistics for conditional volatility*

	Mean	Std. dev.	Min	1% quantile	5% quantile	50% quantil	Max
American Financial Group Inc New	-6.59	3.56	-40.08	-22.15	-12.23	-5.68	-2.90
American International Group Inc	-14.09	10.38	-94.85	-63.47	-31.84	-10.87	-5.57
American National Ins Co	-7.00	3.13	-36.45	-20.39	-12.43	-6.08	-3.96
Associated Banc Corp	-8.11	4.13	-35.22	-25.19	-15.59	-7.11	-2.93
BGC Partners Inc	-24.43	11.38	-70.68	-60.74	-50.57	-20.28	-11.16
BOK Financial Corp	-15.09	10.06	-92.18	-53.91	-32.90	-11.84	-4.86
Bank Of America Corp	-11.76	7.26	-59.73	-48.96	-23.74	-9.91	-4.90
Capital One Financial Corp	-16.26	8.57	-74.73	-52.05	-31.86	-13.82	-7.16
Citigroup Inc	-13.51	8.11	-72.70	-54.15	-26.08	-11.77	-4.60
Cullen Frost Bankers Inc	-7.69	3.67	-29.26	-21.21	-15.23	-6.54	-3.13
Fifth Third Bancorp	-11.86	8.22	-77.47	-55.47	-22.76	-9.55	-5.08
First Citizens Bancshares Inc Nc	-8.07	2.88	-30.59	-18.25	-13.80	-7.35	-4.27
Fulton Financial Corp	-8.72	4.40	-37.69	-27.27	-16.81	-7.79	-3.46
Genworth Financial Inc	-28.19	16.41	-98.17	-91.11	-64.22	-23.05	-9.45
Goldman Sachs Group Inc	-10.59	5.00	-38.10	-31.98	-19.26	-8.87	-4.97
Hancock Holding Co	-9.43	2.89	-32.20	-21.37	-14.51	-8.62	-6.08
Hartford Financial Svcs Grp Inc	-15.19	10.63	-87.93	-68.19	-30.32	-12.15	-5.76
Huntington Bancshares Inc	-12.66	8.52	-74.08	-56.26	-25.61	-10.12	-5.42
J.P. Morgan Chase & Co	-10.61	5.51	-42.69	-34.10	-20.47	-9.17	-4.46
Lincoln National Corp	-12.63	8.20	-78.22	-56.25	-23.71	-10.25	-5.59
MBIA Inc	-18.28	11.28	-71.04	-60.02	-46.18	-14.65	-6.61
Metlife Inc	-11.54	7.01	-61.83	-46.87	-22.20	-9.41	-5.41
Morgan Stanley Group Inc	-14.03	6.95	-73.10	-42.78	-26.53	-11.99	-7.16
Peoples United Financial Inc	-9.37	4.90	-39.46	-26.92	-19.72	-7.71	-3.63
Principal Financial Group Inc	-12.86	9.27	-67.42	-55.65	-27.54	-9.90	-5.03
Prudential Financial Inc	-12.13	8.30	-59.56	-52.92	-23.95	-9.54	-5.72
S V B Financial Group	-17.18	8.05	-68.41	-45.91	-33.40	-14.76	-6.91
S&P 500	-2.41	1.28	-13.15	-7.50	-4.68	-2.05	-1.09
UMB Financial Corp	-6.88	2.85	-34.85	-19.08	-12.07	-6.07	-3.79
Unum Group	-11.85	7.22	-72.58	-45.05	-24.13	-9.57	-5.62
Valley National Bancorp	-7.43	3.84	-30.76	-22.61	-15.41	-6.20	-3.22
Wells Fargo & Co New	-8.62	5.32	-45.58	-35.88	-15.93	-7.46	-3.10
Zions Bancorporation	-11.61	6.74	-49.93	-43.44	-23.29	-9.68	-4.66

