Measuring Systemic Risk: Common Factor Exposures and Tail Dependence Effects

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Abstract

We model systemic risk by including a common factor exposure to market-wide shocks and an exposure to tail dependence effects arising from linkages among extreme stock returns. Specifically our model allows for the firm-specific impact of infrequent and extreme events. When a jump occurs, its impact is in the same direction for all firms (either positive or negative), but its size and volatility are firm-specific. Based on the model we compute three measures of systemic risk: *DD*, *NoD* and *ESR*. Empirical results using data on the four sectors of the U.S. financial industry from 1996 to 2011 suggest that simultaneous extreme negative movements across large financial institutions are stronger in bear markets than in bull markets. Disregarding the impact of the tail dependence element implies a downward bias in the measurement of systemic risk especially during weak economic times. Two measures based on the Broker-Dealers sector (*DD*, *NoD*) and one measure (*ESR*) based on the Insurance sector lead the St. Louis Fed Financial Stress Index (STLFSI).

Keywords: systemic risk, tail dependence effects, correlated jumps, common factor
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1. Introduction

A number of published studies document that the stability of the financial system as a whole is crucial not only to the financial industry itself but also to the real economy. Importantly, monitoring of the whole financial system (and not just the banking industry) is needed to guarantee its soundness. As the 2007-2012 crises (corporate and sovereign) have highlighted a key factor affecting the stability of the financial system and consequently the real economy is the level of systemic risk. Therefore, the accurate measurement of this level is of crucial importance for regulators and investors alike.

As a consequence of this fact, a large literature has explored many systemic risk measures; see for instance Bisias, Flood, Lo, and Valavanis (2012). The measures are usually defined either at the aggregate system level or at the individual-firm level. In the latter case, systemic risk can be thought as driven by both a common-factor exposure to market-wide shocks and additional exposures to other factors, observed and unobserved. No doubt, higher exposures to the common factor result in a higher probability of joint failures in the system, leading to a higher level of systemic risk. However a common factor only can account for the systematic component of systemic risk (Das and Uppal, 2004), but cannot capture the correlation stemming from large and infrequent changes (e.g. the unexpected failure of a major bank). In this vein a promising approach suggesting the relevance of tail dependence effects arising from exposure to unobservable covariates is outlined in Das, Duffie, Kapadia, and Saita (2007). In a tail dependence setting, the arrival of (bad) news about one firm (extreme negative stock returns) causes a jump in the conditional distribution of hidden covariates, and therefore a (negative) jump in the stock returns of any other firms whose stock returns depend on the same unobservable covariates. In fact some recent papers give support to the role of the tail dependence effects exposure providing extra explanatory power to the phenomenon of joint defaults in addition to the impact of the exposure to the common factor.[1] Therefore, the case for considering both components (common factor and tail dependence effects) of systemic risk seems compelling, yet it has received scarce attention until now. In fact, there are no studies, as far as we know, approaching the modeling of systemic risk with exposures to a common factor and to a tail dependence effects factor using a structural-form approach. Our paper is a first attempt to fill this gap in the literature.

Specifically we add a correlated jumps factor (our proxy for tail dependence effects) into the standard Merton (1974) framework. In doing that, we are able to model tail dependence effects by means of the correlation of tail risks arising from stock returns' extreme negative co-movements. Our model allows for the firm-specific impact of infrequent and extreme events. When a jump occurs, its impact is in the same direction for all firms (either positive or negative), but its size and volatility are firm-specific. Additionally, we refine the methodology proposed by Das and Uppal (2004) to capture joint tail risk behavior over time.[2] We consider the financial industry to be composed of different sectors (Commercial Banks, Brokers-Dealers, Insurance Companies, and Others) and study the systemic risk measures within each sector. Based on our model, we develop three indicators of systemic stress in the financial industry: (1) *DD*, the average distance-to-default within a given sector; (2) *NoD*, the number of joint defaults in a given sector; and (3)

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[1] For example, Giesecke and Kim (2011) provide strong evidence for risk increases in the U.S. financial system, after controlling for the exposure of firms to observable risk factors for the period from 1998 to 2009. Moreover, Jorion and Zhang (2009) state that large financial firms have deeper networks of creditors, illustrating that the failure of a large financial institution can cause ripple effects throughout the economy (e.g., Lehman Brothers). Das et al. (2007) observe that traditional credit risk models, where correlations are only induced by common factors, do not fully capture the clustering in default correlations. Default times tend to concentrate in some periods of time in which the probability of default of all firms is increased and which cannot be totally, or even partially, explained by the firms' common dependence on some macroeconomic factors (Giesecke (2004), Giesecke and Goldberg (2004), Elsinger et al. (2006a,b)).

[2] The behavior of joint tail risk is identified by the intensity of correlated jumps and firm-specific jump size.

ESR, the ratio of the aggregate expected shortfall to the aggregate asset value in a given sector.

In the empirical application, we employ stock market data because of its leading role in the price discovery process as exemplified by anticipating trends in subsequent failures (Lehar, 2005) or changes in supervisory ratings four quarters in advance (Krainer and Lopez, 2001) and among other evidence.[3] Specifically we focus on the U.S. financial industry and on the stock returns of the ten largest institutions within its four major sectors: Depositories, Broker-Dealers, Insurance Companies, and Others. The basic reason of concentrating on the biggest firms is their crucial contribution to systemic risk.[4] The sample spans from January 1996 to December 2011. The ten largest institutions in each sector are not the same over time and therefore our sample contains 25 Depositories, 24 Broker-Dealers, 22 Insurance firms and 31 Others. Our empirical findings confirm that simultaneous extreme negative movements across large financial institutions are stronger and more frequent in bear markets than in bull markets. We also show that the likelihood of tail dependence dramatically increased during the financial crisis of 2007-2009. Disregarding the impact of the tail dependence effects element underestimates the measurement of the systemic risk level especially during weak economic times.

We further analyze whether our systemic risk measures are leading indicators of alternative measures based on a model including only common factor effects, or a measure based on a public financial stress index, the St. Louis Fed Financial Stress

[3] A number of papers support the idea of equity market information leading the credit risk price discovery process. Cifuentes, Ferrucci, and Shin (2005) claim that the stock returns are likely to be strongly negative before bad credit events. Zhang, Zhou, and Zhu (2009) observe that credit default swaps are sensitive to jumps on equity returns. Forte and Peña (2009) document that the equity market leads both the CDS and bond market in the price discovery process.

[4] For example, Acharya, Pedersen, Philippon, and Richardson (2010) show that the top six, in terms of contribution of each firm's systemic risk, are also in the top seven in terms of total assets. Recent studies support size as the major indicator of systemic importance, e.g., Brunnermeier and Pedersen (2009). Furthermore the recent evidence also shows that daily stock return correlations among large financial institutions track the level of systemic risk (Patro, Qi, and Sun, 2012).

Index (STLFSI). We show that including the tail dependence effects usually improves forecasting power in comparison with the benchmark model. Measures based on the Broker-Dealers (*DD*, *NoD*) and Insurance (*ESR*) sectors provide some extra forecasting power with respect to the STLFSI.

This study extends current literature in several ways. First, regarding the systemic risk measures, Lehar (2005) and Suh (2012) consider asset correlations which give equal weight to both small and large returns. We however argue that the phenomenon of co-jumps provides important information in assessing the level of systemic risk.[5] Second, although it is not new to include jumps in the Merton Model, e.g. Zhou (2001), the traditional jump-diffusion model only allows for individual-firm jumps both in their arrival time and in their size. Our model instead assumes that the arrival time of jumps is coincident across all firms and, conditional on a jump, the jump size and its volatility is firm-specific. In doing so, we can model tail dependence effects arising from common exposures to extreme events. An especially interesting example is the unexpected failure of a major firm operating in a given sector. Third, we refine the Balla, Ergen, and Migueis (2012) extreme dependence-based measure of systemic risk by using a more robust statistical methodology.[6] Our study extends the results in Acharya et al. (2010) who present an expected-shortfall-based model and the *CoVaR* of Adrian and Brunnermeier (2010).[7] Our study is also related with Giesecke and Kim's (2011) model, which is based on a reduced-form framework which captures the influence of market-wide and sector-specific risk factors, and of

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[5] Bae, Karolyi, and Stulz (2003) argue that one would expect large negative returns to be more influential in a way that small negative returns are not, and extreme dependence is hidden in traditional correlation measures by the large number of days when small shocks happen.

[6] Balla, Ergen, and Migueis (2012) apply extreme value theory and study only the U.S. banking sector whereas we include co-jumps in the Merton Model. Our empirical application is also more comprehensive.

[7] Specifically, they define an institution's contribution to systemic risk as the difference between the CoVaR conditional on the institution's being in distress and the CoVaR at the median state of the institution.

spillover effects. However we take a structural-form approach, and consider two effects (common factor and tail dependence) to characterize their three factors.

Summing up, our contributions are as follows. First, we propose a new structural-form model by including both a common factor exposure and a tail dependence effects exposure. The model captures realistic time-varying characteristics in extreme stock return correlations, overcoming the limitations of standard models of portfolio credit risk due to their inability to capture the fact that higher default correlations occur during bad economic times. Specifically our model allows for the firm-specific impact of infrequent and extreme events. Second, we develop a set of alternative systemic risk indicators according to different perspectives on system-wide stability. Third, we provide empirical results on the U.S. market during the period 1996-2011, and report three key findings: (1) neglecting tail dependence induces a downside bias in systemic risk measures; (2) considering tail dependence effects improves the model's forecasting ability; (3) systemic risk measures based on the Broker-Dealer and Insurance sectors lead the public financial stress index by a month in advance on average.

The rest of paper is organized as follows. Section 2 develops the structural-form model with both common factor and tail dependence effects terms. Section 3 presents the methodology and the systemic risk measures. Section 4 describes the data. Section 5 reports the empirical analysis. Some robustness tests are provided in Section 6. Section 7 concludes.

2. The Merton Model with Co-Jumps

2.1. Asset returns with a common factor and co-jumps

This paper is part of an emerging literature positing bottom-up models of default correlations based on modeling the asset value of an individual financial institution as being exposed to an observable common factor, tail dependence effects and an unobservable individual factor. Our model is closely related to Suh's (2012), where the common factor is featured by a GARCH process and added into the pure-diffusion asset returns process.

We extend the specification of his model by incorporating co-jumps that occur across individual stocks. This is our proxy for tail dependence effects. In order to capture the correlated nature of these jumps, we impose two restrictions. One, the jump is assumed to arrive at the same time across all firms; two, conditional on the jump moving in a given direction (i.e. positive or negative), the jump's size and volatility are assumed to be firm-specific. The two features of the data that we wish our model to capture are (1) correlation between stock returns and a common factor, and (2) infrequent but large changes in stock returns through a jump component.

Let $V_{j,t}$ and $S_{j,t}$ be the firm *j*'s asset value and stock price, respectively, at time *t*. $V_{j,t}$ is not observable, but can be implied from $S_{j,t}$ on the basis of structure of Merton's model. Let X_t, be the common factor. We consider a discrete-time economy for a period of $[0,T]$ where trading takes place at any of the $n+1$ trading points 0, Δt, $2\Delta t,\ldots,n\Delta t$ where $\Delta t = \frac{T}{n}$. We denote the process of the logarithm of asset return ($v_{j,t} \equiv \log\left(V_{j,t}/V_{j,t-1}\right)$) as follows.

$$v_{j,t} = \mu_j + \delta_j\left(x_t - r\right) + w^*_{j,t}\,, \tag{1}$$

$$w^*_{j,t} = w_{j,t} + Q_j N\left(\Delta t\right) - \bar{Q}_j \lambda, \tag{2}$$

$$w_{j,t} \sim N\left(0, \xi_j\right). \tag{3}$$

The μ_j, x_t, and $w^*_{j,t}$ in Eq. (1) represent the mean of firm *j*'s log return, the common factor, and the exposure to other factors. In order to capture the impact of co-jumps across firms' assets, we partition $w_{j,t}^{*}$ into two components displayed in Eq.(2). Specifically, $w_{j,t}$ is the idiosyncratic factor that follows a certain kind of multivariate distribution without considering extreme dependence,[8] where $Q_j N(\Delta t)$ and the adjustment term, $-\bar{Q}_j \lambda$[9] account for the tail dependence exposure term. This term allows the firm's asset value to jump when its equity price suddenly suffers a large movement due news arrival. For instance, extreme stock returns in one given firm may cause a jump in the conditional distribution of hidden covariates, and therefore a jump in the stock returns of other firms whose stock returns depend on the same unobservable covariates

Given our goal of modeling large changes in prices as occurring at the same time across firms' asset returns, we assume that the arrival of jumps is coincident across all firms' asset returns; that is $N_j(\Delta t) = N(\Delta t)$, and $N(\Delta t)$ is the standard Poisson jump counting process with joint mean and variance, $E(N(\Delta t)) = \lambda = Var(N(\Delta t))$. We denote Q_j as the random jump amplitude on the log-return if the Poisson event occurs. Furthermore, let Q_j and $N(\Delta t)$ be mutually independent, and $Q_j N(\Delta t)$ is a Poisson random sum of normal random variables. That is,

$$Q_j N(\Delta t) = \sum_{k=1}^{N(\Delta t)} Q_j^{(k)}(\Delta t), \tag{4}$$

where $Q_j^{(k)}(\Delta t) \sim N(a_j, b_j^{\,2})$ for $k = 1, 2, \ldots$, and $N(\Delta t)$ is a Poisson random variable with parameter λ. We define x_t ($x_t \equiv \log(X_t / X_{t-1})$) as the log-return of

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[8] The specification of $w_{j,t}$ will be described in the following section.

