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Systematic risk measurement in the global banking stock market with time series analysis and CoVaR

Abstract

Motivated by the growing importance of systemic risk in the global banking system, the authors measure the risk of the system and the marginal contributions of the institutions in several ways in terms of stock markets. The undiversifiable risk appearing in specific market sectors is called systematic risk rather than systemic risk. The paper focuses on global banking stocks comprising global systemically important financial institutions (G-SIFIs), and discusses the global systematic risk measurement. To forecast future joint distribution of returns, the authors utilize the multivariate autoregressive moving average generalized autoregressive conditional heteroscedasticity (ARMA-GARCH) model with the multivariate normal tempered stable (MNTS) distributed and multivariate normal distributed innovations. This work statistically demonstrates that the ARMA-GARCH model with the MNTS distributed innovations is a more realistic model for G-SIFI stocks. In line with previous studies, the authors estimate four systematic risk measures: joint probability and conditional probability of negative stock return movements, ΔCoVaR, and ΔCoAVaR. It is found that the joint probability of negative movements is a good indicator for a significant increase in systematic risk. Subsequently, the authors investigate the relationship among the other three measures and find the following. Cross-sectional linkages between AVaR and ΔCoAVaR are few, if any, but there is a strong time series linkage. On the other hand, the conditional probability of negative movements and ΔCoAVaR show similar cross-sectional magnitude relations, though their time series linkage is not clear. Thus, both AVaR and conditional probability of negative movements reinforce each other and serve a useful reference for ΔCoAVaR-based systematic risk measurement.

Keywords: ARMA-GARCH model, multivariate normal tempered stable distribution, CoVaR, CoAVaR, systematic risk measurement, G-SIFIs, global banking stock markets.
JEL Classification: F37, G01, G15, G17, G20, G32.

Introduction

In the modern financial system, global financial institutions become strongly interconnected, leading to awareness of the so-called "systemic risk". According to the definition given by Kaufman and Scott (2003), in contrast to the risk that there will be a breakdown in individual parts or components of the financial system, systemic risk refers to the probability that there will be a breakdown of the entire financial system. Moreover, this risk is evidenced by the comovements of the different parts of the financial system.

We can observe the applicability of this definition of systemic risk in the case of global financial system in 2008, following the bankruptcy of the United States (U.S.) investment banking firm Lehman Brothers. The financial crisis triggered by the failure of Lehman Brothers, referred to as the "Lehman shock", had a spillover effect in every sector of the global financial market (stock, bond, currency, credit markets, and the like).

Following the Lehman shock, the Basel Committee on Banking Supervision (BCBS) began to formulate a new regulatory framework for international banks known as Basel III to mitigate the risk of a reoccurrence of financial crises due to the problem of large financial institutions. One of the most significant enhancements in Basel III relative to Basel I and II is that of protecting the global financial system from systemic risk. More specifically, Basel III calls for additional capital requirements for global systemically important financial institutions (G-SIFIs), in contrast to the uniform capital requirement imposed on every bank in Basel II. More recently, an initial list of 29 G-SIFIs (8 from the United States, 17 from Europe, and 4 from Asia) was identified and published based on the BCBS methodology (Financial Stability Board, 2011). See the Appendix for the list of financial institutions.

The recent debt crisis in Greece calls for greater attention to systemic risk in another way. Because financial institutions typically have large positions in sovereign bonds, there was great concern in the market that a systemic downturn would occur because of the European sovereign debt crisis. This, in fact, did occur for one G-SIFI, Dexia Group, because of exposures to these countries. There are some market observers with such a pessimistic view that if Greece collapses, the adverse impact on the financial system would be greater than that of the Lehman shock.

Motivated by the growing importance of systemic risk, the purpose of this paper is to investigate such risk in the global banking system. This is done by focusing on systemic risk observed in stock markets and investigating stocks that are included in G-SIFIs, as of November 2011. Our methodology involves time series analysis to generate a future joint distribution of stock returns, and accordingly we estimate risk measures.

We emphasize that, strictly speaking, we are not going to quantify systemic risk itself given that we exclusively deal with stock returns. There are *systemic* risk and *systematic* risk. Even though both emerge with a downslide of total market returns, systemic risk is considered as the risk that specifically arises from intense interconnectedness and results in a breakdown of the entire system. Aggregate adverse impact in a specific sector of a market should be classified as systematic risk. For this reason, we hereafter refer to the risk that we quantify based on stock returns as systematic risk rather than systemic risk[1].

For time series analysis, we use a multivariate autoregressive moving average generalized autoregressive conditional heteroscedasticity (ARMA-GARCH) model, where the innovation terms are assumed to follow the multivariate normal tempered stable (MNTS) and multivariate normal distributions. The MNTS distribution is a relatively new non-Gaussian stock return model proposed by Kim et al. (2012). Each marginal of the MNTS distribution is referred to as a univariate normal tempered stable (NTS) distribution. For systematic risk measures, we use the CoVaR methodology proposed by Adrian and Brunnermeier (2011). CoVaR, or more specifically, $\mathrm{CoVaR}^{j|i}$, is defined between two institutions i and j. $\mathrm{CoVaR}^{j|i}$ is the Value at Risk (VaR) of j on a certain condition of i. Setting j as the market index, we consider the difference between CoVaR on i's distress and "normal" conditions, denoted by $\Delta\mathrm{CoVaR}^{index|i}$. $\Delta\mathrm{CoVaR}^{index|i}$ can be interpreted as the marginal contribution of i to the overall market risk.

There are two problems we address in this issue. The first is how to measure and predict systematic risk. The second is how to determine the influence of a financial institution on the entire financial system, i.e., how to quantify the risk spillover effect. From a regulatory perspective, it is critical to recognize signals of a meltdown of the financial system and specify the financial institutions that potentially have considerable influence on the financial system.

For the first problem, we propose the joint probability of negative stock return movements as a measure of systematic risk. This is necessary because although ΔCoVaR can be a measure of marginal contribution to systematic risk, it is not a measure of systematic risk itself. For the second problem, we employ ΔCoVaR to quantify the risk spillover effect. In addition, we extend ΔCoVaR into the counterpart of average VaR (AVaR), which we refer to as ΔCoAVaR. An alternative approach for the risk spillover effect is to describe an institution's power of influence on the system as the probability of a negative comovement of the market return on the condition that a return of the institution moves downward. The idea underlining the use of conditional probability is parallel to the idea of addressing the first problem via joint probability. We examine the relationship among AVaR, ΔCoAVaR, and conditional probability using regression analysis.

The rest of this paper is organized as follows. In section 1, we introduce an ARMA-GARCH-MNTS model for time series analysis. Subsequently, we define the following systematic risk measures: the joint probability and conditional probability of negative movements, ΔCoVaR, and ΔCoAVaR. Section 2 describes the data to be used. Section 3 presents the results and discussion. After we demonstrate that the ARMA-GARCH-MNTS model is a better model for G-SIFI stocks, we present the estimation results of systematic risk measures. We also discuss the relationship among the different types of measures. The final section concludes the paper.

