

Systemic Risk Contributions*

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JEL classification: G21, G28, G14.

Keywords: Distress Insurance Premium, Systemic Risk, Macroprudential Regulation, Large Complex Financial Institution, Too-Big-to-Fail, Too-Connected-to-Fail.

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Abstract

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1 Introduction

The recent global financial crisis has led bank supervisors and regulators to rethink about the rationale of banking regulation. One important lesson is that, the traditional approach to assuring the soundness of individual banks, as in Basel I and Basel II, needs to be supplemented by a system-wide macroprudential approach. The macroprudential perspective of supervision focuses on the soundness of the banking system as a whole and the inter-linkages among those systemically important banks. This has become an overwhelming theme in the policy deliberations among legislative committees, bank regulators, and academic researchers.¹ As stated in the Financial Stability Board’s interim report in June 2010, “Financial institutions should be subject to requirements commensurate with the risks they pose to the financial system.”

However, to implement such a macroprudential perspective in practice is not an easy task. The operational framework needs to provide answers to three crucial questions. First, how to measure the systemic risk in a financial system? Second, how to measure the contributions of individual banks (or financial institutions) to the systemic risk? Third, how to design prudential requirements on individual banks, such as capital surcharge, tax or fee for a financial stability fund, that are connected with their systemic risk contributions?

Against such a background, this paper proposes a consistent framework that provides direct answers to the first two questions, and the results of which can be used as useful inputs to address the above third question. Our systemic risk measure can be interpreted economically as the insurance premium to cover distressed losses in a banking system, which is a concept of risk-neutral market price if such an insurance market were to exist and to function properly (Huang, Zhou, and Zhu, 2009). Within the same framework, the systemic importance of each bank (or bank group) can be properly defined as its marginal contribution to the hypothetical distress insurance premium of the whole banking system. This approach allows us to study the time variation and cross section of the systemic risk contributions of

¹See, for instance, Brunnermeier, Crockett, Goodhart, Persaud, and Shin (2009), Financial Stability Forum (2009a,b), Panetta, Angelini, Albertazzi, Columba, Cornacchia, Cesare, Pilati, Salleo, and Santini (2009), and BCBS (2009), among others. The macroprudential perspective was proposed by Crocket (2000), Borio (2003), and Acharya (2009).

US large and complex financial institutions (LCFIs).

There are advantages in adopting such a consistent approach. Under such a framework, the marginal contribution of each bank adds up to the aggregate systemic risk. As shown in Tarashev, Borio, and Tsatsaronis (2009a), this *additivity* property is desirable from an operational perspective, because it allows the macroprudential tools to be implemented at individual bank levels. In particular, prudential requirements can be a linear transformation of the marginal contribution measures if the latter is additive. One can also decompose our systemic risk measures into different economic channels—e.g., risk premium versus actual default risk, credit risk versus liquidity risk. Finally, since our structural framework uses default probabilities, liability size, and correlations directly as inputs to capture the well publicized characteristics of systemic risk — leverage, too-big-to-fail, and too-connected-to-fail; one can easily swap these inputs with supervisory confidential information for practical policy analysis.

We apply this approach to the 19 bank holding companies (BHCs) covered by the US Supervisory Capital Assessment Program (SCAP) — commonly known as “stress test” — spanning the period from January 2004 to December 2009. Our findings suggest that the systemic risk indicator stood at its peak around 1.1 trillion USD in March 2009 and has since fallen to about 300 billion USD — the level reached before in January 2008. A bank’s contribution to the systemic risk indicator appears to be linearly related to its default probability, but highly nonlinear with respect to institution size and asset correlation. We find that the increase in systemic risk of the US banking sector during the 2007-2009 financial crisis was initially mainly driven by heightened default risk premium and liquidity risk premium, and latter by the deterioration in actual default risk.

More importantly, we can rank order the systemic importance of large and complex financial institutions in the US banking sector. Among the notable largest contributors based on our measure, Bank of America and Wells Fargo are increasing their systemic risk contributions, CitiGroup remains the largest contributor over time, and JPMorgan Chase is decreasing its marginal contribution. It seems that the relative contributions to systemic risk from both consumer banks and regional banks are increasing somewhat recently, possibly due

to the worsening situations in commercial real estate and consumer credit sectors that are typically lagging the business cycles. Overall, our analysis suggests that size is the dominant factor in determining the relative importance of each bank's systemic risk contribution, but size doesn't change significantly overtime, at least within a reporting quarter. The obvious time-variation in the marginal contributions are mostly driven by the risk-neutral default probability and equity return correlation. In essence, the systemic importance of each institution is jointly determined by size, default probability, and asset correlation of all institutions in the portfolio.

Finally, our measure of the systemic importance of financial institutions resembles noticeably with the US Supervisory Capital Assessment Program (SCAP) result. Based on the data up till December 31, 2008, the 19 banks' contributions to the systemic risk indicator are mostly in line with the SCAP estimate of losses under an adverse economic scenario as released on May 9, 2009, with an R-square of 0.62. Goldman Sachs, CitiGroup, and JPMorgan in particular, would be viewed as contributing more to systemic risk by our method (from a risk premium perspective) than by the SCAP results; while Bank of America and Wells Fargo would be viewed as more risky by SCAP (from an expected loss perspective) than by our method. Note that our systemic risk measure is also containing risk premium while SCAP is on the basis of statistical expected loss.

One leading alternative, marginal expected shortfall (MES) by Acharya, Pedersen, Philippon, and Richardson (2010) weighted by bank's tier 1 capital is also highly correlated with SCAP (R-square of 0.71). Relative to SCAP, MES considers Bank of America, JPMorgan, and Goldman Sachs as more risky while Wells Fargo and Citigroup as less risky. The most notable reversals in ranking from our measure to MES are Bank of America and Citigroup. On the other hand, conditional value at risk (CoVaR) by Adrian and Brunnermeier (2009) translated into dollar amount has a similar correlation with SCAP (R-square of 0.63). Compared to SCAP, CoVaR ranks JPMorgan, MetLife, and Goldman Sachs as more risky but CitiGroup and Bank of America as less risky. Again, the most notable reversals from our measure to CoVaR are MetLife and Citigroup. These rankings differences may reflect the fact that distress insurance premium is a risk-neutral based pricing measure while MES and

CoVaR are statistical measure based on physical distributions. The contrast between MES and CoVaR may be due to fact that for heavy tailed distributions the tail percentiles and expectations can diverge significantly.

Along the similar line, Lehar (2005), Chan-Lau and Gravelle (2005), and Avesani, Pascual, and Li (2006) proposed alternative systemic risk indicator — default probability — based on CDS, option, or equity market. Recently, Cont (2010) emphasizes network-based systemic risk measure, while Kim and Giesecke (2010) try to examine the term structure of systemic risk measure. Billio, Getmansky, Lo, and Pelizzon (2010) studies five systemic risk measures based on statistical analysis of equity returns. All these indicators are useful supplementary measures to balance sheet information, such as the Financial Soundness Indicators used in the Financial Sector Assessment Program (FSAP) by International Monetary Fund (IMF). In addition, supervisors sometimes implement risk assessments based on *confidential* banking information, such as the Supervisory Capital Assessment Program (SCAP) implemented by the US regulatory authorities in early 2009 and the European-wide stress testing program sanctioned by the Committee of European Banking Supervisors (CEBS) in July 2010. Finally, the recently enacted Dodd-Frank Wall-Street Reform Bill (United States Congress, 2010) imposes a limit on a bank’s size, which is known as Volcker concentration limit and aims at containing the systemic risk of individual banks.

The remainder of the paper is organized as follows. Section 2 outlines the methodology. Section 3 introduces the data, and Section 4 presents empirical results based on an illustrative banking system that consists of 19 large and complex financial institutions (LCFI) in US. The last section concludes.

2 Methodology

This section describes the methodology used in this paper. The first part constructs a market-based systemic risk indicator for a heterogeneous portfolio of financial institutions, and the second part designs a measure to assess the contribution of each bank (or each group of banks) to the systemic risk indicator.

2.1 Constructing the Systemic Risk Indicator

To construct a systemic risk indicator of a heterogeneous banking portfolio, we follow the structural approach of Vasicek (1991) for pricing the portfolio credit risk, which is also consistent with the Merton (1974) model for individual firm default. The systemic risk indicator, a hypothetical insurance premium against catastrophic losses in a banking system, is constructed from real-time financial market data (Huang, Zhou, and Zhu, 2009). The two key default risk factors, the probability of default (PD) of individual banks and the asset return correlations among banks, are estimated from credit default swap (CDS) spreads and equity price co-movements, respectively.

2.1.1 Risk-Neutral Default Probability

The PD measure used in this approach is derived from single-name CDS spreads. A CDS contract offers protection against default losses of an underlying entity; in return, the protection buyer agrees to make constant periodic premium payments. The CDS market has grown rapidly in recent years, and the CDS spread is considered to be a superior measure of credit risk to bond spreads or loan spreads.² The spread of a T -year CDS contract is given by

$$s_{i,t} = \frac{(1 - R_{i,t}) \int_t^{t+T} e^{-r_t \tau} q_{i,\tau} d\tau}{\int_t^{t+T} e^{-r_t \tau} [1 - \int_t^\tau q_{i,u} du] d\tau} \quad (1)$$

where $R_{i,t}$ is the recovery rate, r_t is the default-free interest rate, and $q_{i,t}$ is the risk-neutral default intensity. The banks are indexed by $i = 1, \dots, N$. The above characterization assumes that recovery risk is independent of interest rate and default risks.

Under the simplifying assumptions of flat term structure of risk-free rate and flat default intensity term structure, the one-year *risk-neutral* PDs of individual banks can be derived from CDS spreads, as in Duffie (1999) and Tarashev and Zhu (2008a):

$$PD_{i,t} = \frac{a_t s_{i,t}}{a_t LGD_{i,t} + b_t s_{i,t}} \quad (2)$$

²See Blanco, Brennan, and March (2005), Forte and Peña (2009) and Norden and Wagner (2008), among others.

where $a_t \equiv \int_t^{t+T} e^{-r_t\tau} d\tau$, $b_t \equiv \int_t^{t+T} \tau e^{-r_t\tau} d\tau$, and $LGD_{i,t} = (1 - R_{i,t})$ is the loss-given-default.

There are three elements in the implied PD estimated from the CDS market: (1) the compensation for expected default losses; (2) default risk premium for bearing the default risk; (3) other premium components, e.g., liquidity or uncertainty risk compensations. Our systemic risk indicator incorporates the combined effects of the above three elements on the price of insurance against distressed losses in the banking system.

One extension in this study is that we allow for the LGD to vary, rather than assuming it to be a constant,³ over time. For example, Altman and Kishore (1996) showed that LGD can vary over the credit cycle. To reflect the comovement in PD and LGD parameters, we choose to use *expected* LGDs as reported by market participants who price and trade the CDS contracts.

2.1.2 Asset Return Correlation

Systemic risk in a financial sector is in essence a joint default event of multiple large institutions, which is captured by the correlations of observable equity returns (Nicolò and Kwast, 2002). At a more fundamental level, such a correlation structure may be driven by the common movements in underlying firms' asset dynamics (Vasicek, 1991). We measure the asset return correlation by the equity return correlation (Hull and White, 2004), as equity is the most liquid financial market and can incorporate new information on an institution's default risk in a timely way. The standard approach is to use the so-called historical correlation, which is based on the past one year of daily return data.

