What can systemic risk measures predict?

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September 6, 2013

Abstract

We compare three prominent systemic risk measures assessing their potential as a monitoring tool for regulators and investigate the dynamics between systemic risk in the banking system and the real economy. We find that systemic risk measures possess substantial forecasting power for a variety of financial market and macro-economic variables. Whereas balance sheet characteristics determine an individual bank's systemic importance, they cannot explain systemic risk at the banking system level. Measures relating to the *Marginal Expected Shortfall* possess superior predictive power and are thus adequate for regulatory purposes.

JEL classification: C15, C32, G01, G21, G28

Keywords: systemic risk, macro-financial linkages, regulation, banking system, MES, CoVaR, DCC GARCH

1. Introduction

How should we measure systemic risk? In the aftermath of the Lehman bankruptcy that triggered an unprecedented international financial crisis, this question has become of vital interest to both regulators and researchers. According to the definition of the International Monetary Fund, systemic risk is the risk of excessive losses within all or parts of the financial

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system with potential negative spill-over effects to the real economy (FSB, IMF, BIS, 2009).

Recent research (e.g. Reinhart and Rogoff, 2009) has shown that systemic financial crises often have substantial adverse effects on the real economy, such as drops in asset prices, output, and employment levels. Thus, the interconnectedness within the financial system and the important role that financial institutions play for the real economy stress the necessity of correctly identifying systemic risk in the financial system.

Over the last years, a number of approaches to measure systemic risk and to identify systemically important financial institutions (SIFIs) have been proposed both by regulators and researchers. The Bank for International Settlements (2011b) identifies SIFIs by various balance and off-balance sheet characteristics, such as size, interconnectedness, and substitutability.[4] The revised Basel III rules stipulate tighter macro-prudential regulation and tackle SIFIs by imposing special requirements such as capital surcharges.

Academia has proposed a whole bunch of different approaches with a strand of literature based on asset prices applying standard risk measures (Adrian and Brunnermeier, 2011; Acharya et al., 2010), extreme value theory (De Jonghe, 2010; Zhou, 2010), principal component analysis (Billio et al., 2010; Kritzman et al., 2011), and default probabilities (Lehar, 2005; Huang et al., 2009; Segoviano and Goodhart, 2009; Huang et al., 2011; Gray and Jobst, 2010). Another strand of literature applies network analysis to analyze systemic risk arising from interbank relationships (Halaj and Kok Sorensen, 2013; Allen et al., 2010; Tarashev et al., 2010, e.g.). For a comprehensive survey on the literature on systemic risk measurement we refer to Bisias et al. (2012).

Despite the multitude of approaches, research on the measures' ability to capture the symptoms of systemic risk in the banking system is rare. However, the assessment of a measure's adequacy as a tool for regulation is crucial. But how can the effectiveness of systemic

[4] This is in line with various studies finding that balance sheet characteristics such as size (Elsinger et al., 2006), leverage (Acharya et al., 2010), and short-term wholesale funding (López-Espinosa et al., 2012) substantially drive the systemic importance of individual banks.

risk measures be determined? Systemic risk measures should be able to pre-identify turmoil in the financial markets that potentially triggers downturns in the real economy. In addition, systemic risk measures should be leading indicators to other financial market-based stress variables in order to function properly as early warning indicators. While it is difficult to assess systemic risk measures at the bank level (because an individual institution's ranking with respect to its systemic importance is predominantly determined by the applied measure), an evaluation of systemic risk measures at the banking system level is more expedient.

This paper contributes to the literature on the assessment of systemic risk measures in several ways. We compare three prominent systemic risk measures such as to assess their adequacy as a monitoring tool for regulatory authorities. We investigate the dynamics and directionalities between the systemic risk measures at the banking system level and the macro-economy. Furthermore, we examine linkages between the systemic risk measures and balance sheet characteristics at both the bank and banking system level.

In particular, we implement and compare the Marginal Expected Shortfall (MES) (Acharya et al., 2010), the SRISK (Brownlees and Engle, 2012), and the Conditional Value at Risk (CoVaR) (Adrian and Brunnermeier, 2011) using a common setup that is in line with Girardi and Ergün (2013) and Brownlees and Engle (2012), i.e., we model the stock return characteristics using a DCC GARCH specification and apply the latter to simulate the systemic risk measures.[5] Over the last years, these measures have had a high impact on academia and regulatory authorities.[6] All three measures rely on publicly available stock price information and balance sheet data and thus can be implemented for all publicly listed banks.

We find that systemic risk measures possess substantial forecasting power for a variety

[5] Note that our assessment framework is independent of the measures and measurement method and does not rely on any technical specifications. We implement the risk measures in a common setup to improve comparability and interpretability (see Section (3)).

[6] The measures are applied by the U.S. Treasury Department (Financial Stability Oversight Council, 2013) to monitor systemic risk in the banking system. Similarly, the European Systemic Risk Board uses CoVaR, among other indicators, to measure systemic risk in the European banking system (European Systemic Risk Board, 2013).

of financial and macro-economic variables including interbank interest rates, real GDP, and economic sentiment. The systemic risk measures are not equally adequate for the regulators' purpose of monitoring systemic risk in the banking system. In general, the MES's and SRISK's performance is superior to the CoVaR. Moreover, we find that an individual bank's systemic importance is well explained by its balance sheet characteristics. However, at the banking system level, aggregate balance sheet characteristics cannot explain systemic risk.

We apply the measures to European banks between July 2005 and June 2013. The European banking system provides a unique setting for the evaluation of systemic risk measures, as European institutions are likely to be affected by both the Subprime Crisis including the subsequent International Financial Crisis of 2007–2009 and the current Euro Crisis. Thus, our sample of European banks allows for a broad analysis and ensures that systemic risk measures are not only evaluated by their performance during the Subprime Crisis.

In a first step, we analyze the measures at the bank level discussing the systemic importance ranking of institutions obtained for the Subprime Crisis and the Euro Crisis periods. We examine to what extent the bank level measures are driven by their balance sheet characteristics. In a second step, we perform a vector autoregression (VAR) analysis to study the measures' ability to act as leading indicators of systemic risk. The VAR analysis furthermore enables us to measure directionalities and causalities between the measures and a set of aggregate financial market, balance sheet and macro-economic variables.[7]

Our paper contributes to a growing body of literature on the MES, SRISK and CoVaR measures. The first body of literature implements MES, SRISK (Acharya and Steffen, 2012; Idier et al., 2013; Engle et al., 2012; Acharya et al., 2012), and CoVaR (López-Espinosa et al., 2012; Van Oordt and Zhou, 2011; Roengpitya and Rungcharoenkitkul, 2011; Gauthier et al., 2010) to analyze financial market conditions and identify determinants of systemic

[7] In contrast to Rodriguez-Moreno and Peña (2013) who assess the performance of systemic risk measures at the banking system level applying an index of systemic events, our analysis does not necessitate the identification of specific systemic events that might be prone to selection biases.

importance. A second body of literature extends those measures. Girardi and Ergün (2013) propose the use of multivariate GARCH estimates to measure CoVaR, Cao (2013) extends the CoVaR measure from one bank being in financial distress to a set of one or more banks being in distress, and Hong (2011) derives an analytical version of the CoVaR measure. A third body of literature compares the measures. Jiang (2012) analyzes the tail dependence structure of MES and CoVaR, Benoit et al. (2013) rank US financial institutions according to MES, SRISK, and CoVaR and find that the risk measures can be proxied by market risk and liabilities, and Löffler and Raupach (2013) estimate the robustness of MES and CoVaR.

The remainder of the paper is structured as follows: Section 2 describes the data used for our analysis and Section 3 introduces and defines the systemic risk measures. In Section 4 we provide an outline of the methodology, in Section 5 we present and discuss our results. Section 6 summarizes and concludes.

2. Data Description

Our empirical analysis focuses on the European banking system. We concentrate on the European Union excluding countries from Eastern Europe to ensure sufficiently homogeneous banking regulation across our sample. However, we include Switzerland given the country's individual banking sector's importance within the European banking system and its similarity in banking regulation.[8] Our sample covers the period from July 2005 to June 2013 including the International Financial Crisis from 2007 to 2009 and the subsequent European Sovereign Debt Crisis.

Our selection of banks is based on two major criteria: First, we select all banks included in the STOXX Europe TMI Banks Index at one point in time within our sample period.[9] Ac-

[8] Our sample selection is in line with Trapp and Wewel (2013); all member states of the European Union and Switzerland implemented the Basel II Directives 2006/48/EC and 2006/49/EC and are introducing the new Basel III criteria.

[9] According to STOXX Limited (2013), the individual banks are admitted into the index based on their free float market capitalization and cover roughly 95% of the free float market capitalization of all banks headquartered in Western Europe. The index composition is updated on a quarterly basis. This leaves us

cording to the European Commission's proposal for a Single Supervisory Mechanism (SSM) for the European Banking Union, banks with total assets above €30bn are supervised directly by the ECB due to their potential systemic relevance (European Commission, 2013). Thus, we rank the institutions with respect to their size in total assets and select those where total assets are above €30bn in at least one of the quarters within the sample period.

To our preselection of banks, we furthermore add the ING Groep N.V., the Bank of Cyprus as well as the Landesbank Berlin Holding AG. STOXX classifies the ING Groep as an insurance company. However, a substantial part of the ING Groep's revenues come from banking related activities. We manually add the Bank of Cyprus in order to better represent the Cyprian banking sector, which is not accounted for by the STOXX Europe TMI Banks Index. We include the Landesbank Berlin Holding AG in order to better capture the German banking sector's substantial role for Europe.

We furthermore exclude penny stocks from our sample. We neglect banks if the price of their stock stays below a threshold of €1 for 20 consecutive trading days. Hence, our sample only contains banks with sound stock price information. To avoid survivorship bias, a preselected bank remains in our sample even if it is excluded from the TMI Index coverage. Thus, over time the number of sample banks diminishes as a results of bankruptcies. The resulting sample contains 87 banks from 16 countries, including Austria, Belgium, Cyprus, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, Spain, Sweden, Switzerland, and the United Kingdom, with a minimum of 53 banks across the entire sample period.

[INSERT TABLES 1 AND 2 ABOUT HERE]

Table 1 displays the names and balance sheet characteristics of the banks in our sample and Table 2 provides a summary of the latter. The institutions' mean total assets over the

with 126 banks. By selecting all banks that are included in the index within the sample period, we ensure that our sample selection adequately reflects the aggregate of traded stocks of banks in Western Europe.

sample period range from €9.8bn (Bank Sarasin & Cie AG) to €1,743bn (BNP Paribas S.A.). The median-sized bank has around €110bn in total assets. The banks' mean market-to-book ratio over the sample period ranges from -0.44 (Bankia S.A.)[10] to 14.39 (Agricultural Bank of Greece S.A.) with a sample median of 1.26 (see Table 2). Our sample banks are leveraged between 3.21 (GAM Holding AG) and 192.58 (Intesa Sanpaolo S.p.A.) with a median leverage of 17.59 (see Table 2) across the sample period.

We obtain daily stock prices and quarterly balance sheet data for our predefined selection of banks from Datastream. The balance sheet data employed in our calculation of risk measures and our later analyses includes total assets, shareholders' equity (book equity), the market values of equity, total net income, as well as the market-to-book ratio of equity. We calculate the total book values of debt as the difference between total assets and shareholders' equity. Furthermore, we define leverage as the ratio of market valued total assets to market valued equity and calculate market valued total assets as the sum of total debt and market valued equity.

For our later analyses, we employ European financial market data as well as macro-economic data from the European Union. To measure the state of the European financial market, we obtain weekly series of the 12 month EURIBOR, the 12 month Euro OIS (overnight indexed swap) rate, and the VSTOXX Index from Datastream.[11]

We measure the state of the European economy employing the following macro-economic variables: the monthly EU Industrial Production Index (excluding Construction) and the monthly EU Economic Sentiment Indicator; the EU House Price Index and real GDP on a quarterly basis; domestic credit to private sector (expressed in percentage of real GDP), nonperforming loans to total gross loans, and government debt to real GDP on an annual

[10] After its IPO in July 2011, Bankia S.A. requested a bailout of €19bn in Mai 2012 and was partially nationalized by the Spanish government. As a consequence, the bank reported on average a negative balance for its book value of equity over the sample period.

[11] The VSTOXX Index measures the volatility of the EURO STOXX 50. The calculation is based on EURO STOXX 50 options prices and thus the index reflects market implied volatility.

basis. The data on government debt are obtained from the European Central Bank, data on domestic credit to the private sector and nonperforming loans are obtained from the Worldbank's database, and all remaining data are from Datastream. All macro-economic variables refer to the EU27.

3. Systemic Risk Measures

In this section, we define the systemic risk measures implemented in this paper: (Multi)MES, SRISK, and (Multi)CoVaR.

3.1. Multi-Period MES

The marginal expected shortfall (MES) proposed by Acharya et al. (2010) measures the average one-period return (loss) of bank i's stock given that the banking system's overall return is in its tail:

$$\mathrm{MES}_t^i = -\mathbb{E}\left[r_{i,t+1} \left| r_{sys,t+1} \leq \mathrm{VaR}_{t,q}\left(r_{sys,t+1}\right)\right.\right]. \tag{1}$$

$r_{i,t+1}$ and $r_{sys,t+1}$ represent the one-period returns of bank i's stock and the banking system and $\mathrm{VaR}_{t,q}$ denotes the value at risk (VaR) of the banking system return $r_{sys,t+1}$ at confidence level q.[12] More intuitively, the MES can be interpreted as the average return of bank i's stock on the q% days in a year where the banking system's return is worst.

Acharya et al. (2012) and Brownlees and Engle (2012) introduce a multi-period extension of the one-period MES, which we henceforth refer to as *Multi-period Marginal Expected Shortfall* (MultiMES). It is defined as bank i's expected cumulative h-period stock return – i.e., over time interval $[t, t+h]$ – conditional on the banking system's cumulative h-period

[12] We are using lagged time indices (e.g. MES_t^i instead of MES_{t+1}^i) for our risk measures throughout the paper. By doing so, we indicate that the risk measures are forward looking and based on information available in t, i.e., on the information set $\mathcal{I}_t$.

return falling below a pre-defined threshold C, indicating distress in the banking system:

$$\text{MultiMES}_t^{i,h}(C) = -\mathbb{E}\left[R_{i;[t,t+h]} \,\middle|\, R_{sys;[t,t+h]} \leq C\right] \tag{2}$$

with $R_{i;[t,t+h]}$ denoting bank i's cumulative stock return over h periods:

$$R_{i;[t,t+h]} = \exp\left(\sum_{\tau=1}^{h} r_{i,t+\tau}\right) - 1. \tag{3}$$

The h-period banking system return, $R_{sys;[t,t+h]}$, is defined analogously. Note that for the ease of interpretation we switch the sign of the risk measure. Thus, an increase in the measure indicates an increase in systemic risk.

3.2. SRISK

Based on the MES, Acharya et al. (2012) and Brownlees and Engle (2012) directly model a bank's expected (time-varying) undercapitalization in a financial crisis. The proposed systemic risk measure, SRISK, therefore incorporates financial market as well as balance sheet data. A bank's capital shortfall or its undercapitalization, respectively, is defined as the amount of capital that a bank would have to raise during a financial crisis in order to prevent bankruptcy. Hence, a bank's capital shortfall is calculated as follows:

$$\text{SRISK}_t^{i,h}(C,k) = \mathbb{E}\left[\text{capital shortfall}_{i;[t,t+h]} \,\middle|\, \text{crisis}\right]. \tag{4a}$$

Bank i's SRISK in period t is defined as its expected capital shortfall over the time interval $[t, t+h]$ given the event of a financial crisis or severe distress in the banking system. For the ease of interpretation, Equation (4a) can be expressed alternatively:

$$\text{SRISK}_t^{i,h}(C,k) = \mathbb{E}\left[\{k \times (\text{debt} + \text{equity}) - \text{equity}\}_{i;[t,t+h]} \,\middle|\, \text{crisis}\right]. \tag{4b}$$

In order to prevent bankruptcy, institution i's equity cushion needs to be larger than a fraction k of the (market valued) total assets. Within the Basel III framework, parameter k can be considered to represent the absolute Tier I capital ratio of 3% (which is consistent with the Basel III maximum Leverage Ratio of 33.3 that must be satisfied even during a crisis). Thus, k can be interpreted as a Basel Capital Adequacy Ratio equivalent on total assets instead of risk weighted assets.[13] The market valued total assets can be determined using current debt balance sheet data and the market value of equity. The market value of equity within a future financial crisis can be expressed as a function of MultiMES:

$$\mathrm{SRISK}_t^{i,h}(C,k) = k \times \mathrm{debt}_{i,t} - (1-k)\left(1 - \mathrm{MultiMES}_t^{i,h}(C)\right) \times \mathrm{equity}_{i,t}. \tag{4c}$$

The higher a bank's SRISK, the higher its capital shortfall during a crisis period. Contrary, a negative SRISK indicates that a bank's equity cushion is sufficiently large in order to avoid bankruptcy.

3.3. Multi-Period CoVaR

The *Conditional Value at Risk* as proposed by Adrian and Brunnermeier (2011) allows for the calculation of an individual bank's contribution to systemic risk in the banking system measuring the value at risk return of the banking system conditional on institution i being at its own value at risk return, i.e., conditional on institution i being in financial distress. The one-period $\mathrm{CoVaR}_t^{sys|\mathcal{C}(r_{i,t+1})}(q)$ is defined as:

$$\mathbb{P}\left(r_{sys,t+1} \leq \mathrm{CoVaR}_t^{sys|\mathcal{C}(r_{i,t+1})}(q) \middle| \mathcal{C}(r_{i,t+1})\right) = q, \tag{5}$$

[13] See Bank for International Settlements (2004) and Bank for International Settlements (2011a) for a more detailed discussion of the Capital Adequacy Ratio and Leverage Ratio.

where $\mathcal{C}(r_{i,t+1})$ denotes the conditioning event concerning institution i with

$$\mathcal{C}(r_{i,t+1}) \in \begin{cases} r_{i,t+1} = \mathrm{VaR}_{t,q}(r_{i,t+1}) \\ r_{i,t+1} = \mathrm{median}_t(r_{i,t+1}) \end{cases}.$$

Hence, institution i is either at its value at risk (indicating financial distress) or at its median state. As for the MultiMES, parameter q indicates the confidence level.[14]

ΔCoVaR gives bank i's marginal contribution to overall systemic risk in the banking system. It is defined as the difference between the system's CoVaR conditional on bank i being in financial distress and the system's CoVaR conditional on bank i being in its median state. In contrast to the "top down" measures MultiMES and SRISK, the "bottom up" measure CoVaR explicitly captures the consequences of institution i's distress for the banking system.

Girardi and Ergün (2013) redefine institution i's "distress CoVaR" to institution i's return being *at* or *below* its value at risk and employ bivariate GARCH estimates for volatilities and correlations to account for a time-varying dependence structure between banks and the banking system. These changes enables the measure to better capture the tail events of distress.

In analogy to the MultiMES and SRISK measures, we define a *Multi-period Conditional Value at Risk* (that we henceforth refer to as MultiCoVaR). $\mathrm{MultiCoVaR}_t^{sys|i\leq \mathrm{VaR},h}$ is the banking system's h-period value at risk return, conditional on bank i's h-period (stock) return being lower or equal to bank i's h-period value at risk:

$$\mathbb{P}\left(R_{sys;[t,t+h]} \leq \mathrm{MultiCoVaR}_t^{sys|i\leq \mathrm{VaR},h}(q) \middle| R_{i;[t,t+h]} \leq \mathrm{VaR}_{t,q}^{i,h} \right) = q \tag{6a}$$

with $\mathrm{VaR}_{t,q}^{i,h}$ denoting bank i's h-period value at risk return. The median state CoVaR is

[14] Adrian and Brunnermeier (2011) calculate the CoVaR using quantile regressions. Moreover, they employ one week market valued total assets growth rates instead of daily stock returns.

given by conditioning on the one standard deviation band around institution i's median h-period return:

$$\mathbb{P}\left(R_{sys;[t,t+h]} \leq \mathrm{MultiCoVaR}_t^{sys|i=\mathrm{median},h}(q) \Big| \left| R_{i;[t,t+h]} - \nu_{i,t}^h \right| \leq \sigma_{i,t}^h \right) = q \tag{6b}$$

where $\sigma_{i,t}^h$ and $\nu_{i,t}^h$ indicate the standard deviation and the median return of institution i's h-period cumulative stock return. Thus, institution i's systemic risk contribution to overall systemic risk in the banking system is defined as:

$$\Delta\mathrm{MultiCoVaR}_t^{i,h}(q) = -\left[\mathrm{MultiCoVaR}_t^{sys|i\leq\mathrm{VaR},h}(q) - \mathrm{MultiCoVaR}_t^{sys|i=\mathrm{median},h}(q) \right]. \tag{6c}$$

Note that we again switch the sign of ΔMultiCoVaR in order to facilitate the comparison of the three different risk measures MultiMES, SRISK, and ΔMultiCoVaR. An increase in ΔMultiCoVaR thus indicates an increase in institution i's contribution to systemic risk in the banking system.

4. Methodology

We model the bivariate return dynamics of institution i $\{r_i\}_t$ and the banking system $\{r_{sys}\}_t$, applying a bivariate conditionally heteroscedastic process as in Brownlees and Engle (2012):

$$r_{sys,t} = \sigma_{sys,t}\epsilon_{sys,t} \tag{7a}$$

$$r_{i,t} = \sigma_{i,t}\left(\rho_{i,sys,t}\epsilon_{sys,t} + \sqrt{1-\rho_{i,sys,t}^2}\epsilon_{i,t} \right) \tag{7b}$$

where $\sigma_{j,t}$, $j \in \{sys, i\}$ denotes the time-varying (conditional) volatilities and $\rho_{j,t}$ the time-varying (conditional) correlations; $r_{j,t} = \ln(P_{j,t}/P_{j,t-1}) - \mu_j$ denotes the detrended logarithmic returns, where $P_{j,t}$ represents either bank i's stock price or the banking system stock price index at time t and μ_j simply stands for the mean return over the full length of our sample period.

