Analysis of Three Decades of Systemic Risk Evolution in the USA: A Comprehensive Commentary

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Abstract

This paper studies the systemic risk evolution of the recent three decades in the U.S. asset market. We present a framework in which idiosyncratic risks, network connectedness, systemic risks and risk spillovers are comprehensively analysed with period classification. We retrospect the financial history of three decades, such as war, stock market bubble, and oil price crash, then classify these years into four categories, namely major crisis, mini crisis, volatile period and stable period. With the quantitative analysed based on our framework, we understand not only why global financial crisis is so bad, but also how regulators have successfully prevented the many historical shocks evolving into crisis. The results shows that there is a rationale for controlling the risk connectedness beforehand that the vulnerability increases when spillover risk channels are strong. However, the evolution processes from shocks to crisis are often disrupted by the stimulated economic growth and bull stock market.

Jel-Codes: C32, C58, G11, G32, Q49

Keywords: Asset market, Systemic risk, Risk spillover, High-dimensional network

I. Introduction

This paper provides a comprehensive commentary on the spillover risk and systemic risk of financial assets. A financial asset is a valuable investment, and can take different classes such as equity (stock), fixed income (bond), cash and cash equivalent, commodity, real estate, and other financial derivatives. Systemic risk is a very important underlying fundamental risk that an economy faces and can be influenced by many factors. A variety of factors such as the disruption of fundamental linkages resulting from established by macroeconomic shocks, changing investors' expectation, information asymmetry issues, the idiosyncratic risk of a given asset that causes negative externalities on other assets (i.e., spillovers) can snowball into systemic risk. As generally recognized, the global financial crisis (GFC) in 2008 is a systemic risk catastrophe where the interactions and linkages played big roles in accelerating the crisis (Dungey and Martin, 2007; Bekaert et al., 2014; Guidolin et al., 2019). Systemic risk is a critical factor in the supervision of financial stability, especially after the GFC (Dicks and Fulghieri, 2019; Jotikasthira et al., 2015). We study the spillover risk and systemic risk at asset level to provide support for policies of crisis precaution and post-crisis recovery. This paper also contributes a better understanding for portfolio management. The existing diversification strategies in portfolio management can be influenced by changes in the correlation between assets, particularly during a crisis period (Dungey and Martin, 2007). The nature and dynamics of spillover risk at asset level help speculate the consequent portfolio return when extreme events occur.

A vast literature focuses on the risk spillover across global markets, see for an example, Raddant and Kenett (2021). However, we argue that the domestic shocks and spillover risks in home occur before spreading across national boundaries. For example, the GFC originated from United States in a relatively small segment of the equity market, namely the subprime mortgage market (Bekaert et al., 2014), emphasising the crucial requirement to understand how spillover risks originate and disseminate. This paper focuses on the evolution of spillover risk network in U.S. as the U.S. financial market always plays the central role of risk exporter to other countries (Raddant and Kenett, 2021)[1]. Our work help understand the domestic spillover relationship and guide risk regulation to take corrective action to prevent a global spread.

In this paper, we study the spillover risk and systemic risk in an inclusive picture with more asset classes, than done in prior studies. Although there is reasonably large literature on the spillover risk at asset level, the prior research focused on limited asset classes[2]. An inclusive picture with more asset classes contributes to formulate effective risk regulation from a policy perspective whilst considering a multi-asset portfolio strategy would help market participants to develop effective trading strategies that take into account the correct risk-return profiles of assets. Hence we study four asset classes, i.e., stocks, commodities, currencies and bonds.

This paper utilizes the panel spanning nearly three decades (1991-2019) to answer three questions. First, how did systemic risk evolve in the U.S. asset market? Since the early 1990s, the U.S. macro economy has developed and financial market integration has always been underway. The financial market interacts and integrates far more today compared to a few

[1] The central role of risk exporter is related to the influential U.S. monetary policies (Fratzscher et al.,), U.S. dollar holding willingness (Maggiori et al., 2020) and other factors such as market size.

[2] For instance, Maghyereh et al. (2016); Zhang (2017); Junttila et al. (2018); Nguyen et al. (2020) study the relationship between oil price and stocks. Baur and McDermott (2010); Bredin et al. (2015); Junttila et al. (2018); Nguyen et al. (2020) focus on the dependence between stock and precious metal (gold and silver). David and Veronesi (2013); Goyenko and Sarkissian (2014); Cieslak and Povala (2015); Hong et al. (2017); Bauer and Rudebusch (2020) and Pitkäjärvi et al. (2020) detect the hedging effects and correlation between bond and stock. Andrew Karolyi and Wu (2021) focuses on the effect of global equity market on currency risk. The research of Dungey(2018) and Yoon et al. (2019) covers the interaction of three types, namely, bonds, currencies and commodities.

decades ago (Billio et al., 2017) intensifying the spillover risk and systemic risk in asset markets. We analyze the evolution of the asset risk spillover network to deepen our understanding of the current situation of the U.S. asset markets and how we evolved in terms of risk to this stage.

Second, what is the difference between long-term and short-term spillovers between assets? The analysis among various asset classes is also meaningful for portfolio strategies and investment decision making. Long-term risk spillover can provide information in permanent investment (Chen et al., 2007), but it will not so with the case in short-term fluctuations. In extreme events, long-term relationships might be broken while short-term relationships could be established in new forms (Dungey and Martin, 2007). The asset groups with high value of spillover risk in the short-term should not be utilized as hedging portfolios. To answer this question, we conduct an analysis of the network connectedness and spillover in both full-period and annual horizon.

Third, we study what the symptoms of a crisis is and investigate how it might be prevented. From the start of 1990s, the Gulf War (1990-1991), Asian Financial Crisis (1997), the Global Financial Crisis (2008), European Sovereign Debt Crisis (2010), stock crashes (e.g. U.S. dotcom bubble crash of 2000–2002) and many other extreme events have impacted the stability of U.S. financial market. The impact of these events on the U.S. financial market has been analyzed at different levels[3]. However, the risk spillover network in asset markets have

[3] For instance, the impacts of wars have been studied by Biswas and Shawky (1997); Xu and Lien (2020); Gong et al. (2020); Auray and Eyquem (2019); Rigobon and Sack (2005). Literature of Muir (2017); Calomiris et al. (2012); Raddant and Kenett (2021); Jordà et al. (2011); Balcilar et al. (2018); Nasir and Ismail (2020); Guidolin et al. (2019); Schularick and Taylor (2012); Maggiori et al. (2020); Cai et al. (2020); Dungey and Renault (2018) studied the 2008 financial crisis. Literature of Dungey and Renault (2018); Kaminsky and Reinhart (1999); Dungey and Martin (2007) studied the 1997 Asian financial crisis. Literature of Lane (2012); Balcilar et al. (2018); Dungey and Renault (2018); Xu et al. (2019) studied the European sovereign debt crisis. Literature of Wang et al. (2009); Nasir and Ismail (2020); Jayech (2016); Gonzalez et al. (2005); Doblas-Madrid (2012) studied the impacts of stock market collapse, bull and bear stock market, and the price cycle. The impacts of wars have been studied by Biswas and Shawky (1997); Xu and Lien (2020); Gong et al. (2020); Auray and Eyquem (2019); Rigobon and Sack (2005).

not been comprehensively measured in a unified framework. Therefore, this paper proposes a period classification based on the magnitude of systemic risk. We adopt Fisher-Jenks' clustering algorithm of Jenks and Caspall (1971) and Fisher (1958) which minimizes the intra-group absolute deviations, to identify the threshold value and conduct classification on a yearly basis. We divide the sample period into four categories, namely major crisis, mini crisis, volatile period and stable period. By concerning all results of idiosyncratic risks, network connectedness, systemic risks and risk spillovers comprehensively, we rationalize the period classification and analyse the features of each category. It enables us to understand what factors in policies, economics and the financial markets have an effect on financial stability. The experience summarized from these historical events can also be applied to prevent a new crisis at the early stage of a shock.

This paper presents a framework in which idiosyncratic risks, network connectedness, systemic risks and risk spillovers are comprehensively analysed with period classification. Firstly, we construct a high-dimensional network with a sparseness setting. Network analysis has provided useful techniques to study the relationship in large dimensions which help overcome the curse of dimensionality. In our paper, the asset network built on the conditional volatility estimated by the best-fitting GARCH models selected by AIC and post-test of ARCH effect on the standardized residuals. With the best-fitted GARCH models, the idiosyncratic risk of each asset is measured by Value-at-risk. Afterwards, we apply a VAR approach where the sparseness of autoregressive matrices is assumed to facilitate high-dimensionality by a LASSO-type algorithm following Barigozzi and Brownlees (2019). The generalized variance decomposition (Diebold and Yilmaz, 2014, 2015; Demirer et al., 2018) is applied to obtain the connectedness measures. The sum of the connectedness among assets measure the impulse response-based interaction from system-wide to pairwise, which is utilized as a measure of spillover risk (Diebold and Yilmaz, 2014). However, as Hautsch et al.