[9] We subtract $\bar{Q}_t \lambda$, where $\bar{Q}_t = E[Q_t]$, to impose the zero mean Poisson process.

the common factor. Our setting implies that the distribution of the jump size is asset-specific in its mean and volatility, but the jump arrives at the same time for all firms. With the setting of our model, a realization of one Poisson process triggers simultaneous large movements across multiple companies.

For the dynamics of the common factor, we employ a GARCH-type model. Specifically, following Heston and Nandi (2000), the common factor is, under the physical measure P, modeled as

$$x_t = r + \lambda^P h_t + \sqrt{h_t}\varepsilon_t, \tag{5}$$

$$h_t = \omega + \alpha\left(\varepsilon_{t-1} - \gamma\sqrt{h_{t-1}}\right)^2 + \eta h_{t-1}, \tag{6}$$

where r is the continuously compounded interest rate for the time interval between t and t-Δ and ε_t is a standard normal disturbance, h_t is the conditional variance of the log return between t and t-Δ.[10] Notice that the conditional variance of an asset return becomes time-varying, i.e.,

$$Var\left(v_{j,t} \mid \varphi_{t-1}\right) \equiv \sigma_{j,t}^2 = \delta_j^2 h_t + \xi_j + \lambda \hat{b}_j^2 \tag{7}$$

Where $\hat{b}_j^2 = a_j^2 + b_j^2$. The derivation is provided in Appendix A1.

2.2. Structural-form model with factor-jump-diffusion process

We define equity S under the risk-neutral measure (RN) as a call option with maturity T as follows:

$$S_{j,t} = e^{-r(T-t)} E^{RN}\left[\max\left(V_{j,T} - D_{j,T}, 0\right)\right],$$

where $S_{j,t}$ denotes the equity price of firm j at time t. Following Duan (1995) we

[10] We set r to be constant during a certain period of time, by using the mean of the risk-free interest rate. This is defined as the 1-year Treasury constant maturity rate obtained from the US Federal Reserve and divided by 252.

assume that the risk-neutral measure RN satisfies the locally risk-neutral valuation relationship (LRNVR) in which the expected return under the RN measure is the risk-free rate, but the one-period ahead conditional variance of the return stays the same under the P and RN measures. Adopting the same assumption, Heston and Nandi (2000) show that under the RN measure, we have:

$$x_t = r - \frac{1}{2}h_t + \sqrt{h_t}\varepsilon_t, \tag{9}$$

$$h_t = \omega + \alpha\left(\varepsilon_{t-1} - \left(\gamma + \lambda^P + \frac{1}{2}\right)\sqrt{h_{t-1}}\right)^2 + \eta h_{t-1}. \tag{10}$$

Heston and Nandi (2000) derive the following conditional generating function of the future common factor:

$$f(\phi) \equiv E_t\left[X_T^{\phi}\right] = X_t^{\phi}\exp\left(A(t;T,\phi) + B(t;T,\phi)h_{t+1}\right), \tag{11}$$

where the coefficients are recursively determined as follows:

$$A(T;T,\phi) = 0, \tag{12}$$

$$A(t;T,\phi) = A(t+1;T,\phi) + \phi r + B(t+1;T,\phi)\omega - \frac{1}{2}\ln\left(1 - 2\alpha B(t+1;T,\phi)\right), \tag{13}$$

$$B(T;T,\phi) = 0, \tag{14}$$

$$B(t;T,\phi) = \phi\left(\lambda^P + \gamma\right) - \frac{1}{2}\gamma^2 + \eta B(t+1;T,\phi) + \frac{\frac{1}{2}(\phi-\gamma)^2}{1\text{-}2\alpha B(t+1;T,\phi)}. \tag{15}$$

Utilizing these facts, we derive the conditional generating function for asset values. First, we note that under the RN measure,

$$\log\frac{V_{j,T}}{V_{j,t}} = \left(r - r\delta_j - \bar{Q}_j\lambda\right)(T-t) + \delta_j \log\frac{X_T}{X_t} + W_{j,t}^T + Q_j N(T), \tag{16}$$

where $W_{j,t}^T \equiv w_{j,t+\Delta t} + \ldots + w_{j,t+n\Delta t}$ and $N(T) = N(\Delta t) + N(2\Delta t) + \ldots + N(n\Delta t)$.[11]

[11] Bates (1991) shows that that the difference between risk-neutral parameters and true parameters of Q_j and N is small either from qualitative or quantitative aspect. Thus, we assume $\bar{Q}_j$ that obtained

Then, we can write:

$$V_{j,T}^{\phi} = V_{j,t}^{\phi} X_t^{-\delta_j \phi} e^{\phi\left(r - r\delta_j - \bar{Q}_j \lambda\right)(T-t) + \phi W_{j,t}^{T} + \phi Q_j N(T)} X_T^{\delta_j \phi}. \tag{17}$$

Therefore, we can derive the conditional generating function for asset values:

$$g_j(\phi) \equiv E_t\left[V_{j,T}^{\phi}\right] = V_{j,t}^{\phi} X_t^{-\delta_j \phi} e^{\phi\left(r - r\delta_j - \bar{Q}_j \lambda\right)(T-t) + \phi^2 \xi_j (T-t)/2} f\left(\delta_j \phi\right) E_t\left[e^{\phi Q_j N(T)}\right], \tag{18}$$

where $E_t\left[e^{\phi Q_j N(T)}\right] = \exp\left(\lambda(T-t)\left(\exp\left(a_j \phi + \frac{1}{2} b_j^2 \phi^2\right) - 1\right)\right)$. See Appendix A2 for details. From the assumption that equity is valued as a European call option, we have the equity valuation formula:

$$\begin{aligned} S_{j,t} &\equiv e^{-r(T-t)} E_t^{RN}\left[\max\left(V_{j,T} - D_{j,T}, 0\right)\right] \\ &= \frac{1}{2} V_{j,t} + \frac{e^{-r(T-t)}}{\pi} \int_0^{\infty} \operatorname{Re}\left[\frac{D_{j,T}^{-i\phi} g_j^*(i\phi + 1)}{i\phi}\right] d\phi - D_{j,t}\left(\frac{1}{2} + \frac{1}{\pi} \int_0^{\infty} \operatorname{Re}\left[\frac{D_{j,T}^{-i\phi} g_j^*(i\phi)}{i\phi}\right] d\phi\right), \end{aligned} \tag{19}$$

where $g_j^*(\cdot)$ is obtained from $g_j(\cdot)$ by replacing λ^P with $-1/2$ and γ with $\gamma^*\left(\equiv \gamma + \lambda^P + 1/2\right)$.[12]

2.3. Dynamics of individual factors

The unobservable individual factors $w_{j,t}$ may be correlated across firms and over time. In particular, we assume that the vector consisting of individual factors $\mathbf{w}_t \equiv \left[w_{1,t} \dots w_{N,t}\right]'$ follows a multivariate normal distribution with time-varying covariance matrix i.e.,

$$\mathbf{w}_t \sim MVN\left[\mathbf{0}, \mathbf{\Omega}_t\right], \tag{20}$$

where the (*j*,*k*) element of $\mathbf{\Omega}_t$ is $\xi_{jk,t}$. Then, we apply the dynamic conditional

under physical probability is as the same as it under risk-neutral probability.

[12] The debt is assumed to grow at the risk-free interest rate, following Lehar (2005).

correlation (DCC) model of Engle (2002) to estimate the time-varying asset return correlations of idiosyncratic components for the dynamics of $\mathbf{\Omega}_t$.[13]

For estimating the time-varying covariance matrix $\mathbf{\Omega}_t$, we first use estimates $\hat{\Theta}_j$ for institution j to estimate the time series $\{V_{j,t}\}$ and $\{v_{j,t}\}$ and then obtain the residuals $\hat{w}_{j,t}$, which are defined as:

$$\hat{w}_{j,t} \equiv v_{j,t} - \left(\hat{\mu}_j + \hat{\delta}_j \left(x_t - r\right) + \left(Q_j N\left(\Delta t\right) - \bar{Q}_j \lambda\right)\right). \tag{21}$$

2.4. Estimation

Parameter estimation proceeds in three steps. First, we estimate the common factor parameters $\{\omega, \alpha, \eta, \gamma\}$ in the system of (5) and (6) via the maximum likelihood method given the common factor data series. Second, we identify λ, a_j, and b_j as in Das and Uppal (2004).[14] Third, we make two assumptions for the estimation of the parameters related to the asset return process of individual institutions. We assume that the maturity of the implied call option is one year in line with previous literature (e.g., Ronn and Verma (1986), Lehar (2005), and Suh (2012)). We use the sum of a half of the long-term debt plus the short-term debt as a proxy for the debt amount $D_{j,t}$ within the assumed maturity of 1 year in accordance with

[13] This is different from approaches in Suh (2012) and Lehar (2005), where the former features the correlation of individual factors based on diagonal-VECH, while the later uses an exponentially-weighted moving average scheme. We claim that DCC is a better model in measuring asset correlations. First, many papers adopt DCC rather than other types of multivariate volatility process models. For example, the DCC method is superior to historical measures in that the correlation output refers to conditional rather than backward-looking correlation measures (Huang, Zhou, and Zhu, 2012. And second, other advantage of using the DCC method is that it allows the correlation matrix to be heterogeneous, i.e., the pair wise correlation coefficients can be different for each pair of firms.

[14] Specifically, the correlated jump intensity is derived from stock market information. As in Das and Uppal (2004), we assume a jump-diffusion process for the stock return process, and we estimate the parameters by minimizing the Root Mean Square Error (RMSE) of two metrics based on co-skewness and excess kurtosis.

KMV's methodology. To be consistent with the literature (Duan (1994) and Duan (2000))[15] we use historical returns to estimate the parameters. For one institution at a time via the maximum likelihood method, we estimate the parameters $\Theta_j = \{\mu_j, \delta_j, \xi_j\}$ for individual institution *j*'s asset return. Given institution *j*'s equity price and debt data $\mathbf{S}_j = \left[S_{j,1} \ldots S_{j,n}\right]', \mathbf{D}_j = \left[D_{j,1} \ldots D_{j,n}\right]'$, and common factor data $\mathbf{x} = \left[x_1 \ldots x_n\right]'$, we derive the following log likelihood function as follows

$$\begin{aligned}\log L\left(\Theta_j \mid \mathbf{S}_j, \mathbf{x}, \mathbf{D}_j\right) = -\frac{n-1}{2}\log(2\pi) - \sum_{t=2}^{n}\log V_{j,t} - \frac{1}{2}\sum_{t=2}^{n}\log\sigma_{j,t}^2 - \sum_{t=2}^{n}\log\left(\frac{\partial S_{j,t}}{\partial V_{j,t}}\right) \\ -\frac{1}{2}\sum_{t=2}^{n}\frac{\left\{v_{j,t} - \left(\mu_j + \delta_j\left(x_t - r\right) + a_j\lambda - \bar{Q}_j\lambda\right)\right\}^2}{\sigma_{j,t}^2}\end{aligned}, \quad (22)$$

$$\begin{aligned}\frac{\partial S_{j,t}}{\partial V_{j,t}} = \frac{1}{2} + \frac{e^{-r(T-t)}}{\pi}\frac{1}{V_{j,t}}\int_0^{\infty}\mathrm{Re}\left[\frac{\left(D_{j,t}e^{r(T-t)}\right)^{-i\phi}\left(i\phi+1\right)g_j^*\left(i\phi+1\right)}{i\phi}\right]d\phi - \frac{D_{j,t}}{\pi V_{j,t}} \\ \times\int_0^{\infty}\mathrm{Re}\left[\left(D_{j,t}e^{r(T-t)}\right)^{-i\phi}g_j^*\left(i\phi\right)\right]d\phi.\end{aligned} \quad (23)$$

where $V_{j,t}, \sigma_{j,t}$ are the solutions to (19) and (7) and $v_{j,t}$ is the log return of $V_{j,t}$.

3. Methodology and Systemic Risk Measures

In the following section, we take the model that only accounts for the exposure to the common factor as the benchmark model. In fact, our model nests the benchmark model when λ=0. We compute risk indicators both based on our model and the benchmark model. The methodological procedure follows.

3.1. Monte Carlo Simulation

We employ Monte Carlo Simulation because no analytical solution is available

[15] We use the 1-year Treasury constant maturity rate obtained from the US Federal Reserve as the risk-free interest rate.

for the systemic risk measures over a multi-period time horizon. We draw standard normal random variables and then simulate a hypothetical future common factor realization according to (5). Next we generate the random variable of co-jumps by drawing from normal random variables with a pre-specified mean and standard deviation of firms' jump magnitudes, and a Poisson random variable with the pre-specified intensity λ. Finally we draw multivariate normal random variables as specified by (20) and repeat the process 10,000 times.