Let $\rho_{i,j}$ denotes the correlation between banks' asset returns $A_{i,t}$ and $A_{j,t}$, which is approximated by the correlation between banks' equity returns, with i and $j \in \{1, \dots, N\}$ and N as the number of banks. To ensure the internal consistency of correlation estimates, we assume that asset returns are underpinned by F common factors $M_t = [M_{1,t}, \dots, M_{F,t}]'$ and N idiosyncratic factors $Z_{i,t}$ (Gordy, 2003):

$$\Delta \log(A_{i,t}) = B_i M_t + \sqrt{1 - B_i' B_i} \cdot Z_{i,t} \quad (3)$$

³A constant LGD is typically assumed by researchers, typically close to 55% as recommended in Basel II.

where $B_i \equiv [\beta_{i,1}, \dots, \beta_{i,f}, \dots, \beta_{i,F}]$ is the vector of common factor loadings, $\beta_{i,f} \in [-1, 1]$ and $\sum_{f=1}^F \beta_{i,f}^2 \leq 1$. Without loss of generality, all common and idiosyncratic factors are assumed to be mutually independent and to have zero means and unit variances.

We estimate the loading coefficients $\beta_{i,f}$ ($i = 1, \dots, N$, $f = 1, \dots, F$) by minimizing the mean squared difference between the target correlations and the factor-driven correlations:⁴

$$\min_{B_1 \dots B_N} \sum_{i=2}^N \sum_{j < i}^N (\rho_{ij} - B_i B_j')^2 \quad (4)$$

In practice, three common factors can explain up to 95 percent of the total variation in our correlation sample estimates. More importantly, besides the “zero mean-unit variance” normalization, this estimation method imposes no restriction on the distribution of the common and idiosyncratic factors.

2.1.3 Hypothetical Distress Insurance Premium

Based on the inputs of the key credit risk parameters — PDs, LGDs, correlations, and liability weights — the systemic risk indicator can be calculated by simulation as described in Gibson (2004); Hull and White (2004); Tarashev and Zhu (2008b). In short, to compute the indicator, we first construct a hypothetical debt portfolio that consists of total liabilities (deposits, debts and others) of all banks. The indicator of systemic risk, effectively weighted by the liability size of each bank, is defined as the insurance premium that protects against distressed losses of this portfolio. Technically, it is calculated as the risk-neutral expectation of portfolio credit losses that equal or exceed a minimum share of the sector’s total liabilities.

To be more specific, let L_i denote the loss of bank i ’s liability with $i = 1, \dots, N$; and $L = \sum_{i=1}^N L_i$ is the total loss of the portfolio. Then the systemic risk of the banking sector or the distress insurance premium (DIP) is given by the risk-neutral expectation of the loss exceeding certain threshold level:

$$\text{DIP} = E^Q [L | L \geq L_{\min}] \quad (5)$$

where L_{\min} is a minimum loss threshold or “deductible” value. The DIP formula can be easily implemented with Monte Carlo simulation (Huang, Zhou, and Zhu, 2009).

⁴Andersen, Sidenius, and Basu (2003) proposes an efficient algorithm to solve this optimization problem.

Notice that, the definition of this “distress insurance premium” (DIP) is very close to the concept of expected shortfall (ES) used in the literature (see, e.g., Acharya, Pedersen, Philippon, and Richardson, 2010), in that both refer to the conditional expectations of portfolio credit losses under extreme conditions. They differ slightly in the sense that the extreme condition is defined by the percentile distribution in the case of ES but by a given threshold loss of underlying portfolio in the case of DIP. Also the probabilities in the tail event underpinning ES are normalized to sum up to one. These probabilities are not normalized for DIP. The value-at-risk measure or VaR — extended by Adrian and Brunnermeier (2009) into CoVaR — is also based on the percentile distribution, but as shown by Inui and Kijima (2005), Yamai and Yoshihara (2005), and Embrechts, Lambrigger, and Wüthrich (2009), ES is a coherent measure of risk while VaR is not.⁵

2.2 Identifying Systemically Important Banks

For the purpose of macroprudential regulation, it is important not only to monitor the *level* of systemic risk for banking sector, but also to understand the *sources* of risks in a financial system, i.e., to measure the marginal contributions of each institutions. This information is especially useful considering the reform effort of the financial regulations across the globe, with the main objective of charging additional capital for systemically important banks and support a resolution regime for these banks. In the following, we propose a method to decompose the credit risk of the portfolio into the sources of risk contributors associated with individual sub-portfolios (either a bank or a group of banks).

Following Kurth and Tasche (2003) and Glasserman (2005), for standard measures of risk, including value-at-risk (VaR), expected shortfall (ES), and distress insurance premium (DIP) used in this study, the total risk can be usefully decomposed into a sum of marginal risk contributions. Each marginal risk contribution is the conditional expected loss from that sub-portfolio, conditional on a large loss for the full portfolio. In particular, if we define L as the loss variable for the whole portfolio, and L_i as the loss variable for a sub-portfolio, the

⁵A coherent measure of risk should satisfy the axioms of monotonicity, subadditivity, positive homogeneity and translation invariance (Inui and Kijima, 2005). In general, VaR is not subadditive.

marginal contribution to our systemic risk indicator, the distress insurance premium (DIP), can be characterized by

$$\frac{\partial \text{DIP}}{\partial L_i} \equiv E^Q[L_i | L \geq L_{\min}] \quad (6)$$

The additive property of the decomposition results, i.e., the systemic risk of a portfolio equals the marginal contribution from each sub-portfolio, is extremely important from an operational perspective. Whereas the macroprudential approach focuses on the risk of the financial system as a whole, in the end regulatory and policy measures are introduced at the level of individual banks. Our approach, therefore, allows a systemic risk regulator to easily link the regulatory capital assessment with risk contributions from each institution.

A technical difficulty is that systemic distresses are rare events and thus ordinary Monte Carlo estimation is impractical for the calculation purpose. Therefore, we rely on the importance sampling method developed by Glasserman and Li (2005) for simulating portfolio credit losses to improve the efficiency and precision. For the nineteen-bank portfolio in our sample, we use the mean-shifting method and generate 200,000 importance-sampling simulations of default scenarios (default or not),⁶ and for each scenario generate 100 simulations of LGDs.⁷ Based on these simulation results we calculate the expected loss of each sub-portfolio conditional on total loss exceeding a given threshold.

2.2.1 Alternative Approaches

There is a rapidly growing literature on systemic risk measurement and management, some are focusing on the interaction between macroeconomy and financial sector (see, e.g., Nicolò and Lucchetta, 2010) and others on financial sector default risk (see, e.g., Kim and Giesecke, 2010). There are three approaches closely related to ours in terms of focusing on identifying systemically important institutions and charging additional capital based on banks' marginal

⁶Importance sampling is a statistical method that is based on the idea of shifting the distribution of underlying factors to generate more scenarios with large losses. See Glasserman and Li (2005) and Heitfield, Burton, and Chomsisengphet (2006) for details.

⁷We assume that, on each day, LGD follows a symmetric triangular distribution around its mean LGD_t and in the range of $[2 \times \text{LGD}_t - 1, 1]$. This distribution was also used in Tarashev and Zhu (2008b) and Huang, Zhou, and Zhu (2009), mainly for computational convenience. Using alternative distribution of LGD, such as beta-distribution, has almost no impact on our results.

contributions.⁸

The most closely related approach is the CoVaR method proposed by Adrian and Brunnermeier (2009). CoVaR looks at the VaR of the whole portfolio conditional on the VaR of an individual institution, defined implicitly as

$$\text{Prob} (L \geq \text{CoVaR}_q | L_i \geq \text{VaR}_q^i) = q \quad (7)$$

where the expectation is taken under the objective measure. In other words, the focus of CoVaR is to examine the spillover or correlation effect from one bank's failure to the whole system but underplays the importance of institutional size by design. By comparison, our definition of distress insurance premium (DIP) is along the same line but focuses on the loss of a particular bank (or a bank group) conditional on the system being in distress.⁹ Nevertheless, a major disadvantage of CoVaR is that it can only be used to identify systemically important institutions but cannot appropriately aggregate the systemic risk contributions of individual institutions.¹⁰

Another alternative is the marginal expected shortfall (MES) proposed by Acharya, Pedersen, Philippon, and Richardson (2010). MES looks at the expected loss of each bank conditional on the whole portfolio of banks performing poorly

$$\text{MES}_q^i \equiv E (L_i | L \geq \text{VaR}_q) \quad (8)$$

where the expectation is taken under the objective measure. Again, in comparison, the MES is similar to our distress insurance premium (DIP) measure in that both focus on each bank's potential loss conditional on the system being in distress exceeding a threshold level, and both are coherent risk measures. They differ slightly in the sense that the extreme condition is defined by the percentile distribution in the MES setting but by a given threshold loss of

⁸Related methods in identifying systemically important institutions include contingent claims approach (Gray, Merton, and Bodie, 2007), extreme value theory (Zhou, 2009), equity volatility/correlation (Brownlees and Engle, 2010), and too-connected-to-fail (Chan-Lau, 2009), among others.

⁹The calculation method is also different, in that Adrian and Brunnermeier (2009) employ a percentile regression approach rather than Monte Carlo simulation.

¹⁰It is important here to distinguish between the additive property of the marginal contribution measures and the (sub)additive property of the systemic risk measures. For instance, VaR is not additive (nor subadditive), but the marginal contribution to VaR using our approach can be additive.

underlying portfolio in the case of DIP. Also the probabilities in the tail event underpinning MES are normalized to sum up to one. These probabilities are not normalized for DIP. The more important difference is that the MES is calculated based on equity return data, while our DIP measure is mainly based on the CDS data. Compared with equity return data, CDS data are better and purer sources of default risk information.

A third alternative is the “Shapley value” decomposition approach by Tarashev, Borio, and Tsatsaronis (2009a,b), which focuses on how to allocate among individual institutions any appropriately defined notion of systemic risk. The “Shapley value” approach, constructed in game theory, defined the contribution of each bank as a weighted average of its add-on effect to each subsystem that consists of this bank. The Shapley value approach derives systemic importance at a different level from our approach. Under its general application, the Shapley value approach tends to suffer from the curse of dimensionality problem in that, for a system of N banks, there are 2^N possible subsystems for which the systemic risk indicator needs to be calculated.¹¹ However, the Shapley value approach has the same desirable additivity property and therefore can be used as a general approach to allocating systemic risk.

3 Data

We applied the methodology outlined above to the 19 bank holding companies (BHCs) covered by the US Supervisory Capital Assessment Program (SCAP) conducted in the spring of 2009. These BHCs all have year-end 2008 assets exceeding 100 billion USD, and collectively hold two-thirds of the assets and more than half of the loans in the US banking system (Federal Reserve Board, 2009a). SCAP is widely claimed as a critical step for transparently revealing the riskiness of the US banking sector and clearly identifying the capital needs of major financial institutions. The subsequent recovery of broad financial markets from the distressed level and the successful new issuance of equity capital and long term bond by

¹¹In a specific application of the Shapley value approach, the systemic event can be defined at the level of the entire system and refers to the same event when calculating the subsystems. Under such an application, the Shapley value approach is equivalent to our method in terms of computation burden and results.

major US banks prove the usefulness of the stress test in building the public confidence of the financial sector. Therefore the 19 banks included in the SCAP represents an important sample of banks, which serves as a benchmark portfolio for comparing various measures of systemic risk.