(2015) argued, the idiosyncratic risk and the connectedness jointly determine the potential distress of the entire asset market. Thus, the systemic risk in this paper is composed from the connectedness network and idiosyncratic risk profile (value-at-risk) of each asset. We analyze risk spillover by utilizing the risk decomposition approach of Das (2016) and Chen et al. (2019). The spillover risks among assets is regarded as a directional topological network, with assets acting as nodes and spillover risks acting as edges. We also derive the risk decomposition approach into group-level horizon and asset-specific systemic risk contribution. By concerning all empirical results, including idiosyncratic risks, network connectedness, systemic risk, spillover risk, and systemic risk contribution, we characterize every type of event in detail.

We use the daily price of 29 assets in four classes, i.e., stocks, commodities, currencies and bonds from Jan 2, 1991 to Dec 31, 2019, for empirical study. Our primary findings include: (1) From 1990s to 21st century, connectedness of the network was accumulating and assets become more and more related with each other. The intensified connectedness caused a weak self-healing capability of financial markets, while the government is passively conscripted to implement policy in speed to prevent crisis. (2) There are high values of connectedness in both long-term and short-term horizons, in the stock group and bond group respectively. (3) The strong connectedness between assets widely exists in the short-term horizon, while there is relatively weak connectedness in the long term. (4) Stocks and commodities are the major risk contributors of systemic risk in both long-term and short-term horizons. (5) There are three significant peaks of systemic risk during the sample period, corresponding to the Persian Gulf war (1991), Global Financial Crisis (2008-2009), and U.S. stock market crash (2011). (6) The Global Financial Crisis of 2008-2009 is featured by the concurrent of high idiosyncratic risk, strong connectedness and a long-time evolutionary process. (7) Mini crises always have a short duration, a limited impact range, and a fast recovery speed, with high value of idiosyncratic risk and the strong connectedness in a minority of assets. Our period classification shows that volatile periods are the transitional periods between stable and crisis periods, where the shocks suppressed by regulation. The stable periods are always accompanied with low idiosyncratic risk and weak connectedness.

The paper proceeds as follows. The methodologies for network connectedness and spillover risk are introduced in section 2. Section 3 describes the data used for network modelling. Section 4 analyses the empirical results of connectedness and difference between the long-term and short-term spillover risk. In section 5, we study specific historical shocks, including the financial crisis, war, and post-crisis era. Finally, section 6 concludes this paper.

II. Methodology

This paper presents a three-step framework in which idiosyncratic risks, network connectedness, systemic risks and risk spillovers are comprehensively analysed with period classification. Firstly, we use several GARCH models and select the best-fitting model based on Akaike information criteria (AIC) and the post ARCH effect test of standardized residual. The series of conditional volatility and Value-at-Risk (VaR) are estimated.

Second, the connectedness measures are based on sparse VAR and generalized variance decomposition, developed from a series of earlier papers that include Diebold and Yilmaz (2014, 2015); Demirer et al. (2018); Barigozzi and Brownlees (2019). The sparseness of autoregressive matrices is assumed to facilitate high-dimensionality by a LASSO-type algorithm called nets in Barigozzi and Brownlees (2019).

Finally, we study the aggregated risk and spillover across assets. We develop the technique of Das (2016) and Chen et al. (2019) to quantify the risk contribution of each asset, and aggregate the risk contribution as systemic risk score in a network. The risk score is a comprehensive measure of idiosyncratic risks, network connectedness, systemic risk and risk spillover in both asset-level and group-level. We measure the spillover effects for each pair of source and target assets. In the end, we calculate the spillover risk in group-level horizon, such as stock, commodity, currency and bond, and study the dynamics.

A. Asset-specific conditional volatility and idiosyncratic risk

We first estimate the conditional volatility and idiosyncratic risk for all the assets. Estimation of the univariate marginal distribution model is fundamental to estimating the VaR of each underlying series. We model the daily return by different variations of ARMA(m,n) model with the standard residuals following Normal, Student-T, and Skewed-T distribution. To model the conditional variance, we utilize several GARCH (p,q)-type (GARCH, IGARCH, EGARCH, GJR-GARCH, and TGARCH) frameworks with different lag lengths (p,q). Based on AIC and post-test of standardized residual, we select the model with the best performance, which is the ARMA (3,3)-GARCH (3,3) model with Gaussian distribution.

The ARMA (3,3)-GARCH (3,3) model with Gaussian distribution is formed as follows. Let $r_{i,t}$ denote the stochastic process of return for the i_{th} series:

(1) $$r_{i,t} = \mu_i + u_{i,t} + \sum_{m=1}^{3} \omega_m r_{i,t} + \sum_{n=1}^{3} \beta_n u_{i,t-\mathrm{n}}$$

where μ_i is the mean term, $u_{i,t} = \varepsilon_{i,t}\sigma_{i,t}$ are the residuals. The white noise process, $\varepsilon_{i,t} \sim i.i.d(0,1)$, a Gaussian distribution. We model the conditional volatility, $\sigma_{i,t}$, for each univariate series by utilizing the GARCH(3,3) specification as:

(2) $$\sigma_{i,t}^2 = \theta_0 + \sum_{p=1}^{3} \theta_p \, {u_{i,t-p}}^2 + \sum_{q=1}^{3} \eta_q \, \sigma_{i,t-q}^2$$

where $\theta_0 > 0$, $\theta_\mathrm{p} > 0, \eta_q > 0$. The idiosyncratic risk is measured by value-at-risk (VaR), which can be estimated by a percentile (i.e., quantile) of the stochastic process of return.

(3) $$VaR_{i,t} = -\left[\widehat{\mu_i} + \sum_{m=1}^{3} \widehat{\omega_m} r_{i,t-m} + \sum_{n=1}^{3} \widehat{\beta_n} u_{i,t-\mathrm{n}} + qnorm(q)\hat{\sigma}_{i,t}\right]$$

where qnorm(q) denotes the corresponding quantile of the Gaussian distribution in quantile level q. We estimate VaR specifications for q = 0.05 for all series. Note that qnorm(q = 0.05) is located in the left of the distribution curve and the quantile value is negative. We obtain the positive series by adding a minus sign in the equation (3) for the convenience of the subsequent calculation.

B. Sparse VAR and nets algorithm

The network representation in the energy sectors is analyzed by applying an ultrahigh-dimensional vector autoregression (VAR) model and the generalized variance decomposition of the DY (2014) framework. With the N-dimensional multivariate time series of estimated conditional volatility $y_t = \{y_{1,t}, y_{2,t}, \dots, y_{N,t}\}$, we estimate the VAR in p-order as:

(4) $$y_t = \sum_{k=1}^{p} A_k \, y_{t-k} + \varepsilon_t, \ \varepsilon_t \sim i.i.d(0, C^{-1})$$

where the autoregressive matrix A_k and the concentration matrix C are $N \times N$ matrices. To maintain the degree of freedom in VAR estimation for high dimensional network, the matrices A_k and C are assumed to be sparse matrices so that the important connections are identified while the weak or insignificant connections are excluded from the network connectedness. Following Barigozzi and Brownlees (2019), we estimate the sparse VAR systems and adopt the nets algorithm for the estimations of network connectedness. The nets algorithm has a LASSO-type estimator as

(5) $$\widehat{d_T} = \arg\min \left[\frac{1}{T} \sum_{t=1}^{T} l(d; y_t, \hat{c}_T) + \lambda_T^G \sum_{k=1}^{p} \sum_{i,j=1}^{n} \frac{|\widetilde{\alpha_{\iota,J,k}}|}{|\widetilde{\alpha_{T,\iota,J,k}}|} + \lambda_T^C \sum_{\substack{l,h=1 \\ l>h}}^{n} \frac{|\rho^{lh}|}{|\tilde{\rho}_T^{l,h}|} \right]$$

where $l(d; y_t, \hat{c}_T)$ denotes the quadratic loss function with the parameters to be estimated. $\lambda_T^G > 0$ and $\lambda_T^C > 0$ denotes the LASSO shrinkage tuning parameters, $\widetilde{\alpha_T}$, $\widetilde{\rho_T}$ and $\hat{c}_T$ are the pre-estimator of the α, ρ and c coefficients.

We adopt the way of Barigozzi and Brownlees (2019) to initialize the pre-estimator and estimate the VAR model. The pre-estimator of the parameter matrix A is the least squares estimator of the VAR, while the pre-estimator of the ρ is the partial correlation estimator of the covariance of the VAR residuals. We initialize matrix C by the reciprocal of each series' sample variances. The value of penalties λ_{GT} and λ_{CT} are determined by a cross-validation procedure. The entire sample is split into estimation and validation sample that respectively corresponds to the first 75% and the last 25% of the entire sample. With a grid of λ_{GT} and λ_{CT} values given, we first estimate the model in the estimation sample and then compute the residual sum of squares (RSS) in the validation sample. We choose the optimal penalty parameters as those that minimize the validation RSS.