3.2. Rolling windows

A rolling window approach is applied to study the extent to which systemic risk measures vary over time and to avoid the problem of look-ahead bias. To study this, we use a one-year rolling window updated every month. Specifically, we construct a subsample for month t, in which the information during months t, t-1,t-2,…,t-11 is used. Then we repeat the calculation for month $t+1$, rolling the sample one month forward. For example, the first subsample corresponding to December 1996 contains data from January 1996 to December 1996. Then, the sample is updated by including the following month and discarding the first one. In the previous example, the second subsample corresponds to January 1997 and contains data from February 1996 to January 1997. We chose the monthly updating frequency to balance accuracy with computational burden.

3.3. Systemic risk measures

Not surprisingly, the literature has proposed a plethora of measures of systemic risks (see Rodriguez-Moreno and Peña (2013) for a review). The measures should detect at least two kinds of situations and cover two different dimensions. Regarding the situations, some measures should warn of the persistent build-up of imbalances within the financial sector (based on monthly or quarterly data) and some other measures should be able to capture the abrupt materialization of systemic risk (using daily or intraday data). Regarding the dimensions, there should be measures based on the aggregate market level (e.g. interbank rates, stock market and CDS indexes) as well as measures at the level of individual institution. Obviously, no single measure is the "best", and alternative measures may be devised according to the objectives of systemic risk analysis. Since our model specifies the dynamics pertaining to both individual institutions and their tail-risk connection, it allows the calculation of a wide range of systemic risk measures. We develop three alternative indicators:

(1) *DD*: the average distance-to-default in a given sector over a fixed time-horizon

The *DD* has been used as proxy for identifying a financial sector's stability. For example, Jokipii and Monnin (2013) and Carlson, King, and Lewis (2011) both use *DD* as the indicator of distress in the financial sector, where the former finds a positive link between this measure and real output growth, especially during the periods of instability, and the latter suggests that *DD* is a leading indicator of real economic activity (e.g., bank lending standards and terms).

We compute the *DD* measure using our structural-form model with and without jump effects. In line with the Merton's *DD* framework, the *DD* is built as the logarithm of asset value minus the logarithm of debt value, and then divided by the standard deviation of this difference. Formally,

$$DD \equiv \frac{E\left[\ln V_T - \ln D_T\right]}{Std\left[\ln V_T - \ln D_T\right]} \tag{24}$$

where V_T and D_T are time T asset's market value and debt's face value respectively. To be specific, at a given time point t and for every firm j in a given sector, we compute daily simulated asset values for the next six months, generated by Monte Carlo simulation. Then we average the difference between log-asset value and log-debt value, and we use this as the numerator and then we take the standard deviation of this difference as the denominator. We then compute the average sector value as the weighted-average of all firms in a given sector, weights based on asset size.[16] We expect that the lower the *DD* measure, the higher the level of systemic risk.

(2) *NoD*: the number of simultaneous defaults in a given sector over a fixed time-horizon.

The rationale of this measure is that if there is a significant number of financial firms default at the same time, the whole financial system (through asset-fire sale or/and network contagion), can be severely affected (Lehar, 2005). A financial institution is assumed to be in default if the market value of its assets falls below of its debt's face value within the next six months. To be specific, at a given time point *t* and for every firm *j* in a given sector, we compute daily simulated asset values for the next six months, generated by Monte Carlo simulation. Then we compare firm *j* asset value against its debt's face. If the latter is higher than the former we assume the firm *j* to be in default. We then compute the number of defaulted firms for each sector. We expect that the larger the *NoD*, the higher the level of systemic risk.

(3) *ESR*: the ratio of the aggregate present value of expected shortfalls to the aggregate asset value in a given sector over a fixed time-horizon.

[16] This is because we assume that the largest institutions should contribute strongly to the overall systemic risk in the financial system.

This systemic risk measure proposed by Huang, Zhou, and Zhu (2009), is associated with the idea of assessing the systemic risk of the financial sector by computing the price of the government's contingent insurance against large default losses in the financial sector. Based on our structural-form model, we consider the amount of financial institutions' debt that cannot be covered by themselves as proxy for this insurance, and name it expected shortfall. The rationale is that, if all the financial institutions' debt is guaranteed by governments, they must pay to the creditors the difference between the face value of debts and the market value of financial institutions' assets.

Following Lehar (2005), the present value of expected shortfall could be regarded as the put option value. In our framework, we compute it by Monte Carlo simulation as we have described before. Formally, we compute the present value of expected shortfalls, ES_t^j, of a firm *j* at time *t* for a horizon of *T* as $e^{-r(T-t)} \times E\left[\max\left(D_T^j - V_T^j, 0\right)\right]$, where D_T^j is the face value of the firm's debt at time *T*, V_T^j is the market value of the firm's assets at time *T*. Moreover, we consider the sector-wide distress as the ratio of the sector's present values of expected shortfalls to the sector's total asset value over the next six months. We call this risk measure *ESR*, and compute it by using the formula of $ESR_t = \sum_i ES_t^j \Big/ \sum_i Asset_t^j$. Intuitively, we would expect that the higher the *ESR* the higher the systemic risk level.

In summary, the indicators rely on intuitive economic interpretations, and we use them to illustrate the temporal trend of the overall systemic risk level. In particular, *DD*, *NoD*, and *ESR* are attractive because they summarize key determinants of systemic risk (firms' size, firms' leverage, the dependence between firms and the whole market) as suggested in Acharya et al. (2010), as well as the interconnectedness, as suggested in Cummins and Weiss (2010) and Jobst (2012).[17] The procedure of Monte Carlo simulation is repeated for each month from December 1996 to December 2011, yielding monthly time series for each measure.

4. Data

4.1. Sample Selection

Our methodology is applied to the sample that comprises large financial institutions in the U.S. financial industry between January 1996 and December 2011. We choose firms with available daily equity prices and quarterly balance sheet information in the CRSP and COMPUSTAT database.[18] We lag all accounting information by 3 months because of reporting delay and substitute missing accounting data with the most recent observation prior to it. The quarterly accounting data is linearly interpolated between quarterly reporting dates at daily frequency. Firms are categorized into four groups according to Acharya et al. (2010) and Brownlees and Engle (2011) including: Depositories, Brokers-Dealers, Insurance Companies, and Others.[19] We use daily equity returns given that jumps probably appear more clearly in high frequency data.[20] We select the biggest firms based on their book value of total assets at the starting date of each estimation sample for each sector at a given time. Furthermore, the sample only contains firms continuously listed in a prior year

[17] Cummins and Weiss (2010) propose three primary indicators of systemic risk, including (1) size, (2) interconnectedness, and (3) lack of substitutability. Also, Jobst (2012) relates short-term liquidity risk to size and interconnectedness.

[18] We collect information of daily equity prices and returns, and outstanding shares from CRSP. We obtain information of total assets, debt in current liability, long-term debt due in one year, and outstanding shares (if missing in CRSP) from COMPUSTAT.

[19] The four groups are characterized by: (1) Depositories (with 2-digit SIC code of 60); (2) Brokers-Dealers (with 4-digit SIC code of 6211); (3) Insurance Companies (with 2-digit SIC code of 63 or 64); (4) Others (with 2-digit SIC codes of 61, 62 except 6211, 65 or 67). We assign Goldman Sachs to the group of Broker-Dealers although its SIC code of 6282, following Acharya et al. (2010).

[20] Lehar (2005) and Suh (2012) use lower frequency data (monthly and weekly).

to ensure a perfect match to the number of observations at firm-level as well as at system-level. To avoid survivorship bias, merged or bankrupt entities are also included in the sample as long as their equity and balance sheet information are available. Our sample contains 25, 24, 22, and 31 firms for Depositories, Broker-Dealers, Insurance Companies, and Others, respectively.

4.2. Monthly-interval observations

By moving the estimation window month by month, we have time-varying estimated parameters and risk measures at the end of each month from December 1996 to December 2011. This sample contains 181 monthly observations for each parameter and measure. Appendix B provides descriptions of the firms we use in the empirical application. We compute SIZE and LVG (leverage), both at firm-level and sector-level, at time *t*, where the former is the logarithm of the book value of total assets (at firm-level), and the logarithm of the summation of all firms in a sector (at sector-level); the latter is the quasi-market value of asset divided by market value of equity (at firm-level), and the weighted average leverage (at sector-level), weights are based on the values of market equity.[21]

Figure 1 shows the annual returns across sectors as well as for the CRSP value-weighted index, which is used to capture the common factor in this paper. The sector-level annual return ending at month *t* for sector *k* is calculated by using the formula of $r_{k,t} = \sum_{j=1}^{10} w_{j,k,t} \times r_{j,k,t}$, where $r_{j,k,t}$ is the firm *j*'s annual return, and $w_{j,k,t}$ is the weight based on market equity for firm *j* at the end of month *t*.

We observe a similar pattern across industries. All sectors show positive performance from 1996 until the end of 1998 where the LTCM crisis appears. There is

[21] Following Acharya et al. (2010), LVG is the standard approximation of leverage, where quasi-market value of assets is obtained from book value of assets minus book value of equity and plus market value of equity.

a slow recovery until the burst of the dotcom bubble in March, 2000. Then a sub period ensues until 2003 where a recovery gains momentum. Between mid-2005 and mid-2007 all sectors show positive performance. Distress symptoms appear around July 2007 signaling the starting point of the Subprime crisis, and then the market bottoms around March 2009. Then there is a strong rebound since mid-2009. Market plunges again around May 2010 and there are no clear recovery signals until the end of 2011. Notice that the Others sector's stock returns seem to be the more volatile of all sectors during the last crisis. Overall the returns of the various sectors mimic the overall market trend with usually larger volatility.

[Insert Figure 1 Here]

Table 1 provides summary statistics by sector. In terms of size there are not clear differences across sectors. Leverage is highest in the Broker-Dealers sector (12.26), followed by Insurance companies (11.93), Others (11.22) and the least leveraged sector by far is Depositories (7.94). The best return/risk ratio is given by Brokers-Dealers (0.54), followed by Insurance Companies (0.35), Depositories (0.34), and Others (0.32). We classify risk measures by using the sub index "ben" for the benchmark-based measures (accounting for common factor only). Measures without sub index are based in the full model (common factor plus tail dependence effects). The *DD* (DD_{ben}) indicates that the distance to default over the next six months, and thus the lower the *DD* the higher the sector's systemic risk. This measure for the Broker-Dealers sector is the closest to default with an average value of 2.59 (6.01), followed by *Others*, 3.45 (5.51), then by *Depositories*, 6.31 (8.0) and *Insurance Companies*, 10.99 (12.18). Next the *NoD* (NoD_{ben}) indicates the number of defaults among the 10 biggest financial institutions. The sector Others on average has the largest number of defaults, 2.38 (1.42), followed by Broker-Dealers, 2.26 (0.96), whereas Depositories and Insurance Companies present lower defaults, 0.79 (0.26) and 0.36 (0.23) respectively. As for *ESR*, (*ESR_{ben}*), which is defined as the ratio of sector's expected shortfalls to the sector's total assets, Others has the largest value, 39.90 (15.07), followed by the Broker-Dealers, 22.22 (2.61), whereas Depositories and Insurance Companies present lower expected shortfalls, 4.50 (0.34) , and 3.75 (1.42) separately. So, based on the above three measures the riskier sectors are Broker-Dealers and Others, followed by Depositories and finally Insurance Companies. Notice that in all cases the measure based on the full model indicates a higher level of systemic risk than the measure based on the benchmark model.

[Insert Table 1 Here]

5. Empirical Analysis

The empirical analysis is designed to explore the effect of combining two factors (common factor and tail dependence effects) on measuring systemic risk. First, this section documents the estimation results of co-jumps and of structural-form models. In the next section, we present a preliminary comparison between the full-model based measures and the benchmark-based ones. Then, we test whether our full-model based systemic risk measures are leading indicators of benchmark-based ones and of the STLFSI.

5.1. Estimation results

5.1.1. Tail dependence parameters

To characterize the sector-level behavior of the tail dependence effects proxied by the correlated jumps, we average firm-specific estimates into one single measure for the mean and the volatility of the size of co-jump by sector, and denote them as *mu_coj* and *std_coj*. By means of the rolling window approach, we compute time series of λ, *mu_coj*, and *std_coj*.[22] These estimates describe the properties of simultaneous shocks occurred in the equity market. Figure 2 reports these three time-varying variables from 1996 to 2011 by sector.[23]

As for λ, Depositories and Insurance Companies present quite similar behavior, moving smoothly and usually below 0.1 before 2006, increasing during 2007, peaking (roughly around 0.3), staying high for a while, dropping to the pre-crisis level in the mid-2009, and increasing again in the mid-2011. In the case of Broker-Dealers this parameter moved steadily and at low levels before 2005, increased slightly in the following two years, and peaked (0.2) near Lehman's failure. After that event it drops to the pre-Lehman level, but looks more unstable than before 2005. Finally the λ of Others fluctuated quite frequently compared with other sectors before 2006. In particular it reaches its peak in the fourth quarter of 2008 (beyond 0.35), and remains at a high level (beyond 0.15) for a longer time during 2008-2009 in contrast with other sectors. Again we observe there was a clear increase since the mid-2011. Overall, across sectors, we find that the intensity of co-jumps began to increase before the subprime loan crisis of 2007, reached its peak by the Lehman's failure, then decreased and increased again in mid-2011, in coincidence with the Eurozone crisis. Overall, the evidence suggests that the probability of simultaneous jumps is higher during crisis times.