Table 1 reports the list of banks included in this study and the summary statistics of equities, liabilities, CDS spreads, and average correlations of individual banks. Figure 1 plots the time variation in key systemic risk input variables: PDs, correlations, and recovery rates. Our sample data cover the period from January 2004 to December 2009 and are calculated in weekly frequency. We retrieve weekly CDS spreads (together with the recovery rates used by market participants) from Markit, compute equity return correlations from equity price data (which start from January 2003) provided by CRSP.¹²

On average, the 19 BHCs have equity capital of 57 billion USD (1 trillion in sum) and total liability of 578 billion USD (10 trillion in sum), which compares to the US GDP level of 14.6 trillion in 2008. By the size of total liability, Bank of America, Citigroup, JP Morgan, and Wells Fargo are the largest ones. Over the three subperiods—January 1, 2004 to December 31, 2006, January 1, 2007 to September 15, 2008, and September 16, 2008 to December 31, 2009—the average CDS spreads have risen sharply from 32 to 240 bps respectively. Average correlations also rose from 44 percent to 62 percent. In our sample set, KeyCorp, MetLife, Citigroup, and Morgan Stanley observe the highest CDS spreads; while average correlations point to the highest ones as JP Morgan, Wells Fargo, Bank of America, and US Bankcorp. These conflicting rankings based on liability size, CDS spread, and average correlation indicate that systemic risk may be nonlinearly related to all three metrics, which is indeed the focus of our proposed methodology in assessing such a systemic importance.

The *risk-neutral* PDs (Figure 1 top panel) are derived from CDS spreads using recovery rates as reported by market participants who contribute quotes on CDS spreads.

¹²Among all the 19 US bank holding companies (BHC), GMAC doesn't have market traded equity price. Instead we use an exchange traded note—ticker GMA for GMAC LLC with 7.30 percent coupon public income note maturing in 2031—to proxy for its asset returns. We also have a set of empirical results excluding GMAC that are available upon request.

The weighted averages (weighted by the size of bank liabilities) are very low—less than 1 percent—before July 2007. With the developments of the financial crisis, risk-neutral PDs of the 19 SCAP banks increased quickly and reached a local maximum around 2 percent in March 2008, when Bear Stearns was acquired by JP Morgan. The second, and the highest, peak occurred in October 2008, shortly after the failure of Lehman Brothers. The risk-neutral PD stayed at elevated levels—4 percent—for a while, before coming back to the pre-Lehman level of 2 percent in December 2009. From a cross-sectional perspective, there were substantial differences across these major banks in term of credit quality, as reflected in the min-max range of their CDS implied default probability, especially around the fourth quarter of 2008 with the maximum reaching above 14 percent.

The other key systemic risk factor, the asset return correlation (Figure 1 middle panel), showed considerable variation around 50 percent before early 2007, then quickly elevated to 75-80 percent until the second half of 2009. Notice that the recovery rates (lower panel) are *ex ante* measures, i.e., expected recovery rates when CDS contracts are priced, and hence can differ substantially from the *ex post* observations of a handful default events during our sample period. In addition, whereas we allow for time-varying recovery rates, they exhibit only small variation (between 33 and 40 percent) during the sample period.¹³

4 Empirical Findings

We apply the methodology described in Section 2 and examine the systemic risk in the US banking system that consists of nineteen banks covered by Supervisory Capital Assessment Program (SCAP), or commonly known as “stress test”. Using these banks as an example, we first report the systemic risk indicator for these institutions as a group and then analyse the systemic importance of individual banks.

Our findings suggest that the systemic risk indicator stood at its peak around 1.1 trillion USD in March 2009 and has since fallen to about 300 billion USD—the level reached in

¹³The original recovery rate data have a significant sparseness problem, in that a large portion of CDS quotes come without the corresponding recovery rates. Therefore, in this paper we use the HP-filtered recovery rates to reflect the time variation in recovery rates, and at the same time to avoid noisy movements in average recovery rates due to data reporting problems.

January 2008. A bank's contribution to the systemic risk indicator is roughly linearly related to its default probability, but highly nonlinear with respect to institution size and asset correlation. An increase in systemic risk related to concentration risk measured by correlation seems to lead the onset of the 2007-2009 financial crisis. Our measure of the systemic importance of financial institutions relates noticeably with the SCAP result, although the former is a risk-neutral pricing measure and the latter is an objective statistical measure. In particular, our systemic risk measure shows sharp contrast with other two leading alternatives — CoVaR and MES — in ranking the systemically important institutions during the peak of financial crisis — the fourth quarter of 2008.

4.1 Systemic Risk Indicator

Figure 2 reports the time variation of the “distress insurance premium” (DIP), in which financial distress is defined as the situation in which at least 10 percent of total liabilities in the banking system go into default. The insurance cost is represented as unit percentage cost in the upper panel and in dollar amount in the lower panel.

The systemic risk indicator for the US banking system was very low at the beginning of the financial and credit crisis. For a long period before the collapse of two Bears Stern hedge funds in early August 2007, the distress insurance premium for the list of 19 SCAP banks was merely one half percentage point (or less than 5 billion USD). The indicator then moved up significantly, reaching the first peak when Bear Stearns was arranged by the US bank regulators to be acquired by JP Morgan on March 16, 2008. The situation then improved significantly in April-May 2008 owing to strong intervention by major central banks. Things changed dramatically in September 2008 with the failure of Lehman Brothers. Market panic and increasing risk aversion pushed up the price of insurance against distress in the banking sector. The distress insurance premium hiked up and hovered in the range of 500-900 billion USD. One week before the stock market reached the bottom, the systemic risk indicator peaked around 1.1 trillion USD. Since the release of US SCAP or stress test result around early May 2009, the distress insurance premium has come down quickly and returned to the pre-Lehman level of 300-400 billion USD.

Table 2 examines the determinants of the systemic risk indicator. The level of risk-neutral PDs is a dominant factor in determining the systemic risk, explaining alone 94 percent of the variation in the distress insurance premium. On average, a one-percentage-point increase in average PD raises the distress insurance premium by 1.7 percent. The level of correlation also matters, but to a lesser degree and its impact is largely washed out once PD is included. This is perhaps due to the strong relationship between PD and correlation for the sample banking group during this special time period. In addition, the recovery rate has the expected negative sign in the regression, as higher recovery rates reduce the ultimate losses for a given default scenario. Interestingly, the dispersion in PDs across the 19 banks has a significantly negative effect on the systemic risk indicator.¹⁴ This partly supports our view that incorporating heterogeneity in PDs is important in measuring the system risk indicator.¹⁵

The results have two important implications for supervisors. First, given the predominant role of average PDs in determining the systemic risk, a first-order approximation of the systemic risk indicator could use the weighted average of PDs (or CDS spreads). This can be confirmed by comparing the similar trend in average PDs (the upper panel in Figure 1) and the distress insurance premium (Figure 2). Second, the average PD itself is only a good approximation but is not sufficient in reflecting the intricate nonlinear relationship between systemic risk indicator and its input variables. Correlations and heterogeneity in PD also matter. In other words, diversification can reduce the systemic risk.

4.2 Risk Premium Decomposition

As mentioned in Section 2, the PDs implied from CDS spreads are a risk-neutral measure and include information not only on expected actual default losses of the banking system but also on default risk premium and liquidity risk premium components. It has been argued

¹⁴Dispersion is represented as the standard deviation of the variable of interest for the sample banks at each particular point in time. The correlation coefficient for a particular bank is defined as the average pairwise correlation between this bank and other banks.

¹⁵In a study of 22 Asia-Pacific banks (Huang, Zhou, and Zhu, 2010), we found that the heterogeneities in both PDs and correlations significantly reduce the systemic risk, which is consistent with the fact that Asia-Pacific banks are much more diverse than their US counterparts.

that, during the crisis period, the risk premium component could be the dominant factor in determining the CDS spreads (see, e.g., Kim, Loretan, and Remolona, 2009). Given that the systemic risk indicator is based on risk-neutral measures, an interesting question is how much of its movement is attributable to the change in the “pure” credit quality (or actual potential default loss) of the banks and how much are driven by market sentiments (change in risk attitude, market panic, etc.) or liquidity shortage.

We run a regression analysis that examines the impact of actual default rates and risk premium factors on the systemic risk indicator. In Table 3, objective default risk (or actual default rates) is measured by average EDFs of sample banks, the default risk premium in the global market is proxied by the difference between Baa- and Aaa-rated corporate bond spreads (see, e.g., Chen, Collin-Dufresne, and Goldstein, 2008), and the liquidity risk premium is proxied by the LIBOR-OIS spread (see, e.g., Brunnermeier, 2009). Individually (regressions 1 to 3), each of the three factors has a significant impact on the systemic risk indicator with an expected positive sign. In particular, one percentage increase in real default probability, default risk premium, and liquidity risk premium will translate into 1.93, 3.07, and 2.52 percentage increase in the systemic risk indicator. Default or credit risk premium has the highest univariate R-square of 76 percent. The last regression includes all three factors, which remain statistically significant, and jointly these driving factors seem to explain 87 percent of aggregate systemic risk variations.

Figure 3 quantifies the contribution of actual default risk, default risk premium and liquidity risk premium in explaining the changes in systemic risk since July 2007. It vividly illustrates the time-varying importance of the three factors at different stages of the global financial crisis. Until September 2009, most of the increase in systemic risk came from the default premium component, while the liquidity premium component only shot up around October 2008 and dominated more than half of the total systemic risk at that time. It was not until January 2009 that the real default risk began to contribute significantly to the systemic risk, and remained at a heightened level before the fourth quarter of 2009, even as the risk premium components already started to fall around May 2009. At the end of our sample period, it was mainly the actual default risk that contributed to riskiness of the

banking system. Overall, the decomposition results provide strong evidence that systemic risk in the US banking sector stemmed not only from a belated reassessment of real default risk but also from an early repricing of credit risk and a sudden dry-up in market liquidity.

4.3 Marginal Contribution to Systemic Risk

The most relevant question is the sources of vulnerabilities, i.e., which banks are systemically more important or contribute the most to the increased vulnerability? Our identification of systemically important institutions can be contrasted with other market based systemic risk measures (e.g., CoVaR and MES) and with confidential supervisory information (e.g., SCAP result). In addition, our measures of institutions' systemic importance change noticeably over time, especially during the financial crisis, and as such can provide important monitoring tools for the market-based macroprudential or financial stability regulation.

Using the methodology described in Section 2, we calculate the marginal contributions of each group of banks to the systemic risk indicator, both in level terms and in percentage terms. Figure 4 shows that, based on our measure, Bank of America and Wells Fargo increased their systemic risk contributions, CitiGroup remained the largest contributor over time, and JPMorgan Chase decreased its marginal contribution. Notice that Wells Fargo acquired Wachovia and Bank of America acquired Merrill Lynch during the height of financial crisis. Figure 4 also reports the systemic risk contributions of other banks which are grouped into four categories.¹⁶ It seems that the relative contributions to systemic risk from both consumer banks and regional banks have increased somewhat recently, possibly due to the worsening situations in commercial real estate and consumer credit sectors that are typically lagging the business cycles.