1. Methodology

Our methodology for the investigation of systematic risk has the following two steps: (1) generating the future joint distribution of stock returns via the ARMA-GARCH model; and (2) deriving systematic risk measures from the predicted joint distribution. We also briefly explain our simulation-based estimation methods.

1.1. ARMA-GARCH-MNTS model. Our time series model for stock returns is the ARMA(1,1)-GARCH(1,1) model given by

$$\begin{aligned} R_{t+1}^j &= \mu_{t+1}^j + \sigma_{t+1}^j \eta_{t+1}^j, \\ \mu_{t+1}^j &= c_j + a_j R_t^j + b_j \sigma_t^j \eta_t^j, \\ (\sigma_{t+1}^j)^2 &= \psi_j + \omega_j (\sigma_t^j)^2 (\eta_t^j)^2 + \xi_j (\sigma_t^j)^2, \end{aligned} \tag{1}$$

where the index j =1, 2,…, J corresponds to each institution, t represents a time period, R_t^j is the stock return, μ_t^j is the conditional mean, σ_t^j is the conditional standard deviation, η_t^j is i.i.d. with zero mean and unit variance, called (standardized) innovation, and the other symbols are model parameters. We describe the multivariate distribution whose every marginal has zero mean and unit variance as standard. Thus, $\eta_t = (\eta_t^1, \eta_t^2, \ldots, \eta_t^J)$ forms a standard multivariate distribution. Note that ARMA(1,1)-GARCH(1,1) is a standard specification for financial data in the GARCH framework.

[1] The basic measure of systematic risk is beta. Similar to beta, we focus on the comovement between the entire system and each institution in the global banking stock market.

There are several candidate models for each marginal η_t^j. We choose the NTS distribution because it has the ability to capture stylized properties of stock return distributions such as fat-tailness and skewness, which the normal distribution lacks. In addition, we use the normal distribution for the purpose of comparison. The standard NTS distribution is characterized by three parameters: two fat-tailness parameters (α, θ) and one skewness parameter β. If we assume common (α, θ) among NTS marginals with β as a still free parameter for calibration, we can join marginals into MNTS via the variance-covariance matrix of η_t without computational difficulty even in a considerably high-dimensional system. See Kim et al. (2012) for the definition and estimation of the MNTS distribution. In the case of the normal model, we can also join marginals into the multivariate distribution via the variance-covariance matrix, because it is the single parameter of the standard multivariate normal distribution. The multivariate distribution of η_t accounts for the dependent structures among stock returns. Following the same approach as Kim et al. (2012), we first estimate the univariate NTS parameters $(\alpha,\theta,\beta)=(\hat{\alpha},\hat{\theta},\hat{\beta})$ for the innovation of the representative stock, i.e., the market index. Then, we use the estimated parameters $(\hat{\alpha},\hat{\theta})$ as those of MNTS. For the CoVaR estimation, Adrian and Brunnermeier (2011) mainly use quantile regressions supplemented with the GARCH model with the normal distributed innovations as a robustness check. Girardi and Ergün (2013) use the GARCH model with Hansen's skewed t distributed innovations. Our methodology is different from the previous studies because we first apply the multivariate tempered stable distribution to the CoVaR estimation. Another advantage of MNTS is that it has the reproductive property; the linear combination of NTS distributed random variables still follows NTS. This property enables us to easily deal with the portfolio of stocks.

Model (1) forecasts the joint distribution of stock returns at $t+1$ period on the basis of the information up to t. We refer to Model (1) with the standard MNTS distributed and standard multivariate normal distributed η_t as the ARMA-GARCH-MNTS (AGMNTS) model and ARMA-GARCH-multivariate normal (AGMNormal) model, respectively. We primarily use an AGMNTS forecast, whereas we use an AGMNormal forecast as a reference.

1.2. Systematic risk measures. Before introducing systematic risk measures, we begin with VaR. VaR is the most standard market risk measure used by financial institutions. Consider the VaR of j's stock return R_t^j at the confidence level $1-q(0\le q\le 1)$, denoted by $VaR_{q,t}^j$. The definition of $VaR_{q,t}^j$ is given by

$$VaR_{q,t}^j = -\inf\{R \mid \mathrm{Prob}(R_t^j \le R)\ge q\}. \tag{2}$$

If R_t^j is continuous, $VaR_{q,t}^j$ is the q-quantile of the distribution of R_t^j, which satisfies

$$\mathrm{Prob}(R_t^j \le -VaR_{q,t}^j) = q. \tag{3}$$

An alternative risk measure is AVaR. The definition of $AVaR_{q,t}^j$ is given by

$$AVaR_{q,t}^j = \frac{1}{q}\int_0^q VaR_{p,t}^j \mathrm{d}p. \tag{4}$$

If R_t^j is continuous, AVaR is equivalent to

$$AVaR_{q,t}^j = -E(R_t^j \mid R_t^j < -VaR_{q,t}^j), \tag{5}$$

which is called expected tail loss. Henceforth, for simplicity, every stock return distribution is assumed to be continuous. AVaR has more desirable properties than VaR as a risk measure (e.g., the ability to account for risk above the VaR level, often referred to as "tail risk")[1]. In literature, AVaR is also called conditional VaR (CVaR[2]) or Expected Shortfall (ES).

While VaR and AVaR are *micro*-prudential risk measures on the premise of an institution being isolated, alternative *macro*-prudential risk measures for systemic risk have recently been explored in the context of global financial turmoil. While some consider probability-based approaches (Segoviano and Goodhart, 2009; Zhou, 2010; Giesecke and Kim, 2011), others put weight on quantifying systemic risk such as CoVaR (Adrian and Brunnermeier, 2011), SES and MES (Acharya et al., 2010). In line with the previous studies of systemic risk, we introduce four systematic risk measures in stock markets on the basis of VaR and AVaR, in which two out of four are probability-based indicators: joint and conditional probabilities of negative movements. The other two are measures to quantify the marginal contribution to systematic risk: ΔCoVaR and ΔCoAVaR.

1.2.1. Joint probability of negative movements (JPNM). We consider systematic risk as simultaneous negative movements of stock returns, where the negative movement simply means the return being less than the conditional mean. Note that this definition is consistent with the definition of systemic risk given by Kaufman and Scott (2003). Accordingly, we introduce the joint probability of negative movements (JPNM),

$$JPNM_t = \mathrm{Prob}\left(\bigcap_{j=1}^{J} R_t^j < \mu_t^j\right), \tag{6}$$

[1] For further information, see Rachev et al. (2008).

[2] Note that CoVaR is a different concept from CVaR, despite the analogous name.

as a measure of systematic risk. Because massive simultaneous negative comovement is a very rare event, the joint probability is low. However, we expect that such a low probability captures the common distress factor among financial institutions and signals crisis. In a previous study, Segoviano and Goodhart (2009) estimate the joint probability of distress among financial institutions from the credit default swaps data.