Regarding the average jump size *mu_coj*, it is close to zero through the whole sample period for Insurance Companies. However this is not the case in other sectors. Negative jumps appear around Lehman's bankruptcy, in Broker-Dealers, Others , and

[22] For instance in the case of parameter λ , we estimate it for a group of ten largest FIs in each sector using data from January 1996 to December 1996, and we assign the value λ calculated in this way to December 1996. Then, the procedure is repeated using data from February 1996 to January 1997 and the value of λ is assigned to January 1997 and so on.

[23] Specific information about the main systemic events from 2007 to 2011 can be found at http://timeline.stlouisfed.org/

Depositories with average sizes of -0.10, -0.07 and -0.05 respectively. Also the Others sector suffered negative jumps in the first-half of 2009, which could be attributed to events related to the crisis and subsequent bailout of Fannie Mae and Freddie Mac given that the Others sector contains many firms related with the mortgage market.[24]

With respect to the jump's volatility *std_coj* its behavior is quite similar across sectors, where it was constantly below 0.05 and very stable until the end of 2007, started increasing at the beginning of 2008, reached to historically highest level around mid-2009, and dropped to lower levels since then.

All in all the evidence matches our intuition with respect to the model's parameters. In most cases λ and *std_coj* are higher and *mu_coj* displays negative values during episodes of systemic risk. The implication is that acute stress situations in the financial industry are coincident with higher frequencies of simultaneous negative extreme jumps in the stock returns of firms included in the industry.

[Insert Figure 2 Here]

Now we examine whether the co-jumps component displays a specific behavior during the 2007-2009 crisis. We analyze the results during the period of 2005-2011, and compare estimates across three periods: Pre-Crisis period (from July 2005 to June 2007), Crisis period (from July 2007 to June 2009), and Post-Crisis period (July 2009 to June 2011). The results are reported in Table 2. The Columns 1, 3, and 5 show the average value of λ, *mu_coj*, and *std_coj* during the "Pre-Crisis", the "Crisis", and the "Post-Crisis" periods respectively. The column 2 and 4 reports the results of the independent sample mean *t-test*. For each parameter, the column 2 (column 4) first reports the difference of average values between Crisis and Pre-Crisis (Post-Crisis)

[24] On March 11, 2009 Freddie Mac announced that it had a net loss of $23.9 billion in the fourth quarter of 2008, and a net loss of $50.1 billion for 2008 as a whole. They also announced that its conservator has submitted a request to the U.S. Treasury Department for an additional $30.8 billion in funding for the company under the Senior Preferred Stock Purchase Agreement with the Treasury.

periods with *p-values* in brackets. Panel A, B, C, and D shows results for Depositories, Broker-Dealers, Insurance Companies, and Others. Overall there are significant differences between the Pre-Crisis and Crisis periods across all groups. As expected, the intensity, and the volatility of co-jumps are higher in the Crisis period and the mean of co-jumps is strongly negative in the crisis period.

[Insert Table 2 Here]

It is worth noting that the Others sector always presents the highest λ. When concentrating on the crisis period, it also has highest value of *std_coj* (0.13) compared with other sectors (0.08), and has the lowest *mu_coj* (-0.02), followed by Broker-Dealers (-0.01). So in the Others sector negative shocks are deeper and more frequent and their size is more volatile. Notice the significant increases in λ during crisis periods. For example in Depositories, it increases more than threefold in comparison with the pre-crisis period (0.13 versus. 0.04), it doubles in size in Broker-Dealers (0.06 versus. 0.03) and also increases noticeably in the Others sector (0.19 versus. 0.10).

Summing up, statistical tests support the intuition of higher probability of simultaneous negative shocks in the equity market during the 2007-2009 financial crisis in comparison with previous and posterior periods.

5.1.2. Common factor parameters

The parameters of the common factor component (benchmark model) are μ, δ, and ξ, which capture the long run mean of asset returns, the exposure to the common factor, and the variance of idiosyncratic factor, respectively. We again average firm-level estimates into sector-level variables. To distinguish estimates of the full model from those of the benchmark-based model, we use notations of μ_{ben}, δ_{ben}, ξ_{ben}, for the latter. Table 3 reports estimates by sector, and results of mean tests between estimates derived from the full model and from the benchmark. There are some things worth mentioning. First we observe that both δ and ξ are significantly lower than $\delta_{\_ben,}$ and $\xi_{\_ben}$ (see Column 3, 6, and 9 of Table 3). The result is not unexpected since, by construction, the term of co-jumps should capture some contributions of asset returns from the common factor and from the idiosyncratic factor. Therefore a decrease in the magnitudes of δ and ξ compared with the benchmark model is likely. Furthermore we find that Insurance Companies has the highest exposure to the common factor (0.72), followed by Broker-Dealers (0.59), whereas Others have the lower exposure (0.35).

[Insert Table 3 Here]

5.2. Systemic risk measures : Preliminary analysis

This section outlines the stylized facts of the three alternative systemic risk measures based on our model and the benchmark. Time series of the risk measures from 1996 to 2011 by sector are in the panels A to C in Figure 3. The red (blue) line corresponds to the full (benchmark) model.

[Insert Figure 3 Here]

5.2.1. DD (distance to default)

The *DD* indicates on average how far a firm's asset value would exceed its default point for a given sector, and thus conversely to conventional risk measures, the lower the *DD* the higher the sector's systemic risk. The *DD* series are in Panel A of Figure 3. Tail dependence effects are of material importance when the red line is below the blue line. This is usually the case in all sectors.

Not surprisingly, we find that the tail dependence effects reduce the distance to default during and/or prior to bad economic events. For example, in the Depositories sector (see the top-left diagram in Panel A of Figure 3), the tail dependence effects appeared: (1) from the end-1997 to mid-1999 (1997 Asian Crisis, 1998 LTCM debacle); (2) from September 2001 to 2003 (9/11 , end of dot-com bubble during mid-2000-mid-2003, credit market deterioration in 2002,[25] and credit market deterioration in 2002); (3) from June 2006 (one year prior to the 2007 Subprime loan crisis) to mid-2010 (2007-2010 financial crisis); and (4) during the second-half year of 2011 (European debt crisis). As for Insurance Companies (see the bottom-left diagram in Panel A of Figure 3), the effect existed for the period of 2005-2009 (2005 automotive-downgrade credit crisis; 2007-2010 financial crisis). As for Others (see the bottom-right diagram in Panel A of Figure 3), the effect occurred: (1) from mid-1998 to mid-1999 (LTCM debacle), (2) from September 2001 to September 2008 (9/11, end of dot-com bubble during mid-2000-mid-2003, credit market deterioration in 2002, low interest rates and high leverage among financial institutions during 2002-2004); and (3) during second-half year of 2011 (European debt crisis). In the period 2008-2009 the measures based on the full model and on the benchmark model signal that the Others sector was very close to default.

5.2.2. NoD (number of defaults)

The *NoD* accounts for the number of defaults among the ten biggest financial institutions for a given sector. This measure is in Panel B of Figure 3. Tail dependence effects are of material importance when the red line is above the blue line. This is usually the case in all sectors.

Tail dependence effects significantly increased the *NoD* during the 2007-2010 financial crises across sectors. Before 2007 tail dependence effects are less noticeable than in the case of the *DD* measures. For example, the effect only appears in 1998 and

[25] Huang, Zhou, and Zhu (2009) documents that systemic risk exhibited substantial increase during the 2002 due to the credit market deterioration.

2002 for Depositories, and from 1996 to 2003 for Broker-Dealers. Third, we find that during 2007-2010 crisis, Others is the most risky sector, with roughly 9 out of 10 largest firms were expected to default, followed by Depositories (8 out of 10), and lastly Insurance Companies (5 out of 10).

Summing up, this measure again indicates that risks in the financial industry increases through the channel of tail dependence in equity market especially in bad times.

5.2.3. ESR (expected shortfall ratio)

The Panel C of Figure 3 reports the time variation of *ESR*, in which financial distress is defined as the ratio of the sector's expected shortfalls to the its aggregate asset value. Tail dependence effects are of material importance when the red line is above the blue line. This is usually the case in all sectors.

The *ESR* measure displays stronger effects of the tail dependence component in recent crisis. For instance, in the Broker-Dealers sector, the *NoD* measure gives a similar level of systemic risk in the cases of the LTCM debacle and in the Lehman's bankruptcy (6 out of 10 defaulting firms), whereas *ESR* signals a higher level of systemic risk in the case of the latter event (200) than in the former (50). The empirical evidence suggests that the inclusion of tail risk dependence effect may improve the model's ability to anticipate stress periods. For example, in the Others sector, *ESR* picks up noticeably by October 2007, when Fannie Mae and Freddie Mac[26] had signaled their troubles due to Subprime loan crisis. In the Broker-Dealers and Depositories sectors *ESR* increases by March 2008, around the Bear Sterns failure. However ESR_{ben} does not present a clear upward trend until September 2008.

[26] Two big mortgage companies belong to this sector.

5.3. Predictability

A key criterion in order to assess the quality of a systemic risk indicator is its forecasting power. First, we examine lead-lag relationship between the full model-based measures and benchmark-based ones. Next, we use Granger Causality tests to study whether our measures are useful in forecasting an index of financial distress. We also run Quandt-Andrews (called QA henceforth) breakpoint test for assessing whether our measures provide early warning signals prior to the 2007-2010 financial crisis.[27]

The financial stress index is the St. Louis Fed Financial Stress Index (STLFSI) proposed by Kliesen and Smith (2010).[28,29] The index is publicly available, and is based on a principal components analysis of a broad range of financial prices and rates from many different financial markets. Figure 4 shows the monthly time series of STLFSI from 12/1996 to 12/2011. Basically, the index shows a local peak near the 1998 LTCM debacle, smoothly increases between 2001 and 2002 (9/11, dot-com bubble), increases from September 2007 (Subprime crisis), reaches its maximum level on September 2008 when Lehman declared bankruptcy, and finally presents two local peaks in mid-2010 and mid-2011 in coincidence with acute stress periods in the Eurozone debt crisis.

[Insert Figure 4 Here]

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[27] Similar testing mechanisms are also implemented by IMF (2011).

[28] The STLFSI is constructed by using 18 data series across different financial variables: Interest Rates (Effective federal funds rate, 2-year Treasury, 10-year Treasury, 30-year Treasury, Baa-rated corporate, Merrill Lynch High-Yield Corporate Master II Index, and Merrill Lynch Asset-Backed Master BBB-rated.), Yield Spreads (Yield curve: 10-year Treasury minus 3-month Treasury, Corporate Baa-rated bond minus 10-year Treasury, Merrill Lynch High-Yield Corporate Master II Index minus 10-year Treasury, 3-month London Interbank Offering Rate–Overnight Index Swap (LIBOR-OIS) spread, 3-month Treasury-Eurodollar (TED) spread, and 3-month commercial paper minus 3-month Treasury bill.), Other Indicators (J.P. Morgan Emerging Markets Bond Index Plus, Chicago Board Options Exchange Market Volatility Index (VIX), Merrill Lynch Bond Market Volatility Index (1-month), 10-year nominal Treasury yield minus 10-year Treasury Inflation Protected Security yield, and Vanguard Financials Exchange-Traded Fund). Furthermore, the index is built by using principal component analysis to extract factors responsible for the co-movement of a group of variables.

[29] We use monthly STLFSI, although the highest frequency is weekly, in order to match the data interval used in this paper.

5.3.1. *Granger Causality test*

Given that unit roots test for our variables give conflicting results,[30] we present Granger Causality (GC) tests on both levels and first differences. The results are in Panel A and B of Table 4 for the former and for the later respectively. All tests are implemented with optimally chosen lags and are corrected after controlling for heteroskedastic and correlated errors.[31]

Regarding the GC results for series in levels between the full model (FM) based measures and the benchmark based ones (see Column 1 and 2 of Panel A of Table 4), FM-based measures lead (usually by one or two months) benchmark-based ones in ten cases out of twelve and there are two cases of bidirectional causality. So it seems that including the co-jump factor does improve the model's forecasting power in most cases in comparison with the benchmark. Next we analyze the GC results between the FM and the STLFSI (see Column 3 and 4 in Panel A of Table 4). In four out of twelve cases FM-based measures lead STLFSI whereas the reverse is true in two out of twelve cases, and there are three cases of bidirectional causality. Two Broker-Dealers sector measures (*DD*, *NoD*) and all Insurance sectors' systemic risk measures lead the STLFSI. The usual average leading period is one month. Therefore measures based on these two sectors are the most informative as leading indicators. If for instance the *DD* and *NoD* measures increase in both sectors in a given month a subsequent increase in the STLFSI index seems very likely indeed.

