Systemic Risk, Financial Markets, and Performance of Financial Institutions

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ABSTRACT

This paper studies the exposure and contribution of financial institutions to systemic risks in financial markets. We employ three popular indicators of a financial institution's exposure to systemic risks: the systemic risk index (SRISK) and marginal expected shortfall (MES) of Brownlees and Engle (2012) and the conditional Value-at-Risk (CoVaR) of Adrian and Brunnermeier (2011). We use a primary database of Taiwan financial institutions for our empirical study. A panel containing data of stock market returns and balance sheets of 31 Taiwan financial institutions for 2005-2014 is grouped in three categories: financial holding companies, bank companies, and insurance companies. We focus on systemic risk analysis so as to understand the dynamics of volatility, interdependency, and risk during the recent financial crisis. We then report the time series dynamics and cross sectional rankings of these systemic risk measures. The main results indicate that although these three measures differ in their definition of the contributions to systemic risk, all are quite similar in identifying systemically important financial institutions (SIFIs). Moreover, we find empirical evidence that systemic risk contributions are closely related to certain institution characteristic factors. The results of the Granger causality tests prove that a systemic risk measure is a great alternative tool for monitoring early warning signals of distress in the real economy.

Key words: Systemic Risk; MES; SRISK; CoVaR; financial crisis

1 Introduction

Ever since the financial crisis of 2007-2008, systemic risk in financial markets has become a very important issue, with the main concern being that the failure of a chain of several financial institutions could result in a severe economic crisis. From 2001 to 2004, the Basel Committee on Banking Supervision (BCBS) published Basel II to promote an international standard for maintaining overall economic stability. In order to promote solvency of financial institutions and develop prevention policies following the recent financial crisis, Basel III in 2010 not only enhances the microprudential regulation of Basel II, but also contains macroprudential supervision with the purpose of preserving financial stability and regulating systemic risk. Therefore, evaluating and measuring systemic risk in financial markets has come to the forefront.

Huang et al. (2009) define systemic risk as multiple simultaneous defaults of large financial institutions. Bartram et al. (2007) consider systemic risk as a large-scale breakdown of financial intermediation with huge economic and social costs. A similar definition has been proposed by Nier et al. (2007), whereby "systemic risk arises when the failure or weakness of multiple banks imposes costs on the financial system and ultimately on the economy as a whole". Schwarcz (2008) and Duan and Zhang (2013) follow a definition that considers systemic risk as an economic shock of market or institutional failure that triggers the series of significant losses to financial institutions. Acharya (2009) defines systemic risk as the joint failure risk arising from the correlation of returns on the asset side of bank balance sheets. Billio et al. (2012) note that systemic risk threatens the stability or public confidence in the financial system, and the European Central Bank (ECB (2010)) defines it as "a risk of financial instability so widespread that it impairs the functioning of a financial system to the point where economic growth and welfare suffer materially".

From the definition of systemic risk given by the Group of Ten (2001), systemic financial risk is when an event triggers a loss of economic value in a substantial portion of a financial system, or even spread to the real economy (see Kaufman, 1999; de Bandt and Hartmann, 2000). In this paper, we adopt the definition of systemic risk focusing on those financial institutions that are so systemically important that a failure by one of them to meet its obligations to creditors and customers would have significant adverse consequences for the financial system and the broader economy. There are three important characteristics of systemic risk: contagion, universality, and negative externality. Contagion effects arise from the failures of one or more financial institutions, because of increasing interlinkages between them. For universality, systemic risk affects a substantial portion of the financial system. Finally, systemic risk involves the spillover of risk from an individual institution to many others. We attempt to measure the potential of systemic financial risk by estimating the dependency between an individual institution and the financial system in a stressed economy.

Many studies have been conducted on the measurement of systemic risk using financial market variables, such as balance sheet data, stock returns or credit default swap (CDS) spreads. In particular, researchers have analysed the interlinkages between financial institutions through the analysis of financial institutions' assets. One can distinguish several major approaches.[1] The first approach is to explore the impact of one financial institution on the market and its contribution to the systemic risk of the global financial system. Acharya et al. (2010) propose a systemic risk index of Systemic Expected Shortfall (SES) to measure the contributions of individual financial institutions to the systemic risk. SES is defined as the expected capital shortage of an individual financial institution conditional on a substantial reduction of the capitalization of the system. They assume that the failures of a systemically important institution can impose an externality on the rest of the economy when the financial system is undercapitalized. However, SES, by using a static structural approach, is estimated to measure each institution's contribution to systemic risk during a crisis. Brownlees and Engle (2012) also argue that a financial institution is unable to function and become systematically related when the whole financial system is unstable. Unlike the static structural approach of Acharya et al. (2010) , Brownlees and Engle (2012) develop an alternative estimation methodology of Marginal Expected Shortfall (MES) and present the Systemic Risk index (SRISK) to expose the systemic risk. They directly attempt to measure expected capital shortages using a dynamic reduced form approach, i.e. using the dynamic conditional correlation (DCC) model of Engle (2002, 2009) to set up the relationship between individual firms' equity returns and market index returns. In addition, SRISK is a broad measure that involves losses due to both an institution's investments in assets and its exposure to fragile liabilities. Banulescu and Dumitrescu (2015) offer a empirical extension. They use the product of MES and the weight of the institution in the financial system to propose a new systemic risk measure called Component Expected Shortfall (CES) to identify the systemically important financial institutions (SIFIs).

The CoVaR of Adrian and Brunnermeier (2011) is one of the more popular proposals in the literature that has received notable attention. They propose the concept of CoVaR, which measures the Value-at-Risk (VaR) of the financial system conditional on some other institutions being in distress, so as to estimate the severity of the systemic risk. Their measure is modeled by the joint dynamics of individual financial institutions' equity returns and of market index returns via a quantile regression approach. They define ΔCoVaR as the contribution of an individual institution to systemic risk which is the difference between CoVaR conditional on the loss of an institution in crisis and that in a normal situation. They find that there is a strong relationship between a firm's VaR and its ΔCoVaR in the time series dimension but a weak relationship in the cross-sectional dimension. MES and ΔCoVaR have already been extensively applied in many studies – see for example, Girardi and Tolga Ergn (2013), Castro and Ferrari (2014), Yun and Moon (2014), etc. Another evaluation is network analysis that can be implemented directly on the structure and the nature of relationships between financial institutions in a financial system. Here this approach can state the transmission of financial stress through the financial system and hence measure systemic risk. Billio et al. (2012) propose a Granger-causality network measure to construct networks of spillover effects among financial institutions while Kritzman et al. (2011)

[1]Bisias et al. (2012) report a survey of systemic risk analytics and also provide taxonomies of systemic risk measures based on different perspectives such as supervisory scope, research directions, and data requirements.

use principal component analysis (PCA), which is a statistical procedure for analyzing the many explicit linkages of financial institutions. Huang et al. (2009) utilize the price of insurance against financial distress to measure the systemic risk of a group of major financial institutions.

In this paper, we investigate systemic risk in the Taiwan financial system by using three popular systemic risk measures: SRISK (systemic risk) index, MES (marginal expected shortfall), and CoVaR (Conditional Value-at-Risk).[2] MES and the SRISK index have been introduced by Acharya et al. (2010) and Brownlees and Engle (2012), respectively, to evaluate the systemic risk contributions of individual financial institutions, while Adrian and Brunnermeier (2011) proposed the CoVaR to measure the severity of the systemic risk by using a quantile regression method.

We apply these methods to explore the impact of systemic risk in the Taiwan financial system through 2005-2014. We construct a panel containing 31 Taiwan financial institutions which are grouped in three categories: financial holding companies, bank companies and insurance companies.[3] We focus on systemic risk analysis so as to understand the dynamics of volatility, interdependency and risk during the crisis and to study the relationship among SRISK, MES, and CoVaR, and what the determinants of systemic risk are. We then report the time series dynamics and cross sectional rankings of SRISK. The main results indicate that these systemic risk measures are quantitatively similar in identifying Taiwan's SIFIs and provide a reliable interpretation of the financial sector's losses observed during the recent financial crisis periods.

The remainder of the paper is organized as follows. Section 2 introduces three systemic risk measures: Marginal Expected Shortfall (MES), the systemic risk (SRISK) index, and the conditional Value-at-risk (CoVaR) . Section 3 presents the results of empirical analysis. Section 4 concludes.

[2]In practice, the report from the Bank for International Settlements (Basel Committee on Banking Supervision (2011)) used one of these systemic risk measures (CoVaR) to identify global systemically important banks. However, these systemic risk measures as supervisory tools are constructed by some research institutions, such as NYU Sterns Volatility Institute (which provides the measures for global financial institutions), the Center for Risk Management at HEC Lausanne (which provides the measures for European financial institutions) etc.

[3]Although the Volatility Laboratory (V-Lab) of the NYU Stern School website provides Taiwan's SRISK index, it only considers several Taiwan financial institutions. V-Lab is a systemic risk measurement provider for U.S. and global financial firms. It is based at New York University Stern School of Business under the direction of NYU Stern Professor Robert Engle (see http://vlab.stern.nyu.edu/).

2 Systemic risk measures

To analyze the systemic risk effects on the Taiwan financial system[4], we make use of three different methodologies that have been proposed in the literature. First, we compute the institution's MES and SRISK index as proposed by Acharya et al. (2010) and Brownlees and Engle (2012), respectively, as our first and second measures of systemic risk. Second, we apply CoVaR of Adrian and Brunnermeier (2011) to estimate the distress of an individual financial institution as its contribution to systemic risk.

2.1 MES

Acharya et al. (2010) are the first to introduce MES (marginal expected shortfall), which measures the contribution of each institution to overall systemic risk, but they only assume that the correlation of an individual institution and the market is constant. Brownlees and Engle (2012) extend their measure by applying a dynamic correlation structure that is more reasonable in empirical situations . We can assume that there is a panel of financial institutions indexed by $i = 1, \ldots, n$ at times $t = 1, \ldots, T$, and respectively denote R_{it} and R_{mt} to be the ith firm's and the market log return on day t. We follow Brownlees and Engle (2012) and define the ith firm's MES as the tail expectation of the ith firm's return conditional on a crisis event:

$$\mathrm{MES}_{it}(C) \equiv E_{t-1}[R_{it}|R_{mt} < C], \tag{1}$$

where a threshold value C is defined as a drop in the market return, and then $\{R_{mt} < C\}$ means the crisis event. MES of a given firm i can be estimated by computing the expectation of the log returns on the firm's stocks conditional on those days that the market experienced its worst C outcomes, like in Brownlees and Engle (2012) who set a daily loss to be -2%.