1.2.2. CoVaR. To investigate and quantify the risk spillover effect, we adopt Adrian and Brunnermeier's CoVaR methodology. CoVaR is a bivariate concept between two institutions *i* and *j*. While $VaR_{q,t}^{j}$ is the *q*-quantile of the *unconditional* distribution of R_t^j, $CoVaR_{q,t}^{j|i}$ is the *q*-quantile of the *conditional* distribution of R_t^j on a certain condition of *i*, more specifically, R_t^i. When we specify the condition of R_t^i as $C(R_t^i)$, we denote $CoVaR_{q,t}^{j|C(R_t^i)}$ instead of $CoVaR_{q,t}^{j|i}$. The implicit definition of $CoVaR_{q,t}^{j|C(R_t^i)}$ for continuous R_t^j is given by

$$\Pr\mathrm{ob}\left(R_t^j \le -CoVaR_{q,t}^{j|C(R_t^i)} \middle| C(R_t^i) \right) = q. \quad (7)$$

Let $C^d(R_t^i)$ and $C^n(R_t^i)$ be the distress and "normal" conditions of R_t^i, respectively. Adrian and Brunnermeier (2011) suggest that the difference of $CoVaR_{q,t}^{j|i}$ between the two conditions $C^d(R_t^i)$ and $C^n(R_t^i)$,

$$\Delta CoVaR_{q,t}^{j|i} = CoVaR_{q,t}^{j|C^d(R_t^i)} - CoVaR_{q,t}^{j|C^n(R_t^i)}, \quad (8)$$

accounts for the risk contribution of *i* to *j*.

For the application of CoVaR to systematic risk in stock markets, we highlight the case of *j* being a market index. $\Delta CoVaR_{q,t}^{index|i}$ is regarded as the marginal contribution of *i* to the overall systematic risk.

Regarding the conditions, Adrian and Brunnermeier (2011) define the distress and normal conditions as the institution's loss and return being exactly at its VaR and median, respectively,

$$\begin{aligned} C^d(R_t^i) &= \{R_t^i = -VaR_{q,t}^{i}\}, \\ C^n(R_t^i) &= \{R_t^i = median_t^i\}. \end{aligned} \quad (9)$$

However, we adopt the modified definition by Girardi and Ergün (2013), where the distress and normal conditions denote the institution's loss and return being above its VaR and within the range of one standard deviation from its mean state, respectively,

$$\begin{aligned} C^d(R_t^i) &= \{R_t^i \le -VaR_{q,t}^{i}\}, \\ C^n(R_t^i) &= \{\mu_t^i - \sigma_t^i \le R_t^i \le \mu_t^i + \sigma_t^i\}. \end{aligned} \quad (10)$$

We make the confidence level 1 − *q* of C^d coincide with that of CoVaR, which is conditioned by C^d. As Girardi and Ergün point out, the modified definition has several merits. First, it focuses on tail risk, i.e., the loss above the VaR level, and thus, the resulting CoVaR becomes more insightful. Second, it allows backtesting of CoVaR. We can apply the ordinary VaR backtesting methods to $CoVaR_{q,t}^{index|C^d(R_t^i)}$ for the days during which VaR violation of *i* occurs. Here, the VaR violation of *i* means the event when the observed loss $-R_t^i$ exceeds $VaR_{q,t}^{i}$; i.e., the condition $C^d(R_t^i)$ actually occurs[1]. The simplest way of VaR backtesting is to observe how often VaR violations occur. If one attempts to estimate 100(1 − *q*)% VaR, violations should occur at 100*q*% of whole observations. Following Girardi and Ergün (2013), we shall use the likelihood ratio (LR) tests of the unconditional and conditional coverages by Christoffersen (1998) as a more sophisticated VaR backtesting method. The conditional coverage test is more desirable than the unconditional one because it can consider the tendency for consecutive violations, which is observed for ordinary VaR during financial turmoil. We define the CoVaR violation of *i* as the event when the observed loss $-R_t^{index}$ exceeds $CoVaR_{q,t}^{index|C^d(R_t^i)}$ during the VaR violation days of *i*. Through the Christoffersen tests, it can be tested whether CoVaR violation occurs with a reasonable probability during VaR violation days; that is, $CoVaR_{q,t}^{index|C^d(R_t^i)}$ is appropriately estimated at the given confidence level. In the conditional test of $CoVaR_{q,t}^{index|C^d(R_t^i)}$, the conditions are considered between two adjacent days of the VaR violations of *i*. The last convenience of the modified definition (10) for our study is to make scenario simulation-based estimation of CoVaR feasible (see section 1.3).

1.2.3. Conditional probability of negative movements (CPNM). We can create an alternative probability-based indicator for the risk spillover effect. Given that systematic risk is the simultaneous negative movement of stock returns, the probability of the market index going down contingent on the institution being distressed is regarded as the indicator for systematic risk originating from that institution. Then, we introduce the conditional probability of negative movements (CPNM),

$$CPNM_{q,t}^{index|i} = \Pr\mathrm{ob}\left(C^d(R_t^{index}) \middle| C^d(R_t^i) \right). \quad (11)$$

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[1] Although we can test $CoVaR_{q,t}^{index|C^n(R_t^i)}$ in the same way, we concentrate on the distress condition C^d, which is more associated with systematic risk, as Girardi and Ergün (2013) do.

We still follow equation (10) regarding the definition of C^d. In this case, CPNM is proportional to the joint probability of both a market index and an individual institution incurring the loss beyond their respective VaRs. Note that, in contrast to the case of JPNM, negative movement does not stand for the return being less than the conditional mean but rather the loss exceeding VaR in the case of CPNM. This is because the joint probability of returns less than conditional means appears insufficient to inspect bivariate tail dependency.

1.2.4. CoAVaR. We can consider the *Co*-version of AVaR by considering equations (4) and (5).

$CoAVaR_{q,t}^{j|C(R_t^i)}$ is defined by

$$CoAVaR_{q,t}^{j|C(R_t^i)} = \frac{1}{q}\int_0^q CoVaR_{p,t}^{j|C(R_t^i)}\mathrm{d}p = = -E\left(R_t^j \middle| \left\{R_t^j < -CoVaR_{q,t}^{j|C(R_t^i)}\right\} \bigcap C(R_t^i)\right). \tag{12}$$

In an analogous fashion to CoVaR, the risk contribution of i to j in terms of CoAVaR is expressed by

$$\Delta CoAVaR_{q,t}^{j|i} = CoAVaR_{q,t}^{j|C^d(R_t^i)} - - CoAVaR_{q,t}^{j|C^n(R_t^i)}. \tag{13}$$

In Adrian and Brunnermeier (2011), CoAVaR is mentioned as CoES. Because AVaR has some merits compared with VaR, we primarily use CoAVaR rather than CoVaR for the assessment of systematic risk.