When using first difference data series (Panel B of Table 4), FM-based measures lead (usually by one or two months) benchmark-based ones in eight cases out of

[30] We employed several unit root tests, including Augmented Dickey-Fuller, GLS Dickey-Fuller, and Perron (1997) with structural breaks in the mean, in the trend and in both elements simultaneously. Detailed results are available on request.

[31] The optimal number of lags has been chosen using the Schwarz (BIC) criterion.

twelve and the reverse is true in two cases. Overall results are largely in agreement with the ones obtained with series in levels. In the case of the comparison between FM measures and the STLFSI index, in five out of twelve cases FM-based measures lead STLFSI whereas the reverse is true in two out of twelve cases. So, in agreement with case of series in levels, two Broker-Dealers sector's systemic risk measures (*DD*, *NoD*) lead the STLFSI. Also one measure form the Depositors sector (*DD*) and another from the Insurance sector (*ESR*) seem to have some explanatory power.

Summing up, in most cases FM-based measures seem to contain more updated information than benchmark-based ones. Two measures based on the Broker-Dealers sector (*DD*, *NoD*) and one measure (*ESR*) based on the Insurance sector provide some leading information on the STLFSI index in all cases (series in levels and in first differences).

[Insert Table 4 Here]

5.3.2. QA test

In addition to test the forecasting power over the whole sample period, it is also interesting to explore whether our measures are capable of identifying earlier warning signals to the 2007-2010 financial crisis in comparison with benchmark-based measures and STLFSI. We apply QA breakpoint test to date structural changes on two perspectives: the persistence and the level. Specifically, break dates are identified by testing structural changes of the coefficient of autoregressive model with order one (AR(1)) for the persistence test, and of the constant term on regressions for the level test.[32] So, the persistence test (the level test) indicates whether the persistence process (the mean) shifts from one stable regression relationship to a different one.

[32] IMF (2011) reports similar tests.

Furthermore, we reduce the sample of 2002-2011 in order to avoid identifying some dates that reveal structural changes due to other big economic shocks before 2002 (such as 1998 LTCM crisis and 9/11), but not to the 2007-2010 financial crisis. Moreover, in QA test, we estimate breakpoints with 25% trimming percentage, which gives the test sample period narrowed down to July 2004-June 2009. This period provides a proper testing ground as it covers three years of pre-crisis period and crisis-period of July 2007-June 2009, but avoiding the concern that tests might identify breakpoints, where risk indicators drop dramatically at the end of crisis, rather the ones before or during crisis. Straightforwardly, the one that provides the earlier date becomes the best indicator to systemic risk events.

Table 5 reports turning points for our systemic risk measures, and their lead-lag relationship with benchmark-based ones and with STLFSI. We document break dates identified based on our measures for the persistence (level) test in first column of Panel A (Panel B). We also analyze how many months that our measures lead or lag to other measures, by using the positive sign of "+" for lead and the negative sign "−" for lag. The numbers nearby signs are their corresponding leading (lagged) numbers of months. There are several noticeable results.

In terms of the persistence test (Panel A) of Table 5, break dates identified by our *DD* measure across sectors are all prior to July 2007, the time point that the subprime loan crisis just started emerging). The earliest two turning points happen in Depositories and Broker-Dealers, February 2006 and March 2006 respectively, indicating that our best measures had signaled the 2007-2010 crisis at least one year in advance. Remarkably they lead to STLFSI by up to three years (35 and 34 months respectively) (see Column 3 of Panel A in Table 5). It reminds us that using solely public financial stress index is not enough to provide warning flags for crises. In comparison with benchmark-based measures, results also document that our measures shows earlier breakpoints across sectors, by 16, 7, 1, and 4 months for Depositories, Broker-Dealers, Insurance Companies, and Others. As for other two risk indicators (*NoD* and *ESR*), the break dates identified by our measures always lead to those by the benchmark and STLFSI especially when we use information from sectors of Broker-Dealers or Insurance Companies. This result suggests that considering tail dependence effects other than common factor does provide extra power of forecasting upcoming distress, and the information within Broker-Dealers are more useful to forecast financial distress.

As for the level test (Panel B of Table 5), we still find stronger evidence that our measures lead (concur) to benchmark-based ones by 8 out of 12 cases (2 out of 12 cases), where our *DD* measures always lead to the benchmark across sectors. In terms of the lead-lag relationship between our measures and STLFSI, we find the *DD* measure on Broker-Dealers is the best one by leading the public index up to 4 months.

Overall the results provided here point out that our *DD* measures are the best risk indicators. Among different financial sectors, the information from Broker-Dealers is mostly useful in forecasting future financial distress. Our measures behavior as the leading indicator to the public financial stress index, and should be able to serve as early detection of vulnerabilities in the financial system, is useful for regulators by earning extra time to prepare contingency plans.

[Insert Table 5 Here]

6. Robustness Test

We consider two robustness checks for predictive analysis, including (1) changing trimming criteria on breakpoint tests; and (2) applying for alternative breakpoint test methodology.

6.1. The 30% trimming criterion on breakpoint test

We concern that under 25% trimming, the test sample covers part of post-crisis period (the first half year of 2009) and could still give breakpoints as crisis is about to be ended, instead of the ones as crisis is just starting. Since our aim is to investigate whether our measures are capable of providing early warning signals, in a more conservative way, we use 30% trimming percentage, where the test sample is ended at December 2008. The results are documented in Table 6. For level test, results are completely the same as previous evidence. For persistence test, there are changes for some cases, but overall it still gives support that our measures lead to benchmark-based measures and our best *DD* measures leads STLFSI by up to three years.

[Insert Table 6 Here]

6.2. Bai and Perron breakpoint test

We apply alternative methodology proposed by Bai and Perron (1998, 2003) to identify structural breaks. We re-examine breakpoints tests implemented in the main content (with 25% trimming percentage), and report in Table 7 In general our results are hardly changed. Specifically for the level test, all breakpoints are dated one month prior to those identified based on QA test, and thus lead-lag relationships are the same as before. For the persistence test, Bai and Perron test gives breakpoints two months prior to those identified by QA test across measures, and lead-lag relationships are almost the same as previous results.

[Insert Table 7 Here]

7. Conclusion

There is growing evidence suggesting that systemic risk has at least two main driving forces. On the one hand there is a common-factor exposure to market-wide shocks. On the other, there is a tail dependence effects factor arising from linkages among extreme stock returns. The way to model the relative importance of these two factors is a research topic of paramount importance. We contribute to this strand of the literature proposing a new structural-form model which includes both factors. In our framework, the common factor component is based on the correlations of individual stock returns with the aggregate macro common factor. The tail dependence effects component is proxied by a correlated jumps factor. The model gives empirical implications that are consistent with the extant evidence at hand and in particular gives the prediction that simultaneous extreme negative movements across large financial institutions are stronger in bear markets than in bull markets.

The empirical application based on stock market data on the four sectors of the U.S. financial industry during 1996-2011 suggests that ignoring the effect of the tail dependence effects component underestimate the measurement of the level of systemic risk. Taking into account tail dependence effects factor provides extra power of forecasting in comparison with the benchmark model. Also, not all sectors provide equally valuable systemic risk indicators. Two measures (*DD*, *NoD*) based on the Broker-Dealers sector and one measure (*ESR*) based on the Insurance sector systematically lead the St. Louis Fed Financial Stress Index (STLFSI).

Looking forward, comparison of our measures with other measures based on alternative asset markets is certainly worth of attention. The way to use our measures for asset pricing, hedging strategies, portfolio diversification, and risk management purposes is another topic that is left for future research.

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Appendix

Appendix A1

We apply the theorem of the law of total variance, which is $Var(Y) = E_X\left[Var(Y \mid X)\right] + Var_X\left[E(Y \mid X)\right]$. In our case, we have

$$Y \equiv Q_j N(\Delta t) = \sum_{k=1}^{N(\Delta t)} Q_j^{(k)}(\Delta t), \text{ and } \quad X = N(\Delta t). \tag{A1}$$

Then,

$$\begin{aligned} Var^P\left(Q_j N(\Delta t)\right) &= E_N\left[b_j^2 N(\Delta t)\right] + Var_N\left[N(\Delta t) a_j\right] \\ &= b_j^2 \lambda + a_j^2 \lambda \\ &= \left[a_j^2 + b_j^2\right]\lambda \end{aligned}, \tag{A2}$$

Finally we assume all random variables appeared in asset-log-return process (Eq. (1)) are all independent. Therefore we can derive the variance of asset return as follows.

$$Var\left(v_{j,t} \mid \varphi_{t-1}\right) \equiv \sigma_{j,t}^2 = \delta_j^2 h_t + \xi_j + \lambda \hat{b}_j^2, \tag{A3}$$

where $\hat{b}_j^2 = a_j^2 + b_j^2$.

Appendix A2

Since Q_k are normally IID random variables and distributed independently of $N(T)$, by iterated expectations,

$$\begin{aligned} E\left[e^{\phi Q_j N(T)}\right] &= E\left[e^{\phi \sum_{k=1}^{N(T)} Q_{j,k}}\right] = E\left[\prod_{k=1}^{N(T)} e^{\phi Q_{j,k}}\right] = E_N\left[E_{Q_j \mid N}\left[\prod_{k=1}^{N(T)} e^{\phi Q_{j,k}} \mid N(T)\right]\right] \\ &= \sum_{i=0}^{\infty} p_i(\lambda T) E\left[\prod_{k=1}^{i} e^{\phi Q_{j,k}}\right] = \sum_{i=0}^{\infty} p_i(\lambda T) \prod_{k=1}^{i} E\left[e^{\phi Q_{j,k}}\right] \\ &= \sum_{i=0}^{\infty} \frac{e^{-\lambda T}(\lambda T)^i}{i!}\left(e^{\left(a_j\phi + \frac{1}{2}b_j^2\phi^2\right)}\right)^i = e^{-\lambda T}\sum_{i=0}^{\infty}\frac{1}{i!}\left(\lambda T e^{\left(a_j\phi + \frac{1}{2}b_j^2\phi^2\right)}\right)^i \\ &= e^{-\lambda T} e^{\lambda T \exp\left(a_j\phi + \frac{1}{2}b_j^2\phi^2\right)} = e^{\lambda T\left(\exp\left(a_j\phi + \frac{1}{2}b_j^2\phi^2\right) - 1\right)} \end{aligned}. \tag{A4}$$