Because the restriction on nets algorithm is that the input of estimation is zero-mean time series, the volatility series that obtained from ARMA (3,3)-GARCH (3,3) model with Gaussian distribution are standardized to have zero mean value. The mean values only affect the intercept term, so the results will not be influenced by the standardization. Specifically, we take the log value of conditional volatility, and then minus the mean value for each asset which is zero-mean standardization.

After the VAR process, we apply H-step-ahead generalized variance decomposition that allows us to generate an adjacency matrix $\theta^H = \left[\theta_{ij}^H\right]$, whose entries are given by

(6) $$\theta_{ij}^H = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' \Theta_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' \Theta_h \Sigma \Theta_h' e_i\right)}$$

where Σ is the variance matrix of the error vector ε_t, σ_{jj} is the standard deviation of the error term for the j_{th} series, and e_i is the selection vector equal to 1 for the j_{th} element and 0 otherwise. For $h = 0,1,2, \ldots$, the $N \times N$ coefficient matrices Θ_h can be obtained using the following iteration

(7) $$\Theta_h = A_1\Theta_{h-1} + A_2\Theta_{h-2} + \cdots + A_p\Theta_{h-p}$$

where Θ_0 is a $N \times N$ identity matrix and $\Theta_h = 0$ for $h < 0$. The direction and magnitude of each node are different based on the degree of connectedness across the time series.

The entries in the adjacency matrix are defined as the proportion of the H-step ahead forecast error variance of i_{th} firm which is accounted for by the innovations in j_{th} firm in the VAR. For each entry in the adjacency matrix, $\theta_{ij}^{H} > 0$ indicates an influence of firm j on firm i. A higher value of θ_{ij}^{H} implies that the corresponding connection between two firms is stronger.

C. Systemic and spillover risk

In the literatures of systemic risk in financial market, the idiosyncratic risk profile always act as the driver of risk spillover and be involved in the systemic risk modeling, see Hautsch et al. (2015) and Adrian and Brunnermeier (2016). Therefore, we measure the systemic risk by combining the connectedness with the idiosyncratic risk. Das (2016) and Chen et al. (2019) provide the technique to quantify the aggregated risk score in a network comprised of related entities by combining adjacency matrix together with a compromise loading. In this paper, we use the VaRs of assets as the compromise level.

With the level of compromises $V = (VaR_1, VaR_2, \dots, VaR_N)^T$ and adjacency matrix θ^H obtained in section 2.2, we estimate the risk aggregated score S_{system} by

(8) $$S_{system}(V, \theta^H) = V^T \theta^H V$$

To measure the systemic risk contribution of each asset, the aggregate risk score S_{system} is decomposed into individual nodal contribution by Euler's theorem[4], as

(9) $$S_{system}(V, \theta^H) = \frac{1}{2}\left[\frac{\partial S}{\partial V_1} V_1 + \frac{\partial S}{\partial V_2} V_2 + \cdots + \frac{\partial S}{\partial V_N} V_N\right]$$

[4] Euler's theorem states that for a function $f(x)$, $x \in R^N$ is homogeneous of degree n, it may be written as $\frac{1}{n}\sum_{i=1}^{N} \frac{\partial f(x)}{\partial x_i} x_i$

where $\frac{\partial S}{\partial V_i} = \sum_{j=1}^{n} \theta_{ij}^{H} + \theta_{ji}^{H} V_j$ is the risk increment that indicates the change in the aggregate network risk score S when the compromise score V_i changes. From the aggregated risk score, we decompose the systemic risk contribution by

(10) $$D_i = \frac{1}{2} \frac{\partial S}{\partial V_i} V_i$$

Then the risk spillover between each pair of series (i, j) can be also decomposed

(11) $$S_{ij} = V_i^T \theta_{ij}^H V_j$$

It is noteworthy that the $S_{system} = \sum_{i=1}^{N} \sum_{j=1}^{N} S_{ij}$, where N denotes the number of companies in this network. The systemic risk score measures the aggregated value of all risk spillovers over the market.

Although in Diebold and Yilmaz (2014), $\theta^H = [\theta_{ij}^H]$ was directly applied to calculate spillover risk, in this paper we propose S_{ij} to measure spillover risk instead of using θ^H for two considerations: (1) The heteroskedasticity of asset return. As we mentioned above, the entries of $\theta^H = [\theta_{ij}^H]$ are the proportion of the H-step ahead forecast error variance of i_{th} node due to the standard error shock in j_{th} node in the vector autoregression, where the error variance of i_{th} node and standard error shock in j_{th} node are static. The S_{ij} considers the ceaseless changes in volatility of the connected nodes. When we use time-varying compromises, such as in daily frequency, the dynamic aggregated risk is obtained. (2) The extreme risks of assets. Even if two assets have the same volatility, the asset with fatter tail signifies more extreme risks. The quantile value that reflects fattailedness and extreme risks is contained in the VaR calculation. The θ^H depends on the standard error. Thus, adding the VaR as compromises consider the difference in spillover risk caused by the extreme risks, not just volatility.

Accordingly, given group M and N as import and export panels, the risk score that measures the spillover from group N to M is specified as

(12) $$S_{MN} = V_M^T \theta_{MN}^H V_N$$

where V_M denotes the panel of idiosyncratic risks that belong to group M. The θ_{MN}^H is the submatrix of adjacency matrix θ^H that indicate the shares of error variance in all series in Group N due to shocks of all series in Group M. Note that $S_{system} = \sum_{M=1}^{G} \sum_{N=1}^{G} S_{MN}$, where G denotes the number of groups.

As shown in this subsection, the risk score is computed based on the idiosyncratic risks and network connectedness, which can be decomposed into risk spillover in both asset-level and group-level. Thus, risk score is a comprehensive measure of idiosyncratic risks, network connectedness, systemic risk and risk spillover. Our investigation on the risk score constitutes a big picture of the risk profile in financial system and provides a new tool to risk management.

III. Data

Our dataset contains daily data of 29 assets in four classes including stock, commodity, currency, and bond traded in U.S. asset market, listed in Table 1. Specifically, we use S&P 500 sectoral index price of 10 industrial sectors, future price of 9 commodities, exchange rate of 5 major currencies to U.S. dollar, ten-year government benchmark index for 5 countries' bonds. The dataset covers the period from Jan 2, 1991 to Dec 31, 2019 (7,565 daily observations). To understand the basic time background of our analysis, Table A1 enumerates the key events in global financial markets during the sample period 1991 to 2019. The log return for each asset is computed by taking the differences between the natural logarithm of two successive prices. In follow-up the daily returns used in estimation are 100 times the log returns. The prices of all assets are plotted in Figure A1. Descriptive statistics of return are provided by group in Table A2.

<< Insert Table 1 here >>

IV. Empirical Results

A. Idiosyncratic Risk and Connectedness

The dynamics of idiosyncratic risks are shown by group in Figure 1. The mean value of VaR for commodity is 3.179, which is much larger than other asset classes. The stock exhibits second highest VaR among the four classes in sample period, but take account for the largest risk during the global financial crisis and other stock market crash. The dynamic VaR of the bonds and currencies are the lowest and second lowest among the four-underlying classes with simultaneous periods of rising and falling trends. At the beginning of 1991, VaRs of stock and commodity show a simultaneous decline. From 2007 to 2009, the VaRs of four asset classes have homogeneous upward and downward dynamics.

<< Insert Figure 1 here >>

With the sparse VAR, nets algorithm and generalized variance decomposition, we estimate the adjacency matrices in full-sample and annual panels. The topological network in Figure 2 show the connectedness among assets in long and short terms. Comparing the long-term and short-term connectedness, we find that the majority of connectedness between two different classes only appeared in short term. We notice that for stock group and bond group, there are strong self-connections in both the long-term and short-term horizon. The strong self-connections inside U.S. stocks may be attributed to the influenced by the similar market-level information that grabs investors' attention and retail investor sentiment (see, Stulz, 2005; Kumar and Lee, 2006; Errunza and Ta, 2015; Huang et al., 2019). Note that in the long term, S&P 500 Sector of Energy, Communication Services, and Utilities have relatively weak connectedness with other stocks. There are three pairs of non-stock assets with long-term connectedness, which are German bond with French bond, oil with ULSD, and gold with silver. Another interesting finding is that the connectedness between Germany bond and French bond are asymmetric in short-term, where Germany bond exports higher impacts on French bond than the opposite direction.