Table 7: *Summary statistics for 1% VaR*

Institution	1% sens.	5% sens.	10% sens.	50% sens.	90% sens.	95% sens.	99% sens.
American Financial Group Inc New	0.55	0.47	0.44	0.27	0.09	0.07	0.04
American International Group Inc	0.25	0.20	0.18	0.11	0.03	0.02	0.01
American National Ins Co	0.54	0.44	0.43	0.24	0.09	0.07	0.03
Associated Banc Corp	0.44	0.37	0.32	0.19	0.08	0.07	0.04
BGC Partners Inc	0.21	0.21	0.18	0.06	0.03	0.02	0.01
BOK Financial Corp	0.29	0.25	0.18	-0.00	-0.00	-0.00	0.00
Bank Of America Corp	0.31	0.23	0.22	0.12	0.08	0.07	0.06
Capital One Financial Corp	0.27	0.25	0.21	0.10	0.07	0.05	0.05
Citigroup Inc	0.24	0.22	0.21	0.11	0.07	0.06	0.04
Cullen Frost Bankers Inc	0.55	0.48	0.40	0.17	0.04	0.04	0.03
Fifth Third Bancorp	0.30	0.23	0.22	0.12	0.06	0.06	0.04
First Citizens Bancshares Inc Nc	0.79	0.55	0.40	0.17	0.05	0.04	0.02
Fulton Financial Corp	0.32	0.30	0.29	0.13	0.05	0.04	0.02
Genworth Financial Inc	0.12	0.11	0.11	0.05	0.01	0.00	0.00
Goldman Sachs Group Inc	0.47	0.37	0.33	0.22	0.15	0.12	0.09
Hancock Holding Co	0.55	0.48	0.43	0.23	0.06	0.04	0.03
Hartford Financial Svcs Grp Inc	0.27	0.18	0.16	0.11	0.06	0.06	0.04
Huntington Bancshares Inc	0.25	0.22	0.21	0.10	0.06	0.04	0.03
J.P. Morgan Chase & Co	0.37	0.32	0.27	0.17	0.09	0.08	0.04
Lincoln National Corp	0.23	0.23	0.19	0.13	0.07	0.06	0.04
MBIA Inc	0.18	0.16	0.15	0.05	0.02	0.02	0.00
Metlife Inc	0.36	0.31	0.28	0.19	0.11	0.10	0.04
Morgan Stanley Group Inc	0.26	0.21	0.20	0.15	0.11	0.11	0.08
Peoples United Financial Inc	0.50	0.42	0.34	0.03	0.01	0.01	0.01
Principal Financial Group Inc	0.29	0.24	0.21	0.14	0.08	0.07	0.06
Prudential Financial Inc	0.27	0.24	0.23	0.17	0.09	0.08	0.08
S V B Financial Group	0.29	0.22	0.18	0.07	0.03	0.02	0.01
S&P 500	1.00	1.00	1.00	1.00	1.00	1.00	1.00
UMB Financial Corp	0.56	0.50	0.49	0.32	0.07	0.04	0.03
Unum Group	0.42	0.30	0.26	0.14	0.04	0.03	0.03
Valley National Bancorp	0.44	0.41	0.36	0.16	0.03	0.03	0.03
Wells Fargo & Co New	0.44	0.36	0.32	0.15	0.10	0.09	0.08
Zions Bancorporation	0.27	0.25	0.23	0.12	0.06	0.05	0.03