In order to estimate MES we consider a bivariate daily time series model of the firm and market returns:

$$\begin{aligned} R_{mt} &= \sigma_{mt}\epsilon_{mt} \\ R_{it} &= \sigma_{it}\left(\rho_{it}\epsilon_{mt} + \sqrt{1-\rho_{it}^2}\epsilon_{it}\right) \\ (\epsilon_{mt}, \epsilon_{it})^\top &\sim D, \end{aligned} \tag{2}$$

where σ_{it} is the conditional standard deviation of the firm return, σ_{mt} is the conditional standard deviation of the market return, ρ_{it} is the conditional correlation of the firm/market return and

[4] Although Taiwan is small measured by its territory and economic scale, based on the 2015 Open Markets Index (OMI) provided by the International Chamber of Commerce (ICC), Taiwan (Chinese Taipei) is ranked with above average openness (28, with a score of 4.1) among 75 countries investigated. In the 2015 Doing Business report, the World Bank ranked Taiwan 19 out of 189 economies for Ease of Doing Business. The 2015 Investment Climate Statement from the U.S. State Department says that "Taiwan ranks in the upper tenth percentile of major global indices measuring ease of doing business, economic freedom, and competitiveness".

the shocks $(\epsilon_{mt}, \epsilon_{it})$ are assumed to be independent and identically distribution ($i.i.d.$) with zero mean, unit variance and zero covariance over time. However, the structure of the firm and market return in (2) is not assumed to have an independent distribution anymore. In this framework, the volatilities are asymmetric GARCH models (say GJR-GARCH, Glosten et al. (1993)) and the correlation is estimated by the DCC model (Engle, 2002). The asymmetric volatility model can be expressed as follows:

$$\begin{aligned} \sigma_{mt}^2 &= \alpha_{m0}^V + \left(\alpha_{m1}^V + \gamma^V I_{mt-1}^-\right) R_{mt-1}^2 + \beta_{m1}^V \sigma_{mt-1}^2 \\ \sigma_{it}^2 &= \alpha_{i0}^V + \left(\alpha_{i1}^V + \gamma^V I_{it-1}^-\right) R_{it-1}^2 + \beta_{i1}^V \sigma_{it-1}^2 \end{aligned}$$

where $I_{it-1}^- = 1$ if $R_{it-1} < 0$ and $I_{mt-1}^- = 1$ if $R_{mt-1} < 0$. In addition, the parameter restrictions for both the market and firm's GJR-GARCH models are $\alpha_0^V \geq 0$, $\alpha_1^V > 0$, $\beta_1^V > 0$, and $\alpha_1^V + 0.5\gamma^V + \beta_1^V < 1$ to ensure positive and stationary volatility dynamics. The parameters of this model can be estimated by QMLE (quasi-maximum likelihood estimate) using standard methods.

We let Ω_{it} be the time-varying correlation matrix of the market and firm return and set

$$Var\begin{pmatrix} R_{it} \\ R_{mt} \end{pmatrix} = D_{it}\Omega_{it}D_{it} = \begin{bmatrix} \sigma_{it} & 0 \\ 0 & \sigma_{mt} \end{bmatrix} \begin{bmatrix} 1 & \rho_{it} \\ \rho_{it} & 1 \end{bmatrix} \begin{bmatrix} \sigma_{it} & 0 \\ 0 & \sigma_{mt} \end{bmatrix}.$$

where Ω_{it} is a positive definite matrix and can be defined as $\Omega_{it} = \text{diag}(Q_{it})^{-1/2} Q_{it} \text{diag}(Q_{it})^{-1/2}$, where Q_{it} is a pseudo correlation matrix. The DCC structure can then be written

$$Q_{it} = (1 - \alpha_C - \beta_C)\Omega_i + \alpha_C \epsilon_{it-1}^* \epsilon_{it-1}^{*'} + \beta_C Q_{it-1},$$

where Ω_i is a constant matrix and $\epsilon_{it}^* = \text{diag}(Q_{it})^{1/2}$ is the rescaled standardized returns. We set $\alpha_C > 0$, $\beta_C > 0, \alpha_C + \beta_C < 1$ as the necessary restrictions.

The measure of MES based on Equation (2) can be expressed as:

$$\begin{aligned} MES_{it}(C) &= E_{t-1}[R_{it}|R_{mt} < C] \\ &= \sigma_{it}\left(\rho_{it}E_{t-1}[\varepsilon_{mt}|\varepsilon_{mt} < C/\sigma_{mt}] + \sqrt{1-\rho_{it}^2}E_{t-1}[\varepsilon_{it}|\varepsilon_{mt} < C/\sigma_{mt}]\right). \end{aligned} \tag{3}$$

The conditional probability of a crisis event is

$$PoS_t(C) = P_{t-1}(R_{mt} < C) = P(\varepsilon_{mt} < C/\sigma_{mt}). \tag{4}$$

The MES formula in Equation (3) is a kind of weighted function of the tail expectation of the standardized market residual and the tail expectation of the standardized idiosyncratic firm residual. It is also like an increasing function of firm's volatility.

2.2 SRISK

Brownlees and Engle (2012) propose the SRISK index to expose the systemic risk. This index is implemented based on publicly available data, and is a function of the degree of leverage, size and

MES of a financial institution. For each firm, we denote that D_{it} and W_{it} are the book value of its debt and the market value of its equity, respectively. We also assume the prudential capital ratio to be k, define a crisis event as a drop in the market return below a threshold value C, i.e. $\{R_{mt} < C\}$, set the ith firm's capital shortfall at time t are $CS_{i,t}$, and then define the SRISK index as:

$$\text{SRISK}_{i,t} = \max\{0, E_{t-1}[CS_{i,t}|Crisis_t]\}, \tag{5}$$

where

$$\begin{aligned} E_{t-1}[CS_{i,t}|Crisis_t] &= E_{t-1}[k(D_{it} + W_{it}) - W_{it}|R_{mt} < C] \\ &= kD_{it} - (1-k)W_{it}\text{MES}_{it}(C). \end{aligned} \tag{6}$$

Here, the firm i's capital shortfall at time t is defined by $k(D_{it} + W_{it}) - W_{it}$ and a crisis event at time t is $R_{mt} < C$. It means that the capital of a firm i is expected to need recover if we have another financial crisis at time t. As discussed above, $\text{MES}_{it}(C) \equiv E_{t-1}[R_{it}|R_{mt} < C]$ is the tail expectation of the ith firm's return conditional on the crisis event. Moreover, the expected loss of equity value of firm i over a potentially long time period (say, the next six months), is called the Long Run MES (LRMES). It can be represented as (Acharya et al., 2012)

$$E_{t-1}[CS_{i,t}|Crisis_t] = kD_{it} - (1-k)\left(1 - \text{LRMES}_{it}(C)\right)W_{it}. \tag{7}$$

The contribution of aggregate SRISK by any firm i can be written as

$$\text{SRISK}\%_{it} = \frac{\text{SRISK}_{it}}{\text{SRISK}_t}, \tag{8}$$

where $\text{SRISK}_t \equiv \sum_{i=1}^{I} SRISK_{it}$ is the total amount of systemic risk in the financial system.

2.3 CoVaR

The CoVaR methodology of Adrian and Brunnermeier (2011) is used to describe what happens to the system's VaR when one particular institution is under financial stress, as measured by its own individual VaR. Recall that VaR_i^q is implicitly defined as the q quantile, i.e., $\Pr(R_{it} \leq \text{VaR}_{it}^q) = q$, where R_{it} is the log return of institution i. Thus, CoVaR is now defined as

$$\Pr(R_{mt} \leq \text{CoVaR}_{m|i,t}^q | R_{it} = \text{VaR}_{it}^q) = q. \tag{9}$$

The expression of CoVaR is the q-th quantile of the market return conditional on the distress event which is firm i's return being less than or equal to its VaR. The contribution of an individual firm i to systemic risk is written as

$$\Delta\text{CoVaR}_{m|i,t}^q = \text{CoVaR}_{j|R_{it}=\text{VaR}_{it}^q,t}^q - \text{CoVaR}_{j|R_{it}=\text{VaR}_{it}^{0.5},t}^q. \tag{10}$$

The ΔCoVaR measure can be estimated via quantile regression. We consider the predicted value of a quantile regression of the financial system $\hat{R}^q_{m|i,t}$ on a particular institution i for the q^{th}-quantile:

$$\hat{R}^q_{m|i,t} = \hat{\alpha}^q_{it} + \hat{\beta}^q_{it} R^q_{it}.$$

From the definition of VaR and for the conditioning event $\{R^q_{it} \leq \mathrm{VaR}^q_{it}\}$, the CoVaR can be given by:

$$\mathrm{CoVaR}^q_{m|R_{it} \leq \mathrm{VaR}^q_{it}} \equiv \mathrm{VaR}^q_{mt} | \mathrm{VaR}^q_{it} = \hat{\alpha}^q_{it} + \hat{\beta}^q_{it} \mathrm{VaR}^q_{it}.$$

Thus, ΔCoVaR can be obtained by

$$\Delta\mathrm{CoVaR}^q_{m|i,t} = \hat{\beta}^q_{it} (\mathrm{VaR}^q_{it} - \mathrm{VaR}^{50\%}_{it}).$$

3 Empirical study

In this paper, we study a panel of financial institutions in the Taiwan stock market from July 1, 2005 to August 29, 2014. We obtain daily log returns, their book value of debt and their market value of equity from the Taiwan Economic Journal (TEJ) database. The sample size is 2277 for each firm. As a proxy for the market's return, we use the TEJ financial market index in our main analysis. Table 1 reports the full list of stock IDs, tickers and company names by industry groups.