The banking system stock price index reflects the stock price movements within our sample and is calculated as the average total asset weighted stock price of our sample of banks.[15] The residuals ϵ_i and ϵ_{sys} are distributed according to the bivariate distribution $\mathcal{F}_i$ capturing the tail dependence of the return series and are assumed to be uncorrelated but not independent. Over time, however, the residuals are assumed to be independent and identically distributed with *zero* mean and *unit* variance.

The time-varying volatilities of institution i's ($\sigma_{i,t}$) and the banking system return ($\sigma_{sys,t}$) are estimated individually for every institution i applying a univariate GARCH(1,1) process[16] as proposed in Bollerslev (1986):

$$\sigma^2_{j,t} = \alpha_{0,j} + \alpha_{1,j} r^2_{j,t-1} + \beta_{1,j}\sigma^2_{j,t-1} \tag{8a}$$

$$\text{with} \qquad \xi_{j,t} = \frac{r_{j,t}}{\sigma_{j,t}}\,; \quad j \in \{i, sys\}\,, \tag{8b}$$

where the $\xi_{j,t}$ denote the (correlated) standardized residuals derived from the univariate GARCH(1,1) processes which we use to model the time-varying correlation coefficient $\rho_{i,sys,t}$. For the estimation of correlations, we apply the Dynamic Conditional Correlation (DCC) GARCH model of Engle (2002).

Rather than directly modeling the correlation between institution i's return and the banking system return, the DCC GARCH approach models the time-varying correlation of the standardized residuals $\xi_{j,t}$, whereas their covariance matrix serves as a proxy for the correlation matrix of returns $r_{i,t}$ and $r_{sys,t}$. The validity for this equivalence follows directly from the bivariate return process of Equation (7).[17]

In contrast to the one-period MES and CoVaR, the multi-period risk measures MultiMES

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[15] Our total-asset-weighted *banking system price index* has a correlation of 97.9% with the STOXX Europe 600 Banks and the TMI Banks Index.

[16] We apply various time series diagnostic tests to the individual banks' series of daily log stock returns. I.e., we test for stationarity, heteroscedasticity, auto-correlation, and non-normality. According to Table B.2, we cannot reject the null hypotheses that the time series are stationary for all series. Most series, however, exhibit heteroscedasticity, strong auto-correlation and non-normality.

[17] See Appendix A for a detailed exposition of the DCC GARCH model.

and MultiCoVaR cannot be expressed in closed-form solution as a function of volatility, correlation, and tail dependence and thus have to be determined via simulation. Based on the simulated returns, we later calculate the pre-defined systemic risk measures for each institution i in our sample of banks. Thus, for each institution i we simulate returns carrying out the following five steps – as suggested by Brownlees and Engle (2012):

1. To model the volatility and correlation dynamics of $\{r_{sys}, r_i\}_t$, we first estimate the parameter vectors of the univariate GARCH(1,1) and the DCC GARCH processes $(\alpha_{0,j}, \alpha_{1,j}, \beta_{1,j})$ and (α, β), respectively.[18]
2. Furthermore, the dynamics of $\{r_{sys}, r_i\}_t$ are assumed to be driven by the distribution $\mathcal{F}_i$ that we model using a t-copula and standard Gaussian marginal distributions.[19] The bivariate t-copula is fitted to the series of residuals $\{\epsilon_{sys}, \epsilon_i\}_t$ from the entire sample period.
3. In a third step, we simulate $S = 500,000$ paths of residuals with $h = 60$ days (a quarter of a year) length each. For every single path s, h independent pairs of residuals are drawn from the parameterized distribution $\hat{F}_i$:

$$\left\{ \begin{array}{c} \epsilon^s_{sys,t+\tau} \\ \epsilon^s_{i,t+\tau} \end{array} \right\}^h_{\tau=1} \sim \hat{F}_i \quad \text{for} \quad s = 1, \ldots, S \tag{9}$$

4. In a fourth step, we employ the drawn residuals to calculate the daily bivariate returns for the simulated time interval $[t, t+h]$ by updating the volatilities $\{\sigma_{sys,t+\tau+1}, \sigma_{i,t+\tau+1}\}^{h-1}_{\tau=1}$ and correlations $\{\rho_{i,sys,t+\tau+1}\}^{h-1}_{\tau=1}$ on a daily basis.[20] This yields

[18] All GARCH(1,1) and DCC GARCH parameters (see Appendix A) are estimated maximizing the corresponding log likelihood functions under the assumption that the residuals be Gaussian. However, this does not imply that the estimated return series are normally distributed over time. In fact, in literature it is well documented that the unconditional return distribution of a GARCH process is heavy-tailed and has excess kurtosis.

[19] Recall that we use Gaussian error terms to estimate the GARCH(1,1) and DCC GARCH parameters. To be consistent with our previous assumptions, we model the univariate residuals as standard Gaussian noise.

[20] The detailed procedure of how the daily correlations are updated is presented in Appendix A.

the following return series:

$$\left\{ \begin{array}{c} r^s_{sys,t+\tau} \\ r^s_{i,t+\tau} \end{array} \right\}_{\tau=1}^{h} \quad \text{for} \quad s = 1, \dots, S \tag{10}$$

5. In the last step, we determine the h-day cumulative returns of simulations $s = 1, \dots, S$ at day t for institution i and the banking system (according to Equation (3)) from which we calculate the MultiMES and MultiCoVaR measures.

We perform the simulation procedures outlined in Steps 3–5 including the calculation of risk measures for each Wednesday within our sample period moving ahead one week in each step. We thus obtain a weekly series of MultiMES and MultiCoVaR values (for every week within the sample period). We calculate the h-day systemic risk measures from the simulated bivariate cumulative h-day returns as follows:

MultiMES

The h-day MultiMES is calculated using the average of institution i's cumulative h-day returns resulting from paths s for which the cumulative return of the banking system is below threshold C:

$$\text{MultiMES}^{i,h}_t (C) = -\frac{\sum_{s=1}^{S} R^s_{i;[t,t+h]} \mathbb{1} \left\{ R^s_{sys;[t,t+h]} \leq C \right\}}{\sum_{s=1}^{S} \mathbb{1} \left\{ R^s_{sys;[t,t+h]} \leq C \right\}}. \tag{11}$$

$\mathbb{1}$ denotes an indicator variable that takes the value 1 if the market return is below threshold level C and *zero* otherwise. We set the threshold level $C = -25\%$.[21]

[21] To calibrate the threshold level C, we observed the performance of the blue ship index STOXX EUROPE 50 during the most severe periods of the international financial crises and the Euro crisis. In both periods, the index dropped on average by around 25% within a 3-month window.

MultiCoVaR

ΔMultiCoVaR is calculated as the residual between bank i's "distress CoVaR" given by

$$\begin{aligned} &\mathrm{MultiCoVaR}_t^{sys|i\leq \mathrm{VaR},h}(q) = \mathrm{VaR}_{t,q}\left(R^s_{sys;[t,t+h]}\right) \\ &\text{with} \quad \left\{R^s_{sys;[t,t+h]} : R^s_{i;[t,t+h]} \leq \mathrm{VaR}_{t,q}\left(R^s_{i;[t,t+h]}\right)\right\} \end{aligned} \tag{12a}$$

and bank i's median state CoVaR given by

$$\begin{aligned} &\mathrm{MultiCoVaR}_t^{sys|i=\mathrm{median},h}(q) = \mathrm{VaR}_{t,q}\left(R^s_{sys;[t,t+h]}\right) \\ &\text{with} \quad \left\{R^s_{sys;[t,t+h]} : \nu^{s,h}_{i,t} - \sigma^{s,h}_{i,t} \leq R^s_{i;[t,t+h]} \leq \nu^{s,h}_{i,t} + \sigma^{s,h}_{i,t}\right\}, \end{aligned} \tag{12b}$$

where $\nu^{s,h}_{i,t}$ is the simulated median h-day return of institution i and $\sigma^{s,h}_{i,t}$ the simulated standard deviation of institution i's h-day return. We set the confidence level $q = 5\%$ for both value at risk calculations.

5. Results

This section divides into two subsections. We commence with an analysis of the determinants of a single bank's systemic importance in the banking system in Section 5.1. Section 5.2 investigates the predictive power of systemic risk measures at the banking system level and analyzes the dynamics and directionalities between systemic risk and the macro-economy.

5.1. Bank Level

The Bank for International Settlements proposes the assessment of a bank's systemic importance by an indicator-based measurement approach (Bank for International Settlements, 2011b) that is directly related to a bank's balance sheet characteristics. Thus, in this section, we analyze to what extent the individual banks' MultiMES, SRISK, and ΔMultiCoVaR measures are determined by their respective balance sheet characteristics.

For a first overview on how the three measures evaluate our sample banks' individual level of systemic risk, we plot the individual banks' time series of systemic risk estimates for each of the three measures.

[INSERT FIGURES 1–3 ABOUT HERE]

Figure 1 exhibits the weekly time series of MultiMES, Figure 2 the weekly time series of SRISK, and Figure 3 the weekly time series of ΔMultiCoVaR, which are calculated as described in Section 4. The ΔMultiCoVaR series exhibit higher cross-sectional correlations than the MultiMES and SRISK series. However, all three systemic risk figures reveal two substantial peaks occurring in the time around the years 2008 and 2011. Thus, we draw two subsamples from the weekly time series of MultiMES, SRISK, and ΔMultiCoVaR. With the first subsample containing all weekly values for the three sets of systemic risk measures within the year 2008. As the year 2008 marks the peak of turmoil in the financial markets caused by the bankruptcies of the two large investment banks Bear Stearns and Lehman Brothers, we henceforth refer to this subsample as the "Subprime Crisis". The second subsample contains all corresponding values within the year 2011 and we accordingly refer to this subsample as the "Euro Crisis".

[INSERT TABLES 3 AND 4 ABOUT HERE]

Tables 3 and 4 exhibit descriptive statistics of the systemic risk estimates for our sample banks within the Subprime Crisis and the Euro Crisis time intervals. Both tables are designed in the same fashion. Panel A exhibits our estimates for MultiMES, Panel B the estimates for SRISK, and Panel C the estimates for ΔMultiCoVaR. We rank the banks according to their average estimates. It is easily observed that the systemic risk measures rank institutions differently. However, when taking a closer look, it is evident that the systemic risk estimates for the banks are driven by their respective balance sheet characteristics.

In the following analysis, we consider the following balance sheet characteristics: leverage (calculated as the ratio of market valued total assets – i.e., the sum of the book value of total debt and market valued equity – and market valued equity) to proxy for balance sheet stability, market-to-book ratio (calculated as the ratio of market valued equity and book value of equity) to measure financial distress, profitability (calculated as ratio of net income and the book value of total assets) to evaluate a banks' current business outlook, and total assets to assess potential default consequences. Taking the ten largest banks (by total assets), we observe that all six systemic importance rankings predominantly reflect the amount of an institution's total assets. Throughout all rankings of Tables 3 and 4, the vast majority of the ten largest banks is found in the upper 30 ranks. As expected, this effect is strongest for the SRISK measure as the latter incorporates balance sheet characteristics by construction.

Leverage also seems to have a substantial impact on an institution's systemic importance. As for total assets, the ten most leveraged banks are predominantly found on the systemically important ranks. This relationship is most clear-cut for the SRISK measure. For MultiMES and ΔMultiCoVaR, the same relationship seems to prevail, though less strongly. We also analyzed the rankings with respect to the ten most profitable banks and the banks with the lowest market-to-book ratio. However, no specific patterns can be observed, so if at all existent, we would expect this relationship to be weak.

To explore if there exists any systematic relationship between the systemic risk estimates and the previously mentioned balance sheet characteristics, we perform the following simple least squares regression:

$$SysRisk_t^{bank} = \alpha + \beta\, SysRisk_{t-1}^{bank} + \gamma\, BalanceSheetCharacteristics_{t-1}^{bank} + \epsilon_t \tag{13}$$

where $SysRisk_t^{bank}$ represents any of the three risk measures ΔMultiCoVaR, MultiMES or SRISK at the institutional level and $BalanceSheetCharacteristics_{t-1}^{bank}$ is a vector consisting of the four lagged balance sheet characteristics leverage (lev), market-to-book ratio (mb), profitability (pf), and the logarithm of total assets (ta) as its elements. Parameters α, β, and $\gamma \equiv (\gamma_{lev}, \gamma_{mb}, \gamma_{pf}, \gamma_{ta})$ denote the regression coefficients and ϵ_t is Gaussian White Noise. Note that we control for the lagged systemic risk measure to correct for endogenous risk persistence. The regression is performed on the basis of monthly time series. Thus, for the weekly series of systemic risk, we calculate monthly averages and we linearly interpolate the quarterly balance sheet data.

[INSERT TABLE 5 ABOUT HERE]

Table 5 presents the regression results for Equation (13) and is organized as follows: Panel A exhibits the results for the MultiMES measure, Panel B the results for the SRISK measure, and Panel C the results for the ΔMultiCoVaR measure. In all three regressions, the risk measures are highly autocorrelated. Thus, systemic risk on the single bank level is stable over time, implying that a bank that is systemically important in the previous month will also be systemically important in this month. This result is most persistent for the SRISK measure.

The influence of log assets is consistently positive and significant at the 1% confidence level. The larger a bank, the higher its systemic risk estimate. This result is in line with our qualitative analysis of the rankings of Tables 3 and 4. For the ΔMultiCoVaR and MultiMES measures, leverage is significant as well, though this is not the case for the SRISK measure. Moreover, the sign of the regression coefficients is ambiguous. Whereas a higher leverage increases MultiMES, it decreases ΔMultiCoVaR. This finding lasts in different regression setups.[22]

As predicted by our prior qualitative analysis, the market-to-book ratio as well as profitability do not have additional predictive power for all three systemic risk measures and thus seem to be already captured by the (simultaneously calculated) lagged systemic risk measures. The same relation holds for the SRISK measure and leverage. As a result, the exogenous variation in systemic risk in the cross-section is mainly driven by size and leverage.

[22] We also perform the same regression without controlling for endogenous risk persistence. As a result, all balance sheet characteristics are significant at the 5% level and thus have explanatory power for future systemic risk levels. Surprisingly, leverage has a negative influence on ΔMultiCoVaR, which seems to be counterintuitive. Furthermore, MultiMES is positively related to the market-to-book ratio. On average, the risk measures are positively related to size and leverage and negatively related to profitability and the market-to-book ratio.

In summary, our analysis shows that besides the lagged systemic risk measures, total assets and leverage are the most important drivers of systemic risk. The systemic importance of banks with high leverage and large total assets disproportionally increase during periods of financial turmoil.

The results imply that regulators can effectively reduce systemic risk at the institutional level by imposing restrictions on bank size and leverage and thus justify new regulatory measures such as the introduction of a leverage ratio on total assets and capital surcharges to SIFI's Tier 1 capital in the range between 1% to 2.5% (Bank for International Settlements, 2011a,b).

5.2. Banking System Level

Having analyzed the determinants of systemic risk at the institutional level, we now turn to the implications of systemic risk at the banking system level. Systemic banking crisis often have substantial adverse effects on the real economy, such as drops in asset prices, output, and employment (Reinhart and Rogoff, 2009). Thus, if useful, systemic risk measures should not only reflect current distress in the financial system but also have predictive power for financial market and macro-economic variables.

In this section, we investigate the two-sided relationship between systemic risk measures and financial market variables, macro-economic variables, and balance sheet characteristics at the aggregate banking system level.

[INSERT TABLE 6 ABOUT HERE]

Table 6 provides a summary of the variables used in our subsequent analyses. To capture movements at the financial markets, we employ the 12 month EURIBOR-OIS spread (which we henceforth simply refer to as EURIBOR-OIS spread) and the VSTOXX Index. The EURIBOR-OIS spread is the residual between the 12 month EURIBOR and the 12 month Euro OIS (overnight indexed swap) rate and captures liquidity and default risk within the European banking system. The data are on a weekly frequency.

In addition to our analyses at the bank level, we explore the two-sided relationship between systemic risk measures and balance sheet characteristics employing the same variables as in Section 5.1 but on the banking system level. I.e., for each of the balance sheet characteristics, we compute weekly time series for the aggregate of all banks included in our sample. Instead of log assets however, we include the annual ratio of nonperforming loans to total gross loans in our analyses to capture the banking sector's core risk.

We measure the linkages between systemic risk and the macro-economy employing the following variables: the Economic Sentiment Indicator of the European Commission and the EU Industrial Production Index (excluding construction), both published on a monthly basis, the EU House Price Index and real GDP, both on a quarterly basis, domestic credit to the private sector and government debt, both expressed in percentage terms of real GDP and on an annual basis. All macro-economic variables refer to the EU27.

To measure the directionalities between the systemic risk measures and these variables, we apply a vector autoregressive (VAR) model. According to the Schwarz criterion, the data suggests a one lag structure. We thus employ a VAR system of the following type:

$$\Delta y_t = a + B\Delta y_{t-1} + \epsilon_t \tag{14}$$

with $y_t \equiv (SysRisk_t^{sys}, x_t)'$, where $SysRisk_t^{sys}$ represents any of the three systemic risk measures ΔMultiCoVaR, MultiMES or SRISK at the banking system level and x_t is the vector of financial market, balance sheet or macro-economic variables. Parameter vector a denotes the intercepts, B is the coefficient matrix of lagged regression variables y_{t-1}, and ϵ_t is a vector of standard Gaussian error terms. The Δs indicate that we are running the regression in first differences to ensure that we do not violate the stationarity requirements.[23]

[23] We perform several time series diagnostics. We test the differenced series $\Delta y_t = y_t - y_{t-1}$ for stationarity, heteroscedasticity, auto-correlation, and non-normality. According to Table B.1 we cannot reject the null hypotheses that the time series are stationary (Panel A) for all series and for most series we cannot reject the homoscedasticity null hypothesis (Panel B). The vast majority of the series exhibits strong auto-correlation (Panel C) and non-normality (Panel D).

Running the regression of Equation (14) requires that we harmonize data with respect to their sampling frequency. We harmonize data on a monthly frequency and achieve this by linearly interpolating all variables sampled on a frequency of lower than a month. For variables with a higher frequency, we calculate monthly averages.

[INSERT FIGURES 4–7 ABOUT HERE]

Figures 4–7 exhibit the time series of the variables used for the regression of Equation (14). Figure 4 exhibits the time series of cross-sectional averages of the monthly averaged bank level systemic risk estimates. As observed in Section 5.1, the cross-section of ΔMultiCoVaR measures is more strongly correlated than the other measures' cross-sections and thus, the aggregate ΔMultiCoVaR series exhibits higher volatility. Nevertheless, all three figures exhibit peaks during the Subprime and the Euro Crises. Figure 5 presents the monthly, linearly interpolated time series of aggregate balance sheet characteristics, Figure 6 the monthly averaged time series of financial market variables, and Figure 7 the monthly, linearly interpolated time series of macro-economic variables.

[INSERT TABLE 7 ABOUT HERE]

Table 7 exhibits the results obtained for our estimated VAR systems on financial market, balance sheet, and macro-economic variables and is organized as follows: Panel A contains the results for the MultiMES, Panel B the results for the SRISK, and Panel C the results for the ΔMultiCoVaR regressions. Each column represents an estimated regression equation with the lagged explanatory variables given in the rows.

The regression of lagged financial market data on the systemic risk measures reveals that volatility possesses significant explanatory power for the MultiMES and SRISK measures. On the one hand, the negative coefficients indicate that an increase in volatility should result in lower levels of systemic risk. On the other hand, the systemic risk measures load significantly positive on volatility. This mechanism can be explained as follows: Systemic risk measures are capable of capturing distress before it is transmitted to the stock market. After distress (as measured by the systemic risk measures) is transmitted and realized as volatility at the financial market, the level of systemic risk declines.

Interestingly, all three risk measures possess explanatory power for the EURIBOR-OIS spread. However, the opposite effect does not prevail, again suggesting that our systemic risk measures indicate financial distress earlier than the interest rate spreads.[24]

In Section 5.1 we analyzed the influence of balance sheet characteristics on systemic risk measures at the bank level and found that total assets and leverage possess substantial additional predictive power. Turning towards aggregate balance sheet characteristics at the banking system level, we find that these do not possess significant additional predictive power for either of the three systemic risk measures. Thus, at the banking system level, balance sheet characteristics are no leading indicators for the level of systemic risk carried in the financial system.

However, the MultiMES and SRISK measures possess substantial predictive power for profitability at the banking system level. The negative coefficient indicates that a spike in systemic risk results in a decrease in profitability. Moreover, SRISK adds predictive power to banking system level balance sheet characteristics such as the market-to-book ratio of equity and leverage. The negative coefficient for leverage indicates that systemic events are linked to periods of significant losses resulting in a reduction of the banks' equity cushion. Thus, the average leverage in the banking system increases.

In the right hand part of Table 7, we analyze interdependencies between macro-economic variables and systemic risk measures. Distress in the banking system may adversely affect the real economy, e.g. through a credit crunch as banks act as important suppliers of credit. Thus, systemic risk measures should – to some extent – anticipate output drops in the real

[24] We also performed one regression in which we applied the 3 month EURIBOR-OIS spread instead of its 12 month counterpart and another regression in which we include both spreads. However, the obtained results do not vary substantially.

economy and add further explanatory power to macro-economic forecasts.