Table 8: *β-coefficients*

Institution	SRISK in $ bn	Marketcap in $ bn	1% VaR quantile in %	50% VaR quantile in %	VaR Diff in %	1% sensitivity	SSVaR in %	VaR Diff in $ bn	SSVaR in $ bn
American Financial Group Inc New	-1.85	9.56	-22.15	-5.68	-16.47	0.55	-9.04	-1.57	-0.86
American International Group Inc	-3.42	53.56	-63.47	-10.87	-52.60	0.25	-13.41	-28.17	-7.18
American National Ins Co	-0.18	3.45	-20.39	-6.08	-14.30	0.54	-7.77	-0.49	-0.27
Associated Banc Corp	-0.63	3.84	-25.19	-7.11	-18.08	0.44	-8.03	-0.69	-0.31
BGC Partners Inc	-0.24	3.84	-60.74	-20.28	-40.46	0.21	-8.69	-1.55	-0.33
BOK Financial Corp	-0.11	6.04	-53.91	-11.84	-42.07	0.29	-12.32	-2.54	-0.74
Bank Of America Corp	-16.70	307.91	-48.96	-9.91	-39.05	0.31	-12.02	-120.23	-37.02
Capital One Financial Corp	-18.46	48.27	-52.05	-13.82	-38.24	0.27	-10.23	-18.46	-4.94
Citigroup Inc	-44.05	196.74	-54.15	-11.77	-42.38	0.24	-10.24	-83.37	-20.14
Cullen Frost Bankers Inc	-0.04	5.98	-21.21	-6.54	-14.68	0.55	-8.08	-0.88	-0.48
Fifth Third Bancorp	-0.38	21.41	-55.47	-9.55	-45.92	0.30	-13.72	-9.83	-2.94
First Citizens Bancshares Inc Nc	-0.60	4.44	-18.25	-7.35	-10.90	0.79	-8.66	-0.48	-0.38
Fulton Financial Corp	-0.35	3.13	-27.27	-7.79	-19.48	0.32	-6.21	-0.61	-0.19
Genworth Financial Inc	-6.44	1.55	-91.11	-23.05	-68.06	0.12	-8.29	-1.06	-0.13
Goldman Sachs Group Inc	-17.77	96.10	-31.98	-8.87	-23.11	0.47	-10.93	-22.20	-10.50
Hancock Holding Co	-0.38	4.22	-21.37	-8.62	-12.75	0.55	-6.97	-0.54	-0.29
Hartford Financial Svcs Grp Inc	-0.39	20.08	-68.19	-12.15	-56.04	0.27	-15.32	-11.25	-3.07
Huntington Bancshares Inc	-0.81	15.74	-56.26	-10.12	-46.14	0.25	-11.36	-7.26	-1.79
J.P. Morgan Chase & Co	-17.55	371.05	-34.10	-9.17	-24.93	0.37	-9.16	-92.49	-34.00
Lincoln National Corp	-7.69	16.82	-56.25	-10.25	-46.00	0.23	-10.72	-7.74	-1.80
MBIA Inc	-0.45	0.67	-60.02	-14.65	-45.37	0.18	-8.29	-0.30	-0.06
Metlife Inc	-20.17	53.20	-46.87	-9.41	-37.45	0.36	-13.64	-19.93	-7.26
Morgan Stanley Group Inc	-20.33	94.86	-42.78	-11.99	-30.80	0.26	-8.11	-29.21	-7.70
Peoples United Financial Inc	-0.23	6.47	-26.92	-7.71	-19.21	0.50	-9.61	-1.24	-0.62
Principal Financial Group Inc	-0.79	20.37	-55.65	-9.90	-45.75	0.29	-13.09	-9.32	-2.67
Prudential Financial Inc	-21.51	48.75	-52.92	-9.54	-43.38	0.27	-11.67	-21.15	-5.69
S V B Financial Group	-0.42	12.33	-45.91	-14.76	-31.16	0.29	-9.00	-3.84	-1.11
S&P 500		23814.81	-7.50	-2.05	-5.45	1.00	-5.45	-1298.65	-1298.65
UMB Financial Corp	-0.00	3.59	-19.08	-6.07	-13.01	0.56	-7.32	-0.47	-0.26
Unum Group	-2.72	12.32	-45.05	-9.57	-35.48	0.42	-15.08	-4.37	-1.86
Valley National Bancorp	-0.33	2.97	-22.61	-6.20	-16.41	0.44	-7.14	-0.49	-0.21
Wells Fargo & Co New	-5.06	298.75	-35.88	-7.46	-28.42	0.44	-12.52	-84.91	-37.40
Zions Bancorporation	-0.49	10.15	-43.44	-9.68	-33.76	0.27	-9.28	-3.43	-0.94