The short-term connectedness widely exists between stocks and fuels (oil and ULSD), which is in line with the studies of interactions between fuel price and stocks (e.g. Maghyereh et al., 2016; Zhang, 2017; Junttila et al., 2018; Nguyen et al., 2020). The short-term connectedness also exists between stock and precious metal (gold and silver), which could be attributed to the safe-haven strategies (see, e.g., Baur and McDermott, 2010; Bredin et al., 2015; Junttila et al., 2018; Nguyen et al., 2020). The connectedness between U.S. bond and stock can be significantly observed in both short and long term, which is in line with literatures David and Veronesi (2013); Goyenko and Sarkissian (2014) and Pitkäjärvi et al. (2020). The connections from bonds to currencies and commodities are significant in both short term, which may be attributed to the fact that a Treasury bond is used in asset valuation as a risk-free asset to calculate equity premium. The interest rate of Treasury bond, as a benchmark, influences the expectations in macroeconomics (such as inflation) and expected return on investment (see, David and Veronesi, 2013; Goyenko and Sarkissian, 2014; Cieslak and Povala, 2015; Hong et al., 2017; Bauer and Rudebusch, 2020).

<< Insert Figure 2 here >>

To portray the dynamics of network connectedness, the Figure 3 provides the sum of connectedness in each year. From 1990s to 21st century, connectedness of the network was accumulating and assets become more and more related with each other. The intensified connectedness caused a weak self-healing capability of financial markets, while the government is passively conscripted to implement policy in speed to prevent crisis. From the top-right graph which presents the sum value of connectedness inside each class of asset, we find that the self-connections in stock group is much higher than those in other asset classes. The self-connections in stock group peaked in 1997, 2007 and 2011, corresponding to Asian financial crisis, U.S. stock market crash of 2007 and 2011. Comparing the bottom-left graph that presents the received connectedness with the bottom-right graph that presents the output connectedness, and it is interesting to note that, during the global financial crisis, stocks exported high value of connectedness to other assets instead of the opposite direction, which is in line with the literature about the development of this crisis evolving from U.S. stock market crash to global crisis. The currency receives more connectedness than bond, while outputs fewer connectedness than bond, which is consistent with the role of bond we mentioned before, such as the expectations in macroeconomics (e.g., inflation) and benchmark return on investment.

<< Insert Figure 3 here >>

B. Systemic and Spillover Risk

Following the technique that quantifies the aggregated risk in a network, the results of systemic risk and systemic risk contribution are shown in Figure 4 and 5. The systemic risk is less than 1000 in normal situation, while there are three peaks in 1991, 2008 and 2011. The event analysis about these time points will be stated in next section. Taking the long view of the three decades, the stocks and commodities are the major risk contributors of systemic risk. Although the average risk contributions of stock and commodity have similar value, the stock experienced more volatile dynamics. Considering the former analysis in section 4.2 that U.S. stocks are closely self-connected, the high value of idiosyncratic risk occurred in extreme event can accumulate inside the stock market and lead to an extremely high systemic risk contribution. The oil, ULSD, and gas contributed great volume of systemic risk. The high contribution of commodities may also influence the commodity market and the growth of commodity-link funds (see, e.g., Nguyen et al., 2015, 2020; Sun et al., 2018; Gao and Nardari, 2018; Daskalaki and Skiadopoulos, 2011; Junttila et al., 2018), which increases connectedness with stock market. This finding is also in line with Hong and Yogo (2012) that indicated movements in commodity market interest predict returns of currency, bond, and stock markets. The groups of currency and bond have insignificant contribution to the systemic risk in the majority of years, although exacerbating the systemic risk during the global financial.

<< Insert Figure 4 here >>

<< Insert Figure 5 here >>

The results of long-term and short-term spillover risk are respectively estimated by full-sample panel and annual panel data, presented in Figure 6. We observe that the strong spillover risks widely exist in short-term horizon, while there are relatively few spillover risks in long term. A majority of short-term spillover risk between specific asset pairs disappeared in long term, such as the spillover risk from ULSD to S&P 500 materials sector. The insignificant spillover risk between these asset pairs are caused by two underlying reasons. Firstly, there is no persistent relationship between the asset pairs. The spillover risk in short-term horizon may be attributed to short-term position changes, such as dramatic short selling of one stock driven by events, attention-grabbing information, and media-expressed tone (Yuan, 2015; Ahmad et al., 2016). Heterogeneous risk exposures, such as regional fluctuations and industry-specific shocks (Korniotis, 2008; Eiling, 2013; James and Kizilaslan, 2014), result in less correlation and lower proportion of strong spillover risk in the long-term horizon. Secondly, the level of idiosyncratic risk is relatively low, which is too safe to cause a spillover risk. The spillover risks that persist in long term often have the following features. The asset-level spillover risk in long-term horizon may be related to assets' similarity (such as oil with ULSD, and gold with silver), development of stock market, as well as the industry chain (e.g., the spillover risk from ULSD to S&P 500 energy sector).

<< Insert Figure 6 here >>

The long-term spillover risk could be useful for policy-making about risk management as well as long-term asset investment, while the short-term spillover risk provides appropriate insight to emergency risk regulator, short-term asset investors and speculators. Among the spillover risk channels that have been investigated by Jotikasthira et al. (2015),Yuan (2015) and, Bekaert et al. (2013, 2016), macroeconomic shocks transmission, equity market openness, telecommunication coverage, average relative equity market capitalization, financial reform orientation, real interest rates, bilateral FDI holdings are changing slowly, so the risk spillover caused by these channels exists in every period. While information transmission, emotional shock, attention-grabbing events are more vulnerable by transient fluctuations, which are considered as the channels of short-term spillover risk. In other words, the long-term spillover risk is led mainly by the first type of channel, while the short-term spillover risk affected by both types of channels. By taking the difference between short-term and long-term risk spillover, we observe the impacts of the transient fluctuations of the second channel, namely the marginal spillover risk.

Table 2 presents the results of long-term, short-term and marginal spillover risk by groups. The stock and commodity groups have high value of marginal spillover risk with each other, indicating that commodities and stocks are likely to be impacted by sentiment-driven fluctuations, attention-grabbing events, and information frictions, resulting in co-movement and similar price fluctuations. Currencies have very small short-term impacts on others, but in long term the impacts are relatively bigger. Negative marginal spillover risk in the item of "currency to currency" means the portfolio constituted by currencies are able to withstand the risks caused by short-term fluctuations. In short-term horizon, stocks and bonds acted as the source of spillover risk, because their input risk is less than the risk output to other classes. The value of spillover risk outputted by stocks is 147.297, while the imported spillover risk is only 134.054, under short-term turmoil and instability, which is in line with our previous finding that the stocks exported high value of connectedness to other assets instead of the opposite direction. In addition, it is noteworthy that bond exports more spillover risk to others than receiving, which may attribute to that Treasury bonds' role of benchmark that influences the expectations in macroeconomics and expected return on investment (see, David and Veronesi, 2013; Goyenko and Sarkissian, 2014; Cieslak and Povala, 2015; Hong et al., 2017; Bauer and Rudebusch, 2020).

<< Insert Table 2 here >>

V. Period Classification and Features

In this sector, we apply the measure of systemic risk score to analyse the historical changes in U.S. financial market in annual panel. The annual estimation results of network connectedness and spillover risk are shown in appendix Figure A6-A8. We identify the thresholds of systemic risk score, and conduct classification on a yearly basis, by adopting

Fisher-Jenks' clustering algorithm of Jenks and Caspall (1971) and Fisher (1958) which minimizes the intra-group absolute deviations. The sample period 1991-2019 is classified into four categories, as shown in Figure 7. Based on the empirical results of idiosyncratic risks, network connectedness, systemic risks and risk spillovers, the features of each category are summarized in Table 3.

<< Insert Figure 7 here >>

<< Insert Table 3 here >>

A. Major Crisis

The years of 2008-2009 are identified as major crisis. From the empirical results, we find that the Global Financial Crisis is featured by the simultaneity of three conditions: (1) high idiosyncratic risk, (2) strong connectedness and (3) long-term evolutionary process.

Firstly, the high idiosyncratic risk from 2008-2009 existed extensively in all asset classes (as shown in Figure 1), reflecting the large decline of asset prices after the collapse in mortgage market. In this time, investors are more likely to get a negative return on investments which bring pessimistic investment return expectations.

Secondly, the empirical results show that the connectedness linked across the asset class barrier and exceeded much more from the connectedness value in the normal state. Apart from the highly self-connected U.S. stock market, some assets in other asset classes such as commodity, currency, and bond also have strong connectedness with each other. Compared with the years before and after the crisis, the heatmaps in 2008 and 2009 have more connectedness coloured by red, as shown in Figure A6a.

Thirdly, the evolution process of a major crisis requires a long duration. The large-scale spread of the crisis takes a long time, often more than one year. From the beginning of the collapse, due to the large decline of asset prices and wide-spread connectedness among the asset market, there appeared to be a loss confidence for the whole asset market which resulted in a flight away from these markets. Fire sale caused a further decline of asset prices, because of the plummeting demand and the sudden increase in assets supply. Along with the continuous risk contagion, the scope of the crisis is constantly expanded, thus forming the huge scale of the GFC. From the empirical result shows that impacts between asset classes gradually replaced the impacts within asset classes. The subsequent macroeconomic downturn possibly caused the financial losses in such a widespread range. If a crisis causes macroeconomic downturn, it will back to impact the asset and intensify the connectedness (IMF, 2009; Giglio et al., 2016; Adrian et al., 2019). The underlying reason is that the amplification mechanism (see, Cifuentes et al., 2005; Brunnermeier and Pedersen, 2009; Glasserman and Young, 2015) and continuous strengthening of connectedness require a relatively long duration.