Table 4 also details each bank's contribution to the systemic risk on several specific dates: August 2007 (crisis started), March 2008 (Bear Stearns was acquired), September and October 2008 (broad market panic), March 2009 (equity market bottom), May 2009 (release

¹⁶These BHCs are classified into four categories: (1) investment banks (Goldman Sachs and Morgan Stanley); (2) consumer banks (GMAC and American Express); (3) regional banks (US Bancorp, Capital One, PNC Financial, SunTrust, BB&T, Regions Financial, Fifth Third, and KeyCorp); (4) processing banks (Bank of NY Mellon, State Street, and Northern Trust). Bank of America, Citigroup, JP Morgan, and Wells Fargo are listed as individual large complex financial institutions (LCFI).

of SCAP result), and December 2009 (end of sample). It is clear that size is the dominant factor in determining the relative importance of each bank’s systemic risk contribution, but size doesn’t change significantly over the time, at least within a reporting quarter. The obvious time-variation in the marginal contributions are mostly driven by the risk-neutral default probability and equity return correlation. In essence, the systemic importance of each institution is nonlinearly determined by size, default probability, and asset correlation of all institutions in the portfolio.

Table 5 examines the determinants of marginal contribution to the systemic risk for each bank, using an OLS regression on the panel data. To control for bias, we use clustered standard errors grouped by banks as suggested by Peterson (2009). The first regression shows that weight, or the size effect, is the primary factor in determining marginal contributions both in level and in relative terms. This is not surprising, given the conventional “too-big-to-fail” concern and the fact that bigger banks often have stronger inter-linkage with the rest of the banking system. Default probabilities also matter, but to a lesser extent and the significance disappears in the relative-term regression.¹⁷ This supports the view for distinguishing between micro- and macroprudential perspectives of banking regulation, i.e., the failure of individual banks does not necessarily contribute to the increase in systemic risk. The second and third regressions suggest that there are significant interactive effects. Adding interactive terms between size and PD or correlation have additional and significant explanatory power. Overall, the results suggest that the marginal contribution is the highest for high-weight (hence large) banks which observe increases in PDs or correlations.

4.4 Alternative Systemic Risk Measures and Policy Implication

As discussed earlier in Section 2, our marginal contribution measure is an alternative measure related to the CoVaR measure suggested by Adrian and Brunnermeier (2009) and the MES measure suggested by Acharya, Pedersen, Philippon, and Richardson (2010). The most important difference is that our distress insurance premium (DIP) based measure of each

¹⁷We find that, although weighted average of PDs represent a good first-order approximation of the systemic risk, individual PDs (weighted by bank size or unweighted) are very poor approximation of their marginal contributions.

bank's systemic importance is a risk-neutral pricing measure that is derived from both CDS and equity market data, while CoVaR and MES are objective distribution based statistical measures that rely only on equity return information. Another important difference is that DIP and MES measure each bank's loss conditional on the system being in distress, while the CoVaR measures the system losses conditioning on each bank being in distress. Finally, both CoVaR and MES ideas only implicitly take into account of size, PD, and correlation of each bank; while for our DIP measure, these characteristics are direct inputs into our systemic risk indicator.

We can further compare different measures of the systemic importance with the SCAP estimate of losses under an adverse economic scenario as released in May 2009 by Federal Reserve Board (2009b).¹⁸ Figure 5 left panel suggests that, based on the data up till December 31, 2008, the 19 banks' contributions to our DIP systemic risk indicator are largely in line with the SCAP estimate of losses, with an R-square of 0.62. Goldman Sachs, CitiGroup, and JPMorgan in particular, would be viewed as contributing much more to systemic risk by our method than by SCAP — from a market risk premium perspective; while Bank of America and Wells Fargo would be viewed more risky by SCAP than by our method — from an expected default loss perspective. The middle panel shows that MES weighted by tier 1 capital has a higher relation with SCAP expected losses, with an R-square of 0.71. Relative to SCAP, MES considers Bank of America, JPMorgan, and Goldman Sachs as more risky while Wells Fargo and Citigroup as less risky. The right panel shows that CoVaR in dollar terms has a similar relation with SCAP results with an R-square of 0.63. Compared to SCAP, CoVaR ranks JPMorgan, MetLife, and Goldman Sachs as more risky but CitiGroup and Bank of America as less risky.¹⁹

Note that our systemic risk measure is a risk-neutral concept, while SCAP and MES

¹⁸SCAP or stress test is a leading example of combining both macroprudential and microprudential perspectives in banking supervision and regulation (see, e.g., Hirtle, Schuermann, and Stiroh, 2009; International Monetary Fund, 2010).

¹⁹We obtain the MES data from NYU Stern Volatility Lab at <http://vlab.stern.nyu.edu/welcome/risk>, and the CoVaR data are kindly provided by Tobias Adrian. We flipped the signs of CoVaR measures so that the higher the CoVaR, the higher the bank contributes to the systemic risk. This is consistent with other measures in the comparative study.

is based on statistical expected loss; consequently MES is supposed to have a stronger connection with SCAP than DIP. Although CoVaR is also a statistical measure, it measures the system's loss conditional on each bank in stress; while MES and DIP measure each bank's loss conditional on the system in stress, yet SCAP measures each bank's loss conditional on the macroeconomy in stress. Also, the tail percentile value (like CoVaR) and tail expected value (like MES or SCAP) can diverge significantly in heavy tailed distributions. These differences in conditioning directions and tail measures may explain the notable differences in rankings of DIP, MES, and CoVaR versus SCAP.²⁰

The nonlinear effect documented in Table 5 is more visible in a hypothetical calibration exercise examining the relationship between our systemic risk indicator and institution's size (total liability), (risk-neutral) default probability, and (average) historical correlation (Figure 6).²¹ The relationship looks roughly linear for default probability, but highly nonlinear with respect to size and to a lesser degree to correlation. In fact, when the bank size is below 10 percent of the total portfolio, the slope of systemic importance with respect to size is very flat; but when the size is beyond 10 percent, the contribution to systemic risk shoots up almost vertically. An intuitive reason is that, when a bank is too big, its failure is considered as a systemic failure by definition. This may indicate a desirable maximum size of the large complex financial institutions (LCFI), for a societal benefit of limiting the systemic risk. The relationship between systemic importance and correlation shows a similar nonlinear pattern but is less dramatic. In other words, systemic importance is a joint effect of an institution's size, leverage, and concentration and is highly nonlinear in nature.

Our finding of the dominant effect of bank size and its pronounced nonlinear impact on bank's systemic risk contribution has important policy implications. In particular, the financial regulation reform bill recently enacted by United States Congress (2010) explicitly

²⁰The *ex post* weighting of MES and CoVaR measures by sizes can raise a question on how to interpret the resulting absolute magnitudes. As shown by the y-axes in Figure 5, the tier 1 capital weighted MES has a scale of 6 billion USD, and CoVaR translated to dollar term of 2,000 billion USD. In comparison, both SCAP and DIP range to 150 billion USD.

²¹The hypothetical portfolios are based on 20 common banks, with average LGD of 0.55 and distress threshold 10 percent. For the impact of size (left panel), PD is 0.02 and correlation is 20 percent; for the impact of PD (middle panel), PD changes from 0.005 to 0.1; for the impact of correlation (right panel), the loading coefficient in a one-factor model ranges between 0.2 and 0.96.

adopts the so-called “Volcker Rule” Concentration Limit — “Any financial company is prohibited from acquiring another company if, on consummation, the combined company’s total consolidated liabilities would exceed 10 percent of the aggregate consolidated liabilities of all financial companies.” Our results indirectly support such a measure based on a calibration exercise tailored to the portfolio of 19 SCAP banks.

5 Concluding remarks

The recent financial crisis has caused policymakers to reconsider the institutional framework for overseeing the stability of their financial systems. A series of reform recommendations have been made covering various aspects of financial regulation and supervision. It has become generally accepted that the traditional microprudential or firm-level approach to financial stability needs to be complemented with a system-wide macroprudential approach, i.e., to pay greater attention to individual institutions that are systemically important.

In this paper we advocate a methodology to measure the systemic importance of individual banks and their marginal contribution to a distressed insurance premium. We apply this methodology to the 19 banks covered by the SCAP or stress test program. Our results suggest that the elevated systemic risk in the banking sector is initially driven by the rising default risk premium and later by heightened liquidity risk premium. But since the fourth quarter of 2008, both real default risk and risk premia are rising as the financial crisis turned into a severe economic recession. A decomposition analysis shows that the marginal contribution of individual banks to the systemic risk is mostly determined by its size, or the “too big to fail” doctrine, although correlation and default probability also matter. Finally, our measure of systemic importance of banks — as a market based risk-neutral price — shows clear association and meaning difference with the estimated SCAP loss as an objective statistical measure.

Our approach can be extended to address important policy questions. For one, the marginal contribution measures and its desirable additive property implies that it is straightforward to design regulatory requirements based on individual banks’ systemic importance.

Such regulatory requirement can be capital surcharges, or individual banks' contribution to a banking tax or a systemic risk insurance fund. Moreover, our finding of the pronounced nonlinear relationship between a bank's systemic risk contribution and its liability size lends indirect support for the Volcker's 10 percent concentration limit adopted in the recent financial regulation reform legislation. Second, although the proposed DIP measure is risk-neutral, the framework can be easily extended by substituting key inputs with the regulator's confidential information or other input variables for the purpose of policy analysis. For instance, one can replace the risk-neutral PDs in our framework with objective measures of PDs²² and calculate the distress insurance premium on an incurred-cost basis. This objective measure, by filtering out the risk premium components, can provide useful complimentary information for supervisors.

²²The Expected Default Frequency (EDF) is one such product that produces objective measures of expected default rates of individual firms. However, it is widely acknowledged that EDFs for financial firms are less reliable, mainly because financial firms typically have much higher leverages than corporate firms. The higher leverage does not necessarily reflect higher default risk but will cause substantial bias in EDF estimates without proper adjustment, which remains a challenging task.

References

- Acharya, Viral V. (2009), “A Theory of Systemic Risk and Design of Prudential Bank Regulation,” *Journal of Financial Stability*, forthcoming.
- Acharya, Viral V., Lasse H. Pedersen, Thomas Philippon, and Matthew Richardson (2010), “Measuring Systemic Risk,” Working Paper, NYU Stern School of Business.
- Adrian, Tobias and Markus Brunnermeier (2009), “CoVaR,” Federal Reserve Bank of New York Staff Reports.
- Altman, Edward and Vellore Kishore (1996), “Almost Everything You Want to Know about Recoveries on Default Bonds,” *Financial Analysts Journal*, vol. 52, 57–64.
- Andersen, Leif, Jakob Sidenius, and Susanta Basu (2003), “All Your Hedges in One Basket,” *Risk*, pages 67–72.
- Avesani, Renzo, Antonio Garcia Pascual, and Jing Li (2006), “A New Risk Indicator and Stress Testing Tool: A Multifactor Nth-to-Default CDS Basket,” IMF Working Paper.
- BCBS (2009), “Comprehensive Responses to the Global Banking Crisis,” Press Release by the Basel Committee on Banking Supervision, September 7, <http://www.bis.org/press/p090907.htm>.
- Billio, Monica, Mila Getmansky, Andrew W. Lo, and Lioriana Pelizzon (2010), “Econometric Measures of Systemic Risk in the Finance and Insurance Sectors,” NBER Working Paper No. 16223.
- Blanco, Roberto, Simon Brennan, and Ian W. March (2005), “An Empirical Analysis of the Dynamic Relationship between Investment-Grade Bonds and Credit Default Swaps,” *Journal of Finance*, vol. 60, 2255–2281.
- Borio, Claudio (2003), “Towards a Macro-Prudential Framework for Financial Supervision and Regulation?” BIS Working Papers.
- Brownlees, Christian T. and Robert Engle (2010), “Volatility, Correlation and Tails for Systemic Risk Management,” Working Paper, NYU Stern School of Business.