Insert Table 1 Here

Figure 1 shows the cumulative average return by industry groups from July 2005 to August 2014. Between July 2005 and June 2007, both the FHC and insurance groups exhibited small growth. Staring from July 2007, the financial institutions fell steeply. The stock market hit the bottom in March 2009 and started a slow recovery until the end of our data period. Table 2 reports the descriptive statistics, which include the 1st quartile, median and 3rd quartiles over three subsamples (pre-crisis, crisis and post-crisis). The results for the average return (Return) in Table 2 exhibit similar tendencies in performance changes as compared with Figure 1. In addition, the estimated volatilities (Vol.) and correlations (Corr.) over three different periods show that the volatilities and correlations during the crisis are higher than for the other two periods. Thus, in this study we apply the bivariate DCC GJR-GARCH model to model the time-varying volatility in the financial industry. Based on the Beta coefficient, the financial system's risk appears to gradually move higher over this period. For the quasi leverage (QLVG), the financial crisis show some institutions in these groups with high levels of leverage.

Insert Figure 1 and Table 2 Here

In this section we use the methods introduced in the previous section to study the impact of one institution on the market and its effect the Taiwan financial system. We focus on the analysis of the tail dependence between firm and market returns and the feature of the considered risk measures (i.e. MES, SRISK index, and CoVaR) in the sample. We begin by studying the characteristics of volatilities and correlations and then compute SRISK using balance sheet data and long term MES predictions.

3.1 Estimation results of the DCC models

To analyze the lower tail expectation conditional on the crisis event, we use DCC-GJR-GARCH model of Engle (2002, 2009) in order to study the tail dependence dynamics between firm and market returns and compute MES measures.

Figures 2-3 present the main results from the DCC estimations and display the time series plots of the averages of volatility and correlation across groups. Figure 2 shows that the average volatility is dynamic and time-varying for each industry group between 2005 and 2014. In addition, the time series of the volatility exhibit the property of volatility clustering during the crisis and show that substantial peaks in volatility broadly correspond to the financial crisis timeline.

Turning to the correlation in Figure 3, the time series patterns of the industry groups are not similar, but the results indicate that the correlations between firm and market returns change over time. For the correlations of FHCs, it shows a strong relationship between financial holding companies and market return in this sample period (almost exceeding 0.75). As with the bank industry, correlations vary considerably across different periods: correlations before the crisis are low; the financial crisis is due to correlations increasing; and correlations begin to slowly go down in the post-crisis period. The correlations of the insurance industry have similar pattern to those of the bank industry.

Insert Figures 2-3 Here

3.2 Individual contribution of systemic risk

In this section, we estimate the daily MES, SRISK, and ΔCoVaR measures for the Taiwan financial institutions during 2005 - 2014. We then examine these estimation results to assess the systemic risk contributions of individual banks in both time series and cross-sectional dimensions, and then compare the three systemic risk measures. In order to compute MES and the SRISK index, we consider data that represent trading for at least two years and calculate 120-step-ahead MES for each firm (around six months ahead prediction) conditional on a market loss of 20%, i.e. $R_{mt} < -20\%$. The SRISK index can then be obtained from using the book value of debt, the market value of equity and the estimates of the marginal expected shortfall. In this study, we set the prudential ratio k to be 8%. On the other hand, the ΔCoVaR measures can be estimated through the predicted value produced by the quantile regression analysis.

We first propose a brief comparison among MES, SRISK, and ΔCoVaR. Table 3 shows the top 10 financial institutions according to their contribution to systemic risk measured by MES, SRISK, and ΔCoVaR, respectively, on a number of selected dates. A star symbol stands for those financial institutions that appear simultaneously in the least two ranking lists. We find that the three rankings seem to capture almost the same risky financial institutions that effectively contributed to systemic risk for the whole financial system during the crisis. Table 4 reports the pairwise (Spearman) cross-sectional correlations for different systemic risk rankings on a number of selected dates. Values of the correlation matrix in bold indicate that the differences are statistically significantly different from zero at the 0.05 level. The table also presents the t value in parentheses.The Spearman rank correlation is used to see whether the information contained in the different rankings is overlapping. Therefore, the Spearman correlation coefficient can be calculated by the following formula:

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)},$$

where ρ is the Spearman rank correlation, d_i is the difference between the ranks of corresponding values, and n is the number of value in each dataset. Similar applications can be found in Puzanova and Dllmann (2013) and Huang et al. (2012). If there is no significant overlapping, then different measures may identify different institutions of systemic importance, or they may be subject to substantial estimation uncertainty and model risk (see Nucera et al. (2015); Danielsson et al. (2015)). The results of the rank correlations are in general rather stable over time and positive (from around 0.2 to 0.7). The highest correlation (0.6996) is between MES and ΔCoVaR for August 31, 2009.

Figure 4 shows the time-varying rank correlation coefficients among three systemic risk measures. The rank correlation coefficients between the measures of SRISK and ΔCoVaR indicate an increase over the selected dates, 2006-2014. In contrast, the correlation between the measures of MES and ΔCoVaR is decreasing over time, but there is the highest rank correlation during 2008-2009 (0.63-0.69). In addition, the results between the measures of SRISK and MES are quite stable (around 0.4) if we ignore nonsignificant coefficients. Overall speaking, the results show that these measures can identify similar SIFIs during the financial crisis.

In Figure 5 we compare the values of MES and ΔCoVaR at four precise dates around the financial crisis. The graph displays that both measures evaluate each firm's systemic risk contribution in a very similar way, and the correlations between the two measures are positive. It is similar to the results in Figure 6 that displays the scatter diagrams between SRISK% and ΔCoVaR. Thus, in cross-sectional analysis for systemic risk contributions across firms, it seems that the values of MES and ΔCoVaR are very similar, i.e. the change in the composition of the top ten in Table 3 is almost consistent with the evidence of Figures 5 and 6.

Table 5 shows the rankings of the systemically riskiest institutions on a number of selected dates based on the SRISK% measure. This lists those institutions that are fragile at that point in time and supervisors and policymakers could have focused on monitoring them. During the crisis period, the riskiest firms are Taishin Financial Holding Co. (TFHC) and Taiwan Cooperative Financial Holdings Co. (TCFHC). In the post-crisis period, Cathay Financial Holdings Co. (CFHC) and

Taishin Financial Holding Co. (TFHC) should be supervised. The last two lines of Table 5 show the value of the accumulated SRISK percentage for the selected dates under the top five and ten systemically riskiest institution. We note that the values of the sum of SRISK% are almost 50% (80%, respectively) for the top five (ten, respectively) systemically riskiest financial institutions. Overall, the results support that these systemic risk measures can identify the most systemically important financial institutions over a certain period.

Insert Tables 3-4 and Figures 4-6 Here

3.3 Aggregate SRISK index

3.3.1 Aggregate SRISK by group

Figure 7 shows the aggregate SRISK plots by financial sub industry groups between July 2005 and August 2014. The aggregate SRISK is the sum of all capital shortfalls in the system. In the pre-crisis period, the total shortfall is estimated to be close to 5,000 bln TWD. For the pre-crisis period, the systemic risk loss of FHCs is about 3,000 bln TWD, the loss for Bank is about 2,000 bln TWD and the loss of Insurance is about 800 bln TWD. In the financial crisis, the results indicate over 10,000 bln TWD in losses from the FHCs contributed the most to the financial sector's under capitalization. This is due to the fact that this group includes several firms with high levels of leverage and high MES. Moreover, the change in the composition of the top ten in Table 5 is consistent with the evidence of Figure 7, i.e. the riskiest industry group is FHCs.

Insert Figure 7 Here

3.3.2 As an early signal for the economy

Since the systemic risk has negative spillover effects on the financial market, we investigate whether the SRISK measure can be an early warning signal. In this section, we consider monthly growth rates of aggregate SRISK, industrial production and unemployment as follows

$$y_t = \begin{bmatrix} \Delta \log(\mathrm{SRISK}_t) \\ \Delta \log(\mathrm{IPI}_t) \\ \Delta \log(\mathrm{UR}_t) \end{bmatrix},$$

where IPI is the industrial production index and UR is the unemployment rate. We use a vector autoregressive (VAR) model to fit the SRISK measure and implement Granger causality tests that test for determining whether one variable is useful in forecasting another. The monthly industrial production index and unemployment rate between July 2005 and July 2014 are obtained from the TEJ database. The VAR model is based on a least squares estimation and the order of the model is one. Table 6 reports the results of the Granger causality test, showing that the SRISK index is not affected by the real variables. On the other hand, IPI is Granger caused by the SRISK index.

For the unemployment rate, UR is not Granger caused by SRISK, but is Granger caused by IPI. Therefore, our results thus support the finding of Brownlees and Engle (2012) that there is an indirect impact of the SRISK shock on unemployment through the industrial production index.

Insert Table 6 Here

3.4 Systemic risk determinants

In order to explore the determinants of the contributions to an individual institution's systemic risk, we conduct a panel data regression analysis with quarterly data. For the dependent variables, we employ the quarterly average of SRISK, MES and ΔCoVaR. First, we transform the SRISK index as log(1 + SRISK) to avoid negative values. For explanatory variables we consider each institution's characteristic variables: Size (log of equity), leverage ratio, m2b (market to book ratio), mm (maturity mismatch), and CR (current ratio). We also include group and government-owned fixed effects for the cross-sectional dimension. Note that the measure of SRISK is a function of size, leverage and MES, and we use the lagged explanatory variables by one quarter to avoid the endogeneity problem.

Table 7 reports the pooled OLS regression estimates for SRISK, MES and ΔCoVaR, respectively. The impact of institution characteristics is similarly the same across regressions, except for the lagged current ratio on SRISK. The results show an the institution's size and leverage have significant positive effects on all of the SRISK, MES and ΔCoVaR measures. Along with this results, m2b has a significant negative effect on all systemic risks across all models. This seems to explain that the negative effect of profitability on the systemic risk is reasonable.

The impact of the group fixed effect on all risk measures is significant negative, implying that the FHCs' contribution to systemic risk is higher than both the bank and insurance companies. On the other hand, the coefficients of the government-owned fixed effect (GOC_FE) are significantly negative when using both the SRISK and MES measures as the dependent variables. The results imply that the government-owned financial institutions have less risk than private financial institutions. The marginal effect of the Maturity Mismatch is significant but not with the expected sign: institutions with a higher degree of mm have higher expected systemic risk. The impact of the current ratio on ΔCoVaR is significant negative: institutions with a good solvency tend to be associated with lower systemic risk. We therefore consider to analyze the panel regression via different groups to discuss the determinants of the systemic risk measures.