Indeed, our results in Table 7 show that systemic risk measures possess significant predictive power for a range of macro-economic variables. Most importantly, the MultiMES and SRISK measures are able to forecast significant drops in real GDP. E.g., a monthly one percentage point increase in MultiMES explains a drop in monthly GDP of around €$0.8bn$, which converts to a drop of around €$10bn$ a year. ΔMultiCoVaR is less adequate for the prediction of future GDP. In fact, the estimated relationship is positive, though the coefficient is insignificant. All three systemic risk measures possess significant predictive power for economic sentiment. An increase in the systemic risk measures forecasts a drop in the European Commission's economic sentiment indicator.

MultiMES loads significantly negative on house prices. Thus, an increase in MultiMES predicts future drops in house prices. This finding might be attributed to the specific house price dynamics during the Subprime Crisis where housing prices acted as a main driver of systemic risk (Longstaff, 2010).

The previous analysis was dedicated to the real effects of systemic risk. In the following, we analyze whether macro-economic variables potentially drive systemic risk. We would expect output-related macro-economic variables, such as real GDP and production, to be less capable of forecasting systemic risk because drops in GDP usually occur after systemic risk materializes as a consequence of distress in the banking system. However, an increase in sovereign debt (expressed as a percentage of GDP) is likely to result in a higher risk of sovereign default, which could then be reflected in the banks' systemic risk estimates. Our results show that SRISK and ΔMultiCoVaR – despite being insignificant – indeed do capture this effect.

Though in general the signs of the macro-economic variables' regression coefficients are as expected, none of them possesses significant explanatory power for systemic risk, which is in line with our initial expectation that systemic risk is a latent leading variable.[25]

[INSERT TABLE 8 ABOUT HERE]

As a robustness check, we perform a regression in which we include all financial market, balance sheet, and macro-economic variables. Our results do not change substantially. An increase in profitability now possesses significant forecasting power for systemic risk. This result is intuitive because higher profitability usually points towards higher leverage and higher risk. The degree to which the systemic risk measures are able to forecast systemic risk also changes slightly. The coefficient for real GDP becomes insignificant in the SRISK regression (Panel B) and even significantly positive in the ΔMultiCoVaR regression (Panel C). Moreover, the ΔMultiCoVaR measure loads positively on production. Overall, our results suggest that the ΔMultiCoVaR measure is less valuable for macro-economic forecasts and thus, regulatory authorities should be aware of the sometimes dubious regression coefficients' signs.

To analyze if our previous results hold for both crisis periods individually, we perform the regression of Equation (14) for the first half (July 2005 – June 2009) and the second half of our sample (July 2009 – June 2013) separately. We henceforth refer to the first half of the sample as the "Subprime Crisis sample" and to the second half of the sample as the "Euro Crisis sample".

[INSERT TABLE 9 ABOUT HERE]

Table 9 exhibits the results for the Subprime Crisis sample. In general, our results of Table 7 are confirmed and even stronger. The significance of an increase of MultiMES on house prices increases beyond the 1%-level and the SRISK measure now loads significantly on house prices at the 5%-level.

[25] As an exercise, we perform regressions including unemployment and inflation in our set of macro-economic variables. However, both variables' regression coefficients are insignificant in both directions.

Our results furthermore shed light on the evolution of the construction boom and the subsequent burst of the housing price bubble in southern European countries that coincided with the American Subprime crisis. The VAR framework captures the dynamics between house prices and systemic risk in the banking system well. As indicated by the regressions in Column 13 (house prices), increases in the risk measures predict subsequent drops in house prices (that are significant for the MultiMES and SRISK measures). This drop is then followed by a further increase in systemic risk.

The results also indicate that for the Subprime Crisis sample, the EURIBOR-OIS spread acts as a significant leading indicator for the SRISK measure which, however, is not the case for the entire sample period (see Table 7).

[INSERT TABLE 10 ABOUT HERE]

Table 10 exhibits the results for the Euro Crisis sample. Most importantly, the systemic risk measures lose their predictive power for house prices. This is intuitive because at the start of the Euro Crisis, the burst of the housing price bubble had already materialized at the financial market.

Compared to Tables 7–9, the overall significance of the coefficients is much weaker. Increases in systemic risk measures no longer predict drops in real GDP. However, the MultiMES and ΔMultiCoVaR measures reflect that increases in GDP result in a decrease in systemic risk. All systemic risk measures continue to possess predictive power for economic sentiment. I.e., an increase in systemic risk leads to a decrease in economic sentiment.

The predictive power of the measures is less strong than in the Subprime Crisis for two reasons: (1) As a result of the European Central Bank's government bond purchase program, the informativeness of the market-based measures might be biased. (2) The Euro Crisis' can be – for the most part – regarded as a government debt crisis. In addition, the downturn in the real economy (that might be even reinforced by austere government spending policies) is – in contrast to the Subprime Crisis – much more concentrated in the peripheral Euro countries and thus less substantial for the European economy as a whole.

6. Conclusion

In this paper, we propose a framework to assess the potential of systemic risk measures as a monitoring tool for regulators. We compare three commonly cited systemic risk measures – the Marginal Expected Shortfall (MES), the SRISK, and the Conditional Value at Risk (CoVaR) – in a DCC GARCH setup. We do so by investigating the dynamics between systemic risk, the financial market, and the real economy applying a VAR system.

We find that systemic risk measures possess substantial forecasting power for a variety of financial market and macro-economic variables. However, aggregate balance sheet characteristics cannot explain systemic risk at the banking system level. When evaluated in comparison to the MES related measures, the CoVaR's predictive power for financial market and macro-economic variables is rather poor and the direction of influence often misleading.

Our results have paramount implications. Regulators should rely on MES-based systemic risk measures as these have much higher predictive power than the commonly applied CoVaR. In the long run, more complex measures such as the SRISK tend to produce better results than simple market indicators such as interest rate spreads that might be prone to capturing market conditions specific to certain crises.

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Figures

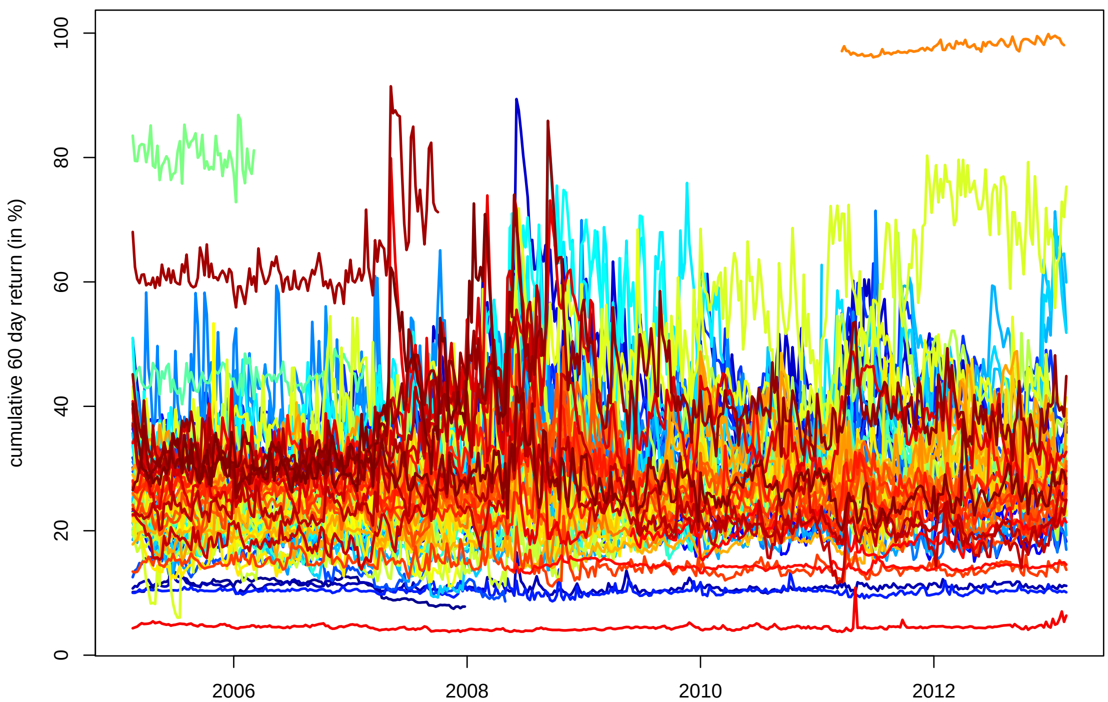

Figure 1 – Time Evolution of MultiMES

The figure presents time series of weekly MultiMES values for all 87 sample banks expressed in percentage terms. The time series of observations cover the period from July 2005 to June 2013. All stock price and balance sheet data are obtained from Datastream.

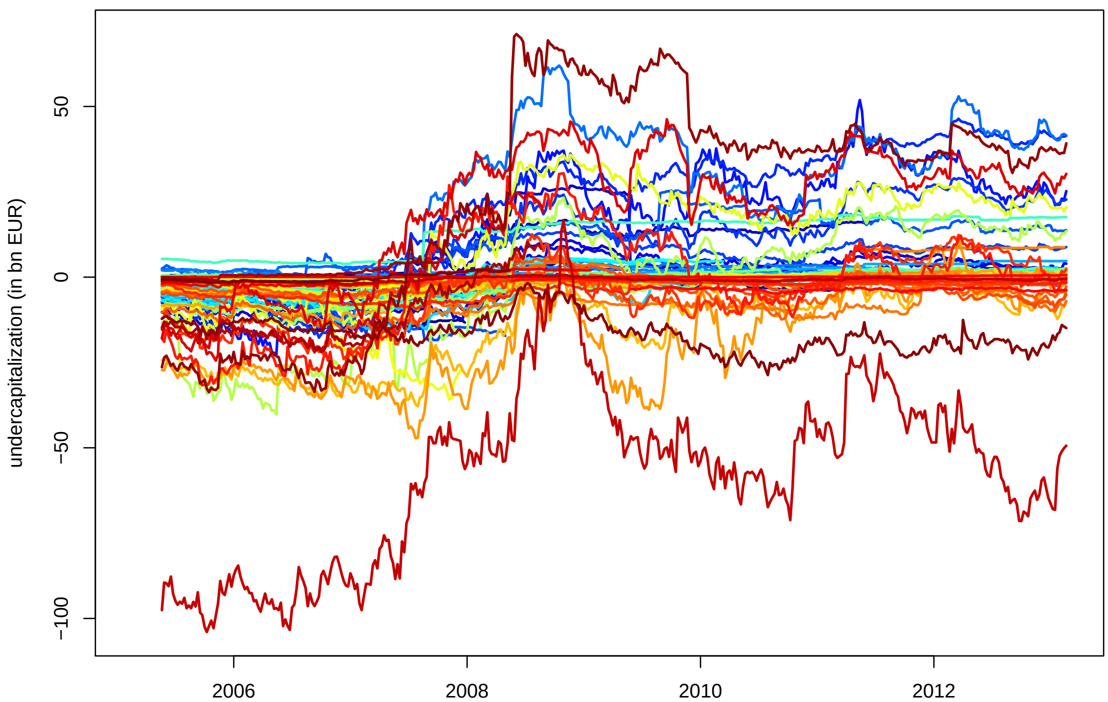

Figure 2 – Time Evolution of SRISK

The figure presents time series of weekly SRISK values for all 87 sample banks expressed in *bn* EUR terms. The time series of observations cover the period from July 2005 to June 2013. All stock price and balance sheet data are obtained from Datastream.

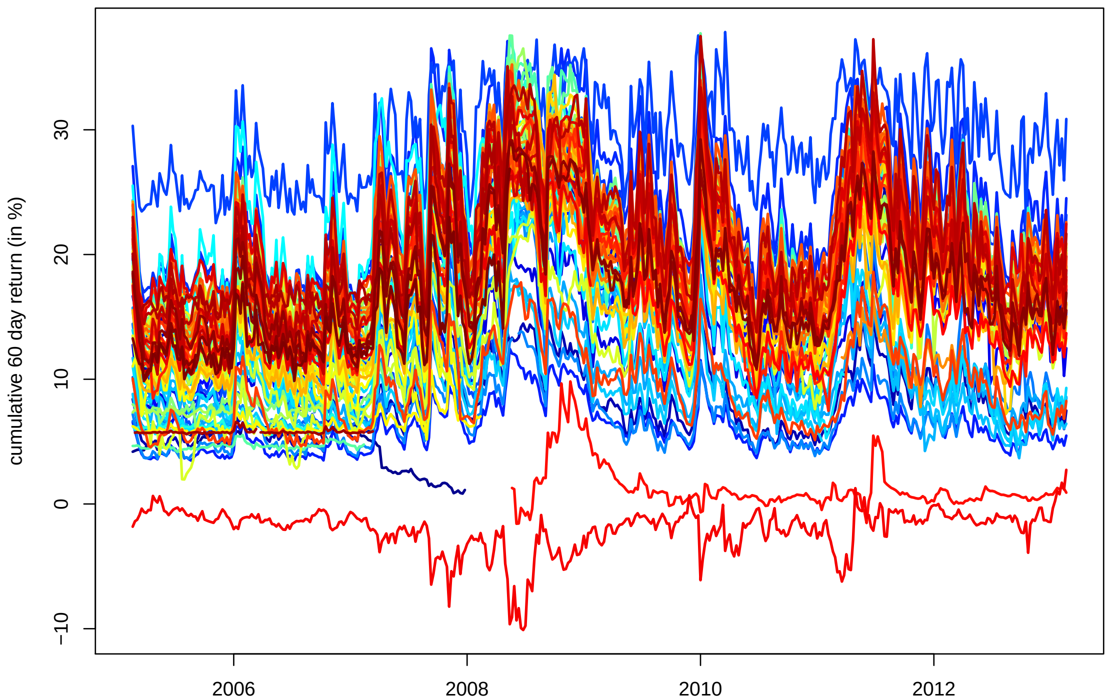

Figure 3 – Time Evolution of ΔMultiCoVaR

The figure presents time series of weekly ΔMultiCoVaR values for all 87 sample banks expressed in percentage terms. The time series of observations cover the period from July 2005 to June 2013. All stock price and balance sheet data are obtained from Datastream.

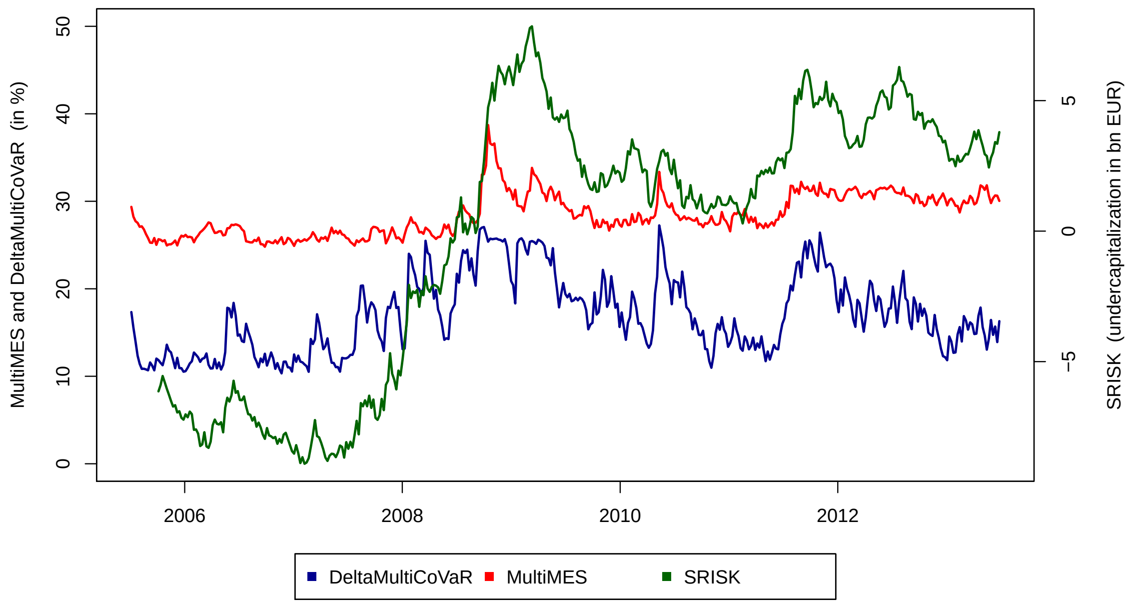

Figure 4 – Time Evolution of Risk Measures

The figure presents averages across the time series of weekly systemic risk measures for all 87 sample banks. The time series of observations cover the period from July 2005 to June 2013. All stock price and balance sheet data are obtained from Datastream.

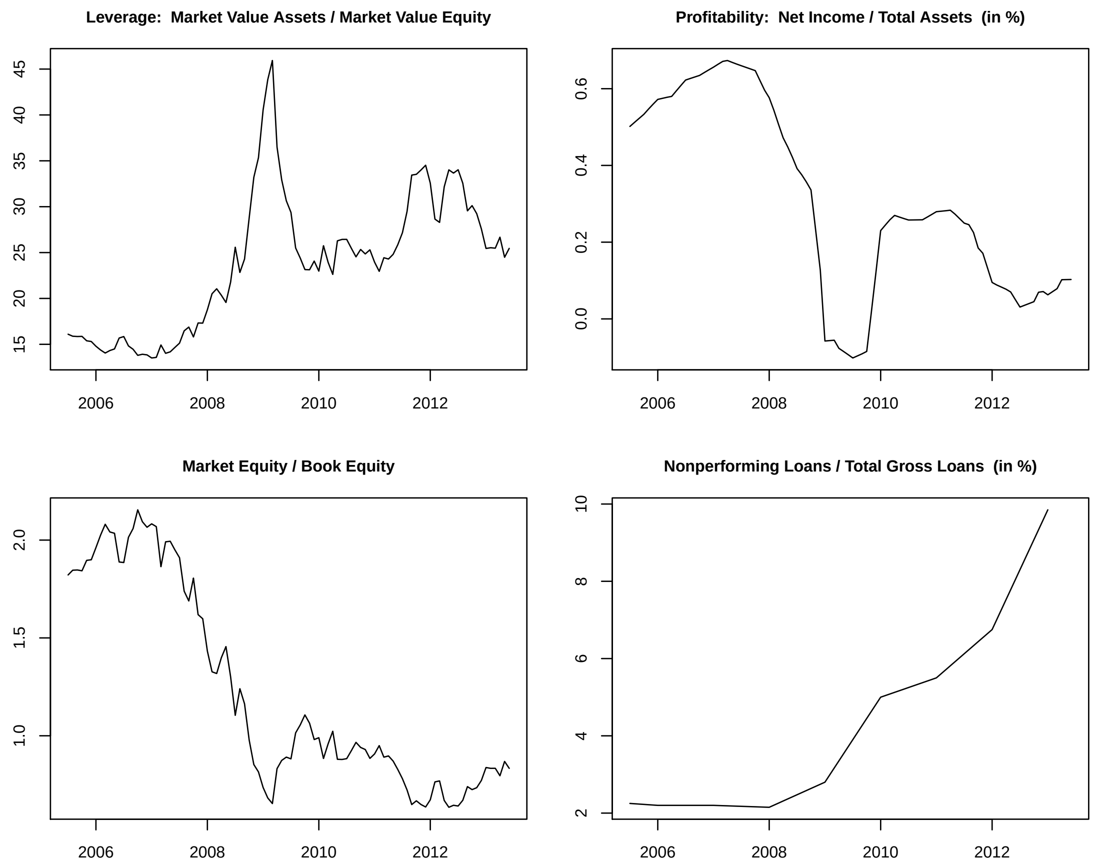

Figure 5 – Time Evolution of Bank Balance Sheet Variables

The figure presents monthly, linearly interpolated time series of characteristic bank balance sheet variables averaged across all 87 sample banks. The time series of observations cover the period from July 2005 to June 2013. Market values, book values, and total assets are obtained from Datastream; data on nonperforming loans is obtained from the Worldbank's database.