- Brunnermeier, Markus, Andrew Crockett, Charles Goodhart, Avinash Persaud, and Hyun Shin (2009), “The Fundamental Principles of Financial Regualtions,” Geneva Reports on the World Economy.
- Brunnermeier, Markus K. (2009), “Deciphering the 2007-08 Liquidity and Credit Crunch,” *Journal of Economic Perspectives*, vol. 23, 77–100.
- Chan-Lau, Jorge A. (2009), “Regulatory Capital Charges for Too-Connected-to-Fail Institutions: A Practical Proposal,” IMF Working Paper.
- Chan-Lau, Jorge A. and Toni Gravelle (2005), “The End: A New Indicator of Financial and Nonfinancial Corporate Sector Vulnerability,” IMF Working Paper No. 05/231.
- Chen, Long, Pierre Collin-Dufresne, and Robert S. Goldstein (2008), “On the Relation between Credit Spread Puzzles and the Equity Premium Puzzle,” *Journal of Economic Perspectives*, forthcoming.
- Cont, Rama (2010), “Measuring Contagion and Systemic Risk in Financial Systems,” Working Paper, Columbia University.
- Crockett, Andrew (2000), “Marrying the Micro- and Macro-prudential Dimensions of Financial Stbility,” Speech before the Eleventh International Conference of Banking Supervisors, Basel.
- Duffie, Darrall (1999), “Credit Swap Valuation,” *Financial Analysts Journal*, pages 73–87.
- Embrechts, Paul, Dominik D. Lambrigger, and Mario V. Wüthrich (2009), “On Extreme Value Theory, Aggregation and Diversification in Finance,” Working Paper, Department of Mathematics, ETH Zurich.
- Federal Reserve Board (2009a), “The Supervisory Capital Assessment Program: Design and Implementation,” Public Document.
- Federal Reserve Board (2009b), “The Supervisory Capital Assessment Program: Overview of Results,” Public Document.
- Financial Stability Forum (2009a), “Reducing Procyclicality Arising from the Bank Capital Framework,” Joint FSF-BCBS Working Group on Bank Capital Issues.

- Financial Stability Forum (2009b), “Report of the Financial Stability Forum on Addressing Procyclicality in the Financial System,” Working Groups on Bank Capital Issues, Provisioning, and Leverage and Valuation.
- Forte, Santiago and Juan Ignacio Peña (2009), “Credit Spreads: An Empirical Analysis on the Informational Content of Stocks, Bonds, and CDS,” *Journal of Banking and Finance*, vol. 33, 2013–2025.
- Gibson, Michael (2004), “Understanding the Risk of Synthetic CDOs,” Working Paper, Federal Reserve Board.
- Glasserman, Paul (2005), “Measuring Marginal Risk Contributions in Credit Portfolios,” *Journal of Computational Finance*, vol. 9, 1–41.
- Glasserman, Paul and Jingyi Li (2005), “Importance Sampling for Portfolio Credit Risk,” *Management Science*, vol. 51, 1643–1656.
- Gordy, Michael B. (2003), “A Risk-Factor Model Foundation for Ratings-Based Bank Capital Rules,” *Journal of Financial Intermediation*, vol. 12, 199–232.
- Gray, Dale F., Robert C. Merton, and Zvi Bodie (2007), “Contingent Claims Approach to Measuring and Managing Sovereign Credit Risk,” *Journal of Investment Management*, vol. 5, 1–24.
- Heitfield, Eric, Steve Burton, and Souphala Chomsisengphet (2006), “Systematic and Idiosyncratic Risk in Syndicated Loan Portfolios,” *Journal of Credit Risk*, vol. 2, 3–31.
- Hirtle, Beverly, Til Schuermann, and Kevin Stiroh (2009), “Macroprudential Supervision of Financial Institutions: Lessons from the SCAP,” Staff Report no. 409, Federal Reserve Bank of New York.
- Huang, Xin, Hao Zhou, and Haibin Zhu (2009), “A Framework for Assessing the Systemic Risk of Major Financial Institutions,” *Journal of Banking and Finance*, vol. 33, 2036–2049.
- Huang, Xin, Hao Zhou, and Haibin Zhu (2010), “Assessing the Systemic Risk of a Heterogeneous Portfolio of Banks During the Recent Financial Crisis,” Working Paper, Federal Reserve Board.

- Hull, John and Alan White (2004), “Valuation of a CDO and an N-th to Default CDS without Monte Carlo Simulation,” *Journal of Derivatives*, vol. 12, 8–23.
- International Monetary Fund (2010), “Systemic Risk and the Redesign of Financial Regulation,” Global Financial Stability Report Chapter 2.
- Inui, Koji and Masaaki Kijima (2005), “On the Significance of Expected Shortfall as a Coherent Risk Measure,” *Journal of Banking and Finance*, vol. 29, 853–864.
- Kim, Baeho and Kay Giesecke (2010), “Systemic Risk: What Defaults Are Telling Us,” Working Paper, Stanford University.
- Kim, Don, Mico Loretan, and Eli Remolona (2009), “Contagion and Risk Premia in the Amplification of Crisis: Evidence from Asian Names in the CDS Market,” BIS Working Paper.
- Kurth, Alexandre and Dirk Tasche (2003), “Credit Risk Contributions to Value-at-Risk and Expected Shortfall,” *Risk*, vol. 16, 84–88.
- Lehar, Alfred (2005), “Measuring Systemic Risk: A Risk Management Approach,” *Journal of Banking and Finance*, vol. 29, 2577–2603.
- Merton, Robert (1974), “On the Pricing of Corporate Debt: The Risk Structure of Interest Rates,” *Journal of Finance*, vol. 29, 449–470.
- Nicolò, Gianni De and Myron Kwast (2002), “Systemic Risk and Financial Consolidation: Are They Related,” *Journal of Banking and Finance*, vol. 26, 861–880.
- Nicolò, Gianni De and Marcella Lucchetta (2010), “Systemic Risk and the Macroeconomy,” International Monetary Fund.
- Norden, Lars and Wolf Wagner (2008), “Credit Derivatives and Loan Pricing,” *Journal of Banking and Finance*, vol. 32, 2560–2569.
- Panetta, Fabio, Paolo Angelini, Ugo Albertazzi, Francesco Columba, Wanda Cornacchia, Antonio Di Cesare, Andrea Pilati, Carmelo Salleo, and Giovanni Santini (2009), “Financial Sector Pro-Cyclicality: Lessons from the Crisis,” Banca D’Italia Occasional Papers.

- Peterson, Mitchell (2009), “Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches,” *Review of Financial Studies*, vol. 22, 435–480.
- Tarashev, Nikola, Claudio Borio, and Kostas Tsatsaronis (2009a), “Allocating Systemic Risk to Individual Institutions: Methodology and Policy Applications,” BIS Working Paper.
- Tarashev, Nikola, Claudio Borio, and Kostas Tsatsaronis (2009b), “The Systemic Importance of Financial Institutions,” BIS Quarterly Review.
- Tarashev, Nikola and Haibin Zhu (2008a), “The Pricing of Portfolio Credit Risk: Evidence from the Credit Derivatives Market,” *Journal of Fixed Income*, vol. 18, 5–24.
- Tarashev, Nikola and Haibin Zhu (2008b), “Specification and Calibration Errors in Measures of Portfolio Credit Risk: The Case of the ASRF Model,” *International Journal of Central Banking*, vol. 4, 129–174.
- United States Congress (2010), “Dodd-Frank Wall Street Reform and Consumer Protection Act,” Public Document H. R. 4173.
- Vasicek, Oldrich A. (1991), “The Limiting Loan Loss Probability Distribution,” KMV Working Paper.
- Yamai, Yasuhiro and Toshinao Yoshiba (2005), “Value-at-Risk versus Expected Shortfall: A Practical Perspective,” *Journal of Banking and Finance*, vol. 29, 997–1015.
- Zhou, Chen (2009), “Are Banks Too Big to Fail? Measuring Systemic Importance of Financial Institutions,” Working Paper, De Nederlandsche Bank.

Table 1 Summary Statistics of Nineteen US Banks in SCAP Program

Bank Name	Sector	Equity ¹	Liability ¹	CDS Spreads ²			Correlation ³		
				Period 1	Period 2	Period 3	Period 1	Period 2	Period 3
American Express Co.	Consumer	14.41	105.40	21.16	83.10	244.69	44.42	62.65	63.44
Bank of America Corp.	BAC	231.44	2082.41	15.92	51.71	155.36	50.83	67.84	68.51
BB&T	Regional	16.19	127.24	16.68	52.62	105.79	54.47	69.27	67.21
Bank of NY Mellon Corp.	Processing	28.98	175.24	16.45	40.67	113.33	44.26	61.13	64.55
Capital One Financial Corp.	Regional	26.59	150.64	53.20	189.96	211.12	32.20	57.32	64.53
Citigroup, Inc.	Citi	152.70	1676.65	15.68	67.33	263.51	48.08	65.87	56.90
Fifth Third Bancorp	Regional	13.50	107.21	9.06	24.95	160.64	44.50	62.50	60.45
GMAC LLC	Consumer	20.84	153.31	274.29	699.58	1226.86	8.84	15.87	19.06
Goldman Sachs Group, Inc.	Investment	70.71	860.66	26.56	73.86	179.73	43.47	63.14	63.67
JPMorgan Chase & Co.	JPM	165.37	1908.99	21.99	52.82	97.79	52.60	67.67	70.50
KeyCorp	Regional	10.66	87.66	19.48	84.24	402.04	49.41	61.17	65.25
MetLife, Inc.	Consumer	33.12	467.98	24.55	63.15	388.33	36.98	59.66	63.58
Morgan Stanley	Investment	46.69	576.82	26.53	97.71	261.94	42.62	61.35	60.83
PNC Fin. Svcs. Gp, Inc.	Regional	29.94	257.77	14.12	26.28	87.94	44.88	65.70	64.43
Regions Fin. Corp.	Regional	17.88	125.16	8.26	17.43	72.42	45.95	65.50	58.73
State St. Corp.	Processing	14.49	128.29	16.17	44.89	143.45	46.16	57.71	63.01
SunTrust Banks, Inc.	Regional	22.42	157.47	15.20	63.39	188.30	52.69	64.71	66.86
U.S. Bancorp	Regional	25.96	235.68	16.26	51.07	125.16	49.39	66.23	67.41
Wells Fargo & Co.	WFC	111.79	1178.83	14.89	50.51	122.69	48.25	67.92	70.55
<i>Mean</i>		55.46	555.97	32.97	96.59	239.53	44.21	61.22	62.08

Notes: ¹In billions of U.S. dollars. Data as of December 2009. ²Average daily CDS spreads in each period, in basis points. “Period 1” runs from January 1, 2004 to December 31, 2006; “Period 2” runs from January 1, 2007 to September 15, 2008; “Period 3” runs from September 16, 2008 to December 31, 2009. ³Average stock return correlation between one bank and all others in each period, in percentage points. Sources: National Information Center; Markit; CRSP.