Table 8 reports the panel regression estimation results for each group's SRISK. We employ four panel data estimation methods – pooled OLS (POLS) , fixed effect (FE), random effect (RE) and dynamic panel models (DP, Arellano and Bond, 1991) – to address the robustness of our results. Among the POLS, fixed effect, and random effect models, our results from the Hausman (1978) test exhibit that the random effect model is most suitable for FHC and that the fixed effect model is preferred for both bank and insurance companies, i.e. the individual specific effects are uncorrelated with the independent variables for FHC, but the individual specific effects are correlated with the independent variables for the bank and insurance groups. For each group, the sign of impact of institution characteristics seems to be similar the same across regressions. In the FHC's regression models, the explanatory variable of the market to book ratio has a negative and significant effect on SRISK. These is also a negative and significant coefficient for SRISK upon the bank group. However, there is a most positive effect on SRISK for the insurance industry.

We also find that the short-term liquidity factor, maturity mismatch, has a significant and positive effect on SRISK for the FHC group in the FE and RE models and has a significant and positive effect on SRISK for the insurance group in all models. In contrast, the bank group's maturity mismatch in the FE and RE models is a significant and negative driver of the contribution to systemic risk. The results exhibit that the bank group has a high degree of maturity mismatch and the FHC and insurance groups with more short-term debt contributes to the system's fragility. For the current ratio, we obtain a significant and positive effect on SRISK in most of models. In addition, we obtain a positive and significant coefficient of the lag SRISK for each group in the dynamic panel models. Along with these results, the institution's size, leverage, profitability, and solvency provide evidence for the determinants of the systemic risk contribution.

Table 9 shows the panel regression estimation results for the SRISK of government-owned companies (GOC) or non-government-owned companies (non-GOC). The significance and impact of company characteristics is similarly the same, although there are some differences across regressions. Again, the results of the Hausman (1978) test indicate that the fixed effect model is preferred for both the GOC and non-GOC groups. For the fixed effect model, we find some different points between GOC and non-GOC institutions. First, the constant term of each regression shows that the systemic risks of the non-GOC group are higher than those of the GOC group if other explanatory variables are assumed be zero. Second, the impact of size is positive but not significant for the GOC institutions. Interestingly, the coefficient of size is negatively and significantly associated with the systemic risk of the non-GOC institutions (-4.2131 and significant at the 5% level). We believe that the competitiveness of large private institutions is relatively better than that of small firms for the ability to reduce risk. Third, for the leverage ratio, there is quite a difference between the GOC and non-GOC groups. The impact of the leverage ratio is negative but not significant for the GOC group, and is positive and significant for the non-GOC group (0.1498 and significant at the 5% level). The results show that private financial institutions might incur risk in order to seek higher profits with respect to the GOC institutions. Fourth, the same sign of the m2b ratio is significant and negative for both the GOC and non-GOC groups. Moreover, the impact of the maturity mismatch has the significant and negative sign for the non-GOC group in all models. Finally, the marginal effect of the current ratio is significantly negative (-0.0069 and significant at the 5% level) for the GOC group but is not significant for the non-GOC group, i.e. the GOC financial institutions with a good solvency tend to be associated with lower systemic risk.

Insert Tables 7 - 9 Here

3.5 Verification

In subsection 3.4 above we have estimated panel regressions of the systemic risk for the 31 Taiwan financial institutions in order to understand the relationship between the contribution of the financial institutions to systemic risk and the impact of their characteristics. Sometimes the regulators and government are interested in prudential supervision requirements for certain institutions that have become systemically relevant. The models considered in this subsection are appropriate for modeling the outcome $y_{it} = 1$ for a SIFI, and 0 if not, to verify whether the determinants of systemic risk could increase the probability of becoming a systemically important institution. We then employ a logit regression model and define a binary variable as

$$y_{it} = \begin{cases} 1 & \text{if } \ y^*_{it} \geq 0 \\ 0 & \text{if } \ y^*_{it} < 0 \end{cases}$$

where y^*_{it} is a latent variable. We assume $y^*_{it} \equiv \text{SRISK}_{it} - L$, and L is a large loss value of systemic risk such as setting $L = 200$ bln TWD in this paper. We set latent variable y^*_{it}, which means the institution i become systemically relevant such that

$$\begin{aligned} y^*_{it} &= x'_{it}\beta + \varepsilon_{it} \\ &= \text{const} + \beta_1 \text{Size}_{i,t-1} + \beta_2 \text{Laverage}_{i,t-1} \\ &+ \beta_3 \text{m2b}_{i,t-1} + \beta_4 \text{mm}_{i,t-1} + \beta_5 \text{CR}_{i,t-1} + \varepsilon_{it} \end{aligned}$$

Thus, the logit model assumes the error term ε_{it} above has logistic distribution and can be written as

$$\pi_{it} = \frac{\exp(x'_{it}\beta)}{1 + \exp(x'_{it}\beta)} = \Lambda(x'_{it}\beta)$$

where the probabilities $\pi_{it} \equiv \Pr(y_{it} = 1|\mathbf{x}_{it})$ depend on a vector of explanatory variables x_{it} and $\Lambda(\cdot)$ is the logistic cumulative distribution function. Here, we do not observe the contribution of an individual institution to systemic risk at time t, but rather only whether or not it exhibit high risk to the financial system. Therefore, our observation y_{it} denotes that the ith institution is a SIFI (=1) or not (=0). Table 10 reports the logit regression estimates based on all financial institutions and the three groups. The impact and significance of the explanatory variables are similarly the same across regressions. The constant terms are significant and negative across all models, meaning that the logistic distribution tends to give smaller probabilities to $y_{it} = 1$ when all other variables are extremely small (or $\Pr(y_{it} = 1|\mathbf{x}_{it}) \approx 0$ when all other variables are zero). The marginal effect of both size and leverage are significant and have the expected positive sign across all models. The impact of the market to book ratio on the probability for triggering a crisis is negative. These results show that the risk probability is higher for poor financial institutions. However, the marginal effects of maturity mismatch and the current ratio are not significant and have different sign across regressions. In summary, an institution's size, leverage, and market to book ratio are the variables that contribute the most in explaining the cross sectional variation in the panel.

$\boxed{\text{Insert Table 10 Here}}$

4 Conclusions

Measuring systemic risk is an important issue in the financial system ever since financial institutions have become more systemically relevant over the past two decades. In this paper we employ SRISK, MES, and CoVaR measures to assess the systemic risk contribution of an individual financial firm as well as the aggregate systemic risk of the whole financial system in the Taiwan financial market. We not only have compared these three systemic risk measures, but have also analyzed the relationships between financial institutions' systemic risk contributions and some of their characteristic variables. We find that these three measures provide similar rankings for the systemic risk, although the definitions of these measures are different, and there are positive correlations among these systemic risk measures. Moreover, for the systemic risk ranking in Taiwan financial institutions, we present that the rankings do not change much in the time period of this study and FHCs (financial holding companies) contribute more systemic risk than any other financial group. The results of SRISK analysis are able to capture the early signs of a crisis and can be a useful tool for monitoring the financial system. Using these systemic risk measures, we have found significant relationships between the size of the institution and its systemic risk contribution in the cross-sectional dimension. Therefore, these risk measures could be used for stress testing in future. The leverages ratios are also closely related to systemic risk contributions from the cross-sectional dimension. We also have seen that the market to book ratio of an individual institution affects its systemic risk contribution. However, maturity mismatch and current ratio are not always associated with a firm's systemic risk contribution across the three industry groups. We also obtain the similar results in the verification study.

Reference

Acharya, V., Engle, R., and Richardson, M. (2012). Capital Shortfall: A New Approach to Ranking and Regulating Systemic Risks. *American Economic Review*, 102(3):59–64.

Acharya, V. V. (2009). A theory of systemic risk and design of prudential bank regulation. *Journal of Financial Stability*, 5(3):224–255.

Acharya, V. V., Pedersen, L. H., Philippon, T., and Richardson, M. P. (2010). Measuring Systemic Risk. SSRN Scholarly Paper ID 1573171, Social Science Research Network, Rochester, NY.

Adrian, T. and Brunnermeier, M. K. (2011). CoVaR. NBER Working Paper 17454, National Bureau of Economic Research, Inc.

Arellano, M. and Bond, S. (1991). Some Tests of Specification for Panel Data: Monte Carlo

Evidence and an Application to Employment Equations. *The Review of Economic Studies*, 58(2):277–297.

Banulescu, G.-D. and Dumitrescu, E.-I. (2015). Which are the SIFIs? A Component Expected Shortfall approach to systemic risk. *Journal of Banking & Finance*, 50:575–588.

Bartram, S. M., Brown, G. W., and Hund, J. E. (2007). Estimating systemic risk in the international financial system. *Journal of Financial Economics*, 86(3):835–869.

Basel Committee on Banking Supervision (2011). Assessment of the macroeconomic impact of higher loss absorbency for global systemically important banks. Technical report, Bank for International Settlements.

Billio, M., Getmansky, M., Lo, A. W., and Pelizzon, L. (2012). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics*, 104(3):535–559.

Bisias, D., Flood, M., Lo, A. W., and Valavanis, S. (2012). A Survey of Systemic Risk Analytics. *Annual Review of Financial Economics*, 4(1):255–296.

Brownlees, C. T. and Engle, R. F. (2012). Volatility, Correlation and Tails for Systemic Risk Measurement. SSRN Scholarly Paper ID 1611229, Social Science Research Network, Rochester, NY.

Castro, C. and Ferrari, S. (2014). Measuring and testing for the systemically important financial institutions. *Journal of Empirical Finance*, 25:1–14.

Danielsson, J., James, K. R., Valenzuela, M., and Zer, I. (2015). Model Risk of Risk Models. SSRN Scholarly Paper ID 2425689, Social Science Research Network, Rochester, NY.

de Bandt, O. and Hartmann, P. (2000). Systemic Risk: A Survey. CEPR Discussion Paper 2634, C.E.P.R. Discussion Papers.

Duan, J.-C. and Zhang, C. (2013). Cascading Defaults and Systemic Risk of a Banking Network. SSRN Scholarly Paper ID 2278168, Social Science Research Network, Rochester, NY.

ECB (2010). Financial Stability Review. Technical report, European Central Bank.

Engle, R. (2002). Dynamic Conditional Correlation. *Journal of Business & Economic Statistics*, 20(3):339–350.