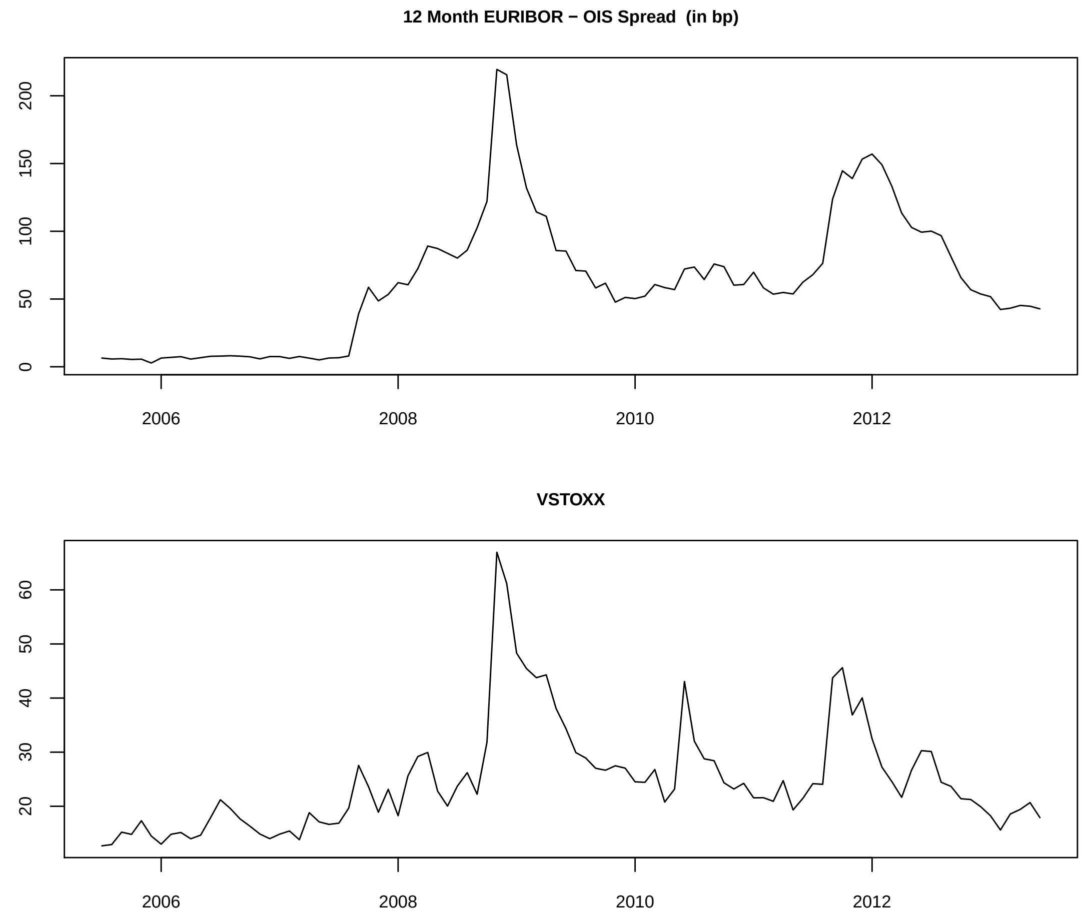

Figure 6 – **Time Evolution of Financial Market Variables**

The figure presents monthly time series of the VSTOXX index and the 12 month EURIBOR-OIS spread calculated as the difference between the 12 month EURIBOR and the Euro 12 month Overnight Index Swap (OIS) rate. The time series of observations cover the period from July 2005 to June 2013. All data are obtained from Datastream.

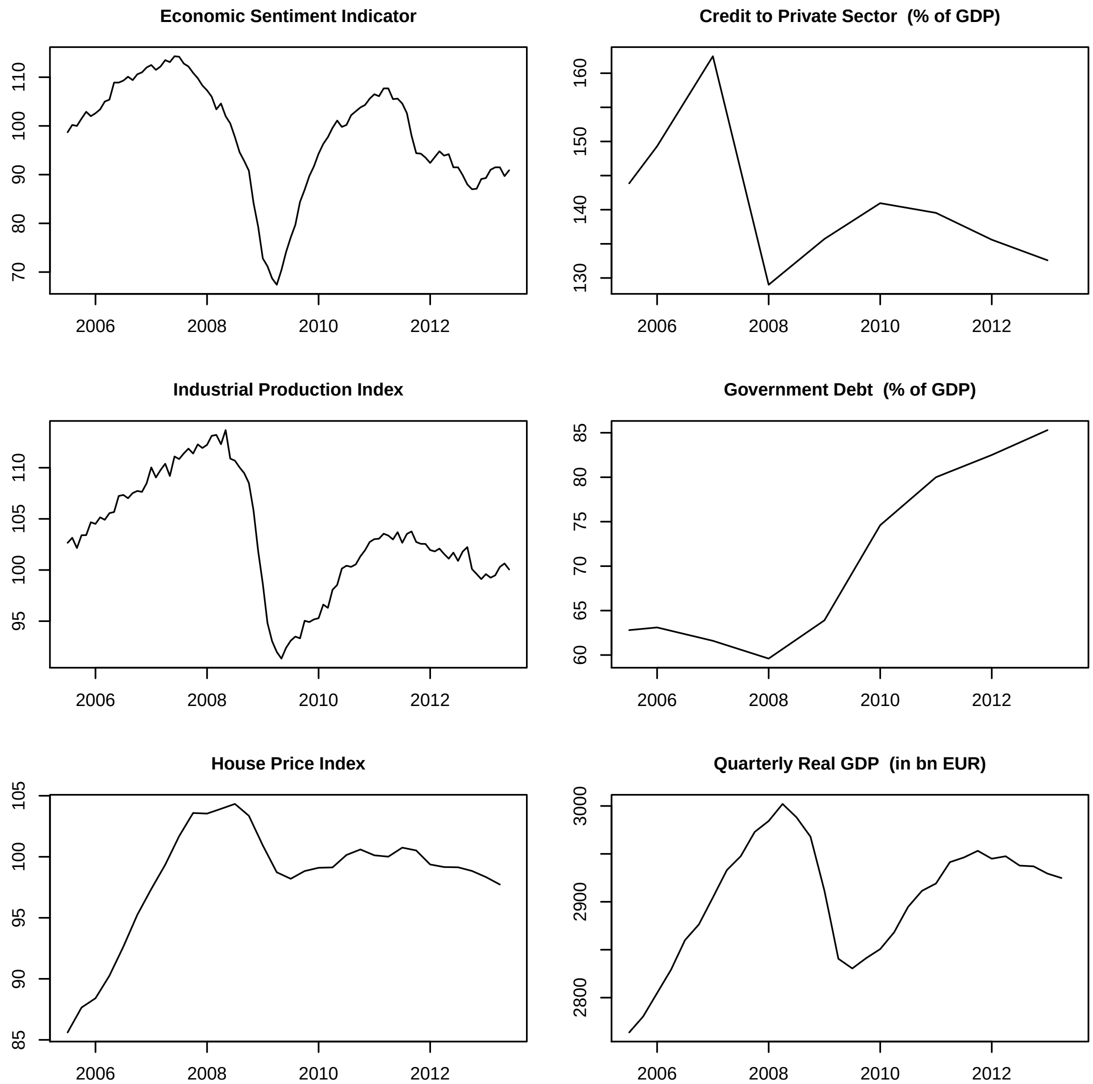

Figure 7 – Time Evolution of Macro-economic Variables

The figure presents monthly (linearly interpolated) time series of macro-economic data from the EU27. The time series of observations cover the period from July 2005 to June 2013. Data on government debt is obtained from the European Central Bank, data on credit to the private sector is obtained from the Worldbank's database, and all remaining data is from Datastream.

Tables

Bank	Country	ISIN	Total Assets	Rank	Market/Book	Rank	Leverage	Rank
ABN AMRO Holding N.V.	Netherlands	NL0000301109	794,905	15	3.39	86	13.24	62
Ageas N.V.	Belgium	BE0974264930	420,419	23	1.36	52	23.17	29
Agricultural Bank of Greece S.A.	Greece	GRS414003004	25,216	82	14.39	87	13.63	61
Alliance & Leicester PLC	United Kingdom	GB0000386143	90,321	49	1.27	45	28.99	25
Allied Irish Banks PLC	Ireland	IE0000197834	148,411	38	1.51	62	10.61	73
Alpha Bank A.E.	Greece	GRS015013006	56,845	61	1.18	38	12.13	67
Banca Antonveneta S.p.A.	Italy	IT0003270102	44,553	68	2.59	84	6.17	85
Banca Carige S.p.A.	Italy	IT0003211601	33,588	72	1.09	29	10.97	71
Banca Civica S.A.	Spain	ES0148873005	74,048	56	0.30	5	83.08	3
Banca Lombarda	Italy	IT0000062197	40,222	69	2.04	82	7.25	83
Banca Monte dei Paschi di Siena S.p.A.	Italy	IT0001334587	196,445	33	0.82	17	27.30	27
Banca Nazionale del Lavoro S.p.A. (BNL)	Italy	IT0001254884	88,283	50	1.75	76	10.57	74
Banca Popolare dell'Emilia Romagna	Italy	IT0000066123	52,307	62	0.89	21	19.05	38
Banca Popolare di Milano	Italy	IT0000064482	45,742	67	0.72	12	17.95	40
Banca Popolare di Sondrio	Italy	IT0000784196	21,916	84	1.42	58	9.85	76
Banca Popolare Italiana S.C.A.R.L.	Italy	IT0000064300	46,138	65	1.79	78	7.13	84
Banche Popolari Unite S.C.A.R.L.	Italy	IT0003487029	109,530	44	0.73	13	17.18	46
Banco Bilbao Vizcaya Argentaria S.A.	Spain	ES0113211835	507,807	19	1.64	70	11.92	68
Banco Comercial Portugues S.A.	Portugal	PTBCP0AM0007	87,428	53	1.30	47	16.79	49
Banco de Sabadell S.A.	Spain	ES0113860A34	88,060	51	1.26	43	14.47	58
Banco Espanol de Credito S.A.	Spain	ES0113440038	104,562	46	1.38	53	16.81	48
Banco Espirito Santo S.A.	Portugal	PTBES0AM0007	70,588	57	0.98	25	16.00	53
Banco Pastor S.A.	Spain	ES0113790085	26,549	79	1.32	49	14.63	56
Banco Popolare Societa CooperativaAz.	Italy	IT0004231566	108,159	45	0.68	10	20.98	35
Banco Popular Espanol S.A.	Spain	ES0113790226	114,220	42	1.44	60	12.35	65
Banco Portugues de Investimento S.A.	Portugal	PTBPI0AM0004	39,802	71	1.70	73	17.75	43
Banco Santander S.A.	Spain	ES0113900J37	1,025,916	10	1.17	37	14.99	54
Bank Austria Creditanstalt AG	Austria	AT0000995006	206,010	32	1.46	61	11.09	70
Bank of Cyprus	Cyprus	CY0000100111	32,947	73	1.38	54	12.35	66
Bank of Greece	Greece	GRS004013009	84,172	55	0.50	6	86.95	2
Bank of Ireland	Ireland	IE0030606259	169,136	37	1.08	28	24.26	28
Bank Sarasin & Cie AG	Switzerland	CH0038389307	9,787	87	1.43	59	7.99	81
Bankia S.A.	Spain	ES0113307021	287,902	27	-0.44	1	76.05	4
Bankinter	Spain	ES0113679I37	50,617	63	1.56	67	16.25	51
Banque Cantonale Vaudoise	Switzerland	CH0015251710	25,552	80	1.74	74	9.76	77
Banque Nationale de Belgique S.A.	Belgium	BE0003008019	100,203	47	0.15	3	75.38	5
Barclays PLC	United Kingdom	GB0031348658	1,633,656	5	1.11	31	37.53	17
Basler Kantonalbank	Switzerland	CH0009236461	22,432	83	0.28	4	44.10	13
Bayerische Hypo- und Vereinsbank AG	Germany	DE0008022005	457,780	21	1.42	57	16.01	52
BNP Paribas S.A.	France	FR0000131104	1,743,205	1	0.95	24	30.68	20
Bradford & Bingley PLC	United Kingdom	GB0002228152	64,273	59	0.88	20	40.82	15
Caisse Regionale de Credit Agricole Mutuel de Paris et d'Ile de France SC	France	FR0000045528	29,870	76	0.58	7	44.59	11
Caixabank S.A.	Spain	ES0140609019	111,228	43	0.79	16	8.73	79
Capitalia S.p.A.	Italy	IT0003121495	138,590	39	1.74	75	8.67	80
Commercial Bank of Greece	Greece	GRS006013007	25,549	81	2.72	85	14.93	55
Commerzbank AG	Germany	DE000CBK1001	663,395	16	0.65	8	57.16	6
Crédit Agricole S.A.	France	FR0000045072	1,465,511	6	0.75	14	49.83	8
Credit Suisse Group AG	Switzerland	CH0012138530	805,461	13	1.54	66	20.68	37
Credito Emiliano S.p.A. CredemAz.	Italy	IT0003121677	27,395	78	1.22	40	14.53	57
Credito Valtellinese S.C.A.R.L. Az.	Italy	IT0000064516	21,571	85	0.66	9	22.27	31
Danske Bank	Denmark	DK0010274414	415,945	24	1.04	27	28.94	26
Depfa Bank	Germany	IE0072559994	223,521	30	1.86	80	44.48	12
Deutsche Bank AG	Germany	DE0005140008	1,722,101	2	0.94	23	47.39	9
Deutsche Postbank AG	Germany	DE0008001009	196,433	34	1.24	41	29.25	24
Dexia S.A.	Belgium	BE0003796134	523,914	18	0.93	22	44.99	10
Erste Group Bank AG	Austria	AT0000652011	194,229	35	1.34	50	17.76	42
Eurobank Ergasias S.A.	Greece	GRS323003004	67,235	58	1.24	42	12.63	63
GAM Holding AG	Switzerland	CH0102659627	13,786	86	1.68	72	3.21	87
HBOS PLC	United Kingdom	GB0030587504	805,950	12	1.76	77	30.57	21
HSBC Holdings	United Kingdom	GB0005405286	1,644,162	4	1.42	56	12.50	64
IKB Deutsche Industriebank AG	Germany	DE0008063306	40,094	70	0.86	18	38.87	16
ING Groep N.V.	Netherlands	NL0000303600	1,220,294	7	1.15	33	30.21	23
Intesa Sanpaolo S.p.A.	Italy	IT0000072626	542,920	17	0.87	19	192.58	1
Investec PLCShs	United Kingdom	GB00B17BBQ50	45,940	66	1.59	68	17.59	44
Irish Bank Resolution Corporation Ltd	Ireland	IE00B06H8J93	87,850	52	1.19	39	23.01	30
Julius Bär	Switzerland	CH0102484968	32,597	74	1.65	71	6.04	86
Jyske Bank	Denmark	DK0010307958	28,094	77	1.40	55	13.68	60
KBC Groep N.V.	Belgium	BE0003565737	318,055	25	1.11	30	17.83	41
Landesbank Berlin Holding AG	Germany	DE0008023227	136,782	40	1.82	79	32.53	19
Lloyds Banking Group	United Kingdom	GB0008706128	798,099	14	1.53	65	21.70	33
Mediobanca - Banca di Credito Finanziario S.p.A.	Italy	IT0000062957	64,004	60	1.26	44	7.88	82
National Bank of Greece S.A.	Greece	GRS003003019	93,762	48	1.17	36	10.32	75
Natixis Banques Populaires	France	FR0000120685	425,956	22	0.69	11	41.18	14
Nordea Bank AB	Sweden	SE0000427361	485,820	20	1.35	51	18.14	39
Northern Rock PLC	United Kingdom	GB0001452795	123,666	41	0.11	2	56.88	7
Piraeus Bank S.A.	Greece	GRS014003008	46,352	64	1.16	34	14.37	59
Pohjola Bank PLC	Finland	FI0009003222	32,148	75	1.16	35	16.40	50
Raiffeisen Bank International AG	Austria	AT0000606306	86,980	54	1.52	64	10.96	72
Royal Bank of Scotland Group PLC	United Kingdom	GB00B7T77214	1,689,769	3	1.15	32	36.26	18
Sanpaolo IMI S.p.A. Az.	Italy	IT0001269361	279,409	28	2.17	83	11.11	69
Skandinaviska Enskilda Banken AB	Sweden	SE0000148884	236,951	29	1.29	46	20.78	36
Société Générale S.A.	France	FR0000130809	1,054,032	9	1.04	26	30.53	22
Standard Chartered PLC	United Kingdom	GB0004082847	299,863	26	1.59	69	9.47	78
Svenska Handelsbanken AB	Sweden	SE0000193120	220,029	31	1.51	63	17.02	47
Swedbank AB	Sweden	SE0000242455	175,054	36	1.31	48	17.49	45
UBS AG	Switzerland	CH0024899483	1,212,246	8	1.99	81	21.82	32
UniCredit S.p.A.	Italy	IT0004781412	850,254	11	0.79	15	21.05	34

Table 1 – Bank Characteristics and Descriptives

The table exhibits figures averaged across the entire time series of quarterly balance sheet characteristics for each of the 87 sample banks. The time series of observations cover the period from July 2005 to June 2013. All data are obtained from Datastream.

Statistics	Total Assets	Market-to-Book	Leverage
Average	334,167	1.40	25.67
Std. deviation	461,416	1.51	25.16
Minimum	9,787	-0.44	3.21
$q = 0.25$	46,039	0.94	12.35
$q = 0.50$	109,530	1.26	17.59
$q = 0.75$	423,187	1.54	30.37
Maximum	1,743,205	14.39	192.58

Table 2 – Summary of Bank Balance Sheet Characteristics

The table gives a summary of Table 1. The time series of observations cover the period from July 2005 to June 2013. All data are obtained from Datastream.

Panel A – MultiMES (in %)									
Bank	rank	# obs	mean	sd	min	$q = 0.25$	median	$q = 0.75$	max
Ageas N.V.	1	53	49.11	17.10	24.25	36.59	47.01	61.52	89.40
Bank of Ireland	2	53	48.41	12.01	29.63	37.87	47.72	56.98	70.39
Royal Bank of Scotland Group PLC	3	53	47.56	7.12	38.29	43.79	45.97	49.94	74.02
Bradford & Bingley PLC	4	39	46.79	11.34	29.15	37.83	43.23	54.00	72.61
Allied Irish Banks PLC	5	53	44.15	9.54	29.79	35.92	41.10	52.91	64.10
HBOS PLC	6	53	44.12	10.60	29.84	35.88	39.98	50.17	74.00
Barclays PLC	7	53	43.79	5.19	33.76	40.01	43.43	47.43	55.52
Lloyds Banking Group	8	53	43.68	6.52	31.81	38.97	42.48	48.12	59.42
ING Groep N.V.	9	53	42.04	10.24	30.13	34.76	37.11	47.17	71.81
IKB Deutsche Industriebank AG	10	53	41.03	8.15	28.75	35.43	38.20	44.86	65.07
Société Générale S.A.	11	53	40.86	5.08	30.47	37.93	40.37	44.49	53.91
Alliance & Leicester PLC	12	53	39.50	11.81	17.79	34.63	40.04	44.98	73.90
Dexia S.A.	13	53	39.38	8.78	27.01	32.15	39.85	43.95	62.97
Landesbank Berlin Holding AG	14	53	38.64	9.40	26.96	31.41	37.54	44.65	63.17
Banca Popolare dell'Emilia Romagna	15	53	38.21	8.52	21.26	32.41	36.99	42.70	58.85
Crédit Agricole S.A.	16	53	37.13	4.61	25.58	34.60	35.92	40.12	46.13
Irish Bank Resolution Corporation Ltd	17	51	36.60	13.82	22.02	25.74	31.04	45.22	71.00
UniCredit S.p.A.	18	53	36.36	7.58	25.76	31.24	33.46	42.09	54.93
KBC Groep N.V.	19	53	36.04	8.62	25.43	29.55	33.17	43.73	56.49
BNP Paribas S.A.	20	53	35.60	4.37	30.31	32.66	34.61	37.49	52.46
Natixis Banques Populaires	21	53	35.10	5.43	26.62	30.73	34.46	38.27	47.29
UBS AG	22	53	34.00	5.29	26.85	30.29	32.75	36.90	48.51
Raiffeisen Bank International AG	23	53	33.35	6.74	24.74	28.82	30.74	36.01	51.66
National Bank of Greece S.A.	24	53	32.61	7.44	18.71	28.47	31.52	36.23	51.45
Erste Group Bank AG	25	53	32.38	6.35	24.49	27.68	29.88	34.57	45.76
Banco Popular Espanol S.A.	26	53	31.35	5.60	18.75	27.17	32.23	35.66	39.61
Deutsche Bank AG	27	53	30.95	7.89	24.26	25.61	27.12	33.24	49.74
Deutsche Postbank AG	28	53	30.90	6.89	20.41	26.07	29.16	34.43	51.08
Skandinaviska Enskilda Banken AB	29	53	30.66	5.59	23.64	26.74	28.79	34.01	47.88
Credit Suisse Group AG	30	53	30.26	6.72	21.32	25.51	28.38	33.26	48.30
Commerzbank AG	31	53	30.22	4.14	23.93	28.41	30.03	31.57	41.82
Standard Chartered PLC	32	53	30.18	4.55	23.39	27.61	29.11	32.16	43.14
Banco Santander S.A.	33	53	29.84	4.37	23.89	26.13	28.75	33.12	38.33
Swedbank AB	34	53	29.54	4.45	23.84	25.93	28.10	32.07	40.59
Investec PLCShs	35	53	29.05	3.41	21.59	26.40	28.66	31.45	36.48
Danske Bank	36	53	28.65	5.86	20.70	24.44	27.13	31.08	46.46
Banco Bilbao Vizcaya Argentaria S.A.	37	53	28.53	4.56	23.15	25.23	26.64	30.05	40.57
Nordea Bank AB	38	53	27.94	5.42	19.50	25.09	26.85	29.97	43.96
Piraeus Bank S.A.	39	53	27.85	4.14	20.66	24.59	27.05	30.58	36.19
Intesa Sanpaolo S.p.A.	40	53	27.63	6.02	20.87	24.35	25.30	28.58	47.07
Svenska Handelsbanken AB	41	53	27.57	5.45	19.25	24.41	26.92	29.35	39.98
Bankinter	42	53	27.19	3.30	21.86	25.26	26.86	29.17	38.17
Banco Popolare Societa CooperativaAz.	43	53	26.69	4.56	20.37	23.24	26.05	29.21	40.40
HSBC Holdings	44	53	26.33	4.93	17.02	23.11	25.08	28.82	38.97
Alpha Bank A.E.	45	53	25.53	5.76	16.70	20.79	25.33	29.34	38.51
Eurobank Ergasias S.A.	46	53	25.36	4.96	18.41	22.12	24.11	27.79	39.06
Banca Carige S.p.A.	47	53	25.33	3.92	18.50	22.44	24.38	27.57	34.15
Banco Portugues de Investimento S.A.	48	53	24.59	4.18	18.14	21.61	24.35	26.79	40.11
Pohjola Bank PLC	49	53	24.46	3.69	17.34	22.18	23.30	27.02	34.74
Banco Comercial Portugues S.A.	50	26	23.85	2.18	19.77	22.79	23.57	24.51	31.13
Agricultural Bank of Greece S.A.	51	53	23.69	4.25	18.57	20.39	23.00	25.04	35.45
Caixabank S.A.	52	53	23.65	3.21	18.69	21.07	23.25	24.98	33.33
Banco Espanol de Credito S.A.	53	53	23.38	2.75	17.83	21.58	23.00	24.43	32.58
GAM Holding AG	54	53	23.30	2.11	19.45	22.10	22.93	24.38	29.04
Banco Espirito Santo S.A.	55	53	23.22	4.60	16.15	19.96	22.35	25.87	38.59
Credito Emiliano S.p.A. CredemAz.	56	53	22.46	2.49	17.92	20.95	22.16	23.26	31.03
Mediobanca - Banca di Credito Finanziario S.p.A.	57	53	22.18	3.00	15.84	19.99	22.51	23.49	29.88
Jyske Bank	58	53	21.94	4.22	16.86	18.46	21.33	23.69	35.27
Banco de Sabadell S.A.	59	53	21.77	3.11	17.38	19.88	21.24	22.51	34.76
Banca Popolare di Milano	60	53	21.63	2.39	16.77	19.92	21.53	23.11	29.77
Commercial Bank of Greece	61	53	21.08	11.18	9.28	11.24	16.14	29.64	47.05
Bank of Cyprus	62	53	21.05	3.06	17.04	18.63	20.39	22.59	29.60
Banca Monte dei Paschi di Siena S.p.A.	63	53	19.97	2.13	17.04	18.79	19.35	20.75	28.66
Banche Popolari Unite S.C.A.R.L.	64	53	19.86	4.06	15.43	17.10	18.55	20.31	30.13
Credito Valtellinese S.C.A.R.L. Az.	65	53	18.20	2.50	13.87	16.82	17.99	19.03	26.02
Bank of Greece	66	53	17.80	3.49	15.01	15.80	16.87	17.80	33.13
Banco Pastor S.A.	67	53	16.93	1.70	14.01	15.65	17.20	17.98	21.04
Banca Popolare di Sondrio	68	53	16.19	5.16	10.84	13.20	15.11	17.53	41.54
Banque Cantonale Vaudoise	69	53	15.44	1.98	13.08	14.17	14.80	16.16	22.62
Bank Sarasin & Cie AG	70	14	13.71	0.48	13.14	13.27	13.63	14.06	14.65
ABN AMRO Holding N.V.	71	17	13.62	1.57	11.07	13.16	13.66	14.63	16.46
Banque Nationale de Belgique S.A.	72	53	11.11	1.08	9.57	10.49	10.87	11.40	16.53
Bayerische Hypo- und Vereinsbank AG	73	37	10.54	1.21	8.64	9.76	10.30	10.96	14.11
Caisse Regionale de Credit Agricole Mutuel de Paris et d'Ile de France SC	74	53	10.27	0.81	8.86	9.72	10.06	10.68	12.32
Bank Austria Creditanstalt AG	75	19	7.94	0.27	7.45	7.80	7.96	8.04	8.55
Basler Kantonalbank	76	53	4.02	0.19	3.72	3.90	3.96	4.15	4.62