Table 2 Determinants of Systemic Risk Indicator: Input Variables

Independent Variables	Regression 1	Regression 2	Regression 3	Regression 4	Regression 5
Constant	-0.16 (3.49)	-4.59 (9.78)	34.92 (5.99)	4.15 (4.47)	1.89 (2.41)
Average PD	1.71 (69.69)			1.74 (54.51)	2.46 (39.83)
Average Correlation		0.13 (14.50)		0.00 (0.95)	0.01 (2.90)
Recovery Rate			-0.52 (5.64)	-0.12 (4.59)	-0.07 (3.05)
Dispersion in PD					-0.78 (12.83)
Dispersion in Correlation					0.01 (0.85)
Adjusted-R ²	0.94	0.40	0.09	0.94	0.96

Notes: The dependent variable is the indicator of systemic risk for 19 US banks, defined as the unit price (in percent) of insurance against distressed losses. Dispersion refers to the standard deviation of the variable of interest (PD or correlation) for the sample banks at each particular point in time. PD refers to the risk-neutral probability of default implied from CDS spreads; correlation refers to a bank's average correlation with the other banks. t-statistics are in parentheses.

Table 3 Determinants of Systemic Risk Indicator: Risk Premiums

Independent Variables	Regression 1	Regression 2	Regression 3	Regression 4
Constant	1.07 (5.1)	-1.68 (6.0)	0.92 (3.2)	-0.91 (3.9)
Average EDF (%)	1.93 (9.8)			1.14 (7.8)
BAA-AAA Spread (%)		3.07 (15.1)		1.64 (6.2)
LIBOR-OIS Spread (%)			2.52 (6.2)	0.91 (3.5)
Adjusted-R ²	0.57	0.76	0.34	0.87

Notes: The dependent variable is the indicator of systemic risk for the 19 SCAP banks, defined as the unit price (in percent) of insurance against distressed losses. Average EDF is from Moody's KMV expected default frequency, BAA-AAA Spread is the difference between Moody's BAA and AAA credit spread indices (as a proxy for credit risk), and LIBOR-OIS Spread is the difference between London Interbank Offered Rate and Overnight Indexed Swap (as a proxy for liquidity risk). t-statistics are in the parenthesis.

Table 4 Marginal Contribution to the Systemic Risk by Banks on Specific Dates

Bank Name	Marginal contribution							<i>SCAP</i>
	08.10.2007	03.16.2008	09.16.2008	10.20.2008	03.09.2009	05.07.2009	12.31.2009	<i>Losses</i>
American Express Co.	1.3101	5.3226	5.9371	9.8578	13.3794	6.1939	1.4770	11.2000
Bank of America Corp.	22.5388	60.7817	91.6920	75.8858	169.6650	143.6174	69.2643	136.6000
BB&T	1.2044	3.2306	6.6060	5.1998	N.A.	6.4492	2.1312	8.7000
Bank of NY Mellon Corp.	0.5898	4.5008	6.9008	7.8521	9.6070	6.7699	2.8365	5.4000
Capital One FiN.A.cial Corp.	1.5410	7.7237	8.6399	9.3357	9.6426	7.3052	2.3955	13.4000
Citigroup, Inc.	40.3117	130.1139	135.7237	133.9047	302.1724	172.9385	71.1229	104.7000
Fifth Third Bancorp	0.9445	1.6278	N.A.	N.A.	1.8262	1.5949	4.1009	9.1000
GMAC LLC	1.5097	4.0589	10.0398	10.9142	8.1019	7.2665	0.6920	9.2000
Goldman Sachs Group, Inc.	20.0346	49.1786	99.3637	60.1561	71.8879	39.1285	19.4087	17.8000
JPMorgan Chase & Co.	25.6174	58.7236	112.7932	85.4109	130.9016	85.9607	32.4703	97.4000
KeyCorp	0.5801	2.3252	8.7862	6.7943	9.2999	6.5864	3.1578	6.7000
MetLife, Inc.	4.2064	16.7281	21.8047	26.2686	68.7519	49.2329	10.7981	9.6000
Morgan Stanley	18.3609	55.4046	105.5172	39.6676	58.7151	31.1108	8.6964	19.7000
PNC Fin. Svcs. Gp, Inc.	0.5867	2.3474	N.A.	N.A.	N.A.	18.9800	3.0893	18.8000
Regions Fin. Corp.	0.7837	0.7996	1.0135	0.7852	1.0652	0.9571	2.1496	9.2000
State St. Corp.	0.5336	4.9617	7.8473	8.8160	8.4989	7.4683	1.5385	8.2000
SunTrust Banks, Inc.	1.5757	6.1166	7.0965	6.3174	9.2881	7.2031	3.3633	11.8000
U.S. Bancorp	2.2136	6.4720	10.8688	7.5888	10.4362	10.1740	3.2525	15.7000
Wells Fargo & Co.	6.1051	17.6868	23.1148	17.3149	93.0329	60.1823	26.7920	86.1000
<i>Total</i>	150.5477	438.1043	663.7452	512.0698	976.2721	669.1198	268.7369	599.3000

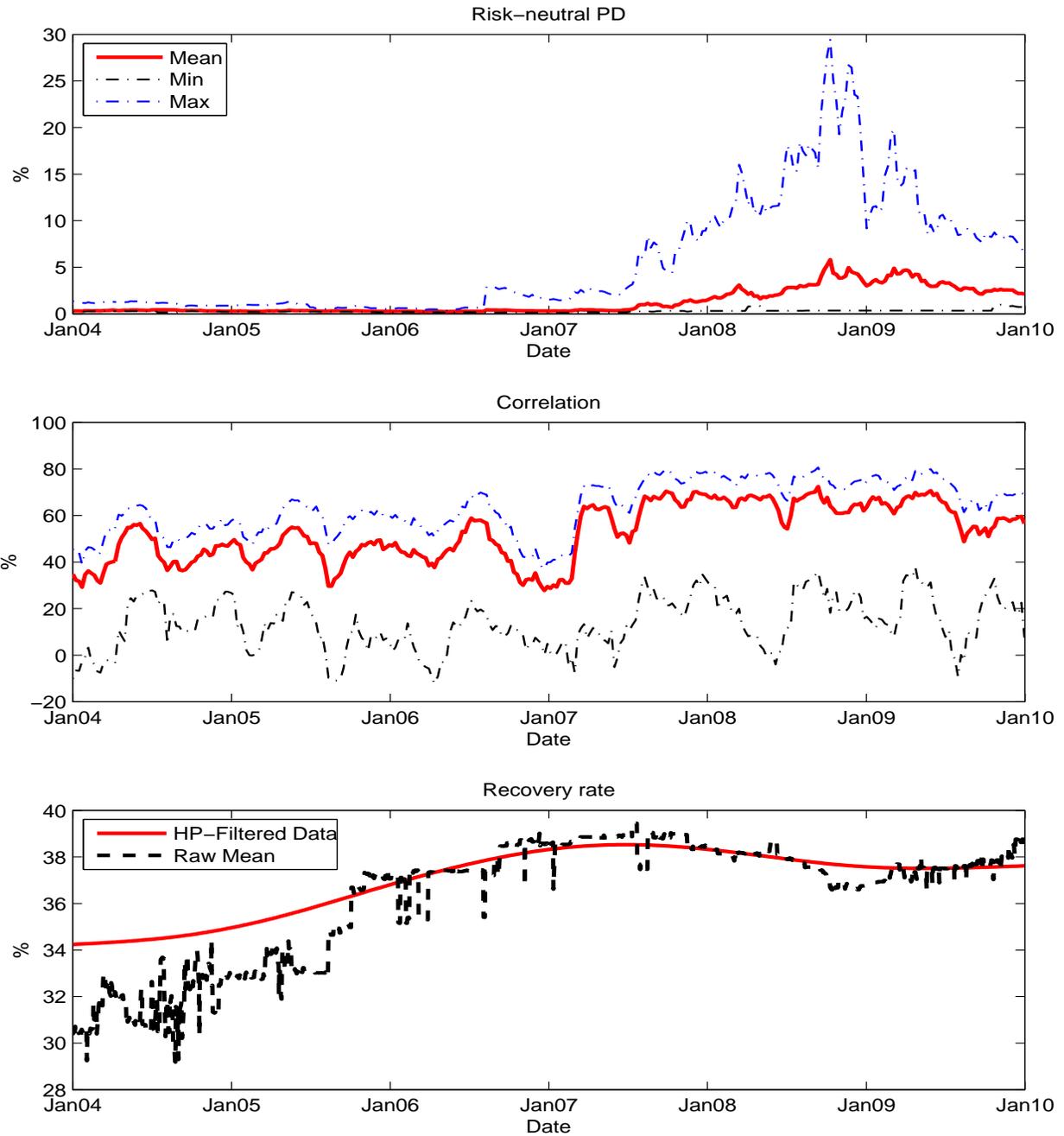
Notes: This table reports the marginal contribution of each banks to the systemic risk indicator on specific dates, in comparison with the SCAP expected losses. All numbers are in billions of US dollars.