1.3. Scenario simulation. We rely on scenario simulation for estimation of systematic risk measures. It flexibly enables the estimations of various risk measures. On the basis of the AGMNTS (AGMNormal) model, we generate a large number S of scenarios about one-period-ahead multivariate stock returns $R_{t+1}^s = (R_{t+1}^{1,s}, R_{t+1}^{2,s}, ..., R_{t+1}^{J,s}), 1 \le s \le S$ via a Monte Carlo simulation. For the AGMNTS model, the random variables that follow the MNTS distribution are easily simulated using its subordinated representation[1]. The risk measures can be estimated from the selected scenarios, where a relevant or conditioning event like $C^d(R_t^i)$ or $C^n(R_t^i)$ is realized out of the overall scenarios. For the estimations of $\Delta CoVaR_{q,t}^{index|i}$, $\Delta CoAVaR_{q,t}^{index|i}$, and $CPNM_{q,t}^{index|i}$, we specify the bivariate ARMA-GARCH model of the market index and institution i.

[1] It is specifically a mixture of the multivariate normal distribution and classical tempered stable (CTS) subordinator. See Kim et al. (2012).

2. Data

For empirical research, we use daily stock logarithmic return data for 28 out of 29 G-SIFIs, as of November 2011. We refer to each stock by its ticker symbol or abbreviation. The list of G-SIFIs is given in the Appendix. The only exclusion is Banque Populaire CdE because it is unlisted. We use the S&P global 1200 financial sector index to represent the global banking stock market. The sample period is from January 1st, 2000 to June 30th, 2012. We exclude the U.S. non-business days from this period, which leads to 3260 observations for each stock. BOC, ACA, and three Japanese G-SIFIs (MUFG, MHFG, and SMFG) do not have sufficient length of historical data to cover the whole sample period. Regarding BOC and ACA, we backfill historical data using Cognity[2]. Regarding the three Japanese G-SIFIs, we extrapolate historical data using those of their representative affiliates, which had been listed before the establishments of holding companies[3]. All stock return data are downloaded from Bloomberg.

We set the $1 - q = 0.95$ confidence level for risk measures unless otherwise noted. The number of scenarios in the Monte Carlo simulation is $S = 10^6$. The forecast of stock returns is made on a daily basis. Each business day, the model parameters are updated from a moving window of the most recent 1250 days' sample return data. It means that we have 2011 daily parameter estimates starting from October 15th, 2004. In individual model parameter estimations, the variance-covariance matrix of η_t is estimated from the most recent 250 days' sample innovations.

3. Estimation results

We present the estimation results of systematic risk measures. The measures are estimated on the basis of the AGMNTS model unless otherwise noted, whereas they are estimated on the basis of the AGMNormal model, if needed for a reference.

First, we validate the usage of the AGMNTS model with G-SIFI stocks. For this validation, we test the standard NTS and normal distributional assumptions for the innovation of each stock in the ARMA(1,1)-GARCH(1,1) model (1) through the Kolmogorov-Smirnov (KS) test. Because we have 2011 daily estimations of the ARMA-GARCH model, the KS test is accordingly applied 2011 times for each stock. Table 1 reports the number of days on which the NTS and normal assumptions for each stock are rejected at three different significance levels: 1%, 5%, and 10%.

[2] Risk management software provided by FinAnalytica, Inc.

[3] Specifically, we substitute Bank of Tokyo-Mitsubishi UFJ (8315 JP) for MUFG, Dai-Ichi Kangyo Bank (8311 JP, until September 2000) and Mizuho Holdings (8305 JP, from October 2000) for MHFG, and Sumitomo Mitsui Banking Corporation (8318 JP) for SMFG.

The result is that NTS provides much better fitting for innovations than normal. The only exception is BOC. Both NTS and normal assumptions are rejected by all 2011 estimations for the innovations of BOC. However, except BOC, the rejections of the NTS assumption are much lower than those of the normal assumption at every significance level. The normal assumption is totally rejected by BOC, BK, MUFG, MHFG, STT, and SMFG even at the 1% significance level. These observations support the usage of AGMNTS model with G-SIFI stocks.

To illustrate the basic risk profiles of G-SIFI stocks, we refer to VaR and AVaR. We adopt an equally weighted portfolio as the most representative portfolio, and consider the VaR and AVaR of the portfolio to be equally weighted by the 28 G-SIFI stocks. Figure 1 represents the time series plot of the VaR and AVaR of the equally weighted portfolio estimated by the AGMNTS and AGMNormal models. AVaR estimated from the AGMNTS model tends to be higher than the AGMNormal model, especially during financial crisis, because of its capability of accounting for fat-tailness, whereas both models give similar VaR at the 95% confidence level. Through a simple graphic comparison, we find that the AGMNTS model and AVaR is the best combination for the purpose of warning of distress of individual institutions or their portfolios in terms of *micro*-prudential perspective. Subsequently, we apply the unconditional and conditional Christoffersen's likelihood ratio tests to the estimated daily VaR of each stock to clarify whether the estimations of VaR are reasonable. Tables 2 and 3 report the number of violation days and p-values of the tests for 90% VaR, 95% VaR, and 99% VaR, respect-tively. Both AGMNTS and AGMNormal models show similar performance on the 90% VaR and 95% VaR estimations. The AGMNTS model gives fewer VaR violations and higher p-values for some stocks, whereas the AGMNormal model does this for other stocks; a higher p-value means less probability of rejection of the VaR estimation. However, this is not the case for the 99% VaR estimation; the AGMNTS model clearly gives a better forecast of VaR than the AGMNormal model. The AGMNTS model generally has fewer violation days and higher p-values. The number of 99% VaR violations based on the AGMNTS model is lower than the AGMNormal model, except for BOC and MUFG. In addition, the number of rejections of each stock's 99% VaR estimation under the unconditional and conditional tests are 10 and 17 at the 5% significance level for AGMNTS, whereas 22 and 25 for AGMNormal, respectively. The fact that the 99% VaR estimation of the AGMNTS model is relatively more accurate than the 90% VaR and 95% VaR estimations implies that the deeper tail structure of the distribution is better captured by the AGMNTS model than the AGMNormal model. This property of the AGMNTS model is desirable for our study because our main interest CoVaR casts a spotlight on the deeper tail structure. Therefore, the AGMNTS model is preferable in terms of risk measure estimation as well as fitting performance.