B. Mini Crisis

In this section we focus on mini crises. As shown in Figure 6, the years classified as mini crisis include the Persian Gulf War (1991), Asian Financial Crisis (1997-1998), Dotcom Bubble Crash and September 11 Attacks (2000-2002), European Sovereign Debt Crisis (2010), and U.S. Stock Market Crash (2011).

The mini crisis can be summarized by three features as follows. The first feature is that the high value of idiosyncratic risk (first requirement of crisis) was partly existing in a minority of assets. The asset class with high idiosyncratic risk depend on the background events, such as the commodities' risk in 1990-1991, and the U.S. stocks' risk in 2011-2012.

Secondly, strong connectedness (second requirement of crisis) was partly existing in a minority of assets. The assets with strong connectedness are always limited in one or two asset class. It is worth noting that in those periods with no crisis, such as in 2012 and 2014, the connections were sometimes strong as well, but because the idiosyncratic risk was low, the two requirements for risk contagion were not met simultaneously. By studying among Figure 3, A6a, and A7a, we discover several frequently occurring situations in mini crises. First of all, the internal linkages of U.S. stocks are very strong, and their independent risks have increased at the same time, causing the risk contagion inside the U.S. stock market. Second, prices of energy commodities, i.e., crude oil, ULSD, and gas commodity, acted as the main systemic risk contributors. Thirdly, in year of 1991, the U.S. stock market has serious impacts to energy commodities. Finally, during mini crises, there are strong connections among bonds of various nations, which may be related to the safe-haven activities.

Finally, mini crises always have a short duration, a limited impact range, and a fast recovery speed. The main reason for only parts of the market to be affected is that the crises was stopped by economic growth, bull stock market, quantitative easing, and other positive policies.

1. Persian Gulf War (1991)

The features in the Persian Gulf War (1991) can be summarized as high idiosyncratic risk of energy commodities, connectedness between stocks and energy commodities, some safe-haven investments (see, Baur and McDermott, 2010; Bredin et al., 2015) in bonds and precious metal, and limited range and short duration of impacts because of the asymmetric connectedness and 1990s economic boom in the United States.

2. Asian Financial Crisis (1997-1998)

There is a strong connectedness inside U.S. stock market in 1997. In 1998, the connectedness outputted and inputted by bonds intensified, which could be attributed to the risk-aversion activity. The Asian Financial Crisis 1997-1998 was a period of prosperity for the U.S. stock market (Radelet et al., 1998; Radelet and Sachs, 2000). In order to obtain greater investment income, hot money from Asia flows to the U.S. financial markets.

3. Dotcom Bubble Crash and September 11 Attacks (2000-2002)

During 2000–2002 when dotcom and internet-based businesses soared causing a rapid escalation in asset prices (Hill, 2018), the S&P 500 sector of information technology achieved a relatively high value of VaR. The connectedness outputted from S&P 500 sector of information technology intensified during 2000 to 2002, while the connectedness inside U.S. stock market grew simultaneously. The spillover risks from U.S. stock to currency & bonds are high during the dotcom bubble crash. For the September 11 attacks of 2001, the idiosyncratic risk of stocks and commodities experienced significant jumps in the short-run but recovered quickly afterwards. From the Figure 5, we see that the sector of consumer discretionary and the sector of industrials contributed a higher value to the systemic risk than other years. This may be related to the regional and sectoral impact of the terrorist attack, which is in line with the finding of Nikkinen et al. (2008). Figure A6a shows that, the terrorist attack in 2001 did not play a significant role in the gradual increase of connectedness between assets in comparison to the dotcom bubble crash of 2000–2002.

4. European Sovereign Debt Crisis (2010)

The European debt crisis is a multi-year crisis which started at the end of 2009 and have a long bailout period[5]. There was increased idiosyncratic risks for all asset classes with the anticipation of the “fear of Greece’s default” in 2010. The precious metal contributed some strong connectedness and spillover risk, which could be attributed to the safe-haven investment activity. The currencies contributed to a relatively higher systemic risk during the European debt crisis, which reflect the impact of European shocks to U.S. market.

The dynamics of connectedness and spillover risk during this period suggests that this crisis has not evolved into a global crisis or seriously impacted U.S. financial market. This could perhaps be due to the fact that the sovereign state bailout/precautionary programmes

[5] The European debt crisis started at the end of 2009 around European Union because of having difficulties in refinancing government debts or repayments of loans to Eurozone countries, European Central Bank (ECB) and International Monetary Fund (IMF).

launched by EFSF/ESM as well as the U.S. bull stock market stimulated by quantitative easing policy that contribute towards decreasing the idiosyncratic risk as well as connectedness.

5. U.S. Stock Market Crash (2011)

Downgrading America's credit rating by Standard & Poor's caused the surge of volatility and idiosyncratic risk in stocks and bonds occurred firstly, followed by the increase risk of currencies and commodities. The direction of connectedness from stock to currency is in line with the lead lag relationship in the price drops of foreign stock markets, which is also proved by Jayech (2016). Another finding is the increased price of safe-haven assets, such as gold, silver and Swiss Franc.

C. Volatile period

There are 10 years are classified as volatile period, including the years of 1996, 1999, 2003-2004, 2006-2007, 2012, 2015-2016, and 2018. The volatile period could be further summarized into tthree types. The first type is the shocks that have been subsided and regulated effectively by the government, such as 1999 Argentina crisis, 2015–2016 stock market selloff, and cryptocurrency crash in 2018. The empirical results show that the common features of these years are (1) high idiosyncratic risk in small range, (2) strong connectedness in small range, and (3) quick recovery that achieved by effective regulations. During the 2015–2016 stock market selloff, the U.S. stock witnessed a jump of idiosyncratic risk and high level of connectedness. The evolution of this shock was interrupted by resurgent economic growth and booming stock market resulted by the blockbuster corporate profits from sweeping tax. Along with new president elect, the U.S. indices increased through the end of the year, as investors bid up stocks in anticipation of deregulation, lower taxes, inflation and infrastructure spending.

The second type is the pre-crisis period. As shown by the Figure A6, the connectedness in 2000-2006 is greatly exceed the value in 1990s, which potentially caused systemic risk and hidden problems. The idiosyncratic risk of stocks maintained at low level because of that the slow steady growth of U.S. stock indices during 2003 to 2007, which limited the generation of a crisis. However, when the U.S. bear stock market started in October of 2007, the risks were spillovered through the strong connectedness, with systemic risk jumped rapidly as consequence. Thus, critical transition point from pre-crisis period to crisis period is the increase of idiosyncratic risk.

The third type is the post-crisis period. The year of 2012 is the post-crisis period after U.S. stock market crash (2011). From Figure A6a and A7a, we find that, although the strong connected structure was apparent in the assets market in 2012, the downtrend and low level of idiosyncratic risk takes the market out of danger. In this period, the Federal Reserve kept interest rates at the lowest level in two centuries to stimulate economic growth. Meanwhile, the dollar declined from 2012, helping exports and boosting economic growth. The strong connections are the catalyst for crisis years, but in the presence of bull market and economic growth, with the lack of first qualifying condition of high idiosyncratic risk, this situation cannot be classified as drastic.

D. Stable Period

As shown in Figure 6, the years of 1992-1995, 2005, 2013-2014, 2017 and 2019 are assessed as stable period. The results show that the stable period does not mean a lifeless economy without vitality, but the best period with economic growth or bull stock market. The idiosyncratic risk and connectedness in the stable period are extremely low.

During 1992-1995, the moderate uptrend of stock price is accelerated by finance-driven technology and R & D development (Brown et al., 2009; Galbraith, 2015), economic growth (Levine and Zervos, 1998), and investment boom (Tevlin and Whelan, 2003). As shown in Figure 1, the idiosyncratic risk of asset remained in a low level without rapid fluctuations during 1992-1995. The average connectedness in 1990s is lower than that in 2000s before Global Financial Crisis. The strong spillover risk among various classes of assets might be a result of the increase of assets global integration and increase in global leverage (Eichengreen, 2010; Mendoza et al., 2009; Fratzscher, 2012; Broner and Ventura, 2016; Caballero, 2016; Devereux and Yu, 2020). The linkages between stocks and non-stock assets are relatively not obvious in 1990s.

After the Global Financial Crisis, various stimulus policies have appeared in turn, such as quantitative easing, trade tariff policies, and changes in crude oil production, all of which are continuously stimulating the U.S. stock market. The stable periods of 2013-2014, 2017 and 2019 are related to these policies. There is strong connectedness in 2010, while the spillover risk remained at a low level. In the initial stage of crisis recovery, the risk of all asset decreased simultaneously, which is the reason of the strong connectedness in 2010. Strong connectedness provides channel and mechanism for crisis evolution (Hautsch et al., 2015; Jayech, 2016; Demirer et al., 2018). However, we find that in the presence of bull markets and economic growth to control the idiosyncratic risk, strong connectedness is not very bad. Thus, although the strong connected structure happened to the assets market, the downtrend or low level of idiosyncratic risk takes the market out of danger.