Appendix B

Type	Name of Company	Start date	End date	# of observations	SIZE (million)	LVG
Depositories	'BANK OF AMERICA CORP'	199601	201112	181	13.556	9.194
Depositories	'BANK OF NEW YORK MELLON CORP'	200310	201112	55	12.037	5.709
Depositories	'BANK ONE CORP'	199601	200406	91	12.101	5.949
Depositories	'BANKAMERICA CORP-OLD'	199601	199809	22	12.391	7.568
Depositories	'BANKERS TRUST CORP'	199601	199905	30	11.693	16.393
Depositories	'BB&T CORP'	200401	201112	72	11.745	7.345
Depositories	'CITICORP'	199601	199809	22	12.510	6.568
Depositories	'FIFTH THIRD BANCORP'	200308	200708	20	11.473	4.391
Depositories	'FIRST CHICAGO NBD CORP'	199601	199809	22	11.639	7.736
Depositories	'FLEETBOSTON FINANCIAL CORP'	199604	200403	69	11.846	5.777
Depositories	'GOLDEN WEST FINANCIAL CORP'	200501	200609	10	11.585	6.224
Depositories	'JPMORGAN CHASE & CO'	199601	201112	181	13.565	10.194
Depositories	'KEYCORP'	199712	200408	27	11.294	7.799
Depositories	'MORGAN (J P) & CO'	199601	200012	49	12.383	12.952
Depositories	'NATIONAL CITY CORP'	199807	200812	109	11.614	6.439
Depositories	'PNC FINANCIAL SVCS GROUP INC'	199711	201112	47	12.049	8.966
Depositories	'REGIONS FINANCIAL CORP'	200704	201112	46	11.856	17.872
Depositories	'STATE STREET CORP'	200305	201112	50	11.875	8.214
Depositories	'SUNTRUST BANKS INC'	199904	201112	142	11.829	9.124
Depositories	'U S BANCORP'	200107	201112	115	12.260	5.103
Depositories	'U S BANCORP/DE-OLD'	200010	200205	9	11.369	4.466
Depositories	'WACHOVIA CORP'	199601	200812	145	12.586	6.926
Depositories	'WASHINGTON MUTUAL INC'	199801	200808	117	12.334	8.449
Depositories	'WELLS FARGO & CO -OLD'	199610	199810	14	11.572	4.678
Depositories	'WELLS FARGO & CO'	199601	201112	165	12.771	5.456
Broker-Dealers	'AMERIPRISE FINANCIAL INC'	200604	201112	58	11.560	11.357
Broker-Dealers	'AXA FINANCIAL INC'	199601	200012	49	11.872	18.052
Broker-Dealers	'BEAR STEARNS COMPANIES INC'	199601	200805	138	12.091	27.973
Broker-Dealers	'BLACKROCK INC'	200701	201112	49	10.378	3.734
Broker-Dealers	'CITIGROUP GLOBAL MKTS HLDGS'	199601	199710	11	12.095	41.126
Broker-Dealers	'CREDIT SUISSE USA INC'	199604	200010	44	11.085	18.551
Broker-Dealers	'DAIN RAUSCHER CORP'	199601	199702	3	7.725	8.450
Broker-Dealers	'E TRADE FINANCIAL CORP'	200002	201112	132	10.338	14.236
Broker-Dealers	'EDWARDS (A G) INC'	199601	200207	49	8.304	1.880
Broker-Dealers	'FRANKLIN RESOURCES INC'	199601	200702	56	8.805	1.194
Broker-Dealers	'GOLDMAN SACHS GROUP INC'	199909	201112	137	13.195	11.249
Broker-Dealers	'INTERACTIVE BROKERS GROUP'	200710	201112	40	10.300	36.641
Broker-Dealers	'JEFFERIES GROUP INC'	200107	201112	97	9.717	7.315
Broker-Dealers	'LEGG MASON INC'	200104	200311	19	8.614	2.492
Broker-Dealers	'LEHMAN BROTHERS HOLDINGS INC'	199601	200808	141	12.393	22.165
Broker-Dealers	'MERRILL LYNCH & CO INC'	199601	200812	145	12.947	12.367
Broker-Dealers	'MORGAN STANLEY'	199601	201112	181	13.173	14.750
Broker-Dealers	'PAINE WEBBER GROUP'	199601	200010	47	10.921	16.013
Broker-Dealers	'QUICK & REILLY GROUP INC'	199603	199801	12	8.117	5.102
Broker-Dealers	'RAYMOND JAMES FINANCIAL CORP'	199703	201112	102	8.975	5.428
Broker-Dealers	'SCHWAB (CHARLES) CORP'	199604	201112	178	10.452	3.052
Broker-Dealers	'SWS GROUP INC'	199707	200202	15	8.316	14.279
Broker-Dealers	'TD AMERITRADE HOLDING CORP'	200301	201112	94	9.667	2.903
Broker-Dealers	'TD WATERHOUSE GROUP INC'	199911	200110	13	9.238	2.259
Insurance Companies	'AETNA INC'	199601	200011	48	11.476	9.204
Insurance Companies	'AFLAC INC'	200904	201112	22	11.314	4.714
Insurance Companies	'ALLSTATE CORP'	199607	201112	175	11.666	5.097
Insurance Companies	'AMERICAN GENERAL CORP'	199601	200107	56	11.336	7.109
Insurance Companies	'AMERICAN INTERNATIONAL GROUP'	199601	201112	181	13.028	36.671
Insurance Companies	'CIGNA CORP'	199601	200508	105	11.479	9.051
Insurance Companies	'CNA FINANCIAL CORP'	199601	200302	63	11.049	9.223
Insurance Companies	'CNO FINANCIAL GROUP INC'	200001	200108	7	10.826	15.516
Insurance Companies	'GENERAL RE CORP'	199601	199705	6	10.476	3.369
Insurance Companies	'GENWORTH FINANCIAL INC'	200410	201112	76	11.587	23.942
Insurance Companies	'HANCOCK JOHN FINL SVCS INC'	200007	200403	34	11.399	9.408
Insurance Companies	'HARTFORD FINANCIAL SERVICES'	199604	201112	178	12.231	19.248
Insurance Companies	'HARTFORD LIFE INC -CL A'	199710	200005	21	11.566	83.438
Insurance Companies	'LINCOLN NATIONAL CORP'	199601	201112	181	11.627	15.279
Insurance Companies	'LOEWS CORP'	199601	201002	106	11.185	7.264
Insurance Companies	'METLIFE INC'	200010	201112	124	12.878	13.855

Insurance Companies	'NATIONWIDE FINL SVCS -CL A'	199807	200812	115	11.490	68.231
Insurance Companies	'PRINCIPAL FINANCIAL GRP INC'	200204	201112	106	11.706	13.231
Insurance Companies	'PROVIDIAN CORP'	199601	199702	3	10.179	6.585
Insurance Companies	'PRUDENTIAL FINANCIAL INC'	200204	201112	106	12.903	17.108
Insurance Companies	'TRANSAMERICA CORP'	199601	199805	12	10.782	9.311
Insurance Companies	'TRAVELERS COS INC'	199610	201112	85	11.542	5.642
others	'AMERICAN EXPRESS CO'	199601	201112	181	11.817	3.668
others	'ANNALY CAPITAL MANAGEMENT'	200207	201112	55	10.721	7.537
others	'APARTMENT INVST & MGMT CO'	200204	200308	6	9.102	2.843
others	'ASSOCIATES FIRST CAP -CL A'	199610	200011	39	10.991	6.809
others	'BENEFICIAL CORP'	199601	199806	19	9.670	5.548
others	'CAPITAL ONE FINANCIAL CORP'	200007	201112	127	11.083	5.916
others	'CAPSTEAD MORTGAGE CORP'	199601	200205	40	9.256	18.884
others	'CIT GROUP INC'	200301	201112	81	10.998	10.818
others	'CIT GROUP INC-OLD'	199804	200105	27	10.143	11.133
others	'CITIGROUP INC'	199601	201112	181	13.683	13.404
others	'CME GROUP INC'	200901	201112	25	10.546	1.644
others	'COUNTRYWIDE FINANCIAL CORP'	199601	200806	139	10.463	5.476
others	'DEAN WITTER DISCOVER & CO'	199601	199705	6	10.476	4.333
others	'DISCOVER FINANCIAL SVCS INC'	200712	201112	38	10.677	6.766
others	'FANNIE MAE'	199601	201006	163	13.400	84.908
others	'FEDERAL HOME LOAN MORTG CORP'	199604	201006	160	13.097	125.524
others	'FINOVA GROUP INC'	199601	200201	44	9.147	23.722
others	'FIRST USA INC'	199601	199705	6	8.864	3.004
others	'GENERAL GROWTH PPTYS INC'	200504	201111	11	10.223	5.368
others	'HELLER FINANCIAL INC'	199810	200109	25	9.679	15.190
others	'HOST HOTELS & RESORTS INC'	200107	200305	12	9.025	3.650
others	'HSBC FINANCE CORP'	199601	200302	75	10.739	3.684
others	'IMPAC MORTGAGE HOLDINGS INC'	200603	200705	4	10.231	37.595
others	'INTERCONTINENTALEXCHANGE INC'	201101	201112	1	10.248	3.902
others	'MF GLOBAL HOLDINGS LTD'	200801	201109	34	10.828	65.259
others	'NELNET INC'	200708	201112	17	10.246	43.709
others	'NEW CENTURY FINANCIAL CORP'	200601	200701	2	10.278	13.369
others	'SIMON PROPERTY GROUP INC'	199901	201102	58	9.564	3.249
others	'SLM CORP'	200210	201112	100	11.578	16.639
others	'STUDENT LOAN CORP'	199607	201012	83	9.841	11.464
others	'THORNBURG MORTGAGE INC'	200310	200811	51	10.414	15.003

Table 1. Summary Statistics.

The table reports summary statistics of several risk measures for each sector of the financial industry from December 1996 to December 2011, totalizing 181 monthly observations. The *SIZE* (in million) is the logarithm of aggregated total assets on the ten biggest firms in each sector. The *LVG* is the quasi-market value of assets divided by market value of equity, weighted averaged based on values of market equity. The *RET* is the annualized return. *DD*, *NoD*, and *ESR* (scaled by multiplying 10^6) are systemic risk measures. The subindex “ben” identify measures computed from the benchmark model (without co-jumps term).

Sector	Statistics	*SIZE*	*LVG*	*RET*	*DD*	*NoD*	*ESR*	DD_{ben}	NoD_{ben}	ESR_{ben}
Depositories	Min	14.380	4.890	-0.530	-0.240	0.000	0.000	1.120	0.000	0.000
	Max	15.800	34.040	1.760	16.230	8.030	69.255	16.730	3.860	9.475
	Mean	15.140	7.940	0.090	6.310	0.790	4.503	8.000	0.260	0.343
	Median	15.070	6.910	0.070	5.900	0.010	0.020	7.430	0.000	0.000
	Std	0.440	3.400	0.260	3.930	1.720	11.765	4.030	0.650	1.123
Broker-Dealers	Min	13.760	6.240	-0.540	-0.660	0.000	0.005	0.020	0.000	0.000
	Max	15.350	40.050	1.380	8.440	6.110	208.445	16.700	5.250	29.956
	Mean	14.540	12.260	0.210	2.590	2.260	22.221	6.010	0.960	2.614
	Median	14.470	10.960	0.160	1.980	2.140	6.334	5.140	0.790	0.693
	Std	0.390	4.800	0.390	2.110	1.820	39.363	3.800	1.060	4.785
Insurance Com.	Min	13.450	4.140	-0.540	0.910	0.000	0.000	0.390	0.000	0.000
	Max	15.020	82.960	2.200	21.230	5.390	41.335	26.290	3.220	22.541
	Mean	14.460	11.930	0.120	10.990	0.360	3.757	12.180	0.230	1.421
	Median	14.600	7.620	0.120	10.870	0.000	0.000	11.880	0.000	0.000
	Std	0.470	14.160	0.340	4.570	1.010	10.084	5.380	0.580	4.281
Others	Min	13.450	4.310	-0.670	-0.780	0.000	0.001	-1.970	0.000	0.000
	Max	15.390	173.300	1.900	7.390	8.900	288.020	11.260	6.770	211.190
	Mean	14.810	11.220	0.110	3.450	2.380	39.902	5.510	1.420	15.074
	Median	14.890	7.690	0.110	3.750	1.450	3.699	6.040	1.000	0.919
	Std	0.490	16.920	0.340	2.170	2.400	78.679	3.150	1.730	39.273

Table 2. Estimation results: co-jumps

The column 1, 3, and 5 show average values of λ, *mu_coj*, and *std_coj* during "Pre-Crisis", "Crisis", and "Post-Crisis" periods respectively. We define "Pre-Crisis" as from July 2005 to June 2007, "Crisis" as from July 2007 to June 2009, and "Post-Crisis" as from July 2009 to June 2011. Each period consists of 24 number of observations. The column 2 and 4 report results of independent samples t-test where the null hypothesis is the means of the two groups are equal. For each parameter, the column 2 (the column 4) first reports the difference of average values of Crisis and of Pre-Crisis (of Post-Crisis) along with *P-values* in brackets. Panel A, B, C, and D shows results for *Depositories*, *Broker-Dealers*, *Insurance Companies*, and *Others* respectively.

	Pre-Crisis (1)	Crisis versus Pre-Crisis (2)	Crisis (3)	Crisis versus Post-Crisis (4)	Post-Crisis (5)
Panel A: Depositories					
λ	0.0394	0.0964 ***	0.1358	0.0828 ***	0.0530
		(<0.0001)		(0.0015)	
mu_coj	0.0049	-0.0135 ***	-0.0086	-0.0078 *	-0.0008
		(0.0007)		(0.1039)	
std_coj	0.0178	0.0653 ***	0.0831	0.0128	0.0702
		(<0.0001)		(0.3478)	
Panel B: Broker-Dealers					
λ	0.0347	0.0258 **	0.0606	0.0074	0.0532
		(0.0244)		(0.5427)	
mu_coj	0.0030	-0.0162 **	-0.0132	-0.0101	-0.0031
		(0.0476)		(0.2235)	
std_coj	0.0318	0.0535 ***	0.0853	0.0256 ***	0.0597
		(<0.0001)		(0.0054)	
Panel C: Insurance Companies					
λ	0.0713	0.0561 ***	0.1274	0.0626 ***	0.0648
		(0.0030)		(0.0011)	
mu_coj	0.0013	-0.0041 ***	-0.0028	-0.0024 **	-0.0004
		(<0.0001)		(0.0177)	
std_coj	0.0206	0.0634 ***	0.0840	-0.0002	0.0842
		(<0.0001)		(0.9896)	
Panel C: Others					
λ	0.1003	0.0963 ***	0.1967	0.1026 ***	0.0941
		(0.0015)		(0.0031)	
mu_coj	-0.0008	-0.0222 **	-0.0230	-0.0234 **	0.0004
		(0.0187)		(0.0160)	
std_coj	0.0273	0.1029 ***	0.1302	0.0483 ***	0.0820
		(<0.0001)		(0.0081)	

Table 3. Estimation results: structural-form parameters.

The table reports average values of estimated parameters from our structural-form model and the benchmark model (along with the notation "ben"). The sample period spans from December 1996 to December 2011, containing 181 number of observations. The reported numbers in μ, $\mu_{\_ben}$, ξ, and $\xi_{\_ben}$ are 10000 times of raw numbers. The "diff." stands for the testing results of independent samples t-test where the null hypothesis is the means of the two groups are equal, for each pair of parameters. The column 3, 6, and 9 first report differences of average values of estimated parameters, along with *P-value* in brackets.