Table 3 – Statistics on Weekly Systemic Risk Estimates (Subprime Crisis 2008)

Panel B – SRISK (in *bn* EUR)									
Bank	rank	# obs	mean	sd	min	$q = 0.25$	median	$q = 0.75$	max
Deutsche Bank AG	1	53	34.31	10.46	18.07	26.86	32.56	40.23	52.67
Barclays PLC	2	53	30.48	7.70	16.59	26.84	30.61	35.37	42.62
Royal Bank of Scotland Group PLC	3	53	28.97	22.66	2.70	16.08	18.53	58.67	71.22
Crédit Agricole S.A.	4	53	21.65	5.56	10.39	17.65	21.26	24.43	32.02
UBS AG	5	53	17.42	5.62	0.74	15.28	18.09	20.30	29.49
HBOS PLC	6	53	15.19	6.84	1.02	11.80	14.62	21.68	24.71
Intesa Sanpaolo S.p.A.	7	53	13.74	0.50	13.06	13.34	13.50	14.15	14.69
ING Groep N.V.	8	53	13.74	11.11	-1.10	5.19	10.13	24.28	33.84
BNP Paribas S.A.	9	53	13.04	8.49	-2.61	8.05	10.92	15.41	36.77
Ageas N.V.	10	53	12.40	8.76	-0.75	4.20	12.87	20.31	24.78
Société Générale S.A.	11	53	11.18	5.97	-2.08	7.50	10.60	14.65	22.09
Commerzbank AG	12	53	10.20	2.57	6.33	8.49	9.14	12.95	15.01
Dexia S.A.	13	53	8.86	4.96	1.95	4.09	10.03	14.25	16.22
Natixis Banques Populaires	14	53	8.84	3.20	2.18	6.46	9.00	11.58	12.82
Danske Bank	15	53	3.09	3.65	-2.96	0.36	2.38	5.01	9.86
Bank of Ireland	16	53	2.25	2.33	-0.80	-0.22	2.74	4.58	5.51
Alliance & Leicester PLC	17	53	1.82	0.55	0.34	1.50	1.98	2.23	2.56
Banque Nationale de Belgique S.A.	18	53	1.58	0.49	1.19	1.27	1.29	2.23	2.50
Bradford & Bingley PLC	19	39	1.46	0.49	0.53	1.10	1.62	1.90	2.10
Lloyds Banking Group	20	53	1.36	5.03	-8.52	-3.08	1.80	5.46	10.28
Landesbank Berlin Holding AG	21	53	1.24	1.15	-0.17	0.12	1.04	2.52	3.23
IKB Deutsche Industriebank AG	22	53	1.19	0.18	0.69	1.12	1.24	1.32	1.46
Skandinaviska Enskilda Banken AB	23	53	1.14	2.18	-1.66	-0.51	0.52	2.45	5.30
Deutsche Postbank AG	24	53	0.56	2.26	-2.31	-1.15	-0.11	3.40	4.79
Caisse Regionale de Credit Agricole Mutuel de Paris et d'Ile de France SC	25	53	0.28	0.10	0.13	0.20	0.24	0.37	0.47
Allied Irish Banks PLC	26	53	0.15	2.91	-3.97	-2.63	0.18	3.10	4.36
Credit Suisse Group AG	27	53	0.11	5.62	-10.63	-3.20	-1.66	2.74	12.54
Swedbank AB	28	53	0.10	2.01	-2.41	-1.71	-0.38	2.12	3.52
Bank of Greece	29	53	0.06	0.31	-0.23	-0.18	-0.08	0.36	0.67
Basler Kantonalbank	30	53	0.05	0.01	0.02	0.04	0.05	0.06	0.07
Investec PLCShs	31	53	0.01	0.38	-0.80	-0.24	-0.05	0.34	0.60
Irish Bank Resolution Corporation Ltd	32	51	-0.51	1.94	-3.40	-2.38	-0.80	0.91	2.68
Banco Portugues de Investimento S.A.	33	53	-0.53	0.51	-2.09	-0.91	-0.39	-0.17	0.19
Credito Valtellinese S.C.A.R.L. Az.	34	53	-0.54	0.10	-0.73	-0.60	-0.54	-0.47	-0.31
Banca Popolare dell'Emilia Romagna	35	53	-0.54	0.50	-1.60	-0.80	-0.45	-0.20	0.35
Pohjola Bank PLC	36	53	-0.60	0.19	-0.89	-0.77	-0.59	-0.45	-0.16
Credito Emiliano S.p.A. CredemAz.	37	53	-0.66	0.28	-1.14	-0.96	-0.56	-0.45	-0.21
Bank Sarasin & Cie AG	38	14	-0.73	0.16	-1.08	-0.75	-0.70	-0.66	-0.54
Commercial Bank of Greece	39	53	-0.83	0.73	-1.63	-1.53	-0.81	-0.09	0.32
Jyske Bank	40	53	-0.85	0.53	-1.71	-1.22	-1.05	-0.63	0.19
Banca Popolare di Milano	41	53	-0.90	0.50	-1.67	-1.29	-0.95	-0.62	-0.04
Banco Pastor S.A.	42	53	-1.03	0.42	-1.96	-1.34	-1.22	-0.64	-0.36
Agricultural Bank of Greece S.A.	43	53	-1.05	0.52	-2.12	-1.32	-1.07	-0.73	-0.20
Banque Cantonale Vaudoise	44	53	-1.05	0.32	-1.74	-1.34	-0.96	-0.79	-0.53
Bankinter	45	53	-1.06	0.47	-2.06	-1.43	-1.10	-0.59	-0.25
Svenska Handelsbanken AB	46	53	-1.25	1.38	-4.50	-1.94	-1.48	-0.61	1.49
Banca Popolare di Sondrio	47	53	-1.58	0.37	-2.23	-1.88	-1.61	-1.28	-0.79
Banco Espirito Santo S.A.	48	53	-1.93	1.05	-4.37	-2.83	-1.57	-1.11	-0.18
Erste Group Bank AG	49	53	-1.93	2.73	-5.27	-3.65	-2.87	-1.33	3.38
Banca Carige S.p.A.	50	53	-1.96	0.51	-2.96	-2.29	-2.13	-1.70	-0.90
Banca Monte dei Paschi di Siena S.p.A.	51	53	-2.17	1.09	-5.11	-2.96	-2.10	-1.22	-0.33
Banco Espanol de Credito S.A.	52	53	-2.25	0.74	-3.75	-2.84	-2.20	-1.66	-1.12
Bank of Cyprus	53	53	-2.47	1.23	-4.79	-3.13	-2.85	-1.31	-0.13
Banco Popolare Societa CooperativaAz.	54	53	-2.64	1.90	-5.08	-3.83	-3.35	-1.51	1.43
Piraeus Bank S.A.	55	53	-2.86	1.54	-5.78	-3.99	-3.30	-1.76	-0.03
Banco de Sabadell S.A.	56	53	-3.19	0.64	-4.81	-3.73	-3.12	-2.67	-2.24
Banco Comercial Portugues S.A.	57	26	-3.46	0.72	-5.24	-3.89	-3.33	-2.90	-2.49
Alpha Bank A.E.	58	53	-3.75	1.88	-6.87	-5.09	-4.53	-2.85	-0.04
Eurobank Ergasias S.A.	59	53	-3.98	2.24	-8.26	-5.68	-4.40	-2.71	0.01
Banco Popular Espanol S.A.	60	53	-4.36	2.18	-8.49	-6.23	-3.74	-2.25	-1.33
Banche Popolari Unite S.C.A.R.L.	61	53	-4.51	1.61	-7.49	-5.64	-4.69	-4.16	-1.51
KBC Groep N.V.	62	53	-5.02	6.52	-14.09	-10.00	-7.45	-1.77	6.46
Mediobanca - Banca di Credito Finanziario S.p.A.	63	53	-5.15	1.16	-6.99	-6.31	-4.86	-4.27	-3.03
Raiffeisen Bank International AG	64	53	-5.34	3.34	-9.63	-7.64	-6.80	-2.49	0.51
Nordea Bank AB	65	53	-5.42	4.24	-11.84	-8.35	-6.91	-3.97	3.49
UniCredit S.p.A.	66	53	-5.93	13.67	-26.26	-15.83	-10.16	8.08	18.10
GAM Holding AG	67	53	-5.97	1.64	-8.54	-7.27	-6.35	-4.52	-2.89
National Bank of Greece S.A.	68	53	-7.31	3.63	-15.33	-9.35	-8.10	-5.96	-0.92
Caixabank S.A.	69	53	-8.69	2.15	-12.82	-10.31	-9.07	-7.47	-4.62
Standard Chartered PLC	70	53	-11.80	4.95	-18.31	-15.93	-12.94	-9.68	-1.71
Bank Austria Creditanstalt AG	71	19	-12.88	0.21	-13.29	-13.07	-12.80	-12.75	-12.49
Bayerische Hypo- und Vereinsbank AG	72	37	-16.23	1.29	-18.59	-17.12	-15.98	-15.11	-14.62
Banco Bilbao Vizcaya Argentaria S.A.	73	53	-18.39	7.77	-32.97	-24.77	-19.54	-15.17	-3.29
Banco Santander S.A.	74	53	-23.73	10.47	-39.49	-30.96	-26.74	-17.86	-0.95
ABN AMRO Holding N.V.	75	17	-31.73	2.22	-35.86	-32.60	-31.77	-30.87	-27.30
HSBC Holdings	76	53	-43.01	13.51	-60.29	-51.57	-47.76	-39.90	-5.37

Table 3 (continued) – Statistics on Weekly Systemic Risk Estimates (Subprime Crisis 2008)

Panel C – ΔMultiCoVaR (in %)									
Bank	rank	# obs	mean	sd	min	$q = 0.25$	median	$q = 0.75$	max
Natixis Banques Populaires	1	53	32.35	3.29	23.04	30.84	33.50	34.78	37.23
Crédit Agricole S.A.	2	53	29.61	4.46	19.89	28.83	30.10	32.35	37.11
Banca Monte dei Paschi di Siena S.p.A.	3	53	28.44	5.99	15.76	25.47	29.89	33.66	36.00
Banche Popolari Unite S.C.A.R.L.	4	53	28.03	5.93	15.34	25.45	28.74	33.18	37.34
Skandinaviska Enskilda Banken AB	5	53	27.88	4.37	17.87	24.72	28.94	31.40	34.71
Irish Bank Resolution Corporation Ltd	6	51	27.31	3.62	18.88	25.20	28.11	30.38	31.98
Commerzbank AG	7	53	27.30	4.12	17.40	25.86	27.77	30.64	33.63
Nordea Bank AB	8	53	27.17	5.15	16.25	24.26	27.44	31.41	35.24
UniCredit S.p.A.	9	53	27.03	4.01	17.92	25.56	27.89	29.85	34.44
Mediobanca - Banca di Credito Finanziario S.p.A.	10	53	26.96	5.44	15.87	23.23	26.05	30.31	36.52
Banco Bilbao Vizcaya Argentaria S.A.	11	53	26.95	4.08	17.09	25.87	27.56	29.94	33.69
Banca Popolare di Milano	12	53	26.89	5.86	15.54	23.13	26.59	31.39	37.56
Banco Santander S.A.	13	53	26.86	3.72	17.60	25.76	27.98	29.08	33.07
Banco Popolare Societa CooperativaAz.	14	53	26.82	4.92	15.33	24.42	27.47	30.39	34.72
Société Générale S.A.	15	53	26.79	3.85	19.00	23.72	27.54	30.19	32.41
Deutsche Bank AG	16	53	26.77	4.26	17.18	25.32	27.15	29.64	33.96
Banco de Sabadell S.A.	17	53	26.71	4.79	15.52	24.33	27.65	30.16	33.26
Investec PLCShs	18	53	26.43	4.35	16.43	23.88	26.62	29.80	35.09
Barclays PLC	19	53	26.37	4.58	16.26	23.50	27.46	30.44	31.64
Allied Irish Banks PLC	20	53	25.92	4.87	15.01	22.09	26.59	29.99	32.38
BNP Paribas S.A.	21	53	25.84	3.63	17.49	24.39	27.05	27.74	31.93
Lloyds Banking Group	22	53	25.83	5.56	15.49	21.67	25.66	31.67	33.65
Credit Suisse Group AG	23	53	25.80	4.46	15.77	23.84	26.81	28.81	33.81
HSBC Holdings	24	53	25.78	4.23	15.74	24.10	26.99	28.99	32.47
Intesa Sanpaolo S.p.A.	25	53	25.54	5.01	14.57	23.95	26.20	28.57	35.78
Swedbank AB	26	53	24.99	4.16	15.79	23.33	26.21	28.32	31.58
ING Groep N.V.	27	53	24.96	4.41	15.86	21.75	24.64	29.09	31.17
Raiffeisen Bank International AG	28	53	24.95	3.88	16.00	22.74	25.96	27.88	31.23
Ageas N.V.	29	53	24.89	4.14	14.94	22.23	25.59	28.31	30.67
Bankinter	30	53	24.49	4.39	14.46	22.21	25.59	28.02	31.00
HBOS PLC	31	53	24.38	3.50	15.54	23.07	25.44	27.02	28.08
Banco Popular Espanol S.A.	32	53	24.27	4.12	15.13	21.95	25.06	27.30	30.20
GAM Holding AG	33	53	24.03	5.59	12.65	20.33	23.86	28.74	34.72
KBC Groep N.V.	34	53	23.95	4.23	14.56	21.69	24.38	27.73	29.72
Dexia S.A.	35	53	23.90	3.69	15.75	22.37	24.46	27.38	29.22
Svenska Handelsbanken AB	36	53	23.48	4.30	14.73	21.24	24.91	26.70	30.42
Erste Group Bank AG	37	53	23.39	4.18	14.54	21.11	24.12	26.20	31.00
UBS AG	38	53	23.03	3.24	15.11	21.89	23.83	25.52	26.62
Credito Valtellinese S.C.A.R.L. Az.	39	53	23.01	5.09	13.60	19.15	23.34	26.04	32.22
Royal Bank of Scotland Group PLC	40	53	22.85	4.43	13.75	20.24	23.57	26.65	29.15
Credito Emiliano S.p.A. CredemAz.	41	53	22.85	4.76	13.41	20.14	23.19	26.87	30.21
Standard Chartered PLC	42	53	22.53	4.40	13.50	19.87	23.47	25.63	29.02
Banca Carige S.p.A.	43	53	22.14	4.23	12.06	19.15	23.53	25.56	28.11
Jyske Bank	44	53	21.75	4.24	12.95	18.59	22.97	24.97	28.29
Danske Bank	45	53	21.50	4.07	13.08	19.11	21.99	24.72	27.17
Banco Espanol de Credito S.A.	46	53	21.39	3.91	12.48	19.71	21.97	24.68	26.18
Pohjola Bank PLC	47	53	21.04	5.33	11.81	17.47	21.17	26.30	30.40
Bank of Ireland	48	53	20.93	4.18	11.68	19.06	21.39	23.94	27.02
Banco Portugues de Investimento S.A.	49	53	20.55	5.27	9.78	16.44	20.93	25.38	28.19
Caixabank S.A.	50	53	20.48	3.94	12.78	18.36	20.54	23.62	28.11
Alliance & Leicester PLC	51	53	20.28	4.38	11.36	17.47	20.57	24.28	26.86
National Bank of Greece S.A.	52	53	19.85	4.25	11.11	17.16	19.94	23.74	25.49
Banco Espirito Santo S.A.	53	53	19.83	4.35	12.01	16.89	19.60	23.21	27.45
Alpha Bank A.E.	54	53	19.31	4.39	10.87	16.26	19.32	22.96	26.71
Piraeus Bank S.A.	55	53	18.88	4.39	9.39	16.39	18.59	23.66	25.04
Banco Pastor S.A.	56	53	18.84	4.14	10.63	16.09	19.02	22.38	24.62
Eurobank Ergasias S.A.	57	53	18.83	4.81	9.48	15.31	18.74	23.97	27.31
Deutsche Postbank AG	58	53	18.06	4.03	8.57	15.82	18.07	21.52	24.59
IKB Deutsche Industriebank AG	59	53	16.99	4.40	9.59	13.55	16.81	21.00	24.54
Bradford & Bingley PLC	60	39	16.99	3.92	11.14	14.21	16.41	19.63	26.88
Agricultural Bank of Greece S.A.	61	53	16.94	4.70	8.91	12.92	16.72	21.75	24.43
Banca Popolare di Sondrio	62	53	16.92	4.19	7.63	14.21	17.24	21.29	23.56
Bank of Cyprus	63	53	15.18	3.32	8.72	12.69	15.59	18.05	20.97
Banca Popolare dell'Emilia Romagna	64	53	14.64	4.33	7.69	11.13	13.67	18.88	22.41
Bank of Greece	65	53	12.90	3.23	7.13	11.00	13.00	15.50	18.71
Banque Cantonale Vaudoise	66	53	12.57	3.46	6.48	10.64	13.11	14.95	17.77
Bayerische Hypo- und Vereinsbank AG	67	37	12.41	3.08	7.42	9.94	12.02	13.72	20.09
Commercial Bank of Greece	68	53	11.75	3.30	6.56	9.07	11.42	13.90	17.72
Banque Nationale de Belgique S.A.	69	53	11.09	2.48	5.74	9.53	11.72	13.13	14.46
ABN AMRO Holding N.V.	70	17	11.04	2.89	5.16	9.97	11.23	12.11	16.84
Landesbank Berlin Holding AG	71	51	9.50	2.46	5.05	7.82	9.45	11.14	13.85
Caisse Regionale de Credit Agricole Mutuel de Paris et d'Ile de France SC	72	53	8.23	2.10	4.33	6.85	8.10	9.69	12.45
Banco Comercial Portugues S.A.	73	26	7.55	1.39	5.80	6.64	7.15	7.95	10.85
Bank Austria Creditanstalt AG	74	19	1.38	0.35	0.83	1.10	1.42	1.62	2.02
Bank Sarasin & Cie AG	75	14	0.17	1.37	-1.58	-0.86	-0.36	1.55	2.10
Basler Kantonalbank	76	53	-4.77	2.40	-10.10	-6.00	-4.38	-2.90	-0.89

Table 3 (continued) – Statistics on Weekly Systemic Risk Estimates (Subprime Crisis 2008)