Engle, R. (2009). *Anticipating Correlations: A New Paradigm for Risk Management*. Princeton University Press.

Girardi, G. and Tolga Ergn, A. (2013). Systemic risk measurement: Multivariate GARCH estimation of CoVaR. *Journal of Banking & Finance*, 37(8):3169–3180.

Glosten, L. R., Jagannathan, R., and Runkle, D. E. (1993). On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks. *The Journal of Finance*, 48(5):1779–1801.

Hausman, J. A. (1978). Specification Tests in Econometrics. *Econometrica*, 46(6):1251–1271.

Huang, X., Zhou, H., and Zhu, H. (2009). A framework for assessing the systemic risk of major financial institutions. *Journal of Banking & Finance*, 33(11):2036–2049.

Huang, X., Zhou, H., and Zhu, H. (2012). Systemic Risk Contributions. *Journal of Financial Services Research*, 42(1-2):55–83.

Kaufman, G. G. (1999). Central Banks, Asset Bubbles, and Financial Stability. In *Central Banking, Monetary Policies, and the Implications for Transition Economies*. Springer US.

Kritzman, M., Li, Y., Page, S., and Rigobon, R. (2011). Principal Components as a Measure of Systemic Risk. *The Journal of Portfolio Management*, 37(4):112–126.

Nier, E., Yang, J., Yorulmazer, T., and Alentorn, A. (2007). Network models and financial stability. *Journal of Economic Dynamics and Control*, 31(6):2033–2060.

Nucera, F., Schwaab, B., Koopman, S. J., and Lucas, A. (2015). The Information in Systemic Risk Rankings. Tinbergen Institute Discussion Paper 15-070/III/DSF94, Tinbergen Institute.

Puzanova, N. and Dllmann, K. (2013). Systemic risk contributions: A credit portfolio approach. *Journal of Banking & Finance*, 37(4):1243–1257.

Schwarcz, S. (2008). Systemic Risk. *Georgetown Law Journal*, 97:193–249.

Yun, J. and Moon, H. (2014). Measuring systemic risk in the Korean banking sector via dynamic conditional correlation models. *Pacific-Basin Finance Journal*, 27:94–114.

Table 1: Stock IDs, tickers, and company names by industry groups.

	FHCs (14)	
2880	HNFHC	Hua Nan Financial Holdings Co., Ltd.
2881	FbFHC	Fubon Financial Holding Co., Ltd.
2882	CFHC	Cathay Financial Holdings Co., Ltd.
2883	CDFHC	China Development Financial Holding Co., Ltd.
2884	ESFHC	E.SUN Financial Holding Co., Ltd.
2885	YFHC	Yuanta Financial Holding Co., Ltd.
2886	MFHC	Mega Financial Holding Company
2887	TFHC	Taishin Financial Holding Co., Ltd.
2888	SKFHC	Shin Kong Financial Holding Co., Ltd.
2889	WFHC	Waterland Financial Holding Co., Ltd.
2890	SFHC	SinoPac Financial Holding Co., Ltd.
2891	CTBCFHC	CTBC Financial Holding Co., Ltd.
2892	FiFHC	First Financial Holding Co., Ltd.
5880	TCFH	Taiwan Cooperative Financial Holdings Co., Ltd.
	Banks (10)	
2801	CHB	Chang Hwa Bank
2809	KTB	King's Town Bank Co., Ltd.
2812	TCB	Taichung Commercial Bank Co., Ltd.
2834	TBB	Taiwan Business Bank
2836	BOK	Bank of Kaohsiung
2837	CB	Cosmos Bank
2838	UBT	Union Bank of Taiwan
2845	FEIB	Far Eastern International Bank
2847	TB	Tachong Bank
2849	ECB	EnTie Commercial Bank
	Insurance (7)	
2816	UIC	Union Insurance Co., Ltd.
2823	CLIC	China Life Insurance Co., Ltd.
2832	TFMIC	Taiwan Fire & Marine Insurance Co., Ltd.
2833	TLIC	Taiwan Life Insurance Co., Ltd.
2850	SKIC	Shingkong Insurance Co., Ltd.
2851	CRC	Central Reinsurance Co., Ltd.
2852	TFIC	The First Insurance Co., Ltd.

Table 2: Descriptive statistics.

	Return	Vol.	Corr.	Beta	QLVG
	Pre-Crisis (2005-07 to 2007-07)				
Q_1	-0.01	23.89	0.52	0.70	8.13
Median	0.02	27.42	0.63	0.82	11.41
Q_3	0.06	30.86	0.67	0.99	16.58
	Crisis (2007-08 to 2009-07)				
Q_1	-0.10	43.02	0.67	0.65	9.54
Median	-0.06	45.43	0.80	0.88	15.75
Q_3	-0.01	51.67	0.84	0.97	21.33
	Post-Crisis (2009-08 to 2014-08)				
Q_1	0.02	22.73	0.62	0.79	9.01
Median	0.04	26.37	0.74	0.96	13.78
Q_3	0.05	28.64	0.83	1.05	19.52

Notes: The table displays the average return (Return), annualized volatility (Vol.), correlation (Corr.), Beta and quasi leverage (QLVG) for the financial firms in the panel. The table reports the 1st quartile, median and 3rd quartile of the statistics. The sample period is from July 1, 2005 to August 29, 2014. Sample size is 2277.

Table 3: The systemic risk rankings of the top 10 financial institutions based on SRISK, MES, and ΔCoVaR.

	2006/8/30			2007/8/30			2008/8/29		
Rank	SRISK	MES	ΔCoVaR	SRISK	MES	ΔCoVaR	SRISK	MES	ΔCoVaR
1	TCFH*	CHB*	HNFHC*	TCFH*	CFHC*	TCFH*	TFHC*	SKFHC*	TCFH*
2	TFHC*	HNFHC*	CFHC*	TFHC	HNFHC*	HNFHC*	TCFH*	YFHC	SKFHC*
3	TBB*	SKFHC	CDFHC*	TBB*	TBB*	FiFHC*	SKFHC*	CFHC	ESFHC*
4	HNFHC*	TBB*	FiFHC*	HNFHC*	SKIC	SKFHC*	TBB	CLIC	CTBCFHC
5	CHB*	TFHC*	CHB*	FiFHC*	YFHC	FbFHC	CHB*	FiFHC*	YFHC
6	FiFHC*	CFHC*	SKFHC*	CHB*	BOK	CHB*	FiFHC*	TFHC*	HNFHC*
7	SKFHC*	CTBCFHC*	CTBCFHC*	ESFHC*	CDFHC*	ESFHC*	HNFHC*	SFHC*	FiFHC*
8	UBT	CDFHC*	FbFHC	UBT	TFIC	CTBCFHC	SFHC*	FEIB	CFHC
9	TB	TCFH*	ESFHC	SKFHC*	CLIC	CDFHC*	ESFHC*	HNFHC*	CHB*
10	TCB	TFIC	SKIC	ECB	TCFH*	CFHC*	MFHC*	CHB*	MFHC*
	2009/8/31			2010/8/31			2011/08/31		
Rank	SRISK	MES	ΔCoVaR	SRISK	MES	ΔCoVaR	SRISK	MES	ΔCoVaR
1	TFHC*	YFHC	CFHC*	TFHC*	CB	CFHC*	CFHC*	ECB	TCFH*
2	TCFH	CFHC*	CTBCFHC	TCFH*	FEIB	CTBCFHC*	TFHC*	YFHC*	YFHC*
3	SKFHC*	TFHC*	YFHC	SKFHC*	SKFHC*	SKFHC*	TCFH*	CDFHC	FbFHC
4	MFHC*	SFHC*	SKFHC*	FiFHC*	CLIC*	YFHC	SKFHC*	CFHC*	CFHC*
5	TBB*	MFHC*	FiFHC*	TBB*	TCFH*	TFHC*	TBB	CB	TFHC*
6	FiFHC*	TBB*	CHB*	HNFHC	TBB*	SFHC*	HNFHC*	TLIC	FiFHC*
7	HNFHC	TB	SFHC*	CFHC*	CTBCFHC*	FiFHC*	FiFHC*	SKFHC*	SFHC*
8	CHB*	CHB*	TFHC*	FbFHC	TB	CHB*	SFHC*	MFHC	HNFHC*
9	CFHC*	SKFHC*	BOK	SFHC*	SFHC*	TLIC	ESFHC	KTB	CTBCFHC
10	FbFHC*	FEIB	FbFHC*	CHB*	CDFHC	CLIC*	TB	HNFHC*	CHB
	2012/08/31			2013/08/30			2014/08/29		
Rank	SRISK	MES	ΔCoVaR	SRISK	MES	ΔCoVaR	SRISK	MES	ΔCoVaR
1	CFHC	ESFHC*	MFHC	CFHC*	YFHC*	FbFHC*	SKFHC	CFHC*	HNFHC*
2	TFHC*	UIC	FEIB	TFHC*	CDFHC	YFHC*	TFHC	FbFHC*	FbFHC*
3	TCFH*	CLIC	TFHC*	TCFH	CFHC*	FiFHC*	TCFH*	CTBCFHC*	FiFHC*
4	SKFHC*	SKFHC*	YFHC	SKFHC	CLIC*	MFHC	CFHC*	YFHC*	MFHC*
5	FbFHC*	TCFH*	CHB*	TBB*	SKIC	TFHC*	FbFHC*	TLIC	TCFH*
6	TBB*	TFHC*	FbFHC*	FiFHC*	TBB*	CLIC*	TBB*	CDFHC	YFHC*
7	FiFHC*	SFHC	TBB*	HNFHC*	TLIC	ESFHC	CTBCFHC*	MFHC*	CTBCFHC*
8	HNFHC*	CTBCFHC*	HNFHC*	FbFHC*	FbFHC*	FEIB	FiFHC*	UIC	CFHC*
9	ESFHC*	TCB	CTBCFHC*	SFHC	KTB	HNFHC*	HNFHC*	CLIC	CHB
10	CHB*	FbFHC*	FiFHC*	CHB	CTBCFHC	CFHC*	SFHC	FEIB	TBB*

Notes: A star symbol highlights those financial institutions that appear simultaneously more than two times among the rankings of the SRISK, MES, and ΔCoVaR.

Table 4: The Spearman's rank correlation matrix for different SIFI's rankings of the Taiwan financial institutions based on three systemic risk measures.