Table 5 Determinants of Marginal Contribution to the Systemic Risk

Independent Variables	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.
1. Level Regressions						
	Regression 1		Regression 2		Regression 3	
Constant	-19.12	(1.70)	-3.14	(3.49)	18.23	(1.59)
$PD_{i,t}$	0.04	(1.76)			-0.03	(9.70)
$Cor_{i,t}$	0.00	(3.74)			0.00	(2.15)
$Rec_{i,t}$	-0.00	(0.34)			-1405.99	(1.82)
$Weight_{i,t}$	238.08	(15.52)	-222.20	(0.77)	-0.01	(1.79)
$PD_{i,t} \times Weight_{i,t}$			1.91	(8.22)	2.27	(17.94)
$Cor_{i,t} \times Weight_{i,t}$			0.02	(2.41)	0.01	(2.15)
$Rec_{i,t} \times Weight_{i,t}$			-0.02	(5.34)	0.36	(1.77)
Adjusted-R ²	0.43		0.93		0.97	
2. Relative-term Regressions						
	Regression 1		Regression 2		Regression 3	
Constant	-0.03	(1.65)			0.01	(0.60)
$PD_{i,t}$	0.01	(1.90)			-0.01	(1.91)
$Cor_{i,t}$	0.02	(1.71)			-0.00	(0.22)
$Rec_{i,t}$	-0.01	(0.84)			-0.02	(1.11)
$Weight_{i,t}$	1.25	(20.12)	0.71	(1.63)	0.47	(1.04)
$PD_{i,t} \times Weight_{i,t}$			0.53	(3.33)	0.66	(3.56)
$Cor_{i,t} \times Weight_{i,t}$			0.59	(1.80)	0.60	(1.53)
$Rec_{i,t} \times Weight_{i,t}$			-0.52	(1.07)	-0.40	(0.67)
Adjusted-R ²	0.90		0.93		0.93	

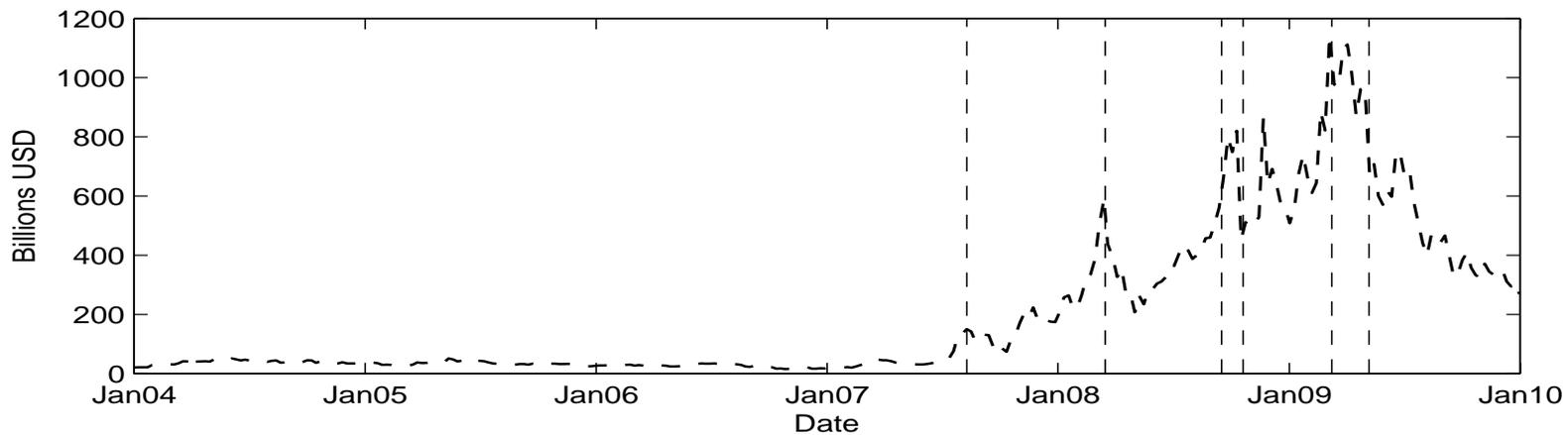
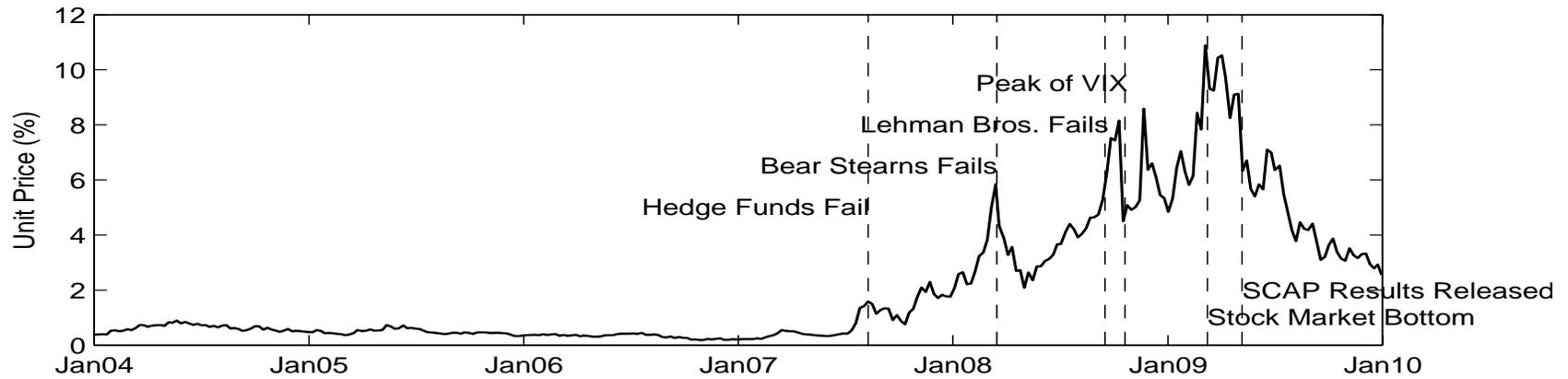
Notes: The dependent variable is the marginal contribution of each bank to the systemic risk indicator, which is represented in level terms (unit cost of insurance, in basis point) in the first panel and in relative terms (as a percentage of total insurance premium) in the second panel. Explanatory variables include PDs, bank-specific correlations (average of pairwise correlations between one bank and all others) and weights of individual banks and interactive terms. Similarly, PDs and correlations refer to level terms in the first panel and relative terms (the ratio over cross-sectional averages) in the second panel. OLS regression is adopted and t-statistics are reported in the parenthesis, using clustered standard errors grouped by banks.

Figure 1 Systemic Risk Input Variables



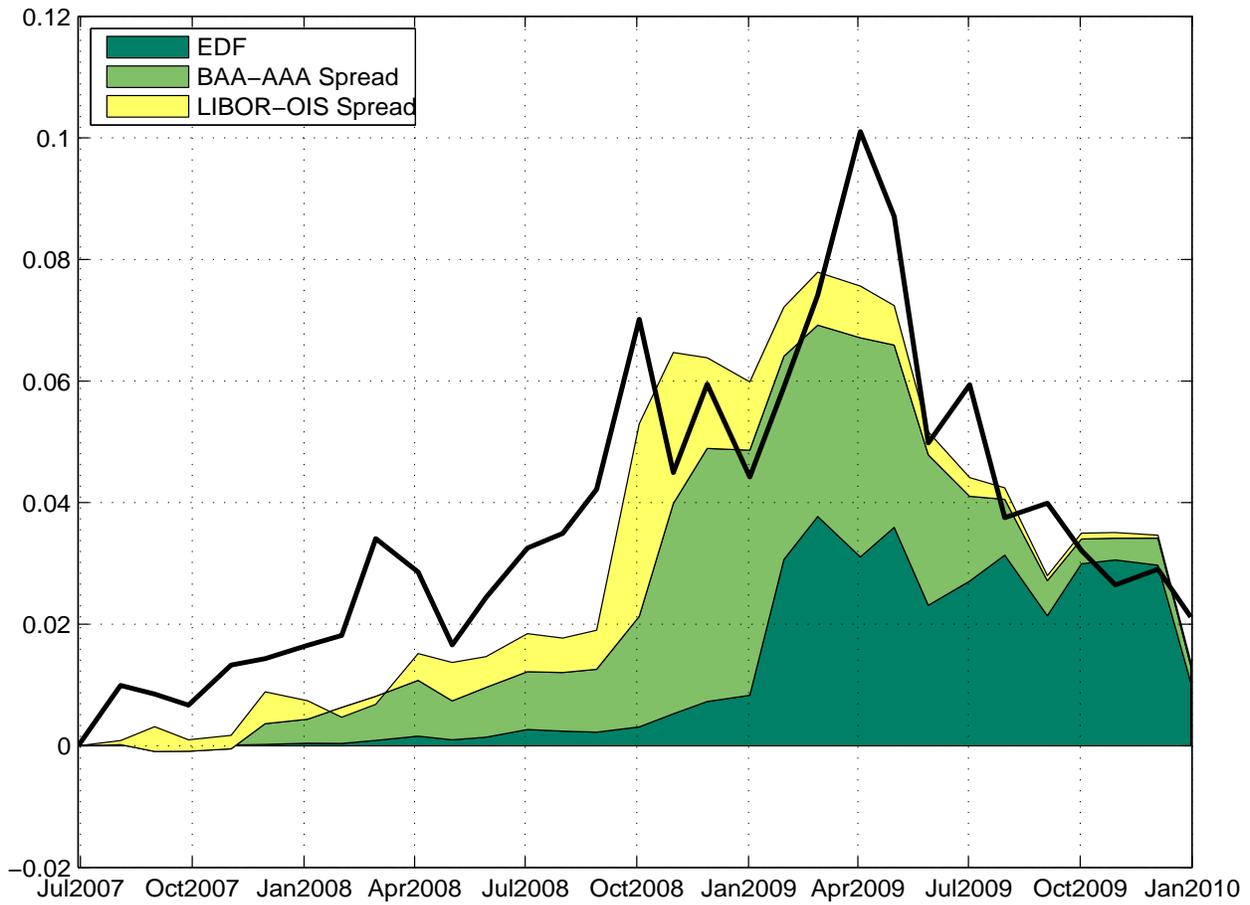
Notes: This graph plots the time series of key systemic risk factors: risk-neutral PDs implied from CDS spreads, correlations calculated from comovement in equity returns, and recovery rates from the CDS quotes.

Figure 2 Systemic Risk Indicator of US 19 SCAP Banks



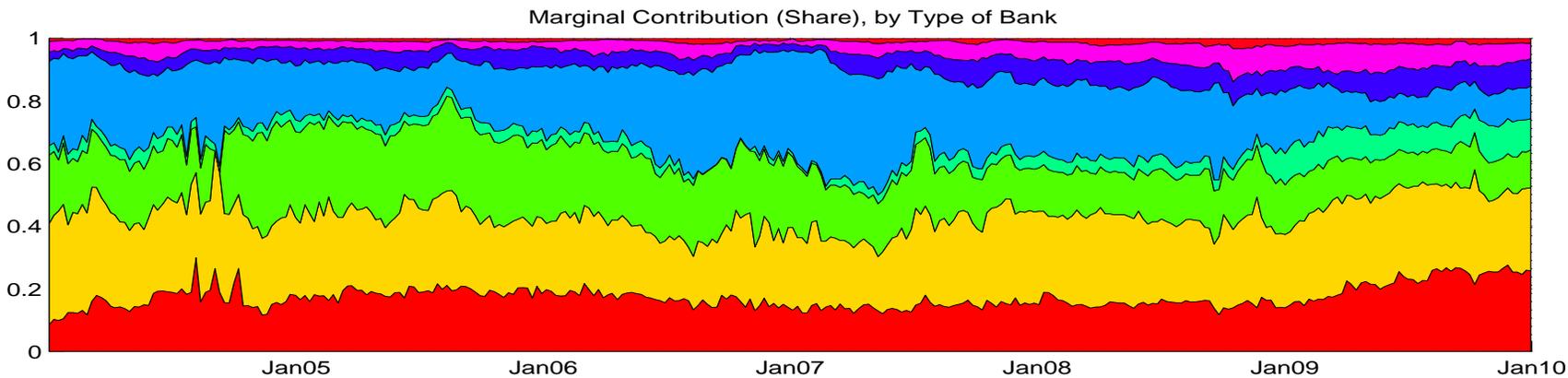
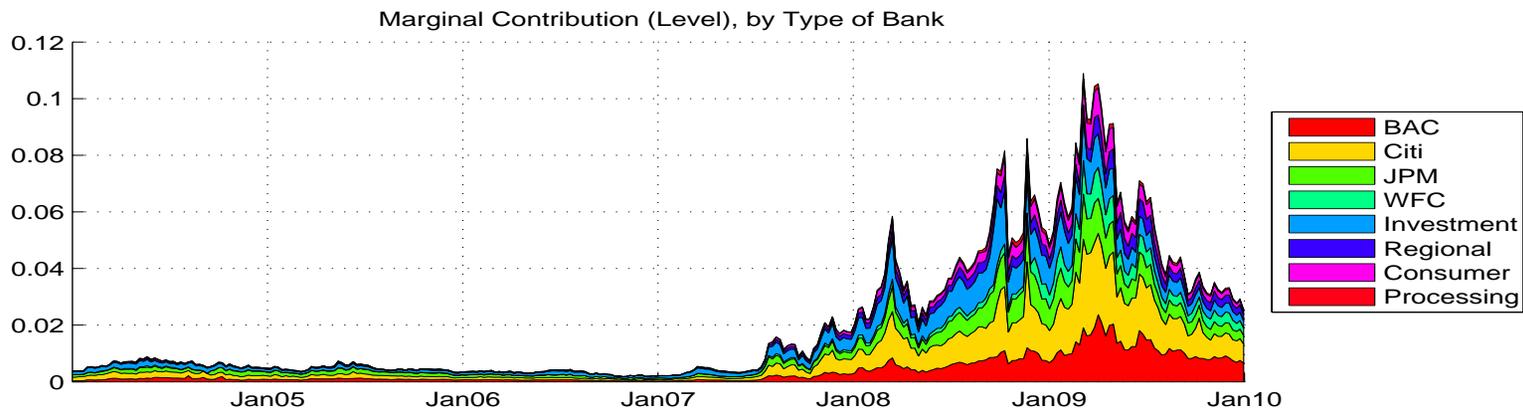
Notes: The graph plots the systemic risk indicator for the SCAP banks, defined as the price for insuring against financial distresses (at least 10% of total liabilities in the banking system are in default). The price is shown as the cost per unit of exposure to these liabilities in the upper panel and is shown in dollar term in the lower panel.