Panel A – MultiMES (in %)									
Bank	rank	# obs	mean	sd	min	$q = 0.25$	median	$q = 0.75$	max
Banca Popolare dell'Emilia Romagna	1	52	56.51	9.72	34.30	50.12	56.21	63.93	72.37
Société Générale S.A.	2	52	46.13	8.12	30.75	40.28	44.35	52.59	62.97
Ageas N.V.	3	52	45.76	6.29	32.00	41.60	46.59	50.21	60.20
ING Groep N.V.	4	52	44.23	6.67	31.22	39.17	44.28	49.90	57.12
UniCredit S.p.A.	5	52	44.15	5.21	36.85	40.07	43.56	47.38	55.95
BNP Paribas S.A.	6	52	40.98	5.15	32.56	37.39	38.53	45.88	53.46
Dexia S.A.	7	44	40.89	7.95	27.96	35.24	39.03	44.93	60.40
KBC Groep N.V.	8	52	40.57	6.16	31.31	36.04	39.47	44.68	57.24
Eurobank Ergasias S.A.	9	52	39.15	6.43	28.83	34.49	37.64	42.48	53.11
Royal Bank of Scotland Group PLC	10	52	39.02	4.75	31.92	36.40	38.25	41.94	53.56
Agricultural Bank of Greece S.A.	11	31	38.83	8.76	26.77	32.56	36.65	43.15	58.62
National Bank of Greece S.A.	12	52	38.37	7.78	27.59	32.44	36.99	43.17	55.26
Piraeus Bank S.A.	13	52	37.59	6.38	28.54	32.73	36.19	41.47	53.04
Barclays PLC	14	52	37.31	6.68	27.55	31.69	36.83	43.22	48.78
Crédit Agricole S.A.	15	52	37.03	5.00	30.72	32.85	35.01	42.12	48.40
Landesbank Berlin Holding AG	16	52	36.33	8.56	26.21	31.14	33.39	38.92	71.44
Alpha Bank A.E.	17	35	34.89	4.48	27.01	31.64	34.02	36.98	49.31
Intesa Sanpaolo S.p.A.	18	52	34.68	3.83	28.39	31.80	34.48	36.90	43.93
Banco Bilbao Vizcaya Argentaria S.A.	19	52	34.33	4.16	28.55	31.46	33.75	35.56	48.59
Banco Santander S.A.	20	52	33.13	4.43	23.61	29.18	33.52	36.04	45.52
Commerzbank AG	21	52	31.95	2.24	28.05	30.34	31.93	33.24	38.10
Commercial Bank of Greece	22	21	31.85	7.68	25.80	27.80	29.76	33.22	62.73
Deutsche Bank AG	23	52	31.33	5.15	24.57	27.23	29.28	35.83	42.42
Banco Espirito Santo S.A.	24	52	31.12	6.02	22.31	26.74	29.84	33.33	48.21
Raiffeisen Bank International AG	25	52	31.06	3.85	26.58	28.24	29.66	32.33	40.50
Banco Popolare Societa CooperativaAz.	26	52	30.07	3.04	24.92	27.86	29.75	31.90	37.71
Natixis Banques Populaires	27	52	29.43	4.45	24.93	25.66	26.93	33.46	38.91
Banche Popolari Unite S.C.A.R.L.	28	52	29.41	3.88	22.07	26.35	29.41	31.46	38.49
Banco Popular Espanol S.A.	29	52	29.22	4.27	21.68	25.79	28.40	31.00	39.25
Bankinter	30	52	28.87	4.33	20.62	25.39	29.11	31.05	41.35
Erste Group Bank AG	31	52	28.75	5.62	21.75	24.55	26.32	34.32	41.16
UBS AG	32	52	27.73	2.93	21.29	25.45	28.12	30.04	32.64
Banca Popolare di Sondrio	33	52	27.68	5.55	16.91	24.08	26.57	32.07	42.50
Swedbank AB	34	52	27.34	2.26	23.42	25.88	26.91	28.24	32.97
Danske Bank	35	52	27.32	5.07	19.76	23.08	25.97	32.38	36.53
Mediobanca - Banca di Credito Finanziario S.p.A.	36	52	27.08	3.36	20.08	25.76	27.16	28.18	34.45
Skandinaviska Enskilda Banken AB	37	52	27.06	2.46	22.70	25.35	26.92	28.42	32.97
Credito Emiliano S.p.A. CredemAz.	38	52	26.91	2.85	21.09	25.07	26.38	28.33	34.42
Banco Portugues de Investimento S.A.	39	33	26.50	2.89	21.46	24.95	26.13	28.40	33.59
Banca Carige S.p.A.	40	52	26.48	3.40	20.67	24.11	26.00	28.85	33.56
Nordea Bank AB	41	52	25.92	3.72	20.04	23.16	24.68	28.68	34.32
Credit Suisse Group AG	42	52	25.84	3.55	17.97	23.51	25.85	27.92	32.60
Standard Chartered PLC	43	52	25.25	2.87	20.07	23.13	25.01	27.71	30.02
Pohjola Bank PLC	44	52	25.13	1.80	22.16	23.95	24.91	25.72	29.56
Banco Espanol de Credito S.A.	45	52	24.97	3.99	18.01	22.15	25.43	27.59	34.33
Banca Popolare di Milano	46	12	24.79	0.58	23.71	24.47	24.70	25.36	25.55
Banca Civica S.A.	47	23	24.06	1.43	22.22	23.07	23.79	24.97	27.82
Banco de Sabadell S.A.	48	52	23.90	4.64	16.37	21.57	23.39	25.58	36.28
Bank of Cyprus	49	48	23.16	2.54	18.89	20.99	22.67	24.90	30.95
Svenska Handelsbanken AB	50	52	23.03	3.06	18.00	20.86	22.47	24.96	29.88
Caixabank S.A.	51	52	22.95	3.07	19.80	21.02	22.06	23.41	36.82
Credito Valtellinese S.C.A.R.L. Az.	52	52	22.04	3.14	17.13	19.22	22.38	24.35	29.67
GAM Holding AG	53	52	21.78	1.38	19.37	20.86	21.59	22.53	26.97
Jyske Bank	54	52	21.56	3.44	16.15	18.98	20.79	23.94	30.80
HSBC Holdings	55	52	21.15	4.39	11.51	19.10	21.46	23.59	29.37
Investec PLCShs	56	52	20.77	1.41	17.88	19.83	20.94	21.79	23.90
Bank of Greece	57	52	20.74	4.28	15.20	18.14	19.49	21.47	37.23
Deutsche Postbank AG	58	52	19.77	2.39	15.64	18.31	19.34	21.22	27.04
Julius Bär	59	52	19.07	2.38	15.59	16.66	19.14	20.91	23.31
Banco Pastor S.A.	60	52	17.74	1.92	14.76	16.17	18.12	18.86	25.93
Bank Sarasin & Cie AG	61	52	14.18	0.51	12.99	13.88	14.17	14.38	15.68
Banque Cantonale Vaudoise	62	52	13.71	1.12	11.69	12.95	13.55	14.18	16.75
Banque Nationale de Belgique S.A.	63	52	10.84	0.39	10.10	10.56	10.82	11.08	11.72
Caisse Regionale de Credit Agricole Mutuel de Paris et d'Ile de France SC	64	52	10.14	0.70	9.14	9.68	10.26	10.42	13.24
Basler Kantonalbank	65	52	4.46	0.93	3.74	4.23	4.34	4.55	10.85

Table 4 – Statistics on Weekly MultiMES Estimates (Euro Crisis 2011)

Panel B – SRISK (in *bn* EUR)									
Bank	rank	# obs	mean	sd	min	$q = 0.25$	median	$q = 0.75$	max
Royal Bank of Scotland Group PLC	1	52	38.58	2.45	34.72	36.96	37.73	39.43	44.97
Crédit Agricole S.A.	2	52	36.33	4.07	29.73	32.90	35.59	40.06	43.92
Deutsche Bank AG	3	52	32.06	8.24	17.57	27.40	31.02	39.65	44.17
BNP Paribas S.A.	4	52	31.35	8.83	16.71	25.05	28.68	38.88	51.89
Barclays PLC	5	52	30.52	8.61	15.12	26.58	32.05	36.50	42.58
ING Groep N.V.	6	52	20.85	4.59	12.36	17.52	19.56	25.39	27.67
Société Générale S.A.	7	52	18.65	6.56	9.25	12.69	15.10	25.93	27.87
Commerzbank AG	8	52	18.29	2.14	14.92	16.56	18.22	19.63	22.83
Intesa Sanpaolo S.p.A.	9	52	17.22	0.63	16.35	16.62	17.22	17.57	18.24
Dexia S.A.	10	44	15.11	0.85	13.60	14.29	15.11	15.97	16.23
UniCredit S.p.A.	11	52	12.57	5.41	4.15	7.51	12.11	17.77	20.40
Natixis Banques Populaires	12	52	7.72	2.09	3.83	6.37	8.38	9.16	11.11
KBC Groep N.V.	13	52	4.76	1.42	2.91	3.54	4.29	5.87	7.73
Danske Bank	14	52	4.55	1.93	1.68	2.70	4.67	6.01	7.85
Deutsche Postbank AG	15	52	3.09	0.40	2.10	2.79	3.27	3.39	3.57
Bank of Greece	16	52	2.89	0.55	2.45	2.52	2.61	3.03	3.86
Banco Popolare Societa CooperativaAz.	17	52	1.77	0.66	0.45	1.25	1.97	2.31	2.65
Landesbank Berlin Holding AG	18	52	1.69	0.37	1.21	1.40	1.58	1.90	2.85
Eurobank Ergasias S.A.	19	52	1.61	0.53	0.84	1.15	1.48	2.19	2.38
Banque Nationale de Belgique S.A.	20	52	1.51	0.26	1.07	1.44	1.55	1.68	1.98
Credit Suisse Group AG	21	52	1.45	6.00	-7.60	-2.81	-0.39	8.13	10.20
Banche Popolari Unite S.C.A.R.L.	22	52	1.19	0.76	-0.25	0.80	1.16	1.88	2.17
Banca Civica S.A.	23	13	1.17	0.02	1.11	1.16	1.17	1.18	1.20
Piraeus Bank S.A.	24	52	0.96	0.40	0.28	0.61	0.87	1.33	1.51
Banco Espanol de Credito S.A.	25	52	0.92	0.39	0.27	0.58	0.99	1.21	1.60
Banca Popolare dell'Emilia Romagna	26	52	0.81	0.24	0.29	0.62	0.82	1.01	1.18
National Bank of Greece S.A.	27	52	0.78	1.34	-1.64	-0.63	0.74	2.14	2.63
Alpha Bank A.E.	28	35	0.64	0.31	0.15	0.31	0.70	0.90	1.30
Banco Portugues de Investimento S.A.	29	33	0.61	0.11	0.44	0.51	0.61	0.69	0.77
Agricultural Bank of Greece S.A.	30	31	0.51	0.19	-0.01	0.50	0.54	0.62	0.75
Banco Espirito Santo S.A.	31	52	0.46	0.55	-0.28	-0.04	0.39	0.81	1.50
Caisse Regionale de Credit Agricole Mutuel de Paris et d'Ile de France SC	32	52	0.43	0.06	0.32	0.38	0.41	0.50	0.53
Ageas N.V.	33	52	0.40	0.68	-0.78	-0.24	0.30	1.02	1.35
Banca Popolare di Milano	34	12	0.34	0.04	0.28	0.31	0.33	0.36	0.42
Commercial Bank of Greece	35	21	0.30	0.07	0.22	0.23	0.26	0.35	0.49
Banco Pastor S.A.	36	52	0.21	0.06	0.05	0.16	0.23	0.26	0.29
Credito Valtellinese S.C.A.R.L. Az.	37	52	0.20	0.09	0.07	0.12	0.20	0.26	0.37
Bankinter	38	52	0.12	0.12	-0.11	0.02	0.14	0.21	0.33
Basler Kantonalbank	39	52	0.11	0.06	-0.01	0.04	0.11	0.17	0.22
Banco Popular Espanol S.A.	40	52	0.03	0.43	-0.67	-0.32	-0.01	0.43	0.81
Credito Emiliano S.p.A. CredemAz.	41	52	-0.09	0.22	-0.45	-0.29	-0.16	0.11	0.19
Bank of Cyprus	42	48	-0.11	0.56	-1.18	-0.54	-0.19	0.39	0.87
UBS AG	43	52	-0.21	5.99	-11.70	-4.40	-1.74	5.14	10.37
Banco de Sabadell S.A.	44	52	-0.40	0.28	-0.90	-0.58	-0.43	-0.23	0.23
Jyske Bank	45	52	-0.42	0.34	-0.89	-0.75	-0.40	-0.09	0.12
Pohjola Bank PLC	46	52	-0.53	0.19	-0.80	-0.71	-0.51	-0.39	-0.16
Investec PLCShs	47	52	-0.56	0.32	-1.23	-0.80	-0.62	-0.24	0.09
Banca Popolare di Sondrio	48	52	-0.56	0.15	-0.80	-0.67	-0.57	-0.47	-0.22
Banca Carige S.p.A.	49	52	-0.73	0.24	-1.22	-0.91	-0.74	-0.54	-0.30
Bank Sarasin & Cie AG	50	52	-0.84	0.19	-1.17	-0.97	-0.88	-0.63	-0.50
Skandinaviska Enskilda Banken AB	51	52	-1.32	1.92	-4.03	-3.24	-1.50	0.44	1.71
Raiffeisen Bank International AG	52	52	-1.67	1.93	-3.87	-3.20	-2.54	-0.12	1.92
GAM Holding AG	53	52	-1.68	0.36	-2.19	-2.05	-1.75	-1.31	-1.14
Erste Group Bank AG	54	52	-1.70	2.83	-5.05	-3.86	-3.48	1.26	3.49
Swedbank AB	55	52	-1.76	1.06	-3.19	-2.67	-1.90	-1.16	0.61
Mediobanca - Banca di Credito Finanziario S.p.A.	56	52	-1.94	0.66	-2.77	-2.47	-2.02	-1.62	-0.32
Banque Cantonale Vaudoise	57	52	-2.08	0.18	-2.50	-2.17	-2.11	-1.95	-1.65
Svenska Handelsbanken AB	58	52	-3.03	1.40	-5.75	-3.88	-3.12	-1.95	-0.54
Julius Bär	59	52	-3.79	0.43	-4.85	-4.00	-3.75	-3.49	-3.03
Nordea Bank AB	60	52	-4.45	4.39	-12.40	-7.68	-5.26	-0.04	1.83
Banco Santander S.A.	61	52	-5.76	5.57	-15.98	-10.86	-6.41	-0.27	4.03
Banco Bilbao Vizcaya Argentaria S.A.	62	52	-6.12	2.21	-9.63	-8.07	-6.16	-4.52	-1.16
Caixabank S.A.	63	52	-10.20	1.35	-12.32	-11.63	-10.10	-9.11	-7.69
Standard Chartered PLC	64	52	-19.91	3.09	-27.05	-22.12	-19.19	-17.68	-13.22
HSBC Holdings	65	52	-41.43	13.44	-71.20	-48.58	-42.44	-28.69	-22.40

Table 4 (continued) – Statistics on Weekly Systemic Risk Estimates (Euro Crisis 2011)

Panel C – ΔMultiCoVaR (in %)									
Bank	rank	# obs	mean	sd	min	$q = 0.25$	median	$q = 0.75$	max
Natixis Banques Populaires	1	52	30.84	3.45	24.14	28.01	30.90	33.77	37.25
Crédit Agricole S.A.	2	52	25.97	5.21	17.96	20.48	25.68	30.84	34.07
Skandinaviska Enskilda Banken AB	3	52	24.72	5.93	16.77	19.24	23.14	30.57	34.64
Investec PLCShs	4	52	23.87	6.49	16.27	17.91	21.61	29.95	37.26
Société Générale S.A.	5	52	23.32	3.95	17.29	19.90	22.74	26.34	32.04
Commerzbank AG	6	52	23.10	5.74	14.32	17.62	22.21	29.04	31.61
Banche Popolari Unite S.C.A.R.L.	7	52	23.05	6.72	11.94	17.77	21.91	29.19	34.68
Deutsche Bank AG	8	52	22.94	5.31	15.09	17.85	21.57	28.42	30.84
Banco Popolare Societa CooperativaAz.	9	52	22.89	5.24	14.89	17.97	22.11	27.46	32.37
Banco Santander S.A.	10	52	22.85	5.32	15.03	17.91	21.00	27.90	31.84
Nordea Bank AB	11	52	22.68	6.48	14.12	16.59	20.64	29.20	34.26
Barclays PLC	12	52	22.55	5.32	13.54	17.75	20.79	27.72	32.13
Banco Bilbao Vizcaya Argentaria S.A.	13	52	22.51	5.76	15.03	17.05	19.91	28.76	31.12
Mediobanca - Banca di Credito Finanziario S.p.A.	14	52	22.11	4.24	16.20	18.57	20.93	25.07	32.46
UniCredit S.p.A.	15	52	21.96	4.02	15.99	18.22	20.82	25.73	29.57
Banco de Sabadell S.A.	16	52	21.91	6.33	13.40	16.06	20.21	27.71	33.44
Credit Suisse Group AG	17	52	21.55	6.49	13.33	15.74	19.36	28.27	32.87
Raiffeisen Bank International AG	18	52	21.44	4.58	15.05	17.08	20.45	25.59	29.16
BNP Paribas S.A.	19	52	21.35	3.91	15.54	17.59	21.04	24.40	28.30
Swedbank AB	20	52	21.32	5.59	13.82	15.88	19.74	27.03	29.78
Banco Popular Espanol S.A.	21	52	21.17	6.06	13.02	15.47	19.34	27.40	32.33
Intesa Sanpaolo S.p.A.	22	52	21.16	5.51	13.59	16.01	19.90	26.51	30.75
Ageas N.V.	23	52	21.15	5.22	13.87	16.22	19.50	26.41	30.79
HSBC Holdings	24	52	20.98	6.49	12.93	15.10	17.83	27.87	33.00
ING Groep N.V.	25	52	20.95	4.96	13.77	16.55	19.40	25.52	30.60
Bankinter	26	52	20.93	5.97	13.40	15.11	18.96	26.68	32.52
Pohjola Bank PLC	27	52	20.42	6.73	11.73	14.47	17.62	26.91	33.18
UBS AG	28	52	20.32	5.30	12.97	15.24	19.00	25.67	29.37
KBC Groep N.V.	29	52	20.00	4.79	13.99	15.96	18.15	24.38	29.32
Erste Group Bank AG	30	52	19.94	5.57	12.37	14.57	18.09	24.80	30.19
Svenska Handelsbanken AB	31	52	19.94	5.60	12.06	14.68	18.27	25.49	29.35
Banca Popolare di Sondrio	32	52	19.68	4.09	13.14	15.77	18.88	23.32	26.98
Credito Valtellinese S.C.A.R.L. Az.	33	52	19.52	5.58	11.23	14.38	18.26	25.10	30.19
Dexia S.A.	34	44	19.35	4.57	13.11	15.57	17.08	23.25	28.67
Royal Bank of Scotland Group PLC	35	52	19.06	4.79	12.67	14.74	17.32	23.83	28.26
Credito Emiliano S.p.A. CredemAz.	36	52	18.66	4.84	12.20	14.18	17.40	23.26	28.53
Standard Chartered PLC	37	52	18.64	4.99	12.55	14.14	16.94	23.93	28.17
Banca Popolare di Milano	38	12	18.37	1.65	16.42	17.06	18.58	19.27	22.17
Banca Carige S.p.A.	39	52	18.18	4.31	9.23	15.03	17.33	21.60	26.30
Caixabank S.A.	40	52	17.69	5.11	9.72	13.60	15.79	22.48	27.69
GAM Holding AG	41	52	17.43	7.61	7.47	10.71	13.18	25.01	32.24
Jyske Bank	42	52	17.22	5.45	9.83	12.16	16.24	22.16	26.55
Banco Espanol de Credito S.A.	43	52	17.05	4.75	10.17	12.44	16.00	21.90	25.31
Banco Portugues de Investimento S.A.	44	33	16.98	3.22	12.08	14.83	16.26	18.03	24.72
Danske Bank	45	52	16.42	5.12	9.64	11.75	14.59	20.61	27.11
Julius Bär	46	52	15.93	5.54	9.97	10.97	12.58	21.64	26.13
Banco Espirito Santo S.A.	47	52	15.86	4.74	9.31	11.51	14.56	19.37	25.53
Banco Pastor S.A.	48	52	15.28	4.11	9.87	11.42	13.98	18.95	23.75
Banca Popolare dell'Emilia Romagna	49	52	14.77	4.51	7.60	10.78	14.57	18.80	23.38
Banca Civica S.A.	50	23	13.58	1.24	11.66	12.86	13.56	14.29	16.52
Deutsche Postbank AG	51	52	13.34	4.35	8.37	9.42	11.95	17.20	21.51
National Bank of Greece S.A.	52	52	13.25	3.46	8.17	9.58	12.80	15.86	19.13
Alpha Bank A.E.	53	35	12.60	2.50	9.65	10.79	11.41	14.20	18.86
Bank of Cyprus	54	48	12.08	3.30	8.24	9.14	10.95	15.01	20.40
Eurobank Ergasias S.A.	55	52	11.93	3.11	7.63	9.08	11.25	14.25	17.98
Piraeus Bank S.A.	56	52	11.63	4.04	5.62	7.57	11.85	15.49	18.85
Bank of Greece	57	52	10.03	2.87	6.21	7.32	9.46	12.95	16.12
Banque Cantonale Vaudoise	58	52	9.90	4.38	5.12	6.26	7.16	14.46	18.62
Banque Nationale de Belgique S.A.	59	52	8.56	3.24	4.73	5.61	7.35	11.64	15.39
Agricultural Bank of Greece S.A.	60	31	7.84	1.27	5.26	6.94	7.69	8.41	10.54
Landesbank Berlin Holding AG	61	51	7.11	2.68	3.84	4.68	5.94	9.73	13.57
Commercial Bank of Greece	62	21	6.63	0.72	5.08	6.16	6.75	7.04	8.07
Caisse Regionale de Credit Agricole Mutuel de Paris et d'Ile de France SC	63	52	6.54	2.05	3.99	4.73	5.74	8.49	11.17
Bank Sarasin & Cie AG	64	52	0.98	1.42	-1.52	0.32	0.59	1.09	5.48
Basler Kantonalbank	65	52	-2.17	1.63	-6.22	-2.60	-2.06	-1.12	1.26