VI. Conclusion

In this paper, we build a high-dimensional network with 29 nodes in four asset classes, i.e., stock, commodity, currency and bond, with sample period from 1991 to 2019. We focus on specific historical shocks, including financial crisis, war, and post-crisis era. To our best knowledge, although firm-level and country-level connectedness has become a popular research area, impact of the listed events to the network connectedness and spillover risks in asset level have not been considered comprehensively. By concerning the all results of idiosyncratic risks, network connectedness, systemic risks and risk spillovers, we analyze the features and impacts of events mentioned above.

Based on the conditional volatility estimated by the best-fitting GARCH model, we apply a VAR approach and generalized variance decomposition to measure the connectedness in asset network. Motivated by Barigozzi and Brownlees (2019), the sparseness of autoregressive matrices is assumed to facilitate high-dimensionality by a LASSO-type algorithm of nets. The systemic risk is aggregated from the connectedness network and idiosyncratic risk profile of each asset. We analyze systemic risk contribution and risk spillover by utilizing risk decomposition approach of Das (2016) and Chen et al. (2019).

The empirical results show that in both long-term and short-term horizon, there are strong self-connections inside stock group and bond group. The majority of connectedness between two different classes appeared mainly in short term. The stock and commodity groups often have high spillover risk during transient fluctuations. Currencies have very small short-term impacts on other asset classes, but in long term the impacts are relatively bigger. In short-term horizon, stocks and bonds mainly acted as the sources of spillover risk. The strong spillover risks between assets widely exist in short-term fluctuation, while there are relatively few spillover risks in long-term horizon. From 1990s to 21st century, connectedness of the network was accumulating and assets become more and more related with each other. The intensified connectedness caused a weak self-healing capability of financial markets, while the government is passively conscripted to implement policy in speed to prevent crisis.

The sample period 1991-2019 are classified into four categories, namely major crisis, mini crisis, volatile period and stable period. By concerning the all results of idiosyncratic risks, network connectedness, systemic risks and risk spillovers comprehensively, we analyze the features of each category. The only identified major crisis, Global Financial Crisis of 2008-2009, is featured by the concurrent of high idiosyncratic risk, strong connectedness and longtime evolutionary process. Mini crises always have a short duration, a limited impact range, and a fast recovery speed, with high value of idiosyncratic risk and the strong connectedness existing with a minority of assets. The events of volatile period were always happened in a sector with lower systemic influence, such as Argentina crisis, Chinese stock market selloff, and cryptocurrency crash, there are normal limitations to spillover and evolve into a crisis. Thus, there is a rationale for controlling the risk connectedness beforehand that the vulnerability increases when spillover risk channels are strong. The stable periods are always accompanied with low idiosyncratic risk and weak connectedness. The economic growth or bull stock market stimulated by positive policies such as quantitative easing, and bailout/precautionary programmes act as the firewalls to prevent the volatile period from developing into a crisis.

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TABLE 1

Sample assets and class classification

No.	Asset Name	Abbreviation	Class
1	S&P500 ES HEALTH CARE	SP5EHCR	Stock
2	S&P500 ES CONSUMER DISCRETIONARY	SP5ECOD	Stock
3	S&P500 ES ENERGY	SP5EENE	Stock
4	S&P500 ES FINANCIALS	SP5EFIN	Stock
5	S&P500 ES INDUSTRIALS	SP5EIND	Stock
6	S&P500 ES COMM. SVS	SP5ETEL	Stock
7	S&P500 ES MATERIALS	SP5EMAT	Stock
8	S&P500 ES CONSUMER STAPLES	SP5ECST	Stock
9	S&P500 ES INFO TECHNOLOGY	SP5EINT	Stock
10	S&P500 ES UTILITIES	SP5EUTL	Stock
11	NYM-LIGHT CRUDE OIL CONTINUOUS	OIL	Commodity
12	NYM-NY HARBOR ULSD CONTINUOUS	ULSD	Commodity
13	NYM-NATURAL GAS CONTINUOUS	GAS	Commodity
14	CMX-GOLD 100 OZ CONTINUOUS	GOLD	Commodity
15	CMX-SILVER 5000 OZ CONTINUOUS	SILVER	Commodity
16	CMX-HIGH GRADE COPPER CONTINUOUS	COPPER	Commodity
17	CBT-WHEAT COMPOSITE FUTURES CONTINUOUS	WHEAT	Commodity
18	CSCE-COFFEE 'C' CONTINUOUS	COFFEE	Commodity
19	CSCE-COCOA CONTINUOUS	COCOA	Commodity
20	EURO TO USD	EUR	Currency
21	SWISS FRANC TO USD	CHF	Currency
22	GBP TO USD	GBP	Currency
23	AUD TO USD	AUD	Currency
24	CAD TO USD	CAD	Currency
25	US BENCHMARK 10 YEAR DS GOVT. INDEX	BMUS	Bond
26	BD BENCHMARK 10 YEAR DS GOVT. INDEX	BMBD	Bond
27	UK BENCHMARK 10 YEAR DS GOVT. INDEX	BMUK	Bond
28	JP BENCHMARK 10 YEAR DS GOVT. INDEX	BMJP	Bond
29	FR BENCHMARK 10 YEAR DS GOVT. INDEX	BMFR	Bond

TABLE 2

Intergroup spillover risk in short-term, long-term and marginal horizon

In the Panel A and B of Table 2, spillover risk is obtained by the equation (11), where we use the adjacency matrix estimated respectively in full-period and annual horizon. In the Panel C, the marginal spillover risk equals to the value in Panel B minus the value in Panel A, representing the risk spillover that caused by transient fluctuation.

Panel A: long term spillover risk

	Stock	Commodity	Currency	Bond	From
Stock	107.185	0.883	0.348	0.712	109.127
Commodity	0.883	121.202	0.273	0.208	122.566
Currency	0.349	0.273	7.949	0.411	8.982
Bond	0.712	0.208	0.41	7.855	9.185
To	109.128	122.567	8.98	9.187	249.861

Panel B: short term spillover risk

	Stock	Commodity	Currency	Bond	From
Stock	116.664	11.828	2.142	3.42	134.054
Commodity	19.879	124.134	2.666	3.602	150.281
Currency	6.091	4.144	7.144	2.184	19.563
Bond	4.664	2.92	0.969	8.224	16.776
To	147.297	143.026	12.921	17.43	320.674

Panel C: marginal spillover risk (= Panel B - Panel A)

	Stock	Commodity	Currency	Bond	From
Stock	9.479	10.945	1.794	2.709	24.927
Commodity	18.996	2.932	2.393	3.394	27.715
Currency	5.742	3.871	-0.805	1.772	10.581
Bond	3.952	2.711	0.559	0.369	7.591
To	38.169	20.46	3.941	8.244	70.813

TABLE 3

Summarized features of period categories

Table 3 reports the summarized features for four categories of period, based on the empirical results of idiosyncratic risks, network connectedness, systemic risks and risk spillovers.

Classification	Major Crisis	Mini Crisis	Volatile	Stable
Criteria	Systemic risk score ≥1008.8949 (Threshold5)	281.7657 (Threshold3) <Systemic risk score ≤1008.8949 (Threshold5)	190.3795 (Threshold2) <Systemic risk score ≤281.7657 (Threshold3)	Systemic risk score <190.3795 (Threshold2)
Years	2008-2009	1991, 1997-1998, 2000-2002, 2010- 2011	1996, 1999, 2003-2004, 2006-2007, 2012, 2015-2016, 2018	1992-1995, 2005, 2013-2014, 2017, 2019
Events	Global Financial Crisis	Persian Gulf war; Asian Financial Crisis; Dotcom bubble crash and September 11 attacks; European sovereign debt crisis; U.S. stock market crash	Energy price shocks; Argentina crisis; Chinese stock market selloff; Cryptocurrency crash; Pre-GFC period; Post-crisis period after U.S. stock market crash	Economic booms; Stimulus policies, such as quantitative easing, trade tariff policies, and changes in crude oil production
Risk Features	Major crisis is featured by the following three points. ● High idiosyncratic risk (first requirement of crisis) was widely existing ● Strong connectedness (second requirement of crisis) was widely existing ● Long duration of evolutionary process	Mini crisis is featured by the following three points. ● High idiosyncratic risk (first requirement of crisis) was partly existing in a minority of assets. The asset class with high idiosyncratic risk depends on the background events. ● Strong connectedness (second requirement of crisis)	The features of volatile periods vary with the background events. In sum, the two requirements were not met simultaneously. ● In pre-crisis period, some assets were stagnated in downward risk, while other assets prices increased. The connectedness was accumulating.	● The stable period does not mean a lifeless economy without vitality, but the best period with economic growth or bull stock market. ● The idiosyncratic risk in the stable period is extremely low. ● The strong connectedness sometimes occurs sporadically in the