Sector	μ (1)	$\mu_{\_ben}$ (2)	*diff.* (3)	δ (4)	$\delta_{\_ben}$ (5)	*diff.* (6)	ξ (7)	$\xi_{\_ben}$ (8)	*diff.* (9)
Depositories	0.9996	0.9247	0.0749	0.4486	0.5193	-0.0707 ***	0.2714	0.4960	-0.2246 ***
			(0.8814)			(<0.0001)			(<0.0001)
Broker-Dealers	2.8938	3.1188	-0.2250	0.5945	0.6326	-0.0381 ***	0.5957	1.0429	-0.4472 ***
			(0.6611)			(0.0012)			(<0.0001)
Insurance Companies	-0.9960	-0.1626	-0.8334	0.7224	0.7842	-0.0618 ***	0.5299	1.5100	-0.9800 ***
			(0.2683)			(0.0003)			(<0.0001)
Others	2.7060	3.2008	-0.4948	0.3534	0.4157	-0.0622 ***	0.1897	0.8126	-0.6229 ***
			(0.2911)			(<0.0001)			(<0.0001)

Table 4. Granger causality test 1996-2011

The table reports results of Granger Causality tests of full-model (FM) systemic risk indicators to the benchmark-based ones, and the public financial stress index, STLFSI. The testing sample contains 181 monthly observations spanning from December 1996 to December 2011. Panel A and B are results based on levels and first differences respectively. We implement tests for each risk indicator across industries. Four industries are classified as *Depositories*, *Broker-Dealers*, *Insurance Companies*, and *Others*. The Column 1 and 2 (3 and 4) shows results of whether our systemic risk indicators granger cause to benchmark-based measures (STLFSI) and their corresponding reverse direction. Granger Causality tests with lag-lengths selected according to the rule of the Schwarz criterion, and heteroskedastic and correlated errors are corrected. For each test, the *p*-value is reported in bracket, and the lag-length of VAR is also reported for statistically significant cases. Moreover ***, **, and * are significant at 1, 5, and 10 percent level respectively.

		FM leads Benchmark (1)	Benchmark leads FM (2)	FM leads STLFSI (3)	STLFSI leads FM (4)
Measure	Sector	*P*-value	*P*-value	*P*-value	*P*-value
Panel A: levels					
DD	*Depositories*	(0.009)*** lag(1)	(0.695)	(0.015)** lag(1)	(0.105)
	Broker-Dealers	(0.001)*** lag(1)	(0.305)	(0.001)*** lag(1)	(0.588)
	Insurance Com.	(0.005)*** lag(1)	(0.502)	(0.046)** lag(2)	(0.015)** lag(2)
	Others	(0.000)*** lag(1)	(0.218)	(0.094)* lag(1)	(0.016)** lag(1)
NoD	*Depositories*	(0.001)*** lag(6)	(0.000)*** lag(6)	(0.912)	(0.005)*** lag(1)
	Broker-Dealers	(0.009)*** lag(1)	(0.547)	(0.026)** lag(2)	(0.986)
	Insurance Com.	(0.000)*** lag(5)	(0.188)	(0.014)** lag(2)	(0.039)** lag(2)
	Others	(0.000)*** lag(1)	(0.111)	(0.146)	(0.943)
ESR	*Depositories*	(0.047)** lag(2)	(0.802)	(0.249)	(0.001)*** lag(2)
	Broker-Dealers	(0.000)*** lag(1)	(0.216)	(0.366)	(0.325)
	Insurance Com.	(0.000)*** lag(2)	(0.063)* lag(2)	(0.017)** lag(2)	(0.104)
	Others	(0.000)*** lag(1)	(0.249)	(0.718)	(0.167)
Panel B: first differences					
DD	*Depositories*	(0.014)** lag(1)	(0.342)	(0.450)	(0.017)** lag(1)
	Broker-Dealers	(0.013)** lag(2)	(0.119)	(0.006)*** lag(1)	(0.909)
	Insurance Com.	(0.529)	(0.590)	(0.024)** lag(1)	(0.211)
	Others	(0.002)*** lag(2)	(0.199)	(0.798)	(0.177)
NoD	*Depositories*	(0.045)** lag(2)	(0.000)*** lag(2)	(0.501)	(0.443)
	Broker-Dealers	(0.034)** lag(1)	(0.696)	(0.009)*** lag(1)	(0.943)
	Insurance Com.	(0.000)*** lag(4)	(0.088)* lag(4)	(0.017)** lag(4)	(0.117)
	Others	(0.050)** lag(1)	(0.852)	(0.880)	(0.922)
ESR	*Depositories*	(0.025)** lag(1)	(0.776)	(0.378)	(0.025)** lag(1)
	Broker-Dealers	(0.000)*** lag(2)	(0.289)	(0.239)	(0.344)
	Insurance Com.	(0.109)	(0.115)	(0.009)*** lag(1)	(0.511)
	Others	(0.021)** lag(3)	(0.405)	(0.736)	(0.441)

Table 5. Early turning points: Quandt-Andrews breakpoint test

The table reports turning points for each of our systemic risk measures, and its lead-lag relationship with benchmark-based measures and with the STLFSI. We use Quandt-Andrews breakpoint test on both the persistence and the level by means of autoregressive regressions: $X_t = c + \rho_s X_{t-1} + \varepsilon_t$. In the test, we consider the 25% trimming percentage on the sample period of 2002-2011, and thus the test sample is from July 2004 to June 2009 with number of breaks compared of 60. We document break dates of our measures for tests on the persistence and on the level in first column of Panel A and Panel B respectively. Furthermore, results document that break points of STFSI is January 2009 and November 2007 for tests on persistence and level separately. We also analyze how our measures lead or lag to benchmark-based measures and to the STLFSI. They are deployed along with items of "Lead-Lag (vs. benchmark)" and "Lead-Lag (vs. STLFSI)". Furthermore, we use the positive sign of "+" (the negative sign "-") to indicate our measures lead (lag) to alternative measures, and the numbers nearby signs are their corresponding leading (lagged) numbers of months. Black boldface values represent that our measures are earlier than or concurrent with those from alternative measures.

Indicators	Type	Break Date (1)	Lead-Lag (vs. benchmark) (2)	Lead-Lag (vs. STLFSI) (3)	Break Date (4)	Lead-Lag (vs. benchmark) (5)	Lead-Lag (vs. STLFSI) (6)
		Panel A: Persistence (ρ_s) test			Panel B: Level (c) test		
DD	*Depositories*	Feb-06	**+16**	**+35**	Sep-07	**+3**	**+2**
	Broker-Dealer	Mar-06	**+7**	**+34**	Jul-07	**+4**	**+4**
	Insurance Companies	Jun-07	**+1**	**+19**	Jan-08	**+1**	-2
	Others	Feb-07	**+4**	**+23**	Sep-07	**+2**	**+2**
NoD	*Depositories*	Mar-09	**0**	-2	Mar-08	-3	-4
	Broker-Dealer	Oct-06	**+12**	**+27**	Aug-07	**+2**	**+3**
	Insurance Companies	Nov-08	**+1**	**+2**	Sep-08	**0**	-10
	Others	Apr-09	-1	-3	Sep-07	**+2**	**+2**
ESR	*Depositories*	Feb-09	**+1**	-1	Jun-08	-3	-7
	Broker-Dealer	Nov-08	**+1**	**+2**	Mar-08	**+2**	-4
	Insurance Companies	Oct-08	**+1**	**+3**	Sep-08	**0**	-10
	Others	Apr-09	-1	-3	Nov-07	**+10**	**0**

Table 6. Turning Points Tests on 30% trimming percentage: Quandt-Andrews test

The table reports turning points for each of our systemic risk measures, and its lead-lag relationship with benchmark-based measures and with the STLFSI. We use Quandt-Andrews breakpoint test on both the persistence and the level by means of autoregressive regressions: $X_t = c + \rho_s X_{t-1} + \varepsilon_t$. In the test, we consider the 30% trimming percentage on the sample period of 2002-2011, and thus the test sample is from January 2005 to December 2008 with number of breaks compared of 48. We document break dates of our measures for tests on the persistence and on the level in first column of Panel A and Panel B respectively. Furthermore, results document that break points of STFSI is November 2008 and November 2007 for tests on persistence and level separately. We also analyze how our measures lead or lag to benchmark-based measures and to the STLFSI. They are deployed along with items of "Lead-Lag (vs. benchmark)" and "Lead-Lag (vs. STLFSI)". Furthermore, we use the positive sign of "+" (the negative sign "-") to indicate our measures lead (lag) to alternative measures, and the numbers nearby signs are their corresponding leading (lagged) numbers of months. Black boldface values represent that our measures are earlier than or concurrent with those from alternative measures.

Indicators	Type	Break Date (1)	Lead-Lag (vs. benchmark) (2)	Lead-Lag (vs. STLFSI) (3)	Break Date (4)	Lead-Lag (vs. benchmark) (5)	Lead-Lag (vs. STLFSI) (6)
		Panel A: Persistence (ρ_s) test			Panel B: Level (c) test		
DD	*Depositories*	Feb-06	**+16**	**+33**	Sep-07	**+3**	**+2**
	Broker-Dealer	Mar-06	**+7**	**+32**	Jul-07	**+4**	**+4**
	Insurance Companies	Jun-07	**+1**	**+17**	Jan-08	**+1**	-2
	Others	Feb-07	**+4**	**+21**	Sep-07	**+2**	**+2**
NoD	*Depositories*	Aug-08	-1	**+3**	Mar-08	-3	-4
	Broker-Dealer	Oct-06	**+12**	**+13**	Aug-07	**+2**	**+3**
	Insurance Companies	Nov-08	**+1**	**0**	Sep-08	**0**	-10
	Others	Nov-08	**0**	**0**	Sep-07	**+2**	**+2**
ESR	*Depositories*	Dec-08	**0**	-1	Jun-08	-3	-7
	Broker-Dealer	Nov-08	**+1**	**0**	Mar-08	**+2**	-4
	Insurance Companies	Oct-08	**+1**	**+1**	Sep-08	**0**	-10
	Others	Dec-08	**0**	-1	Nov-07	**+10**	**0**

Table 7. Early turning points on 25% trimming percentage: Bai and Perron test

The table reports turning points for each of our systemic risk measures, and its lead-lag relationship with benchmark-based measures and with the STLFSI. We use Bai and Perron breakpoint test on both the persistence and the level by means of autoregressive regressions: $X_t = c + \rho_s X_{t-1} + \varepsilon_t$. In the test, we consider the 25% trimming percentage on the sample period of 2002-2011, and thus the test sample is from July 2004 to June 2009 with number of breaks compared of 60. We document break dates of our measures for tests on the persistence and on the level in first column of Panel A and Panel B respectively. Furthermore, results document that break points of STFSI is November 2008 and October 2007 for tests on persistence and level separately. We also analyze how our measures lead or lag to benchmark-based measures and to the STLFSI. They are deployed along with items of "Lead-Lag (vs. benchmark)" and "Lead-Lag (vs. STLFSI)". Furthermore, we use the positive sign of "+" (the negative sign "-") to indicate our measures lead (lag) to alternative measures, and the numbers nearby signs are their corresponding leading (lagged) numbers of months. Black boldface values represent that our measures are earlier than or concurrent with those from alternative measures.