Table 4 (continued) – Statistics on Weekly Systemic Risk Estimates (Euro Crisis 2011)

Panel A – MultiMES (in %)

Lagged variables	estimate	std error	t-value	p-value
Intercept	-0.2137	0.3753	-0.5694	0.5691
MultiMES	0.9455	0.0043	220.4346	0.0000
Leverage	0.0011	0.0007	1.6112	0.1072
Market-to-Book	0.0232	0.0158	1.4715	0.1412
Profitability	-0.0037	0.0089	-0.4167	0.6769
Log Assets	0.1442	0.0334	4.3195	0.0000
	mean sum sq	R^2	F-value	p-value
Summary Stats	3.5062	0.9023	11825.7400	0.0000

Panel B – SRISK (in *bn* EUR)

Lagged variables	estimate	std error	t-value	p-value
Intercept	-1.0347	0.2107	-4.9112	0.0000
SRISK	0.9878	0.0019	519.1386	0.0000
Leverage	0.0001	0.0004	0.2513	0.8016
Market-to-Book	0.0075	0.0087	0.8625	0.3885
Profitability	0.0066	0.0049	1.3559	0.1752
Log Assets	0.0923	0.0176	5.2561	0.0000
	mean sum sq	R^2	F-value	p-value
Summary Stats	1.9268	0.9801	60842.4000	0.0000

Panel C – ΔMultiCoVaR (in %)

Lagged variables	estimate	std error	t-value	p-value
Intercept	-0.7231	0.2681	-2.6974	0.0070
ΔMultiCoVaR	0.9237	0.0049	189.7274	0.0000
Leverage	-0.0014	0.0005	-2.8269	0.0047
Market-to-Book	0.0025	0.0112	0.2246	0.8223
Profitability	0.0056	0.0063	0.8919	0.3725
Log Assets	0.1732	0.0245	7.0747	0.0000
	mean sum sq	R^2	F-value	p-value
Summary Stats	2.4787	0.8786	9204.1450	0.0000

Table 5 – Determinants of Systemic Risk at the Bank Level

Table 5 – continued:

All figures are estimated from monthly averaged time series of systemic risk measures at the bank level and monthly (linearly interpolated) time series of bank level balance sheet characteristics covering the period from July 2005 to June 2013. We estimate the equation $SysRisk_t^{bank} = \alpha + \beta\, SysRisk_{t-1}^{bank} + \gamma\, BalanceSheetCharacteristics_{t-1}^{bank} + \epsilon_t$, where $SysRisk_t^{bank}$ represents any of the three risk measures MultiCoVaR, MultiMES or SRISK at the bank level and $BalanceSheetCharacteristics_{t-1}^{bank}$ is a vector consisting of the four lagged balance sheet characteristics leverage (lev), market-to-book ratio (mb), profitability (pf), and the logarithm of total assets (ta) as its elements. Parameters α, β, and $\gamma \equiv (\gamma_{lev}, \gamma_{mb}, \gamma_{pf}, \gamma_{ta})$ denote the regression coefficients and ϵ_t is Gaussian White Noise. The table is organized as follows. Panel A presents the results for the regression with $SysRisk$ = MultiMES, Panel B the results for $SysRisk$ = SRISK, and Panel C the results for $SysRisk = \Delta$MultiCoVaR. The names of the lagged explanatory variables to which the regression coefficients refer are given in the respective rows. We provide the coefficients' estimates, standard errors, t- and p-values as well as various summary statistics in the columns. For a detailed description of the regression variables, we refer to Table 6.

Label	Description	Sampling Frequency	Data Source
Financial Market Variables			
EURIBOR-OIS Spread	EURIBOR 12 month rate – EURO 12 month OIS rate (in %)	weekly	Datastream
Volatility	VSTOXX index (in %)	weekly	Datastream
Balance Sheet Variables			
Leverage	market valued total assets / market valued equity, where market valued total assets = book valued total debt + market valued equity	quarterly	Datastream
Market-to-Book	market valued equity / book valued equity	quarterly	Datastream
Profitability	net income / book valued total assets (in %)	quarterly	Datastream
Nonperforming Loans	nonperforming loans / total gross loans (EU27, in %)	annual	Worldbank
Macro-economic Variables			
Sentiment	Economic Sentiment Indicator (by the European Commission)	monthly	Datastream
Production	Industrial Production Index excluding construction (EU27)	monthly	Datastream
House Prices	EU House Price Index (EU evolving)	quarterly	Datastream
Credit Private	domestic credit to the private sector (EU27, in % of GDP)	annual	Worldbank
Government Debt	government debt (EU27, in % of GDP)	annual	ECB
Real GDP	real quarterly gross domestic product (EU27, in *bn* EUR)	quarterly	Datastream

Table 6 – Description of Variables used in the VAR Regressions

	FINANCIAL MARKET			BALANCE SHEET					MACRO-ECONOMY						
	Systemic Risk	EURIBOR-OIS Spread	Volatility	Systemic Risk	Leverage	Market-to-Book	Profitability	Nonperforming Loans	Systemic Risk	Sentiment	Production	House Prices	Credit Private	Government Debt	Real GDP
Panel A – MultiMES (in %)															
MultiMES	0.040	0.085 ***	3.580 ***	-0.011	-0.062	-0.004	-0.006 **	0.000	0.009	-0.455 ***	0.069	-0.053 ***	0.027	-0.004	-0.842 ***
EURIBOR-OIS Spread	1.468	0.174	-0.967												
Volatility	-0.080 ***	0.004	-0.031												
Leverage				0.013	0.385 **	-0.004	0.000	-0.002							
Market-to-Book				0.489	3.107	-0.041	0.011	-0.025							
Profitability				5.004	-4.511	0.060	0.684 ***	-0.439 ***							
Nonperforming Loans				-0.999	-2.907	0.108	0.018	0.982 ***							
Sentiment									0.067	0.401 ***	0.261 ***	0.029 **	0.021	-0.005	0.493 **
Production									-0.058	0.213	-0.260 **	0.028	-0.047	0.001	1.329 ***
House Prices									-0.277	1.258 *	0.121	0.805 ***	-0.341	-0.040	1.890
Credit Private									-0.029	-0.061	-0.136 *	0.009	0.885 ***	-0.007	-0.207
Government Debt									-0.447	2.194 ***	0.416	-0.173 **	-0.130	0.911 ***	-1.136
Real GDP									-0.001	0.008	0.076 ***	-0.004	0.007	-0.002	0.600 ***
R squared	0.090	0.515	0.479	0.024	0.139	0.031	0.472	0.935	0.011	0.530	0.570	0.891	0.796	0.924	0.869
p-value (F stat)	0.036	0.000	0.000	0.837	0.027	0.750	0.000	0.000	0.996	0.000	0.000	0.000	0.000	0.000	0.000
Panel B – SRISK (in *bn* EUR)															
SRISK	0.298 ***	0.094 ***	5.381 ***	0.271	0.897 **	-0.041 **	-0.018 ***	-0.004	0.221 *	-1.122 ***	-0.054	-0.034	0.138 *	0.008	-1.026 **
EURIBOR-OIS Spread	1.039	0.135	-2.809												
Volatility	-0.043 **	0.002	-0.144												
Leverage				0.090	0.271	0.000	0.002	-0.001							
Market-to-Book				2.326	8.712 *	-0.276	-0.075	-0.047							
Profitability				0.190	-5.193	0.023	0.634 ***	-0.437 ***							
Nonperforming				-0.877	-3.207	0.126	0.021	0.983 ***							
Sentiment									-0.040	0.279 ***	0.266 ***	0.028 **	0.035	-0.004	0.384
Production									-0.147	0.269	-0.224 **	0.035 *	-0.053	0.000	1.349 ***
House Prices									0.013	0.913	0.123	0.813 ***	-0.359	-0.042	1.539
Credit Private									-0.082	-0.130	-0.135 *	0.012	0.885 ***	-0.007	-0.256
Government Debt									-0.030	1.928 **	0.319	-0.196 **	-0.084	0.915 ***	-1.328
Real GDP									0.020	0.011	0.070 ***	-0.005	0.009	-0.002	0.605 ***
R squared	0.108	0.336	0.487	0.104	0.180	0.090	0.491	0.933	0.128	0.640	0.582	0.881	0.800	0.924	0.862
p-value (F stat)	0.018	0.000	0.000	0.112	0.006	0.177	0.000	0.000	0.138	0.000	0.000	0.000	0.000	0.000	0.000
Panel C – ΔMultiCoVaR (in %)															
ΔMultiCoVaR	0.052	0.022 ***	1.511 ***	-0.013	-0.037	0.001	0.002	0.000	0.000	-0.207 ***	0.041	-0.005	-0.004	0.000	0.083
EURIBOR-OIS Spread	0.734	0.212	2.302												
Volatility	-0.074	0.003	-0.104												
Leverage				0.058	0.378 **	-0.004	0.000	-0.002							
Market-to-Book				-0.092	2.701	-0.010	0.059	-0.028							
Profitability				-0.671	-4.817	0.019	0.619 ***	-0.436 ***							
Nonperforming				-2.815	-2.960	0.107	0.017	0.982 ***							
Sentiment									-0.113	0.360 ***	0.270 ***	0.028 **	0.020	-0.005	0.516 **
Production									0.206	0.202	-0.259 **	0.024	-0.044	0.001	1.258 ***
House Prices									1.527	1.350 *	0.102	0.807 ***	-0.340	-0.040	1.858
Credit Private									-0.184	-0.064	-0.134 *	0.011	0.883 ***	-0.007	-0.158
Government Debt									-0.147	2.323 ***	0.392	-0.166 *	-0.131	0.912 ***	-1.083
Real GDP									-0.079	0.015	0.075 ***	-0.003	0.007	-0.002	0.602 ***
R squared	0.027	0.215	0.318	0.018	0.139	0.029	0.446	0.935	0.053	0.514	0.572	0.870	0.795	0.924	0.853
p-value (F stat)	0.485	0.000	0.000	0.912	0.027	0.775	0.000	0.000	0.716	0.000	0.000	0.000	0.000	0.000	0.000

Table 7 – VAR Regression Results (Full Sample) – Part I

Table 7 – continued:

All figures are estimated from monthly averaged time series of systemic risk measures at the banking system level and monthly (linearly interpolated) time series of financial market, aggregate balance sheet, and macro-economic variables covering the period from July 2005 to June 2013. We estimate the VAR system $\Delta y_t = a + B\Delta y_{t-1} + \epsilon_t$ with $y_t \equiv (SysRisk_t^{sys}, x_t)'$, where $SysRisk_t^{sys}$ represents any of the three systemic risk measures MultiCoVaR, MultiMES or SRISK at the banking system level and x_t is the vector of financial market, balance sheet or macro-economic variables. Parameter vector a denotes the intercepts, B is the coefficient matrix of the lagged regression variables y_{t-1}, and ϵ_t is a vector of standard Gaussian error terms. The Δs indicate that we are running the regression in first differences. The table is organized as follows. Panel A presents the results for the VAR systems with $SysRisk$ = MultiMES, Panel B the results for $SysRisk$ = SRISK, and Panel C the results for $SysRisk$ = ΔMultiCoVaR. The names of the lagged explanatory variables to which the regression coefficients refer are given in the respective rows and the dependent variables' names are given in the respective column headers. For a detailed description of the regression variables, we refer to Table 6. For ease of exposition, we suppress the intercepts' values. The regression coefficients are assigned asterisks if they are statistically significant. (*** = 1%-confidence level; ** = 5%-confidence level; * = 10%-confidence level)

		FINANCIAL MARKET		BALANCE SHEET				MACRO-ECONOMY					
	Systemic Risk	EURIBOR-OIS Spread	Volatility	Leverage	Market-to-Book	Profitability	Nonperforming Loans	Sentiment	Production	House Prices	Credit Private	Government Debt	Real GDP
Panel A – MultiMES (in %)													
MultiMES	-0.033	0.078 ***	2.912 ***	-0.043	-0.004	-0.005 **	0.000	-0.283 **	0.106	-0.049 ***	0.018	0.000	-0.712 ***
EURIBOR-OIS Spread	1.225	0.075	0.201	1.299	-0.050	-0.060 **	-0.018	-1.970	0.347	-0.292 *	0.560	-0.163 *	-0.563
Volatility	-0.082 **	0.005	-0.104	-0.053	0.002	0.000	-0.001	-0.016	-0.017	0.007 *	-0.015	0.000	0.045
Leverage	0.062	0.002	0.415	0.297	-0.004	0.001	-0.001	-0.481 ***	-0.184 **	-0.034 **	-0.037	0.002	-1.261 ***
Market-to-Book	1.103	-0.135	-20.412 **	1.952	-0.098	0.015	-0.010	-4.494	-2.636	-0.490	-1.534	-0.130	-19.616 ***
Profitability	13.633 **	0.440	-2.036	0.433	-0.326	0.432 ***	-0.430 ***	1.858	1.940	0.423	-0.596	-1.636 ***	21.339 *
Nonperforming Loans	-2.112	-0.318 *	-0.674	-1.456	0.115	0.036	0.967 ***	-0.338	0.429	-0.384	-0.169	-0.034	-6.681
Sentiment	-0.060	-0.005	0.264	-0.189	0.006	-0.001	0.001	0.114	0.176 **	0.020	0.026	0.002	0.118
Production	-0.036	0.019	1.066 *	-0.361	0.014	0.004	0.001	0.042	-0.341 ***	0.016	-0.063	0.007	0.781 **
House Prices	-0.582	-0.057	0.352	-0.582	0.003	0.024 *	-0.020	1.195 *	0.148	0.750 ***	-0.295	-0.002	0.807
Credit Private	-0.018	0.000	0.385	-0.001	0.015 *	0.000	0.000	0.020	-0.088	0.013	0.906 ***	-0.008	0.067
Government Debt	-0.547	0.018	-1.138	-0.179	-0.005	0.029 **	-0.013	2.352 ***	0.376	-0.177 **	-0.073	0.982 ***	-1.632
Real GDP	-0.015	0.004	-0.077	0.087	-0.001	0.001	0.001	0.061	0.089 ***	-0.002	0.007	0.000	0.649 ***
R squared	0.165	0.596	0.617	0.195	0.135	0.600	0.943	0.650	0.617	0.904	0.803	0.947	0.909
p-value (F stat)	0.341	0.000	0.000	0.181	0.558	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel B – SRISK (in *bn* EUR)													
SRISK	0.329	0.141 ***	6.409 ***	1.149 **	-0.047 **	-0.010 *	-0.001	-1.283 ***	0.075	0.006	0.276 **	0.013	-0.520
EURIBOR-OIS Spread	0.795	0.015	-2.693	0.496	-0.020	-0.055 **	-0.017	-1.189	0.372	-0.313 *	0.402	-0.169 *	-0.527
Volatility	-0.048 **	0.004	-0.147	-0.057	0.003	0.000	-0.001	-0.010	-0.018	0.007 *	-0.017	0.000	0.051
Leverage	0.097	-0.004	0.033	0.129	0.001	0.002	0.000	-0.344 **	-0.164 **	-0.041 **	-0.071	0.001	-1.308 ***
Market-to-Book	2.971	0.424	6.518	8.151	-0.342	-0.028	-0.016	-10.450 ***	-2.267	-0.307	-0.103	-0.056	-20.510 ***
Profitability	2.500	0.902	10.879	-3.709	-0.220	0.406 ***	-0.426 ***	2.457	2.836	-0.168	-1.361	-1.692 ***	14.649
Nonperforming Loans	-0.329	-0.294	0.995	-1.255	0.112	0.035	0.969 ***	-0.468	0.367	-0.427 *	-0.020	-0.022	-6.736
Sentiment	-0.072	-0.006	0.195	-0.230	0.007	-0.001	0.001	0.147	0.193 ***	0.021	0.016	0.001	0.101
Production	-0.106	0.017	0.846	-0.478 *	0.017	0.004	0.001	0.139	-0.308 ***	0.019	-0.086	0.007	0.737 *
House Prices	0.035	-0.037	1.159	-0.276	-0.011	0.022	-0.021	0.869	0.154	0.778 ***	-0.270	-0.003	0.796
Credit Private	-0.101	0.001	0.389	0.009	0.014 *	0.000	0.000	-0.002	-0.085	0.017	0.899 ***	-0.009	0.058
Government Debt	0.086	0.036	0.165	0.402	-0.024	0.028 *	-0.013	1.904 **	0.292	-0.162 *	0.061	0.989 ***	-1.436
Real GDP	0.015	0.004	-0.001	0.121 *	-0.002	0.001	0.001	0.036	0.081 ***	-0.002	0.017	0.001	0.663 ***
R squared	0.206	0.475	0.568	0.252	0.195	0.591	0.941	0.704	0.620	0.897	0.810	0.947	0.899
p-value (F stat)	0.164	0.000	0.000	0.049	0.212	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel C – ΔMultiCoVaR (in %)													
ΔMultiCoVaR	-0.008	0.011	0.967 ***	-0.016	0.000	0.001	0.000	-0.130 *	0.080 *	0.001	-0.024	-0.004	0.345 **
EURIBOR-OIS Spread	-0.040	0.131	3.418	1.248	-0.053	-0.060 **	-0.018	-2.355	0.556	-0.311 *	0.519	-0.172 *	-0.172
Volatility	-0.085	0.004	-0.164	-0.052	0.002	0.000	-0.001	-0.008	-0.021	0.007 *	-0.014	0.000	0.031
Leverage	0.175	0.015	0.883 *	0.290	-0.005	0.000	-0.001	-0.526 ***	-0.167 **	-0.042 ***	-0.034	0.002	-1.382 ***
Market-to-Book	2.207	-0.151	-11.591	1.799	-0.095	0.047	-0.011	-5.957 *	-1.552	-0.350	-1.989	-0.206	-11.918 *
Profitability	4.322	1.328 **	29.329	-0.031	-0.368	0.370 ***	-0.427 ***	-1.085	2.957	-0.150	-0.313	-1.625 ***	12.015
Nonperforming Loans	-1.932	-0.310	-0.216	-1.463	0.115	0.036	0.967 ***	-0.395	0.461	-0.386	-0.176	-0.035	-6.594
Sentiment	-0.199	-0.002	0.400	-0.191	0.006	-0.001	0.001	0.101	0.181 ***	0.018	0.026	0.002	0.091
Production	0.307	0.027	1.282 *	-0.365	0.014	0.003	0.001	0.024	-0.337 ***	0.010	-0.059	0.008	0.677 *
House Prices	1.462	-0.079	-0.667	-0.567	0.004	0.025 *	-0.020	1.308 *	0.093	0.760 ***	-0.290	0.000	0.826
Credit Private	-0.202	-0.001	0.302	0.000	0.015 *	0.000	0.000	0.031	-0.094	0.013	0.908 ***	-0.008	0.043
Government Debt	0.158	-0.029	-2.912	-0.152	-0.003	0.032 **	-0.013	2.526 ***	0.309	-0.149	-0.082	0.983 ***	-1.233
Real GDP	-0.084	0.001	-0.179	0.088	0.000	0.001	0.001	0.071 *	0.085 ***	0.000	0.007	0.000	0.675 ***
R squared	0.103	0.346	0.451	0.195	0.133	0.580	0.943	0.642	0.624	0.890	0.804	0.947	0.906
p-value (F stat)	0.792	0.001	0.000	0.182	0.575	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 8 – VAR Regression Results (Full Sample) – Part II

Table 8 – continued:

All figures are estimated from monthly averaged time series of systemic risk measures at the banking system level and monthly (linearly interpolated) time series of financial market, aggregate balance sheet, and macro-economic variables covering the period from July 2005 to June 2013. We estimate the VAR system $\Delta y_t = a + B\Delta y_{t-1} + \epsilon_t$ with $y_t \equiv (SysRisk_t^{sys}, x_t)'$, where $SysRisk_t^{sys}$ represents any of the three systemic risk measures MultiCoVaR, MultiMES or SRISK at the banking system level and x_t is the vector comprising all financial market, balance sheet, and macro-economic variables. Parameter vector a denotes the intercepts, B is the coefficient matrix of the lagged regression variables y_{t-1}, and ϵ_t is a vector of standard Gaussian error terms. The Δs indicate that we are running the regression in first differences. The table is organized as follows. Panel A presents the results for the VAR systems with $SysRisk$ = MultiMES, Panel B the results for $SysRisk$ = SRISK, and Panel C the results for $SysRisk$ = ΔMultiCoVaR. The names of the lagged explanatory variables to which the regression coefficients refer are given in the respective rows and the dependent variables' names are given in the respective column headers. For a detailed description of the regression variables, we refer to Table 6. For ease of exposition, we suppress the intercepts' values. The regression coefficients are assigned asterisks if they are statistically significant. (*** = 1%-confidence level; ** = 5%-confidence level; * = 10%-confidence level)