	2006/8/30			2007/8/30			2008/8/29		
	SRISK	MES	ΔCoVaR	SRISK	MES	ΔCoVaR	SRISK	MES	ΔCoVaR
SRISK	1	**0.4760**	**0.2252**	1	0.0712	**0.2329**	1	**0.3636**	**0.4550**
		(3.3884)	(1.8119)		(0.6206)	(1.8348)		(2.4150)	(3.0486)
MES	-	1	**0.5988**	-	1	**0.4702**	-	1	**0.6306**
			(4.0207)			(2.8648)			(4.3699)
ΔCoVaR	-	-	1	-	-	1	-	-	1
	2009/8/31			2010/8/31			2011/08/31		
	SRISK	MES	ΔCoVaR	SRISK	MES	ΔCoVaR	SRISK	MES	ΔCoVaR
SRISK	1	**0.4827**	**0.4858**	1	**0.4376**	**0.5600**	1	0.1448	**0.4723**
		(3.0949)	(3.1621)		(2.8428)	(3.8515)		(1.1941)	(3.6665)
MES	-	1	**0.6996**	-	1	**0.3077**	-	1	**0.4145**
			(5.2645)			(1.7384)			(2.4494)
ΔCoVaR	-	-	1	-	-	1	-	-	1
	2012/08/31			2013/08/30			2014/08/29		
	SRISK	MES	ΔCoVaR	SRISK	MES	ΔCoVaR	SRISK	MES	ΔCoVaR
SRISK	1	**0.5376**	**0.4274**	1	0.0140	**0.4368**	1	**0.2409**	**0.6213**
		(3.5417)	(2.8554)		(0.4269)	(2.9670)		(1.7484)	(4.6744)
MES	-	1	**0.2536**	-	1	0.0911	-	1	**0.3145**
			(1.4093)			(0.4905)			(1.7813)
ΔCoVaR	-	-	1	-	-	1	-	-	1

Notes: Values of correlation matrix in bold are significantly different from 0 at the 0.05 level and the t-value is indicated in parentheses.

Table 5: Systemic risk contributions of Taiwan financial institutions on a number of selected dates.

	2006/8/30			2007/8/30			2008/8/29		
1	5880	TCFH	21.73%	5880	TCFH	22.21%	2887	TFHC	20.75%
2	2887	TFHC	20.45%	2887	TFHC	21.54%	5880	TCFH	14.65%
3	2834	TBB	11.41%	2834	TBB	12.38%	2888	SKFHC	11.57%
4	2880	HNFHC	8.75%	2880	HNFHC	10.05%	2834	TBB	8.79%
5	2801	CHB	7.96%	2892	FiFHC	7.00%	2801	CHB	6.21%
6	2892	FiFHC	5.27%	2801	CHB	5.49%	2892	FiFHC	6.04%
7	2888	SKFHC	4.51%	2884	ESFHC	3.39%	2880	HNFHC	5.29%
8	2838	UBT	2.53%	2838	UBT	3.18%	2890	SFHC	4.79%
9	2847	TB	2.46%	2888	SKFHC	2.64%	2884	ESFHC	4.35%
10	2812	TCB	2.38%	2849	ECB	2.25%	2886	MFHC	2.86%
Top 5			70.29%			73.19%			61.98%
Top 10			87.44%			90.14%			85.32%
	2009/8/31			2010/8/31			2011/8/31		
1	2887	TFHC	14.16%	2887	TFHC	14.12%	2882	CFHC	17.04%
2	5880	TCFH	12.20%	5880	TCFH	13.55%	2887	TFHC	15.65%
3	2888	SKFHC	8.69%	2888	SKFHC	11.76%	5880	TCFH	13.72%
4	2886	MFHC	7.84%	2892	FiFHC	8.06%	2888	SKFHC	12.26%
5	2834	TBB	6.93%	2834	TBB	7.69%	2834	TBB	7.96%
6	2892	FiFHC	6.89%	2880	HNFHC	5.70%	2880	HNFHC	6.19%
7	2880	HNFHC	5.44%	2882	CFHC	4.72%	2892	FiFHC	4.78%
8	2801	CHB	5.25%	2881	FbFHC	4.24%	2890	SFHC	4.01%
9	2882	CFHC	5.18%	2890	SFHC	4.11%	2884	ESFHC	3.63%
10	2881	FbFHC	5.03%	2801	CHB	4.09%	2847	TB	2.25%
Top 5			49.83%			55.18%			66.62%
Top 10			77.62%			78.04%			87.48%
	2012/8/31			2013/8/30			2014/8/29		
1	2882	CFHC	16.05%	2882	CFHC	15.47%	2888	SKFHC	14.22%
2	2887	TFHC	12.46%	2887	TFHC	14.22%	2887	TFHC	13.86%
3	5880	TCFH	11.35%	5880	TCFH	12.67%	5880	TCFH	12.94%
4	2888	SKFHC	10.79%	2888	SKFHC	12.14%	2882	CFHC	9.85%
5	2881	FbFHC	9.40%	2834	TBB	7.14%	2881	FbFHC	7.57%
6	2834	TBB	5.51%	2892	FiFHC	5.00%	2834	TBB	6.33%
7	2892	FiFHC	4.77%	2880	HNFHC	4.94%	2891	CTBCFHC	6.03%
8	2880	HNFHC	4.29%	2881	FbFHC	4.86%	2892	FiFHC	4.95%
9	2884	ESFHC	3.78%	2890	SFHC	3.08%	2880	HNFHC	4.13%
10	2801	CHB	3.47%	2801	CHB	2.68%	2890	SFHC	2.82%
Top 5			60.05%			61.64%			58.45%
Top 10			81.88%			82.21%			82.71%

Notes: The rankings of the systemical riskies institutions are based on the SRISK% measure. The results contain rankings, stock IDs, company names ,and SRISK% on a number of selected dates.

Table 6: Granger causality tests.

		j		
		SRISK	IPI	UR
	SRISK		0.88	2.16
i	IPI	3.11**		2.43*
	UR	1.84	4.89***	

Notes: The table reports the results of the Granger causality test, which assesses if variable j Granger causes variable i. Asterisks denote the level of statistical significance (one asterisk, $P < 0.05$; two asterisks, $P < 0.01$; three asterisks, $P < 0.001$).

Table 7: Determinants of individual systemic risk measures.

Variables	SRISK	MES	ΔCoVaR
const	-37.7243**	-37.4336**	76.8924
	(9.1492)	(4.6627)	(87.5139)
Bank_FE	-1.8137**	-1.6354**	-73.9678**
	(0.8128)	(0.4892)	(10.4633)
Insurance_FE	-11.2082**	1.7430**	-56.6538**
	(0.9144)	(0.7296)	(13.0193)
GOC_FE	-2.0223**	-0.8763**	1.4566
	(0.2614)	(0.2385)	(5.3320)
Size(-1)	2.3031**	2.5415**	6.0910*
	(0.3678)	(0.1907)	(3.5006)
Leverage(-1)	0.5800**	0.1279**	2.2945**
	(0.0343)	(0.0153)	(0.3516)
m2b(-1)	-2.6727**	-1.1404**	-18.2591**
	(0.2864)	(0.4011)	(4.9181)
mm(-1)	-0.0034	-0.0091**	-0.1951**
	(0.0082)	(0.0026)	(0.0656)
CR(-1)	0.0728**	-0.0138	-0.4628**
	(0.0193)	(0.0107)	(0.2022)
n	1116	1116	1116
R^2	0.5187	0.3252	0.1290

Notes: The dependent variable is the systemic risk measure for 31 Taiwan financial institutions, including SRISK, MES and ΔCoVaR, respectively. The explanatory variables are Size (log of equity), leverage ratio, m2b (market to book ratio), mm (maturity mismatch), CR (current ratio), the bank and insurance fixed effects, and government-owned companies (GOC) fixed effect. The lagged explanatory variables are considered in the table. Sample size n and adjusted R^2 are also in the table. The symbols *, **, and *** denote statistical significance at the 10%, 5%, 1 % levels, respectively. Standard errors are in parentheses.

Table 8: Determinants of SRISK for each group.

FHC	SRISK	POLS	FE	RE	DP
	const	-9.9936	75.2459**	65.3152**	-7.5005
		(23.2616)	(27.3260)	(26.3628)	(6.2596)
	Size(-1)	1.2757	-1.8972*	-1.5071	0.6200**
		(0.9362)	(1.1105)	(1.0518)	(0.2576)
	Leverage(-1)	0.2941**	0.0376	0.0472	0.0987***
		(0.0418)	(0.0301)	(0.0857)	(0.0283)
	m2b(-1)	-3.6549**	-6.8362**	-6.8785**	-0.9274**
		(1.0912)	(1.2934)	(1.0769)	(0.4240)
	mm(-1)	-0.0179**	0.0173**	0.0167**	-0.0020
		(0.0079)	(0.0064)	(0.0058)	(0.0025)
	CR(-1)	0.0333*	0.0157*	0.0159	0.0117
		(0.0183)	(0.0084)	(0.0170)	(0.0090)
	SRISK(-1)				0.6039***
					(0.0324)
	n	504	504	504	504
	R^2	0.0441	0.1693	-	-
Bank		POLS	FE	RE	DP
	const	-19.2242*	142.5014**	56.5655**	1.3511
		(9.8318)	(35.5687)	(16.6851)	(3.2427)
	Size(-1)	1.6707**	-5.0132**	-1.4131**	0.1553
		(0.4054)	(1.4676)	(0.7007)	(0.1392)
	Leverage(-1)	0.4210**	0.1538	0.3383**	0.1235***
		(0.0669)	(0.1197)	(0.0553)	(0.0173)
	m2b(-1)	-6.6013**	-0.7511	-4.1351**	-1.7106***
		(1.3282)	(1.6401)	(0.9904)	(0.3069)
	mm(-1)	0.0070	-0.2924**	-0.2616**	-0.0943***
		(0.0631)	(0.0597)	(0.0647)	(0.0218)
	CR(-1)	0.2218	-0.2333	-0.1659	-0.0658
		(0.1367)	(0.1673)	(0.1421)	(0.0466)
	SRISK(-1)				0.7917***
					(0.0243)
	n	360	360	360	360
	R^2	0.3294	0.3102	-	-
Insurance		POLS	FE	RE	DP
	const	-114.1391**	7.4422	-8.7831	-17.7884***
		(16.2346)	(5.0481)	(5.4218)	(2.5402)
	Size(-1)	5.1726**	-0.1295	0.5808**	0.7668***
		(0.7567)	(0.2220)	(0.2357)	(0.1151)
	Leverage(-1)	0.4748**	0.0946**	0.1380**	0.0557***
		(0.0559)	(0.0181)	(0.0147)	(0.0087)
	m2b(-1)	-0.9907**	0.6556**	0.4484**	0.4972***
		(0.2668)	(0.1462)	(0.1204)	(0.0548)
	mm(-1)	0.1113**	0.0211**	0.0313**	0.0162***
		(0.0206)	(0.0050)	(0.0079)	(0.0037)
	CR(-1)	0.0747**	0.0342**	0.0370**	0.0128***
		(0.0168)	(0.0062)	(0.0071)	(0.0035)
	SRISK(-1)				0.8588***
					(0.0173)
	n	252	252	252	252
	R^2	0.9369	0.5772	-	-

Notes: The dependent variable is SRISK for FHC, bank, and insurance companies. POLS, FE, RE and DP stand for pooled OLS, a fixed effect model, a random effect model and a dynamic panel model, respectively. The explanatory variables are Size (log of equity), leverage ratio, m2b (market to book ratio), mm (maturity mismatch), and CR (current ratio). The symbols *, **, and *** denote statistical significance at the 10%, 5%, 1% levels, respectively. Standard errors are in parentheses.