Figure 3 Contributing Factors to the Systemic Risk Indicator



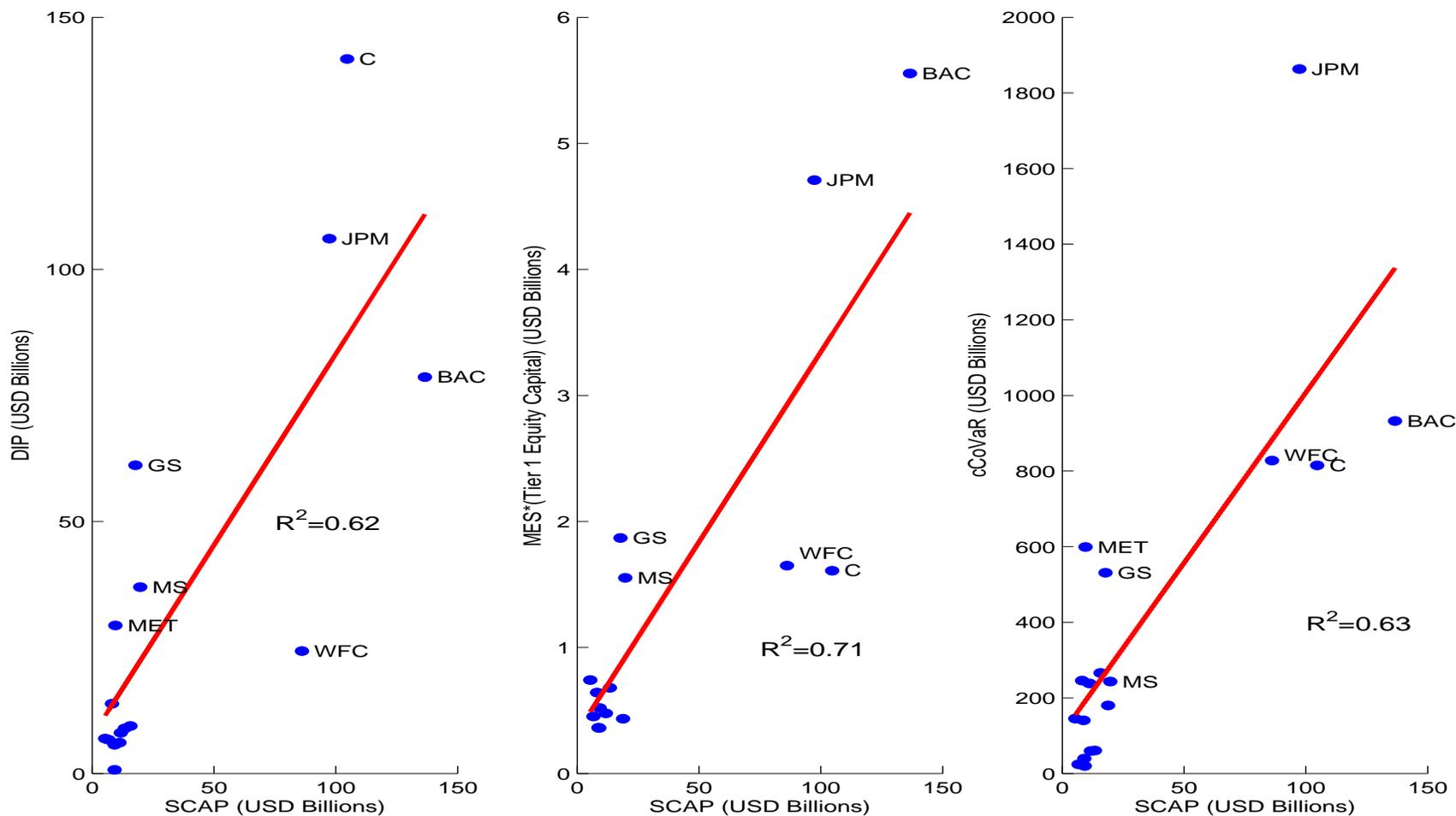
Notes: The graph plots the contribution effect of actual default risk, default risk premium, and liquidity risk premium in determining the changes in the systemic risk indicator since July 2007. It is based on the regression results as specified in regression 4 of Table 3.

Figure 4 Marginal Contribution to Systemic Risk by Each Group of Banks



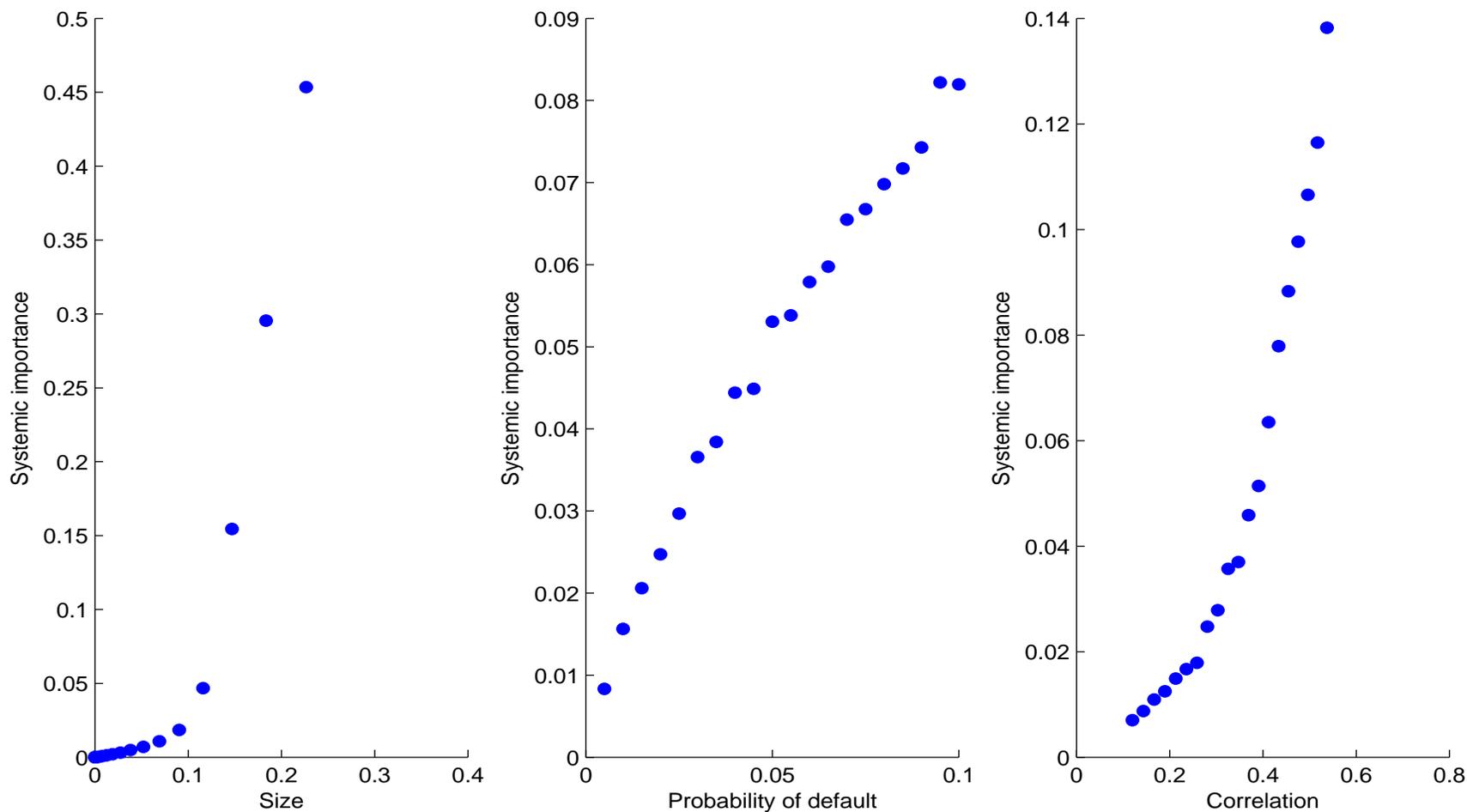
Notes: The figure shows the marginal contribution of each banks or banking group to the systemic risk indicator, the distress insurance premium in unit cost term. The contribution is shown in level term in the upper panel and as a percentage of the total risk in the lower panel.

Figure 5 Comparing Systemic Risk Measures: DIP, MES, and CoVaR versus SCAP Results



Notes: This graph compares three systemic risk measures, distressed insurance premium (DIP) proposed by this paper, marginal expected shortfall (MES by Acharya, Pedersen, Philippon, and Richardson, 2010) weighted by bank's tier-1 capital, and conditional value-at-risk (CoVaR by Adrian and Brunnermeier, 2009) in dollar term. These measures are compared to the SCAP stress test result on 19 largest US BHCs for the period of fourth quarter 2008.

Figure 6 Relationship between Systemic Risk Indicator and Bank Size, PD, and Correlation



Notes: This figure plots a hypothetical calibration exercise based on 20 common banks, with average LGD of 0.55 and distress threshold 10 percent. For the impact of size (left panel), PD is 0.02 and correlation is 20 percent; for the impact of PD (middle panel), PD changes from 0.005 to 0.1; for the impact of correlation (right panel), the loading coefficient in a one-factor model ranges between 0.2 and 0.96.