Table 1. Number of rejections of distributional assumptions for each stock on the basis of the KS test (out of 2011 estimations)

	Significance level: 10%		Significance level: 5%		Significance level: 1%	
	AGMNTS	AGMNormal	AGMNTS	AGMNormal	AGMNTS	AGMNormal
BAC	1463	2007	1219	2007	400	1979
BOC	2011	2011	2011	2011	2011	2011
BK	1890	2011	1617	2011	997	2011
BARC	4	1635	4	1017	2	302
BNP	16	1527	4	1345	3	841
C	1446	1960	1224	1846	523	1460
CBK	694	2002	486	2002	59	1963
CSGN	1388	2011	943	2011	152	1548
DBK	367	1898	72	1553	6	864
DEXB	1076	2009	547	1888	6	1176
GS	893	1883	591	1608	3	855
ACA	138	1744	38	1502	0	918
HSBA	159	2011	13	2008	1	1421
INGA	1183	1804	765	1551	4	571
JPM	1437	2011	891	1984	82	1601
LLOY	342	1945	93	1838	15	1092
MUFG	1775	2011	1436	2011	436	2011
MHFG	1558	2011	1288	2011	385	2011
MS	1718	1807	1087	1476	272	1205
NDA	663	2011	577	2010	317	1528
RBS	628	2011	396	1927	100	1556

Table 1 (cont.). Number of rejections of distributional assumptions for each stock on the basis of the KS test (out of 2011 estimations)

	Significance level: 10%		Significance level: 5%		Significance level: 1%	
	AGMNTS	AGMNormal	AGMNTS	AGMNormal	AGMNTS	AGMNormal
SAN	1677	1930	1453	1640	654	888
GLE	665	1988	334	1855	9	913
STT	1311	2011	1198	2011	961	2011
SMFG	1695	2011	1352	2011	770	2011
UBSN	1449	2010	1012	1960	245	1111
UCG	74	1256	4	1027	1	555
WFC	722	1425	597	1272	409	1164

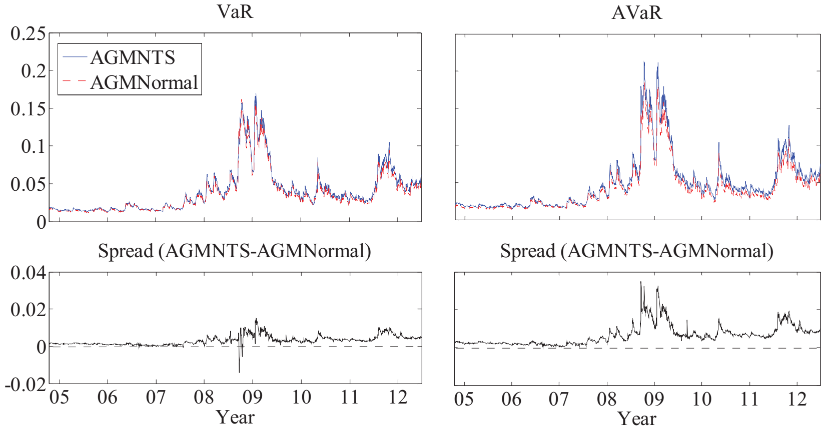

Fig. 1. Time series of the VaR and AVaR of the equally weighted portfolio

Table 2. Number of VaR violations (out of 2011 estimations)

	90% VaR		95% VaR		99% VaR	
	AGMNTS	AGMNormal	AGMNTS	AGMNormal	AGMNTS	AGMNormal
BAC	214	178	111	112	29	46
BOC	155	151	75	79	29	29
BK	188	186	104	104	35	39
BARC	214	196	112	113	31	42
BNP	216	202	118	116	24	35
C	219	203	120	124	34	48
CBK	203	195	102	100	31	34
CSGN	204	189	100	102	21	28
DBK	226	205	126	122	23	36
DEXB	235	216	131	129	33	44
GS	209	187	109	109	25	29
ACA	218	198	109	105	29	35
HSBA	212	188	103	105	31	38
INGA	239	220	126	122	26	35
JPM	211	196	99	94	27	33
LLOY	220	204	107	104	31	39
MUFG	180	167	91	85	26	24
MHFG	186	173	89	80	20	23
MS	217	203	108	111	28	37
NDA	211	180	112	104	27	36
RBS	211	196	104	105	36	45
SAN	239	225	124	130	23	43
GLE	236	206	116	113	32	41
STT	168	141	84	80	22	35
SMFG	179	161	99	87	22	24
UBSN	221	199	118	118	21	34
UCG	247	235	140	139	25	41
WFC	202	195	116	115	33	42

Table 3. p-values of the likelihood ratio test for VaR

	90% VaR				95% VaR				99% VaR			
	Unconditional		Conditional		Unconditional		Conditional		Unconditional		Conditional	
	AGMNTS	AGMNormal	AGMNTS	AGMNormal	AGMNTS	AGMNormal	AGMNTS	AGMNormal	AGMNTS	AGMNormal	AGMNTS	AGMNormal
BAC	0.342	0.080	0.175	0.026	0.293	0.250	0.063	0.061	0.062	0.000	0.037	0.000
BOC	0.000	0.000	0.000	0.000	0.006	0.022	0.006	0.012	0.062	0.062	0.043	0.037
BK	0.325	0.256	0.167	0.105	0.726	0.726	0.655	0.457	0.003	0.000	0.001	0.000
BARC	0.342	0.704	0.128	0.052	0.250	0.211	0.061	0.029	0.024	0.000	0.000	0.000
BNP	0.273	0.947	0.040	0.041	0.082	0.122	0.036	0.074	0.398	0.003	0.176	0.001
C	0.189	0.888	0.081	0.394	0.053	0.020	0.050	0.020	0.005	0.000	0.000	0.000
CBK	0.888	0.649	0.015	0.002	0.882	0.955	0.044	0.084	0.024	0.005	0.018	0.004
CSGN	0.830	0.364	0.017	0.008	0.955	0.882	0.364	0.413	0.843	0.095	0.487	0.059
DBK	0.069	0.773	0.068	0.695	0.012	0.033	0.011	0.032	0.527	0.001	0.334	0.001
DEXB	0.014	0.273	0.000	0.001	0.003	0.005	0.000	0.000	0.008	0.000	0.004	0.000
GS	0.559	0.289	0.248	0.048	0.393	0.393	0.393	0.393	0.291	0.062	0.187	0.043
ACA	0.215	0.817	0.003	0.023	0.393	0.651	0.012	0.126	0.062	0.003	0.043	0.002
HSBA	0.421	0.325	0.311	0.294	0.803	0.651	0.019	0.057	0.024	0.000	0.018	0.000
INGA	0.006	0.166	0.001	0.006	0.012	0.033	0.000	0.007	0.207	0.003	0.002	0.000
JPM	0.465	0.704	0.395	0.659	0.874	0.498	0.588	0.307	0.142	0.008	0.087	0.007
LLOY	0.166	0.830	0.000	0.030	0.513	0.726	0.131	0.430	0.024	0.000	0.014	0.000
MUFG	0.111	0.009	0.048	0.003	0.321	0.103	0.320	0.099	0.207	0.398	0.115	0.176
MHFG	0.256	0.033	0.063	0.011	0.228	0.029	0.003	0.009	0.980	0.527	0.015	0.021
MS	0.243	0.888	0.155	0.535	0.451	0.293	0.131	0.193	0.095	0.001	0.062	0.001
NDA	0.465	0.111	0.002	0.027	0.250	0.726	0.232	0.241	0.142	0.001	0.089	0.001
RBS	0.465	0.704	0.019	0.004	0.726	0.651	0.022	0.009	0.001	0.000	0.000	0.000
SAN	0.006	0.081	0.004	0.031	0.020	0.004	0.018	0.004	0.527	0.000	0.334	0.000
GLE	0.011	0.717	0.002	0.062	0.122	0.211	0.025	0.102	0.014	0.000	0.003	0.000
STT	0.012	0.000	0.005	0.000	0.082	0.029	0.078	0.026	0.676	0.003	0.416	0.001
SMFG	0.095	0.002	0.063	0.001	0.874	0.156	0.030	0.120	0.676	0.398	0.212	0.176
UBSN	0.145	0.876	0.006	0.047	0.082	0.082	0.021	0.036	0.843	0.005	0.018	0.000
UCG	0.001	0.014	0.000	0.001	0.000	0.000	0.000	0.000	0.291	0.000	0.020	0.000
WFC	0.947	0.649	0.674	0.608	0.122	0.148	0.052	0.029	0.008	0.000	0.004	0.000
# of p-values less than 5%	7	6	16	19	6	9	16	13	10	22	17	25
# of p-values less than 1%	4	4	11	10	3	3	5	6	5	22	8	22