Table 9: Determinants of SRISK for government-owned companies (GOC) or private companies (non-GOC).

GOC	SRISK	POLS	FE	RE	DP
	const	-90.7207**	18.4436**	14.0231	-24.2315***
		(4.7717)	(8.2736)	(10.1997)	(3.1343)
	Size(-1)	4.0180**	0.0412	0.2239	1.1196***
		(0.2059)	(0.3365)	(0.4107)	(0.1419)
	Leverage(-1)	0.6697**	-0.0018	0.0060	0.1583***
		(0.0306)	(0.0134)	(0.0221)	(0.0187)
	m2b(-1)	2.3144*	-1.8161**	-1.9492**	-0.0960
		(1.2129)	(0.4036)	(0.4885)	(0.3331)
	mm(-1)	5.4374**	-0.6206	-0.5751	1.0563***
		(1.4429)	(0.3974)	(0.3754)	(0.3429)
	CR(-1)	0.0680**	-0.0069**	-0.0065	0.0094*
		(0.0294)	(0.0032)	(0.0049)	(0.0055)
	SRISK(-1)				0.7273***
					(0.0282)
	n	396	396	396	396
	R^2	0.5257	0.0611	-	-
non-GOC	SRISK	POLS	FE	RE	DP
	const	-94.5863**	119.7586**	103.3972**	-28.4340***
		(7.7635)	(15.4073)	(15.8919)	(2.6220)
	Size(-1)	4.7253**	-4.2131**	-3.5350**	1.3916 ***
		(0.3297)	(0.6391)	(0.6464)	(0.1203)
	Leverage(-1)	0.6011**	0.1498**	0.1718**	0.1761 ***
		(0.0273)	(0.0574)	(0.0540)	(0.0162)
	m2b(-1)	-5.3454**	-0.8455*	-1.0731**	-0.9687 ***
		(0.4139)	(0.4637)	(0.4761)	(0.1706)
	mm(-1)	-4.2583**	-4.0203**	-3.8550**	-1.1669 ***
		(1.6345)	(1.7947)	(1.4973)	(0.3921)
	CR(-1)	-0.0824**	0.0271	0.0213	-0.0209 **
		(0.0274)	(0.0267)	(0.0313)	(0.0096)
	SRISK(-1)				0.6911 ***
					(0.0210)
	n	720	720	720	720
	R^2	0.4394	0.1206	-	-

Notes: The dependent variable is SRISK for GOC or non-GOC. POLS, FE, RE and DP stand for pooled OLS, a fixed effect model, a random effect model and a dynamic panel model, respectively. The explanatory variables are Size (log of equity), leverage ratio, m2b (market to book ratio), mm (maturity mismatch), and CR (current ratio). The symbols *, **, and *** denote statistical significance at the 10%, 5%, 1% levels, respectively. Standard errors are in parentheses.

Table 10: Verification of systemic risk using the logit regression model.

	FULL	FHC	Bank	Insurance
const	-50.2943**	-20.6510**	-242.1725**	-127.4043**
	(3.3863)	(4.6979)	(56.3120)	(41.6465)
Size(-1)	2.0903**	0.6726**	10.0504**	5.5796**
	(0.1394)	(0.1762)	(2.3427)	(1.7913)
Leverage(-1)	0.1008**	4.6666**	0.8048**	0.3296**
	(0.0123)	(1.0818)	(0.2112)	(0.1150)
m2b(-1)	-2.5831**	-1.3655**	-20.3489**	-9.4227**
	(0.2577)	(0.3056)	(5.4232)	(3.0395)
mm(-1)	-0.0016	-0.0033	0.2247	0.0378
	(0.0020)	(0.0020)	(0.1834)	(0.1497)
CR(-1)	0.0026	-0.0044	0.3422	-0.0398
	(0.0053)	(0.0066)	(0.4077)	(0.0298)
R^2	0.3639	0.1188	0.9004	0.7083

Notes: The dependent variable is a binary variable that is one if SRISK $\geq 2 \times 10^{10}$, and zero if otherwise. The explanatory variables are size (log of equity), leverage ratio, m2b (market to book ratio), mm (maturity mismatch), and CR (current ratio). The symbols *, **, and *** denote statistical significance at the 10%, 5%, 1% levels, respectively. Standard errors are in parentheses.

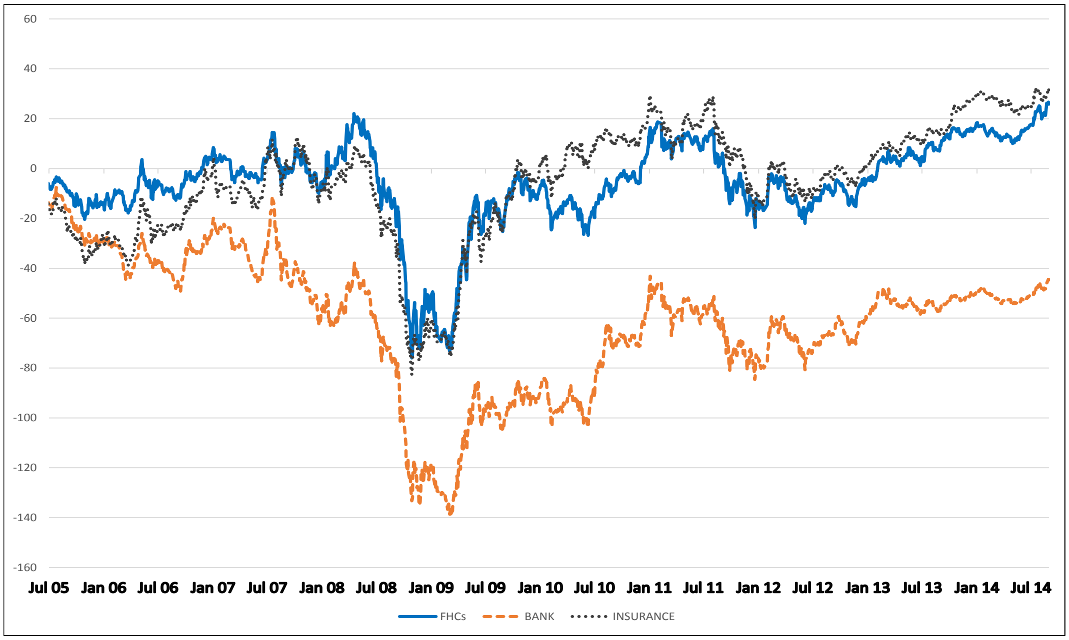

Figure 1: Cumulative average return by industry group.

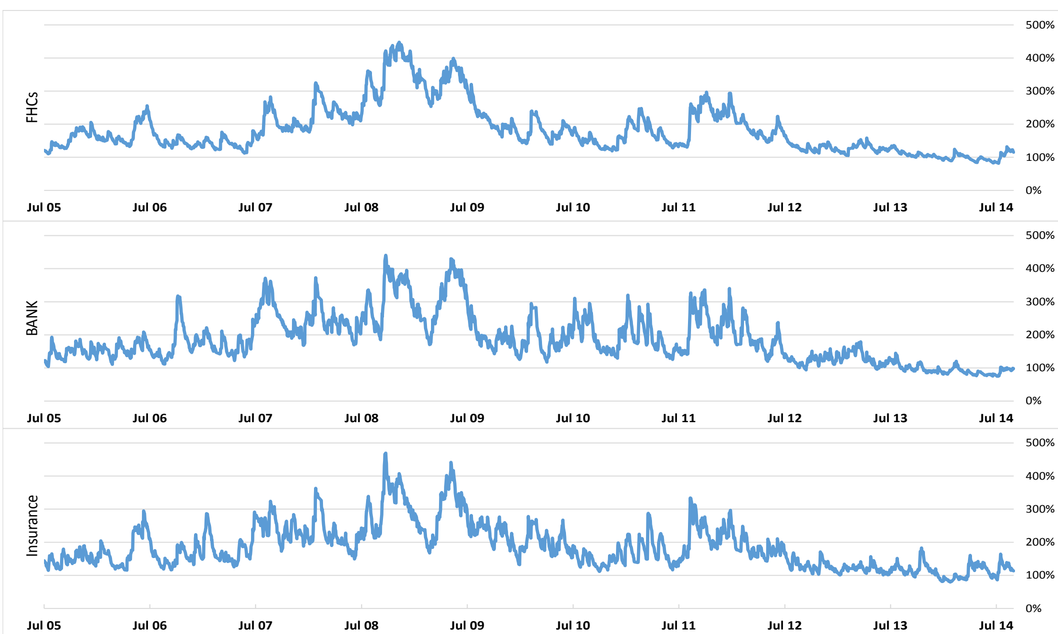

Figure 2: Plots of the average in-sample volatilities between July 2005 and August 2014 for each group.