		was partly existing in a minority of assets. The assets with strong connectedness are always limited in one or two asset class. ● Short duration, a limited impact range, and a fast recovery speed.	● In post-crisis period, the strong connectedness widely existed, with low value of idiosyncratic risk. ● In shocks which are handled by treating measures and policies, a few of assets have high idiosyncratic risk, and the connectedness is not as strong as major crisis.	asset market, but the downtrend or low level of idiosyncratic risk takes the market out of danger.
Explanation / Interpretations	● Falling asset price and pessimistic expectation brought the peak of idiosyncratic risk. ● The strong and market-wide connectedness is reflected in the flight away of all asset classes, i.e., sheep-flock effect and fire sale. ● With amplification mechanisms such as continuous strengthening of liquidity shortage and the subsequent macroeconomic downturn, the connectedness and idiosyncratic risk evolved and intensified gradually, forming a large-scale and long-duration crisis.	● This crisis has not evolved into a global crisis for reasons such as economic growth, and positive policies. If the crash happened in a sector with lower systemic influence, it is a normal limitation to spillover and evolve. In addition, if the crisis did not cause a serious damage to the real economy, it did not adversely affect other assets, disrupting the evolutionary of a market-wide crisis.	● In the volatile period, the appropriate emergency policies (such as quantitative easing, bid of investment, encouragement of domestic trade, etc) have encouraged the market expectation and faltered the high value of idiosyncratic risk (first requirement of crisis). ● The control on idiosyncratic risk contained the amplification mechanisms and disrupted the connectedness intensification, faltering the high value of connectedness (second requirement of crisis).	● When the driving forces of economic growth and booming stock market are strong, the high rate of asset return reduces the possibility of loss, that is, the idiosyncratic risk is reduced. ● The strong connectedness sometimes occurs sporadically in the asset market, while the connectedness always reflects the same trend and relation in decreasing risk and rising price among the asset market.

FIGURE 1

Value-at-risk by group

Figure 1 reports the daily value-at-risk averaged by group. Based on the sample data, we utilize the best-fitting model ARMA (3,3)-GARCH (3,3) with Gaussian distribution and estimate the daily value-at-risk in q = 0.05.

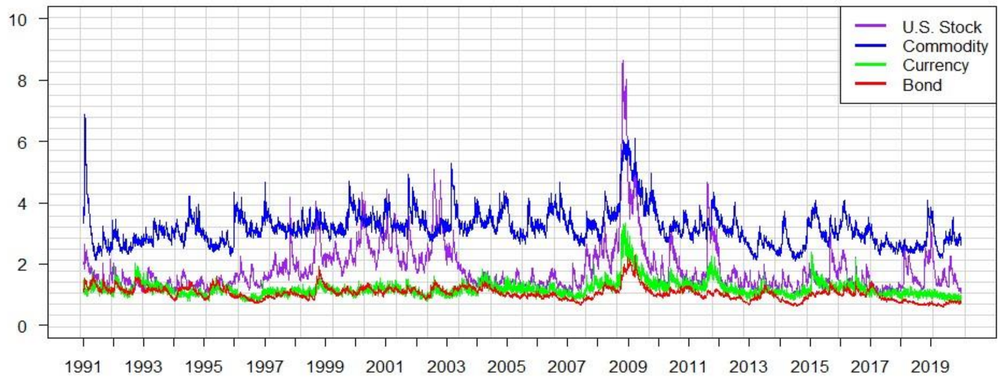


FIGURE 2

Topological network of connectedness

Figure 2 shows the topological network representation of adjacency matrix in long-term (left) and short-term (right) horizon, calculated by generalized variance decomposition in equation (6-7). The asset class of stock, commodity, currency, and bond are respectively indicated by blue, orange, carmine, and green. The long-term results of connectedness are estimated by full sample panel with T = 7,565, P = 1, H = 12, lambda = (19.531, 8750.000). The short-term results of connectedness is the averaged result over sample period, estimated by annual sample with T = 252, P = 1, H = 12, and lambda = (1.221, 78.125).

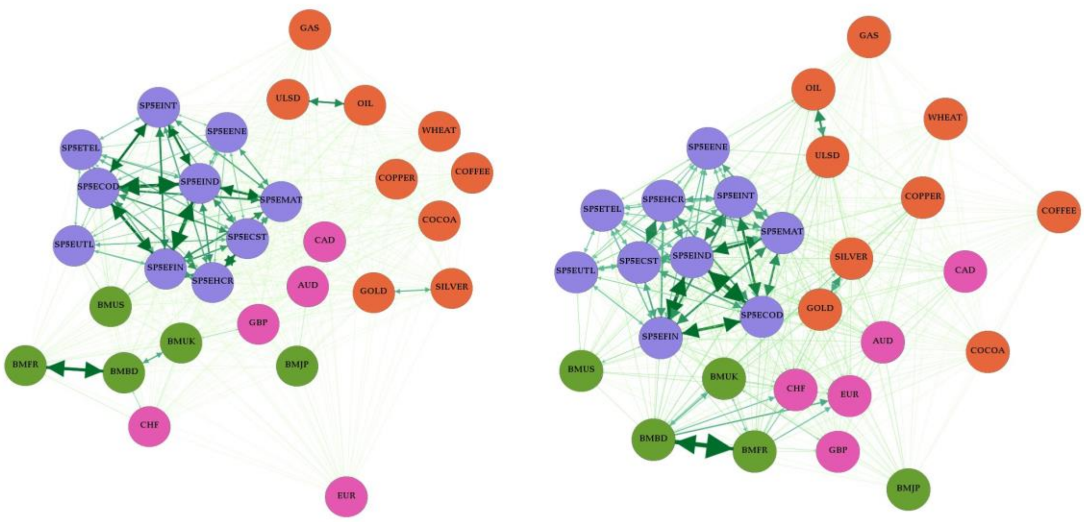


FIGURE 3

Dynamics of connectedness

In Figure 3, the top-left graph presents the sum value of connectedness for all asset classes. The top-right graph presents the sum value of connectedness inside each class of asset. The bottom-left graph presents the sum value of connectedness received by each class from other three classes. For example, the purple line in the bottom-left graph shows the sum of connectedness received by U.S. stocks and their output by other three asset classes. The bottom right graph presents the sum value of connectedness outputted by each class to other three classes. For example, the purple line in the bottom-right graph shows the sum of connectedness output by U.S. stocks and received by other three asset classes. The results of connectedness are calculated by generalized variance decomposition in equation (6-7), estimated by annual sample panel of zero-mean log conditional volatility, with T = 252, P = 1, H = 12, and lambda = (1.221, 78.125).

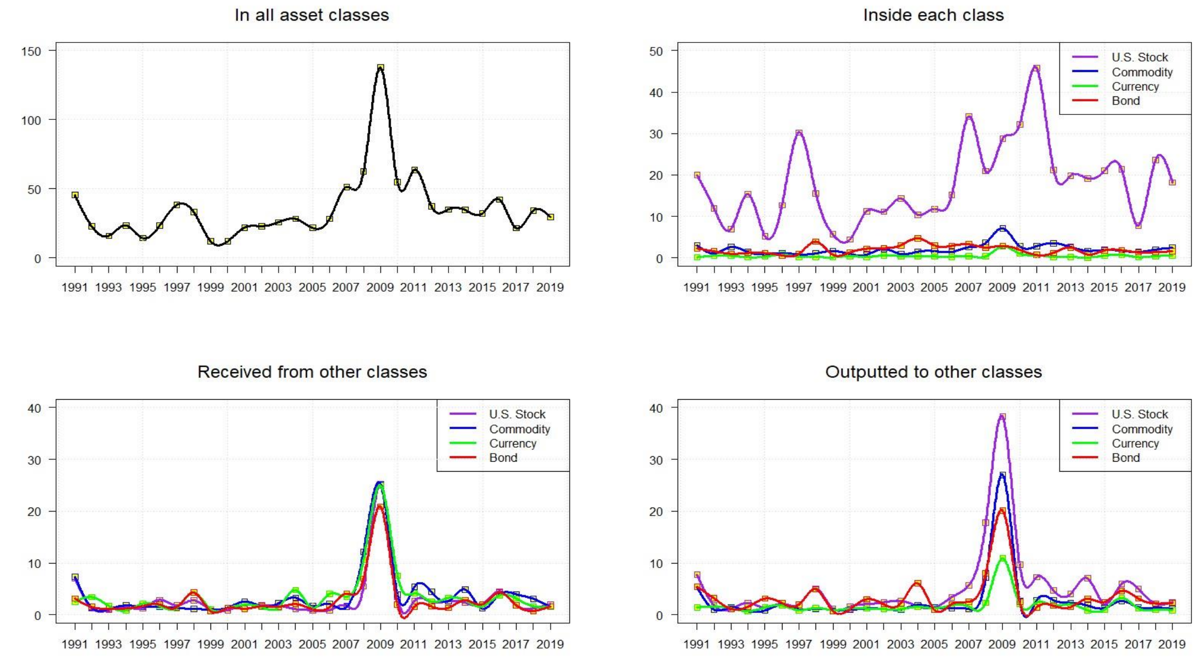


FIGURE 4

Systemic risk score

Figure 4 shows the systemic risk score obtained by equation (8), with annual panel adjacency matrices and daily VaR in q = 0.05 as composition level.