Table 9: *Result table*

Institution	SRISK	Daily	Weekly	Monthly	e-GARCH	Student-t	2000-	2004-	2010-	2015-
S&P 500		-1298.69	-4378.40	-7712.45	-1066.86	-1589.83	-1931.85	-1977.03	-835.82	-638.31
Wells Fargo & Co New	-5.06	-37.40	-107.71	-63.37	-28.26	-45.21	-42.39	-43.16	-12.00	-7.46
Bank Of America Corp	-16.70	-37.02	-79.17	-47.27	-24.48	-43.33	-41.78	-33.27	-17.13	-11.50
Jpmorgan Chase & Co	-17.55	-34.00	-124.57	-116.07	-25.16	-40.66	-43.90	-45.77	-18.08	-11.24
Citigroup Inc	-44.05	-20.15	-66.19	-47.27	-14.53	-24.19	-24.82	-24.09	-10.70	-7.75
Goldman Sachs Group Inc	-17.77	-10.50	-35.02	-22.20	-8.75	-12.59	-12.11	-12.05	-6.68	-3.41
Morgan Stanley Group Inc	-20.33	-7.70	-24.43	-22.59	-5.39	-9.19	-11.73	-10.28	-6.00	-4.15
Metlife Inc	-20.17	-7.26	-22.56	-9.09	-5.76	-8.52	-8.33	-7.03	-3.17	-2.39
American International Group Inc	-3.42	-7.18	-15.81	-6.02	-5.35	-8.73	-7.18	-6.30	-3.02	0.25
Prudential Financial Inc	-21.51	-5.69	-14.21	-7.24	-5.27	-6.70	-6.73	-5.81	-2.09	-1.45
Capital One Financial Corp	-18.46	-4.94	-11.94	-6.94	-3.61	-5.74	-5.73	-6.06	-2.03	-2.92
Hartford Financial Svcs Grp Inc	-0.39	-3.07	-4.80	-2.98	-2.38	-3.67	-2.95	-2.34	-1.11	-0.46
Fifth Third Bancorp	-0.38	-2.94	-6.75	-2.83	-1.89	-3.53	-3.10	-2.86	-0.80	-0.64
Principal Financial Group Inc	-0.79	-2.67	-5.68	-4.07	-2.28	-3.11	-3.22	-2.50	-0.96	-0.80
Unum Group	-2.72	-1.86	-3.49	-2.71	-1.22	-2.23	-2.05	-1.87	-0.59	-0.60
Lincoln National Corp	-7.69	-1.80	-5.26	-3.02	-1.83	-2.18	-2.53	-2.11	-0.98	-0.88
Huntington Bancshares Inc	-0.81	-1.79	-4.49	-2.55	-1.24	-2.14	-2.03	-2.13	-0.70	-0.65
S V B Financial Group	-0.42	-1.11	-2.60	-1.76	-0.81	-1.32	-1.34	-1.13	-0.53	-0.49
Zions Bancorporation	-0.49	-0.94	-2.87	-2.29	-0.76	-1.11	-0.94	-1.06	-0.52	-0.34
American Financial Group Inc New	-1.85	-0.86	-2.32	-1.81	-0.63	-1.05	-1.18	-1.19	-0.49	-0.38
B O K Financial Corp	-0.11	-0.74	-1.62	-1.20	-0.45	-0.83	-0.48	-0.49	-0.27	-0.28
Peoples United Financial Inc	-0.23	-0.62	-1.83	-2.45	-0.47	-0.74	-0.69	-0.81	-0.28	-0.24
Cullen Frost Bankers Inc	-0.04	-0.48	-2.14	-0.92	-0.38	-0.58	-0.59	-0.53	-0.30	-0.19
First Citizens Bancshares Inc Nc	-0.60	-0.38	-1.59	-0.98	-0.27	-0.46	-0.60	-0.61	-0.22	-0.18
B G C Partners Inc	-0.24	-0.33	-0.71	-0.20	-0.27	-0.39	-0.39	-0.37	-0.16	-0.09
Associated Banc Corp	-0.63	-0.31	-1.15	-0.76	-0.24	-0.37	-0.37	-0.33	-0.16	-0.14
Hancock Holding Co	-0.38	-0.29	-1.32	-1.05	-0.20	-0.36	-0.37	-0.40	-0.22	-0.11
American National Ins Co	-0.18	-0.27	-0.78	-0.81	-0.18	-0.32	-0.43	-0.48	-0.21	-0.08
U M B Financial Corp	-0.00	-0.26	-0.82	-0.59	-0.19	-0.32	-0.36	-0.38	-0.19	-0.05
Valley National Bancorp	-0.33	-0.21	-0.76	-0.57	-0.17	-0.26	-0.29	-0.31	-0.17	0.01
Fulton Financial Corp Pa	-0.35	-0.19	-0.70	-0.80	-0.16	-0.24	-0.26	-0.31	-0.19	
Genworth Financial Inc	-6.44	-0.13	-0.18	-0.03	-0.09	-0.15	-0.14	-0.14	-0.08	
M B I A Inc	-0.45	-0.06	-0.11	-0.04	-0.04	-0.06	-0.05	-0.06	-0.03	-0.04
Total Systemic Risk excluding S&P 500	-210.56	-193.17	-553.60	-382.48	-142.74	-230.29	-229.05	-216.21	-90.06	-58.65
Total sample size		232.848	48.213	11.088	232.848	232.848	149.424	116.292	66.429	24.915
Intercept		-3.55	-3.51	-3.96	-3.43	-3.55	-3.41	-3.56	-2.95	-2.61
Slope		0.50	0.18	0.22	0.71	0.42	0.44	0.45	1.29	2.14
t-value		3.38	3.63	3.40	3.45	3.37	3.60	3.47	4.29	4.70
p-value		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
adj. R^2		0.28	0.30	0.28	0.28	0.27	0.30	0.29	0.38	0.44
Pearson		0.53	0.55	0.53	0.53	0.52	0.55	0.54	0.62	0.66
Spearman		0.71	0.72	0.73	0.71	0.71	0.72	0.71	0.71	0.76

Table 10: *Result table robustness test*