We now proceed to the estimation results of systematic risk measures. Figure 2 illustrates the time series of JPNM[1]. We can see that JPNM has high sensitivity to important financial events. We distinguish three turmoil periods when JPNM rapidly goes up: Period 1 is from July 2007 to September 2008 (subprime loan problem and Lehman's collapse), Period 2 is from April 2010 to March 2011 (dawn of Greek sovereign problem), and Period 3 is from August 2011 to May 2012 (U.S. credit rating downgrading and Greek political turmoil). It is remarkable that JPNM warns the adverse impact of the very recent Greek crisis (Period 3) even more seriously than the Lehman shock (Period 1), whereas VaR or AVaR in Figure 1 describes Period 3 relatively moderately. JPNM could be a reference for a forthcoming crisis beyond VaR or AVaR.

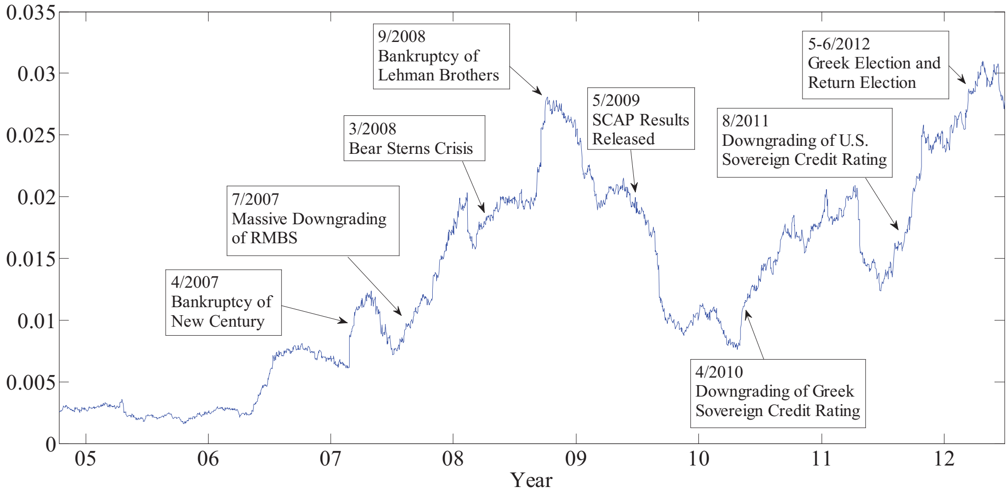

Fig. 2. Time series of JPNM

To quantify risk spillover effects, we estimate $\Delta CoVaR_{q,t}^{index|i}$ and $\Delta CoAVaR_{q,t}^{index|i}$. We backtest $CoVaR_{q,t}^{index|C^d(R_t^i)}$ as well as VaR, on the basis of the Christoffersen tests. Tables 4 and 5 report the violation rates and *p*-values of the tests for 90% CoVaR, 95% CoVaR, and 99% CoVaR, respectively[2]. Note that it is not the number of CoVaR violations but the rate of CoVaR violations to VaR violations that is reported in Table 4, because the number of VaR violations differs among individual stocks. In general, the rates of CoVaR violations are lower and the *p*-values of the tests are higher for the AGMNTS model than for the AGMNormal model. The number of rejections of each stock's 95% CoVaR estimation under the unconditional and conditional tests are 3 and 8 at the 5% significance level for AGMNTS, whereas 26 and 27 for AGMNormal, respectively. The AGMNormal estimation of CoVaR is rejected by almost all stocks. These imply that, unlike the case of VaR, the AGMNTS model gives a better forecast of CoVaR than the AGMNormal model regardless of significance levels. As can be observed from the definition, CoVaR addresses tail dependencies among stocks. A better estimation of CoVaR reflects the superior descriptive power for tail dependencies of the MNTS distribution.

Table 4. Rate of CoVaR to VaR violations

	90% CoVaR		95% CoVaR		99% CoVaR	
	AGMNTS	AGMNormal	AGMNTS	AGMNormal	AGMNTS	AGMNormal
BAC	0.150	0.213	0.063	0.143	0.034	0.065
BOC	0.142	0.146	0.067	0.139	0.034	0.103
BK	0.186	0.210	0.087	0.135	0.029	0.051
BARC	0.136	0.179	0.071	0.124	0.032	0.048
BNP	0.144	0.163	0.076	0.138	0.000	0.057
C	0.146	0.197	0.067	0.137	0.029	0.021
CBK	0.138	0.190	0.088	0.170	0.032	0.059
CSGN	0.162	0.196	0.090	0.127	0.048	0.071
DBK	0.128	0.156	0.071	0.139	0.043	0.056

[1] The resulting value of JPNM is in the order of 10^{-2}. The number of simulation, $S = 10^6$, is enough for the estimation because the standard deviation of the estimated JPNM is about $\sqrt{\hat{p}(1-\hat{p})/S} \cong 10^{-4}$.

[2] We do not deal with the likelihood ratio tests for 99% CoVaR because 99% VaR violations are not frequently observed to test 99% CoVaR.