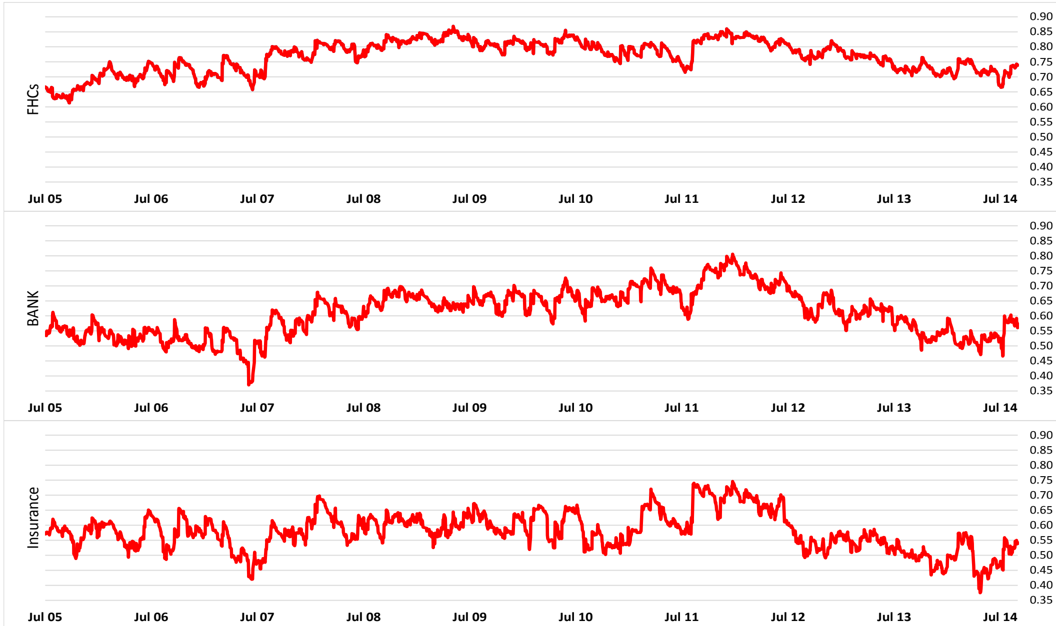

Figure 3: Plots of the average in-sample correlation with the market return between July 2005 and August 2014 for each group.

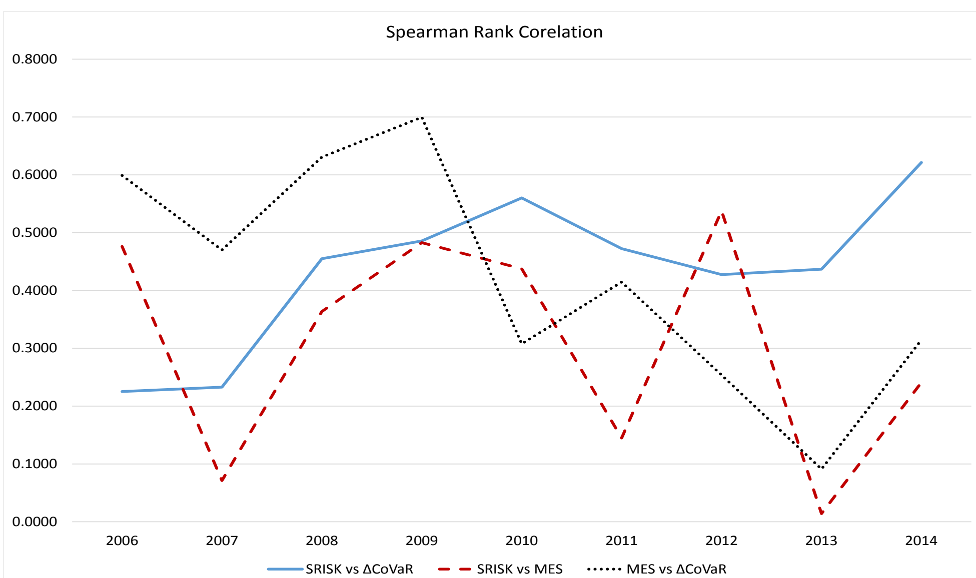

Figure 4: Comparisons of the Spearman rank correlation among rankings of the systemic risk measures.

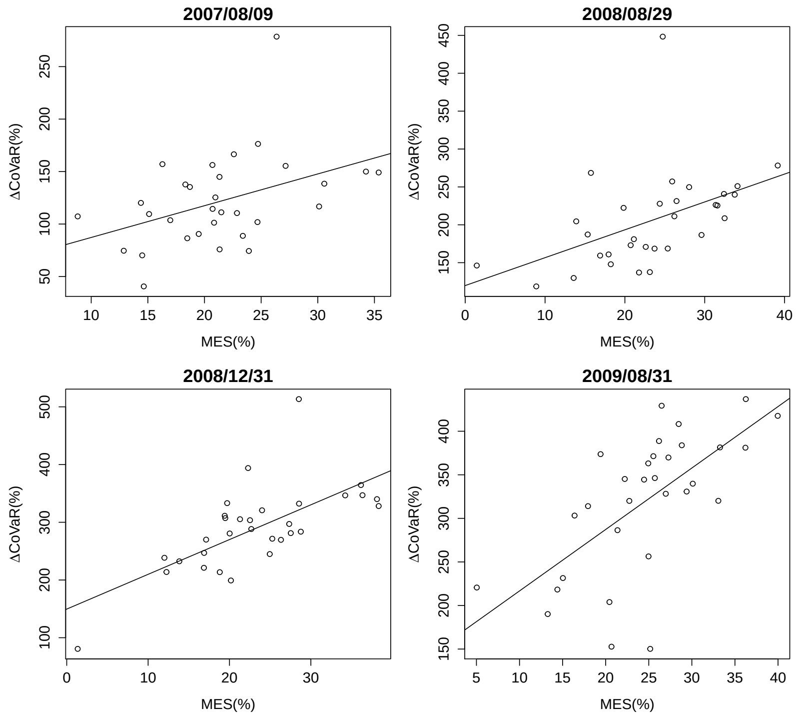

Figure 5: Comparisons between MES and ΔCoVaR during the financial crisis of 2007-2008 .

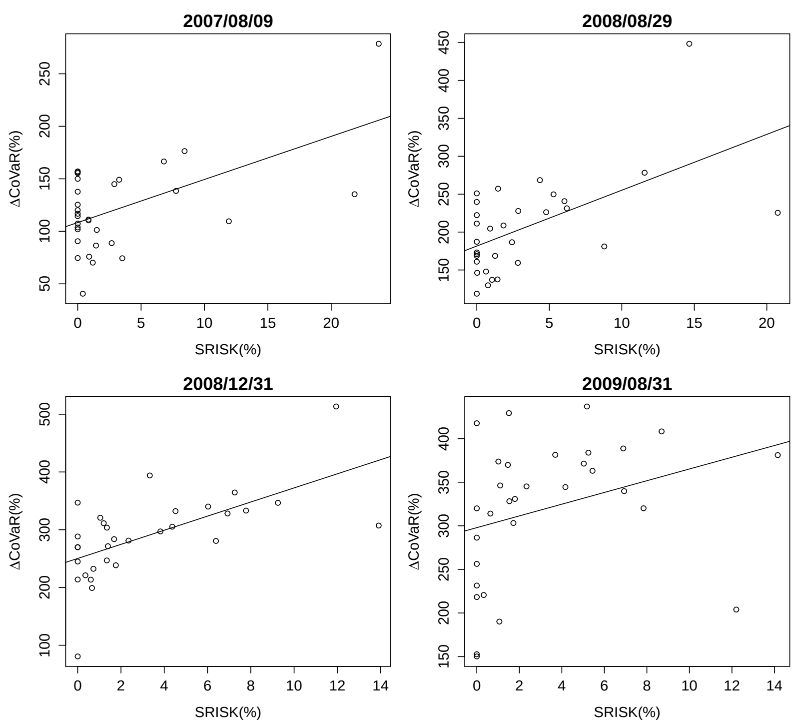

Figure 6: Comparisons between SRISK% and ΔCoVaR during the financial crisis of 2007-2008 .

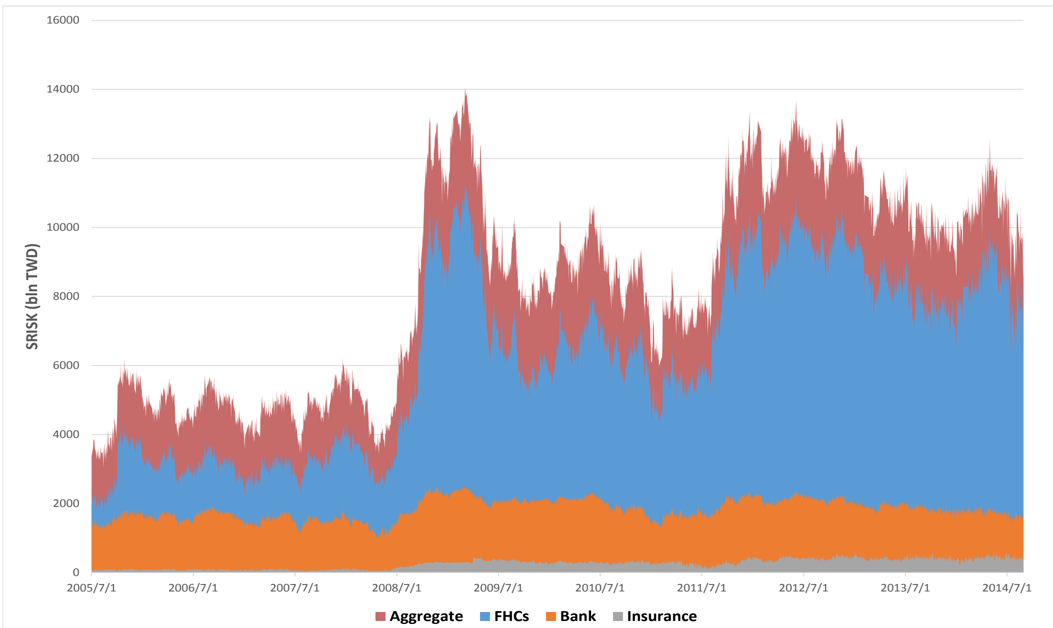

Figure 7: Aggregate SRISK by group. The plot shows the aggregate SRISK by financial sub industry groups between July 2005 and August 2014.