	FINANCIAL MARKET			BALANCE SHEET					MACRO-ECONOMY						
	Systemic Risk	EURIBOR-OIS Spread	Volatility	Systemic Risk	Leverage	Market-to-Book	Profitability	Nonperforming Loans	Systemic Risk	Sentiment	Production	House Prices	Credit Private	Government Debt	Real GDP
Panel A – MultiMES (in %)															
MultiMES	0.065	0.098 ***	3.579 ***	-0.112	-0.025	-0.010	-0.004	0.001	0.022	-0.493 **	-0.007	-0.066 ***	0.048	-0.003	-1.346 ***
EURIBOR-OIS Spread	2.093	0.081	-1.492												
Volatility	-0.118 **	0.005	0.025												
Leverage				0.080	0.141	0.006	0.000	0.000							
Market-to-Book				-0.222	0.056	0.021	0.023	0.006							
Profitability				11.843	-26.419 **	0.835	0.573 ***	-0.425 ***							
Nonperforming Loans				3.450	-15.586 **	0.425	-0.062	0.932 ***							
Sentiment									0.201	0.326	0.326 ***	0.037 *	0.072	-0.003	0.584
Production									-0.143	0.471	-0.302 **	0.032	-0.075	0.002	1.852 ***
House Prices									-0.873	1.835	0.216	0.763 ***	-0.788	-0.120	2.401
Credit Private									-0.050	-0.081	-0.174 *	0.004	0.894 ***	-0.003	-0.245
Government Debt									-0.242	2.782	1.348	-0.127	-0.536	0.797 ***	-1.120
Real GDP									0.022	-0.014	0.095 ***	-0.002	0.013	-0.002	0.506 ***
R squared	0.129	0.618	0.574	0.055	0.315	0.076	0.385	0.934	0.052	0.502	0.678	0.919	0.801	0.916	0.903
p-value (F stat)	0.118	0.000	0.000	0.798	0.008	0.657	0.001	0.000	0.951	0.000	0.000	0.000	0.000	0.000	0.000
Panel B – SRISK (in *bn* EUR)															
SRISK	0.303 **	0.099 ***	5.534 ***	0.429	1.078 *	-0.058 *	-0.024 ***	-0.001	0.197	-1.061 ***	-0.092	-0.069 **	0.231	0.010	-1.751 **
EURIBOR-OIS Spread	2.824 **	-0.032	-6.808												
Volatility	-0.089 **	0.007	0.069												
Leverage				0.054	0.031	0.008	0.001	0.000							
Market-to-Book				3.041	6.584	-0.308	-0.113	-0.005							
Profitability				-3.084	-27.295 ***	0.627	0.487 ***	-0.399 ***							
Nonperforming Loans				-2.537	-16.764 ***	0.417	-0.072	0.945 ***							
Sentiment									-0.043	0.229	0.344 ***	0.036	0.101	-0.002	0.434
Production									-0.169	0.467 *	-0.248 *	0.034	-0.078	0.000	1.660 **
House Prices									-0.570	0.912	0.118	0.730 ***	-0.700	-0.121	1.017
Credit Private									-0.075	-0.101	-0.171 *	0.010	0.895 ***	-0.003	-0.229
Government Debt									-0.355	1.222	1.139	-0.285	-0.353	0.797 ***	-4.327
Real GDP									0.038	-0.016	0.086 **	-0.006	0.013	-0.002	0.497 ***
R squared	0.230	0.313	0.529	0.153	0.369	0.153	0.463	0.932	0.182	0.562	0.708	0.916	0.810	0.917	0.889
p-value (F stat)	0.016	0.002	0.000	0.272	0.003	0.272	0.000	0.000	0.377	0.000	0.000	0.000	0.000	0.000	0.000
Panel C – ΔMultiCoVaR (in %)															
ΔMultiCoVaR	0.168	0.025 *	1.384 ***	-0.042	-0.093	0.004	0.003	-0.001	0.088	-0.135	0.080	-0.012	-0.022	-0.005	0.142
EURIBOR-OIS Spread	2.919	0.202	6.032												
Volatility	-0.168 *	0.004	-0.138												
Leverage				0.129	0.126	0.003	-0.001	0.000							
Market-to-Book				-2.461	-1.456	0.107	0.078	-0.008							
Profitability				1.683	-25.494 **	0.566	0.438 ***	-0.387 ***							
Nonperforming Loans				-6.690	-15.279 **	0.332	-0.109	0.946 ***							
Sentiment									-0.210	0.339	0.333 ***	0.039 *	0.068	-0.003	0.663
Production									-0.249	0.353	-0.319 **	0.015	-0.056	0.002	1.430 **
House Prices									1.658	1.806	0.270	0.763 ***	-0.808	-0.123	2.663
Credit Private									-0.077	-0.056	-0.162 *	0.009	0.886 ***	-0.004	-0.100
Government Debt									-1.871	2.233	1.264	-0.207	-0.450	0.798 ***	-3.099
Real GDP									-0.074	-0.017	0.091 **	-0.003	0.015	-0.002	0.472 ***
R squared	0.102	0.186	0.191	0.078	0.319	0.067	0.381	0.934	0.133	0.425	0.694	0.894	0.801	0.917	0.872
p-value (F stat)	0.206	0.033	0.029	0.643	0.007	0.722	0.001	0.000	0.569	0.002	0.000	0.000	0.000	0.000	0.000

Table 9 – VAR Regression Results (July 2005 – June 2009)

Table 9 – continued:

All figures are estimated from monthly averaged time series of systemic risk measures at the banking system level and monthly (linearly interpolated) time series of financial market, aggregate balance sheet, and macro-economic variables covering the period from July 2005 to June 2009. We estimate the VAR system $\Delta y_t = a + B\Delta y_{t-1} + \epsilon_t$ with $y_t \equiv (SysRisk_t^{sys}, x_t)'$, where $SysRisk_t^{sys}$ represents any of the three systemic risk measures MultiCoVaR, MultiMES or SRISK at the banking system level and x_t is the vector of financial market, balance sheet or macro-economic variables. Parameter vector a denotes the intercepts, B is the coefficient matrix of the lagged regression variables y_{t-1}, and ϵ_t is a vector of standard Gaussian error terms. The Δs indicate that we are running the regression in first differences. The table is organized as follows. Panel A presents the results for the VAR systems with $SysRisk$ = MultiMES, Panel B the results for $SysRisk$ = SRISK, and Panel C the results for $SysRisk$ = ΔMultiCoVaR. The names of the lagged explanatory variables to which the regression coefficients refer are given in the respective rows and the dependent variables' names are given in the respective column headers. For a detailed description of the regression variables, we refer to Table 6. For ease of exposition, we suppress the intercepts' values. The regression coefficients are assigned asterisks if they are statistically significant. (*** = 1%-confidence level; ** = 5%-confidence level; * = 10%-confidence level)

	FINANCIAL MARKET			BALANCE SHEET					MACRO-ECONOMY						
	Systemic Risk	EURIBOR-OIS Spread	Volatility	Systemic Risk	Leverage	Market-to-Book	Profitability	Nonperforming Loans	Systemic Risk	Sentiment	Production	House Prices	Credit Private	Government Debt	Real GDP
Panel A – MultiMES (in %)															
MultiMES	-0.045	0.059 ***	3.595 ***	-0.005	0.606 *	-0.012	-0.008 *	-0.007	-0.128	-0.456 *	0.221 *	-0.007	-0.011	-0.008	0.357
EURIBOR-OIS Spread	1.858	0.331 **	-2.383												
Volatility	-0.060 **	0.002	-0.079												
Leverage				0.134	1.322 ***	-0.028 *	-0.008	-0.024 ***							
Market-to-Book				6.563	40.427 **	-0.865 *	-0.273	-0.755 ***							
Profitability				3.975	21.639 **	-0.757 **	0.624 ***	-0.759 ***							
Nonperforming Loans				-1.542	-0.457	0.015	0.014	0.951 ***							
Sentiment									0.051	0.309 *	0.139 *	0.019	0.006	0.005	0.247
Production									0.120	-0.391	-0.286 *	0.043	0.007	0.008	0.743 *
House Prices									1.100	-0.455	0.742	0.635 ***	0.089	0.090	-0.159
Credit Private									-8.072	-3.097	-7.176 *	0.374	0.874	0.050	-18.855 *
Government Debt									8.252	7.130	8.223 **	-0.504	-0.068	0.772	21.561 *
Real GDP									-0.134 *	0.021	-0.020	0.009	-0.002	-0.001	0.604 ***
R squared	0.098	0.345	0.355	0.047	0.250	0.176	0.566	0.907	0.107	0.566	0.457	0.648	0.869	0.895	0.805
p-value (F stat)	0.224	0.000	0.000	0.881	0.063	0.216	0.000	0.000	0.779	0.000	0.003	0.000	0.000	0.000	0.000
Panel B – SRISK (in *bn* EUR)															
SRISK	0.182	0.092 ***	5.444 ***	-0.022	0.770	-0.012	-0.007	-0.002	0.130	-1.204 ***	0.120	0.009	-0.016	-0.013	0.064
EURIBOR-OIS Spread	-1.647	0.305 **	-4.010												
Volatility	-0.010	-0.001	-0.309 **												
Leverage				0.150	0.981 **	-0.022	-0.004	-0.021 **							
Market-to-Book				1.851	34.537 **	-0.738	-0.174	-0.644 **							
Profitability				4.155	18.651 *	-0.701 **	0.662 ***	-0.727 ***							
Nonperforming Loans				0.654	-1.056	0.025	0.019	0.952 ***							
Sentiment									0.047	0.198	0.176 **	0.018	0.003	0.003	0.303
Production									0.080	-0.165	-0.347 **	0.044	0.012	0.011	0.658
House Prices									0.764	-0.871	1.093	0.620 ***	0.075	0.080	0.449
Credit Private									5.776	0.220	-8.413 **	0.403	0.942 *	0.101	-20.746 *
Government Debt									-7.009	3.392	9.323 **	-0.520	-0.138	0.720	23.137 *
Real GDP									0.041	0.066	-0.037	0.009	-0.001	0.000	0.577 ***
R squared	0.113	0.443	0.486	0.070	0.203	0.153	0.530	0.902	0.131	0.741	0.411	0.648	0.870	0.896	0.798
p-value (F stat)	0.166	0.000	0.000	0.754	0.142	0.300	0.000	0.000	0.664	0.000	0.009	0.000	0.000	0.000	0.000
Panel C – ΔMultiCoVaR (in %)															
ΔMultiCoVaR	-0.020	0.018 ***	1.672 ***	0.145	0.193	-0.006	0.002	0.000	-0.096	-0.237 ***	0.011	-0.001	0.003	0.003	0.027
EURIBOR-OIS Spread	0.661	0.259	-7.232												
Volatility	-0.027	0.003	-0.069												
Leverage				0.867	1.136 **	-0.024	-0.005	-0.022 **							
Market-to-Book				39.006	36.196 **	-0.842 *	-0.065	-0.636 **							
Profitability				10.198	21.376 **	-0.774 **	0.685 ***	-0.730 ***							
Nonperforming Loans				-1.616	-0.482	0.016	0.013	0.950 ***							
Sentiment									0.123	0.237	0.172 **	0.018	0.004	0.003	0.301
Production									1.172 *	-0.220	-0.338 **	0.045	0.009	0.009	0.657
House Prices									4.191	-0.507	1.097	0.626 ***	0.059	0.068	0.384
Credit Private									0.857	-0.880	-8.310 **	0.409	0.931 *	0.093	-20.680 *
Government Debt									-3.575	4.906	9.154 **	-0.534	-0.108	0.743	23.077 *
Real GDP									-0.188	0.056	-0.036	0.009	-0.001	0.000	0.577 ***
R squared	0.003	0.276	0.539	0.089	0.213	0.185	0.541	0.902	0.147	0.615	0.400	0.647	0.869	0.895	0.798
p-value (F stat)	0.987	0.003	0.000	0.637	0.121	0.190	0.000	0.000	0.584	0.000	0.012	0.000	0.000	0.000	0.000

Table 10 – VAR Regression Results (July 2009 – June 2013)

Table 10 – continued:

All figures are estimated from monthly averaged time series of systemic risk measures at the banking system level and monthly (linearly interpolated) time series of financial market, aggregate balance sheet, and macro-economic variables covering the period from July 2009 to June 2013. We estimate the VAR system $\Delta y_t = a + B\Delta y_{t-1} + \epsilon_t$ with $y_t \equiv (SysRisk_t^{sys}, x_t)'$, where $SysRisk_t^{sys}$ represents any of the three systemic risk measures MultiCoVaR, MultiMES or SRISK at the banking system level and x_t is the vector of financial market, balance sheet or macro-economic variables. Parameter vector a denotes the intercepts, B is the coefficient matrix of the lagged regression variables y_{t-1}, and ϵ_t is a vector of standard Gaussian error terms. The Δs indicate that we are running the regression in first differences. The table is organized as follows. Panel A presents the results for the VAR systems with $SysRisk$ = MultiMES, Panel B the results for $SysRisk$ = SRISK, and Panel C the results for $SysRisk$ = ΔMultiCoVaR. The names of the lagged explanatory variables to which the regression coefficients refer are given in the respective rows and the dependent variables' names are given in the respective column headers. For a detailed description of the regression variables, we refer to Table 6. For ease of exposition, we suppress the intercepts' values. The regression coefficients are assigned asterisks if they are statistically significant. (*** = 1%-confidence level; ** = 5%-confidence level; * = 10%-confidence level)

Appendix A. DCC GARCH

Recalling the bivariate return process from Equation (7) and the setup of the univariate GARCH(1,1) models from Equations (8a) and (8b), the following relationship holds:

$$\xi_{sys,t} = \epsilon_{sys,t} \tag{A.1a}$$

$$\xi_{i,t} = \rho_{i,sys,t}\epsilon_{sys,t} + \sqrt{1-\rho^2_{i,sys,t}}\epsilon_{i,t}. \tag{A.1b}$$

It is obvious that within the bivariate process the correlation variable $\rho_{sys,i,t}$ entirely captures the correlation between institution i and the banking system. Therefore, the residuals $\epsilon_{i,t}$ and $\epsilon_{sys,t}$ are uncorrelated by definition. However, this is not the case for the (correlated) residuals $\xi_{i,t}$ and $\xi_{sys,t}$ from the univariate GARCH(1,1) processes. This fact is used by Engle (2002) to estimate time-varying return correlations.

Using matrix notation the return vector of the market and institution i is given by

$$R_t = \Sigma_t^{\frac{1}{2}}\epsilon_t \tag{A.2}$$

where

$$\Sigma_t = \begin{bmatrix} \sigma^2_{sys,t} & \rho_{i,sys,t}\sigma_{i,t}\sigma_{sys,t} \\ \rho_{i,sys,t}\sigma_{i,t}\sigma_{sys,t} & \sigma^2_{i,t} \end{bmatrix} \tag{A.3}$$

is the covariance matrix of the return vector $R_t = (r_{sys,t}, r_{i,t})$ and $\Sigma_t^{1/2}$ the corresponding Cholesky transformation of Σ_t. The covariance matrix can be further decomposed to the following form:

$$\Sigma_t = D_t P_t D_t \tag{A.4a}$$

$$= \begin{bmatrix} \sigma_{sys,t} & 0 \\ 0 & \sigma_{i,t} \end{bmatrix} \begin{bmatrix} 1 & \rho_{i,sys,t} \\ \rho_{i,sys,t} & 1 \end{bmatrix} \begin{bmatrix} \sigma_{sys,t} & 0 \\ 0 & \sigma_{i,t} \end{bmatrix} \tag{A.4b}$$

with P_t representing the correlation matrix of the return vector R_t. Since the residuals $\xi_{i,t}$ and $\xi_{sys,t}$ have *zero* mean and *unit* variance, the covariance matrix of the return vector and the covariance matrix of the residuals are equivalents and can be used to calculate the time-varying correlation variable $\rho_{i,sys,t}$. Following Engle (2009), the bivariate DDC GARCH model at time t is fully specified by:

$$\rho_{i,sys,t} = \frac{q_{i,sys,t}}{\sqrt{q_{i,i,t} q_{sys,sys,t}}} \tag{A.5a}$$

$$q_{i,sys,t} = (1 - \alpha - \beta)\,\overline{q}_{i,sys} + \alpha \xi_{i,t-1} \xi_{sys,t-1} + \beta q_{i,sys,t-1} \tag{A.5b}$$

$$q_{sys,sys,t} = (1 - \alpha - \beta)\,\overline{q}_{sys,sys} + \alpha \xi_{sys,t-1} \xi_{sys,t-1} + \beta q_{sys,sys,t-1} \tag{A.5c}$$

$$q_{i,i,t} = (1 - \alpha - \beta)\,\overline{q}_{i,i} + \alpha \xi_{i,t-1} \xi_{i,t-1} + \beta q_{i,i,t-1} \tag{A.5d}$$

$$\overline{q}_{i,sys} = \frac{1}{n} \sum_{t=1}^{n} \xi_{i,t} \xi_{sys,t} \tag{A.5e}$$

where $\overline{q}$ is the average correlation within the sample period and the q values are the quasi-correlations extracted from residuals $\xi_{i,t}$ and $\xi_{sys,t}$. The decomposition of ρ_t into quasi-correlations ensures that the correlation matrix is positive definite. In analogy to the volatility GARCH models, the time-varying correlation of the DCC GARCH is heteroscedastic and depends on the lagged quasi-correlation values as well as on the lagged values of the GARCH(1,1) residuals $(\xi_{sys,t}, \xi_{i,t})$. Again, parameters α and β are estimated using the maximum likelihood method. For a detailed discussion of the DCC GARCH framework, we refer to Engle (2009).

Appendix B. Time Series Diagnostics

	MEASURES			FINANCIAL MARKET		BALANCE SHEET				MACRO-ECONOMY					
	MultiMES	SRISK	ΔMultiCoVaR	EURIBOR-OIS Spread	Volatility	Leverage	Market-to-Book	Profitability	Nonperforming Loans	Sentiment	Production	House Prices	Credit Private	Government Debt	Real GDP
Panel A – Unit Roots & Stationarity: Augmented Dickey-Fuller Test															
pval	0.990	0.785	0.990	0.990	0.990	0.987	0.969	0.705	0.529	0.780	0.867	0.721	0.699	0.177	0.509
statistic	-4.232	-2.878	-5.208	-4.147	-4.726	-4.000	-3.677	-2.684	-2.255	-2.867	-3.077	-2.724	-2.670	-1.399	-2.207
Panel B – Heteroscedasticity: Breusch-Pagan Test															
pval	0.840	0.839	0.907	0.943	0.779	0.519	0.007	0.951	0.000	0.891	0.577	0.102	0.000	0.954	0.555
statistic	0.041	0.041	0.014	0.005	0.079	0.416	7.217	0.004	24.825	0.019	0.310	2.674	23.388	0.003	0.348
Panel C – Auto-correlation: Durbin-Watson Test															
pval	0.937	0.006	0.752	0.002	0.785	0.001	0.370	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
statistic	2.007	1.453	1.956	1.387	1.965	1.345	1.833	0.698	0.229	0.720	1.301	0.213	0.230	0.109	0.210
Panel D – Non-normality: Jarque-Bera Test															
pval	0.000	0.000	0.000	0.000	0.000	0.000	0.399	0.000	0.006	0.018	0.000	0.787	0.000	0.111	0.000
statistic	489.662	31.785	38.633	808.111	607.850	68.788	1.838	394.400	10.344	8.006	47.433	0.480	30.112	4.399	70.487

Table B.1 – Time Series Diagnostics (First Differences): *p*-Values and Test Statistics

The above table exhibits *p*-values of various statistical diagnostic tests on the first differenced monthly (interpolated) time series used in our regressions in Section 5. The financial market and balance sheet data are obtained from Datastream; the macro-economic data is obtained from the European Central Bank (government debt), the Worldbank (domestic credit to the private sector and nonperforming loans), and Datastream (all other macro-economic data). All time series of observations range from 2005 to 2013. The table is organized as follows: *Panel A* exhibits the results of the Augmented Dickey-Fuller test with the null hypothesis that the time series are stationary, i.e., there is no unit root. *Panel B* presents the results of the Breusch-Pagan test with the null hypothesis that the time series are homoscedastic, i.e., there is no heteroscedasticity. *Panel C* gives the results of the Durbin-Watson test with the null hypothesis that the time series exhibit no auto-correlation. *Panel D* presents the results of the Jarque-Bera test with the null hypothesis that the time series follow the Gaussian distribution.

Statistic	#series	mean	min	$q = 0.25$	$q = 0.50$	$q = 0.75$	max	$\#p : p < 0.1$ (in %)	$\#p : p < 0.05$ (in %)	$\#p : p < 0.01$ (in %)
Augmented Dickey-Fuller	87	0.9900	0.9900	0.9900	0.9900	0.9900	0.9900	0.00	0.00	0.00
Breusch-Pagan	87	0.1685	0.0000	0.0000	0.0003	0.1899	0.9883	71.26	63.22	56.32
Durbin-Watson	87	0.1627	0.0000	0.0001	0.0443	0.1987	0.9510	66.67	54.02	36.78
Jarque-Bera	87	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	100.00	100.00	100.00

Table B.2 – **Diagnostics of Sample Bank's Daily Log Return Series: *p*-Values and Test Statistics**

The above table exhibits p-values of various statistical diagnostic tests on the daily log return series. All stock price data are obtained from Datastream and the analyzed time series range from 2005 to 2013. We perform the following tests: the Augmented Dickey-Fuller statistic tests the null hypothesis that the time series are stationary, i.e., there is no unit root; the Breusch-Pagan statistic tests the null hypothesis that the time series are homoscedastic, i.e., there is no heteroscedasticity. The Durbin-Watson statistic tests the null hypothesis that the time series exhibit no auto-correlation and the Jarque-Bera statistic tests the null hypothesis that the time series follow the Gaussian distribution. Column one gives the abbreviations for the respective test statistics. Column two gives the number of series tested and thus the number of test results. Column three gives the mean p-value of the test results, columns four to eight the quantiles, and columns nine to eleven provide the percentage of test results significant at the 10%, 5%, and 1% confidence levels.