Table 4 (cont.). Rate of CoVaR to VaR violations

	90% CoVaR		95% CoVaR		99% CoVaR	
	AGMNTS	AGMNormal	AGMNTS	AGMNormal	AGMNTS	AGMNormal
DEXB	0.132	0.190	0.084	0.155	0.030	0.091
GS	0.139	0.182	0.083	0.147	0.040	0.069
ACA	0.147	0.182	0.083	0.143	0.034	0.057
HSBA	0.108	0.149	0.087	0.114	0.000	0.053
INGA	0.121	0.164	0.087	0.139	0.000	0.029
JPM	0.142	0.199	0.111	0.191	0.037	0.061
LLOY	0.118	0.157	0.075	0.144	0.000	0.026
MUFG	0.094	0.120	0.055	0.094	0.000	0.042
MHFG	0.086	0.110	0.022	0.088	0.000	0.000
MS	0.147	0.187	0.056	0.135	0.036	0.081
NDA	0.147	0.222	0.089	0.163	0.037	0.083
RBS	0.133	0.173	0.077	0.143	0.000	0.022
SAN	0.121	0.160	0.081	0.131	0.043	0.070
GLE	0.127	0.155	0.095	0.133	0.000	0.024
STT	0.179	0.213	0.095	0.188	0.045	0.086
SMFG	0.101	0.112	0.051	0.103	0.000	0.000
UBSN	0.140	0.181	0.076	0.144	0.048	0.059
UCG	0.134	0.162	0.079	0.122	0.000	0.000
WFC	0.168	0.200	0.095	0.148	0.030	0.071

Table 5. *p*-values of the likelihood ratio test for CoVaR

	90% CoVaR				95% CoVaR			
	Unconditional		Conditional		Unconditional		Conditional	
	AGMNTS	AGMNormal	AGMNTS	AGMNormal	AGMNTS	AGMNormal	AGMNTS	AGMNormal
BAC	0.023	0.000	0.023	0.000	0.543	0.000	0.250	0.000
BOC	0.099	0.078	0.082	0.076	0.528	0.003	0.289	0.002
BK	0.000	0.000	0.000	0.000	0.120	0.001	0.115	0.001
BARC	0.098	0.001	0.079	0.001	0.327	0.002	0.138	0.000
BNP	0.044	0.005	0.012	0.001	0.223	0.000	0.084	0.000
C	0.032	0.000	0.019	0.000	0.424	0.000	0.181	0.000
CBK	0.087	0.000	0.067	0.000	0.108	0.000	0.104	0.000
CSGN	0.006	0.000	0.005	0.000	0.097	0.002	0.033	0.000
DBK	0.172	0.013	0.079	0.013	0.298	0.000	0.115	0.000
DEXB	0.118	0.000	0.042	0.000	0.102	0.000	0.102	0.000
GS	0.076	0.001	0.060	0.001	0.152	0.000	0.055	0.000
ACA	0.030	0.000	0.007	0.000	0.152	0.000	0.055	0.000
HSBA	0.684	0.036	0.026	0.010	0.114	0.009	0.039	0.002
INGA	0.286	0.004	0.172	0.002	0.081	0.000	0.023	0.000
JPM	0.053	0.000	0.038	0.000	0.015	0.000	0.003	0.000
LLOY	0.381	0.012	0.380	0.012	0.272	0.000	0.226	0.000
MUFG	0.802	0.408	0.535	0.353	0.831	0.094	0.426	0.034
MHFG	0.516	0.671	0.454	0.307	0.183	0.162	0.172	0.069
MS	0.028	0.000	0.026	0.000	0.795	0.001	0.377	0.000
NDA	0.032	0.000	0.013	0.000	0.084	0.000	0.084	0.000
RBS	0.130	0.002	0.127	0.002	0.241	0.000	0.205	0.000
SAN	0.286	0.005	0.002	0.002	0.149	0.000	0.144	0.000
GLE	0.181	0.013	0.180	0.013	0.047	0.001	0.012	0.000
STT	0.002	0.000	0.001	0.000	0.089	0.000	0.032	0.000
SMFG	0.980	0.624	0.467	0.313	0.982	0.044	0.463	0.044
UBSN	0.058	0.001	0.037	0.001	0.223	0.000	0.084	0.000
UCG	0.092	0.003	0.006	0.003	0.151	0.001	0.047	0.001
WFC	0.003	0.000	0.002	0.000	0.047	0.000	0.012	0.000
# of *p*-values less than 5%	10	24	16	24	3	26	8	27
# of *p*-values less than 1%	4	20	7	21	0	25	1	25

An alternative approach to risk spillover effects is CPNM. We compare ΔCoAVaR and CPNM separately, both in time series and cross-section directions. Recall that CoAVaR is preferable to CoVaR for risk assessment.

To compare time series, we prepare three regional portfolios in the United States, Europe, and Asia. These are equally weighted portfolios comprising G-SIFI stocks belonging to each region, and are intended to represent the time series of stock returns in each region. In Figure 3, the AVaR of regional portfolios and ΔCoAVaR and CPNM of each regional portfolio on the market index are plotted in the time series direction. The estimations are made using both AGMNTS and AGMNormal models. We observe that the AGMNTS model gives more conservative estimations of systematic risk measures than the AGMNormal model because of its superior descriptive power for tail dependencies. From a comparison among risk measures, ΔCoAVaR is found to move significantly parallel to AVaR in the time series direction. It is a natural consequence that higher risk leads to higher risk spillover effects. On the other hand, neither does CPNM show strong linkage with AVaR or ΔCoAVaR, nor it is very sensitive to global adverse impacts. However, ΔCoAVaR and CPNM agree with the magnitude relation; the influence of Asia on the system is relatively lower than that of the United States and Europe. It also follows our assumption regarding the regional power of influence on the global financial system.