Indicators	Type	Break Date (1)	Lead-Lag (vs. benchmark) (2)	Lead-Lag (vs. STLFSI) (3)	Break Date (4)	Lead-Lag (vs. benchmark) (5)	Lead-Lag (vs. STLFSI) (6)
		Panel A: Persistence (ρ_s) test			Panel B: Level (c) test		
DD	*Depositories*	Dec-05	**+16**	**+35**	Aug-07	**+3**	**+2**
	Broker-Dealer	Jan-06	**+7**	**+34**	Juln07	**+4**	**+4**
	Insurance Companies	Apr-07	**+1**	**+19**	Dec-07	**+1**	-2
	Others	Dec-06	**+4**	**+23**	Aug-07	**+2**	**+2**
NoD	*Depositories*	Jan-09	**0**	-2	Feb-08	-3	-4
	Broker-Dealer	Aug-06	**+12**	**+27**	Jul-07	**+3**	**+3**
	Insurance Companies	Sep-08	**+1**	**+2**	Aug-08	**0**	-10
	Others	Feb-09	-1	-3	Aug-07	**+2**	**+2**
ESR	*Depositories*	Dec-08	**+1**	-1	May-08	-3	-7
	Broker-Dealer	Sep-08	**+1**	**+2**	Feb-08	**+2**	-4
	Insurance Companies	Aug-08	**+1**	**+3**	Aug-08	**0**	-10
	Others	Feb-09	-1	-3	Oct-07	**+10**	**0**

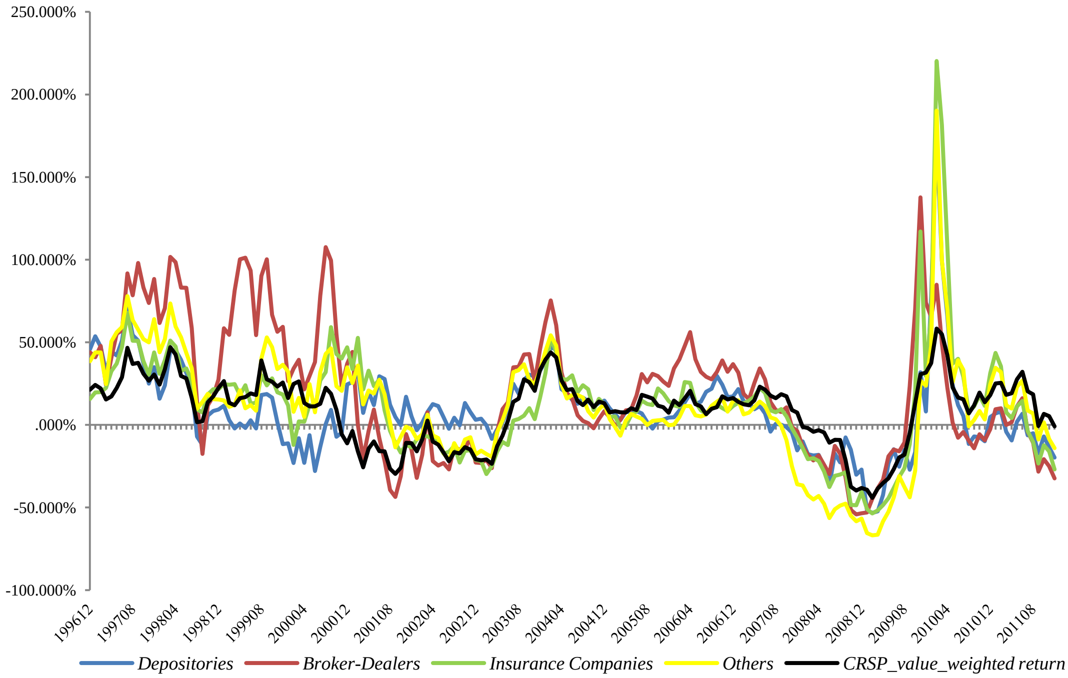


Fig. 1. Annualized equity returns by sector. The figure shows annualized equity returns, calculated by summing daily returns over the past one year at the end of every month, spanning from December 1996 to December 2011. The blue, red, green, and yellow lines represent *Depositories*, *Broker-Dealers*, *Insurance Companies*, and *Others* respectively. The black line represents the annual return on CRSP value-weighted index.

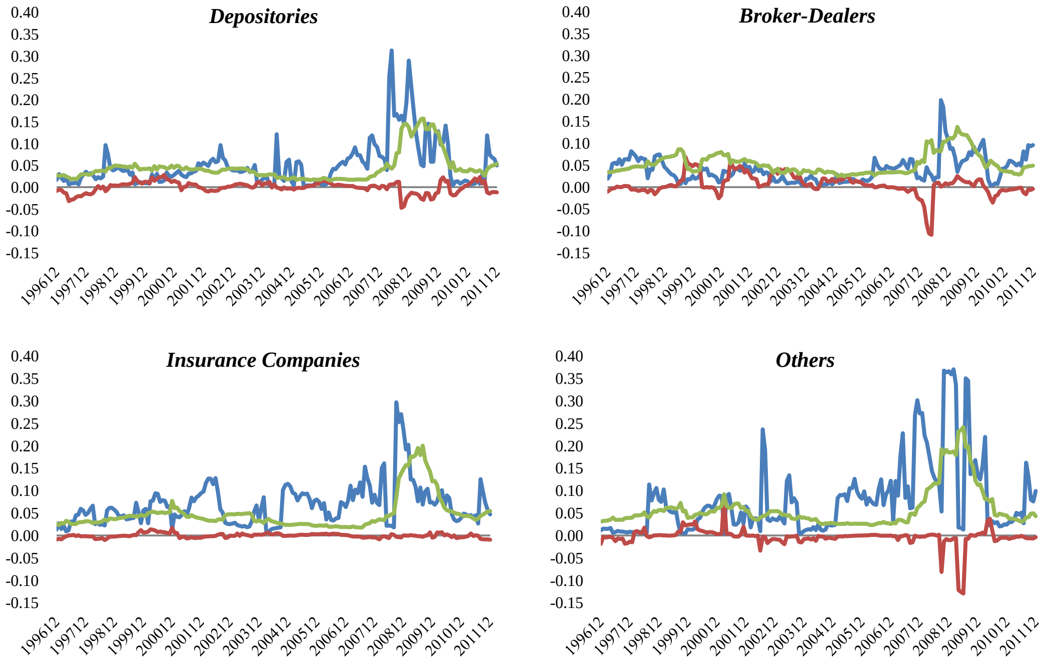
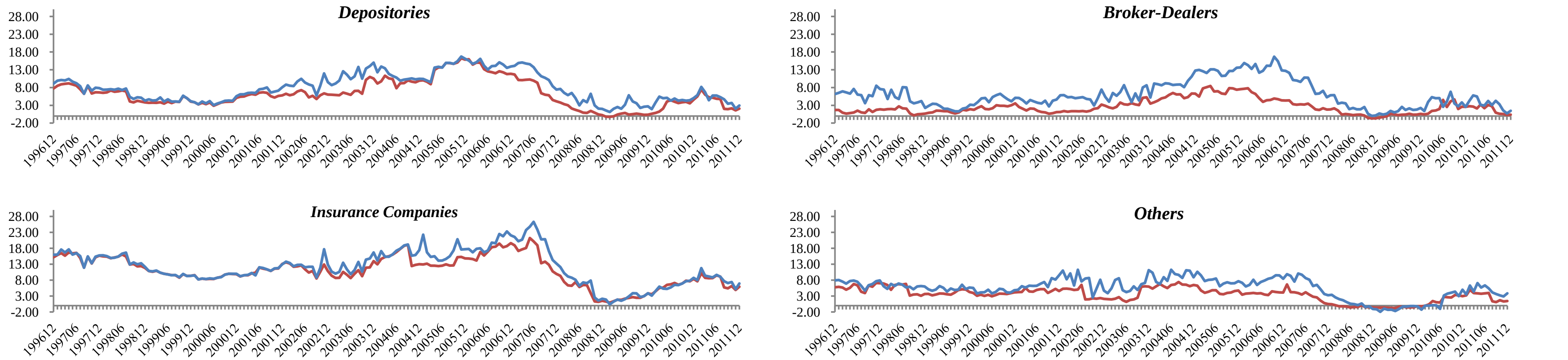
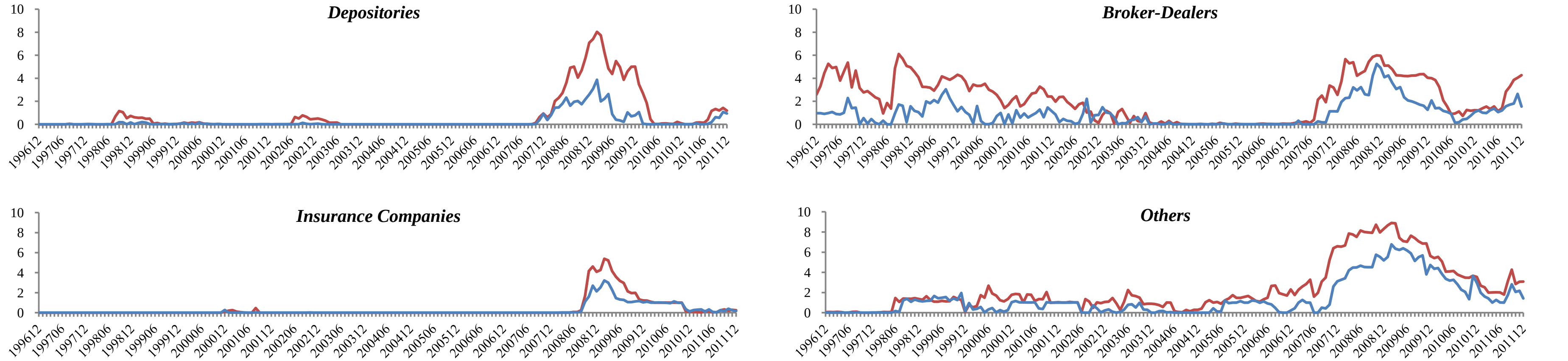


Fig 2. Jump process parameters. The figure shows the three time series obtained from the estimation of co-jumps in each sector. The result is plotted at the end of each rolling window sample, and thus there are 181 monthly observations for each time series. The blue, red, and green lines represent λ (the intensity of co-jumps), *mu_coj* (the average value of jump size on ten big financial institutions), and *std_coj* (the average value of standard deviation of jump size on ten big financial institutions).

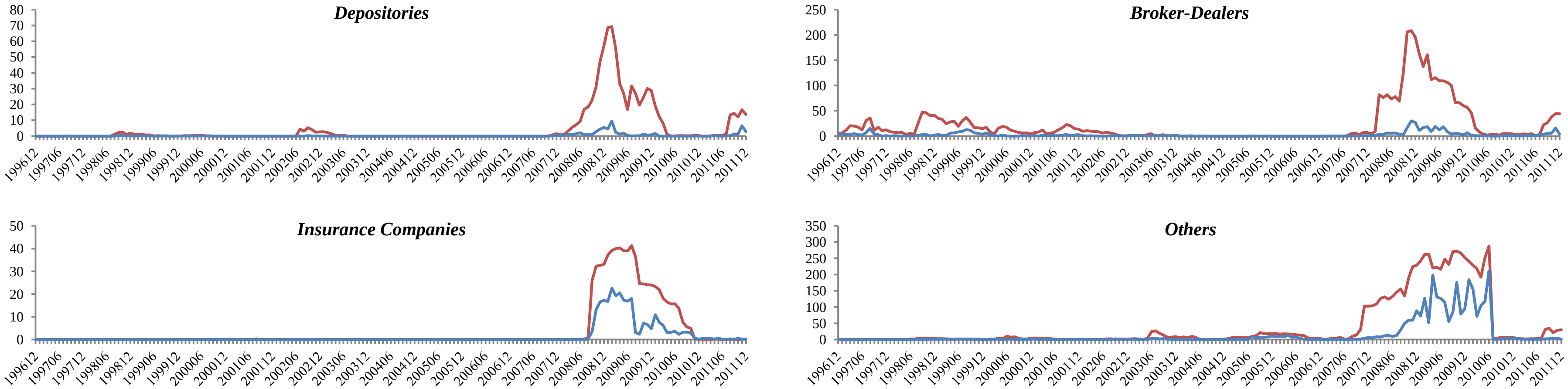


Panel A: *DD*



Panel B: *NoD*

Fig. 3. This figure plots three alternative systemic risk measures, *DD* and *NoD*, and *ESR* from during 1996-2011, by industry. The *DD* (Panel A) is the average distance-to-default, and the *NoD* (Panel B) is the expected number of defaults over the following six months. The red and blue line represent measures derived from our model and the benchmark. (Conti.



Panel C: *ESR*

Fig. 3 (Conti.). This figure plots an alternative systemic risk measure, *ESR*, from during 1996-2011, by industry. The *ESR* (Panel C) is the ratio of the aggregate present value of expected shortfalls to the aggregate asset value**.** The red and blue line represent measures derived from our model and the benchmark respectively.

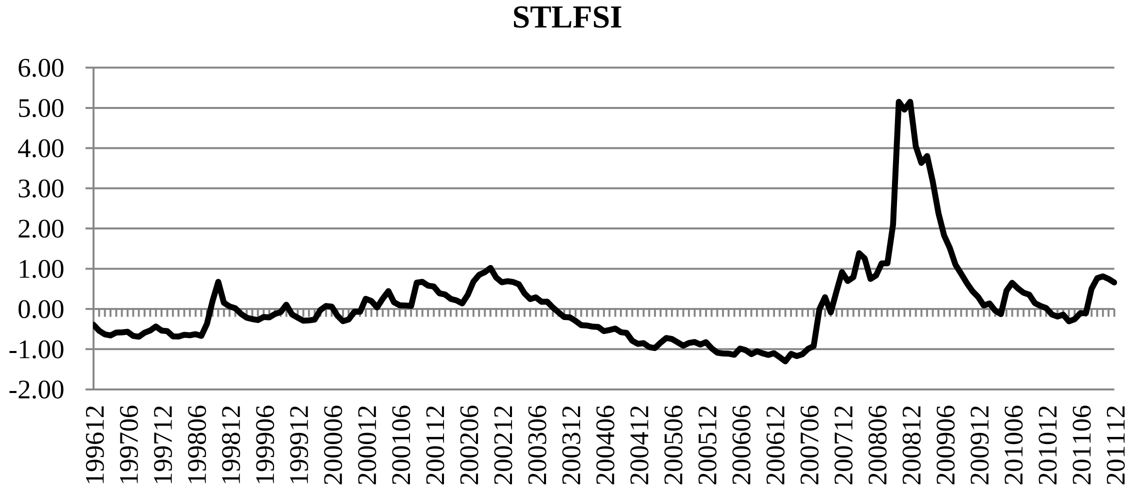


Fig. 4. This figure contains monthly data of the St. Louis Fed Financial Stress Index (STLFSI), from 12/1996 to 12/2011.