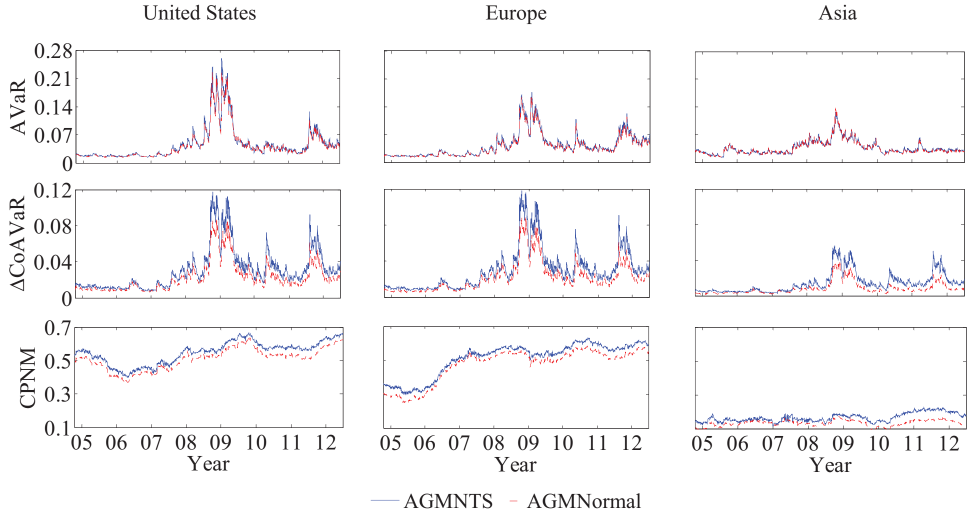

Fig. 3. Time series of AVaR, ΔCoAVaR, and CPNM by region

The situation is different in the cross-section direction. To gain visual understanding, the scatter plots of cross-sectional ΔCoAVaR vs. AVaR and ΔCoAVaR vs. CPNM are depicted in the upper and lower halves of Figure 4, respectively, where the average of risk measures is taken over each stock's time series during the three turmoil periods suggested by JPNM in Figure 2. It appears that the cross-sectional AVaR has very weak linkage with the cross-sectional ΔCoAVaR. This result supports the idea that the institution that has higher risk is not necessarily the same one as the institution whose risk contribution to the entire system is larger. The contribution to systematic risk should be dependent not only on the institution's stand-alone risk measured by, for example, VaR, but also on other factors such as interconnectedness with other institutions. By contrast, CPNM has strong positive linear linkage with ΔCoAVaR. Though four points corresponding to the Asian G-SIFIs outlie others in each scatter plot, they still appear to be on a line. This suggests that ΔCoAVaR and CPNM are consistent when ranking the power of influence on the entire system among institutions at the same time. This consentience is already observed about the ranking among three regions in Figure 3. We further investigate the relationship among cross-sectional AVaR, ΔCoAVaR, and CPNM via the single linear regression, where the explained variable is ΔCoAVaR and the explanatory variables are AVaR and CPNM. Because we have 2011 daily cross-sectional datasets for 28 G-SIFI stocks, we iteratively run the regression 2011 times. Table 6 reports the number of significantly non-zero regression coefficients at the 1% level by signs and average R^2 out of 2011 tests by risk measures at three different confidence levels. For AVaR, significantly positive coefficients at the 1% level to ΔCoAVaR are obtained from less than 10% of all trials and R square is, on average, quite low regardless of confidence levels. For CPNM, in contrast, all trials result in a significantly positive coefficient at the 1% level with very high average R^2. Therefore, from statistical evidence, we confirm that AVaR has almost nothing to do with ΔCoAVaR, but that CPNM has very strong positive linkage with ΔCoAVaR in the cross-section direction.

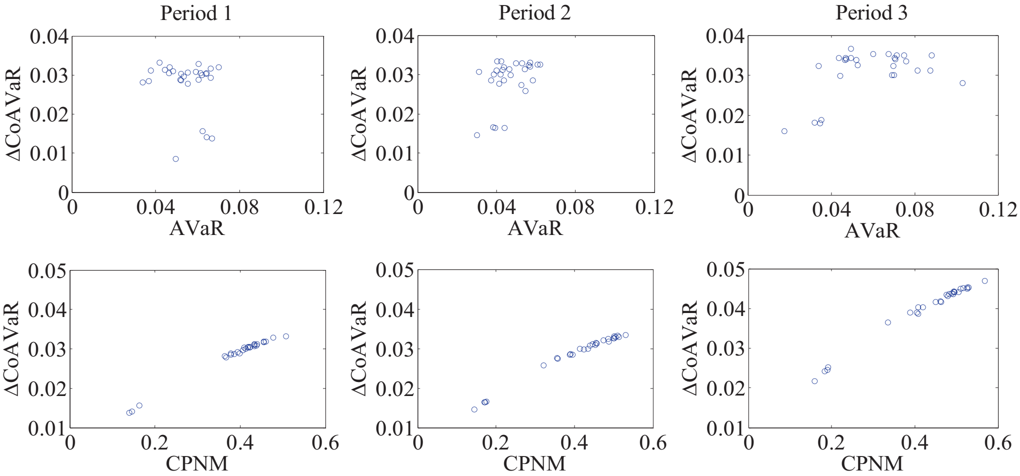

Fig. 4. Cross-sectional linkage among AVaR, ΔCoAVaR, and CPNM

Table 6. Iterative single regression analysis for 2011 cross-sectional datasets among AVaR, ΔCoAVaR, and CPNM

Explanatory variable		Sign of coefficient	Confidence level: 90%	Confidence level: 95%	Confidence level: 99%
AVaR	# of significant coefficients at the 1% level	Positive Negative	155 231	170 218	188 177
	Average R^2		0.129	0.127	0.124
CPNM	# of significant coefficients at the 1% level	Positive Negative	2011 0	2011 0	2011 0
	Average R^2		0.982	0.973	0.943

Concluding remarks

In this paper, we measure global systematic risk and the marginal contributions to it of the institutions by using stock return data of G-SIFIs, which constitute a large portion of the global banking system. To generate the future joint distribution of stock returns, we utilize the ARMA-GARCH-MNTS and ARMA-GARCH-MNormal models. The statistical tests demonstrate that the ARMA-GARCH-MNTS model is highly preferable to the ARMA-GARCH-MNormal model, mainly because of its capability of describing fat-tailness and skewness of stock return distributions.

We prepare both probability-based indicators and measures to quantify the marginal contribution to systematic risk. To be specific, we estimate the joint probability and conditional probability of negative stock return movements, ΔCoVaR, and ΔCoAVaR against the market index. The joint probability of negative movements turns out to vividly describe a significant increase of systematic risk. It provides information that VaR or AVaR lacks and could be referred to as a signal of financial turmoil. The other measures are for risk spillover effects rather than systematic risk itself. We find that AVaR has very weak linkage with ΔCoAVaR in the cross-section direction, even though both are strongly connected to each other in the time series direction, implying that the institution having higher risk is not necessarily the institution having a larger power of influence on the entire system. Therefore, exclusively referring to VaR can be misleading for a *macro*-prudential purpose. These results are consistent with those of Adrian and Brunnermeier (2011) for the U.S. financial institutions. On the other hand, the probability of negative movements of the market index on the condition of the instituion's distress tends to provide very similar implications to ΔCoAVaR about the ranking of the institution's power of influence on the entire system. The relative merit of ΔCoAVaR to conditional probability is a stronger sensitivity to adverse impact on the global financial system and the ability to quantify the impact, whereas the relative merit of conditional probability to ΔCoAVaR is the easiness of estimation. From these observations, we conclude that combining AVaR and the conditional probability of negative movements would give a useful reference for ΔCoAVaR-based systematic risk measurement.

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Appendix

Table A1. List of 29 G-SIFIs as of November 2011[1]

United States	Europe	Asia
Bank of America (BAC) Bank of New York Mellon (BK) Citigroup (C) Goldman Sachs (GS) JP Morgan Chase (JPM) Morgan Stanley (MS) State Street (STT) Wells Fargo (WFC)	Banque Populaire CdE Barclays (BARC) BNP Paribas (BNP) Commerzbank (CBK) Credit Suisse (CSGN) Deutsche Bank (DBK) Dexia (DEXB) Group Crédit Agricole (ACA) HSBC (HSBA) ING Bank (INGA) Lloyds Banking Group (LLOY) Nordea (NDA) Royal Bank of Scotland (RBS) Santander (SAN) Société Générale (GLE) UBS (UBSN) Unicredit Group (UCG)	Bank of China (3988) Mitsubishi UFJ FG (8306) Mizuho FG (8411) Sumitomo Mitsui FG (8316)

Note: Characters in parentheses stand for the ticker symbols in each domestic market. We refer to G-SIFIs by their ticker symbol except the Asian G-SIFIs. We refer to the Asian G-SIFIs by their abbreviations: BOC (Bank of China), MUFJ (Mitsubishi UFJ FG), MHFG (Mizuho FG), and SMFG (Sumitomo Mitsui FG).

[1] The most recent list contains revisions owing to the update on November 2012. See Financial Stability Board (2012).