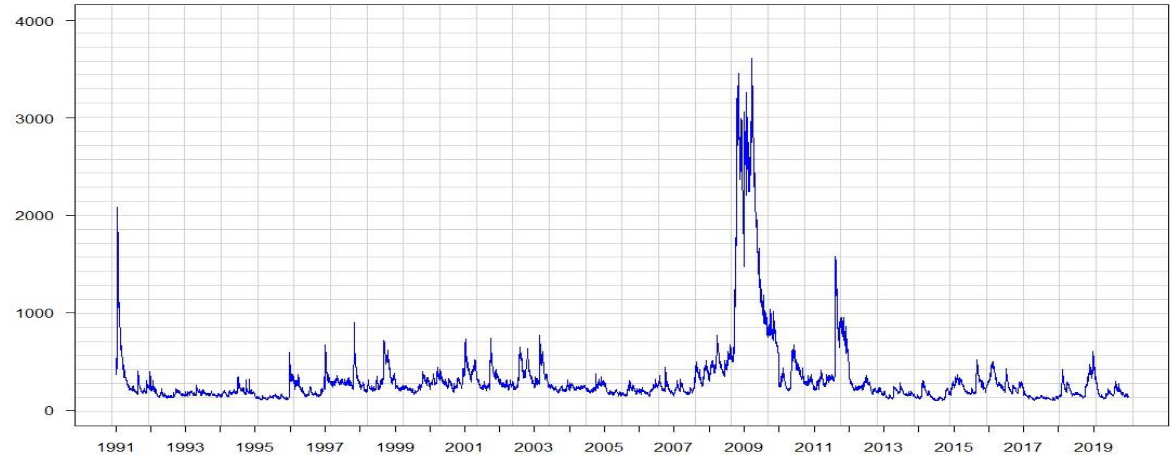


FIGURE 5

Risk contribution

Figure 5 reports the systemic risk contributions induced from annual adjacency matrix and the daily VaR in q = 0.05 as composition level, based on equation (10). For the risk contribution of each asset class in each year, darker color marks the value which is bigger. The rows marked as Average (G1), (G2), (G3), (G4) respectively report the average risk contribution of stock, commodity, currency, and bond. The row marked as Average (all) reports the average risk contribution of all assets.

	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
SP5EHCR	16.67	4.86	6.11	3.58	2.67	6.68	19.41	16.39	7.93	12.31	6.45	12.88	8.07	3.48	2.69
SP5ECOD	18.66	6.3	4.05	6.03	2.3	5.47	15.11	20.84	9.5	11.45	25.05	17.57	14.42	5.34	5.32
SP5EENE	5.4	3.4	2.6	4.09	1.87	4.27	15.91	8.46	7.4	9.37	8.95	19.17	4.33	4.92	7.25
SP5EFIN	12.39	5.07	4.64	5.94	3.21	7.44	20.47	24.54	12.38	17.28	19.1	20.4	13.97	4.97	3.72
SP5EIND	17.11	5.58	2.95	5	2.96	5.36	17.37	18.29	8.09	11.42	24.18	20.63	11.97	5.75	5.02
SP5ETEL	9.51	2.91	3.26	4.94	2.93	5.21	14.33	11.88	8.17	11	10.79	19.55	10.61	4.68	3.45
SP5EMAT	15.39	5.13	2.31	5.2	2.79	2.09	15.7	10.11	5.34	9.17	17.66	18.32	10.99	6.71	5.46
SP5ECST	12.9	4.28	2.97	3.91	2.1	5.51	16.14	11.91	4.37	7.12	5.16	7.8	5.8	2.73	3.23
SP5EINT	9.11	5.56	5.67	7.42	6.13	8.25	19.97	20.36	13.42	23.79	44.81	22.98	17.29	5.81	5.04
SP5EUTL	5.55	2.94	2.09	4.37	1.78	3.62	6.11	3.53	3.83	6.24	10.39	12.53	4.62	2.53	3.92
OIL	66.73	7.5	9.69	8.81	5.79	15.78	11.74	24.74	19.91	21.03	22.61	15.33	20.25	19.36	15.92
ULSD	75.61	11.97	10.43	12.82	7.74	19.52	12.17	19.07	21.35	30.18	24.16	22.21	28.18	22.02	21.59
GAS	18.27	33.41	27.89	31.29	28.6	68.49	50.61	34.93	29.67	36.78	58.16	38.09	50.44	36.17	30.11
GOLD	6.8	1.23	5.59	2.66	1.23	1.61	2.33	2.92	3.79	4.14	3.94	3.64	3.87	5.18	3.05
SILVER	7.45	2.79	9.53	6.48	5.65	1.32	6.11	11.16	6.14	3.39	4.01	4.94	5.35	13.67	7.36
COPPER	4.77	3.43	5.67	7.05	6.27	10.24	7.5	7.67	7.9	4.95	5.26	6.15	6.05	10.83	8.23
WHEAT	7.8	5.94	7.86	5.48	6.62	9.42	7.5	7.88	8.86	9.13	6.44	10.25	9.47	10.49	8.9
COFFEE	9.01	12.13	20.1	33.37	14.29	15.28	32.38	17.33	26.92	26.42	15.06	20.15	14.04	16.78	16.51
COCOA	11.21	11.69	11.33	9.21	6.13	4.77	7.64	5.91	12.62	12.67	16.08	11.36	15.16	13.13	12
EUR	2.79	2.71	2.36	1.52	2	1.37	1.31	2.07	1.91	2.48	2.43	1.52	2.32	2.56	2.21
CHF	2.8	3.64	2.92	2.1	3.3	1.55	2.13	2.59	2.5	3.11	3.45	2.28	2.22	3.01	2.4
GBP	3.85	4.52	4.15	1.64	2.37	1.55	2.18	1.68	2.09	2.42	1.82	1.88	2.81	3.28	2.55
AUD	1.16	1.83	1.52	1.17	1.13	0.94	1.67	3.44	1.75	2.05	2.76	1.58	1.63	3.74	2.28
CAD	0.49	0.73	0.75	0.6	0.6	0.93	0.78	0.93	0.74	0.91	0.73	1.13	1.19	1.25	1.32
BMUS	0.59	0.81	0.63	1.47	0.76	1.95	1	1.01	0.87	0.62	1.12	2.01	1.63	1.39	0.46
BMBD	8.85	5.26	2.6	2.26	4.29	1.13	2.6	5.18	2.23	3.67	5.76	3.34	6.03	7.13	2.97
BMUK	4.44	3.87	2.35	1.8	1.78	1.18	1.46	3.41	1.29	1.88	2.18	2.63	2.69	4.98	2.3
BMJP	3.53	2.38	2.65	2.42	4.73	1.59	2.15	6.75	2.79	1.93	2.01	2.14	1.81	2.34	1.7
BMFR	7.47	3.49	2.02	2.6	2.42	1.06	2.07	5.05	2.12	4.03	4.47	2.78	4.4	6.86	2.44
Average (G1)	12.27	4.6	3.67	5.05	2.87	5.39	16.05	14.63	8.04	11.91	17.25	17.18	10.21	4.69	4.51
Average (G2)	23.07	10.01	12.01	13.02	9.15	16.27	15.33	14.62	15.24	16.52	17.3	14.68	16.98	16.4	13.74
Average (G3)	2.22	2.69	2.34	1.41	1.88	1.27	1.61	2.14	1.8	2.19	2.23	1.68	2.04	2.77	2.15
Average (G4)	4.98	3.16	2.05	2.11	2.8	1.38	1.86	4.28	1.86	2.43	3.11	2.58	3.31	4.54	1.97
Average (All)	12.63	5.7	5.75	6.39	4.64	7.36	10.89	10.69	8.13	10.03	12.24	11.22	9.71	7.97	6.53

	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Average
SP5EHCR	3.63	11.51	57.04	16.1	12.3	28.76	6.54	6.24	7.48	9.48	8.33	2.2	12.11	5.93	10.96
SP5ECOD	6.09	14.46	67.07	105.74	20.6	36.63	8.7	7.8	7.1	10.67	10.11	3.52	14.57	10.46	16.93
SP5EENE	8.66	15.05	57.82	34.67	23.48	44.92	11.23	7.67	8.85	10.82	14.36	2.53	12.21	9.98	12.75
SP5EFIN	6.36	21.34	99.21	205.1	23.87	48.1	12.94	8.56	7.89	12.94	14.42	5.27	14.93	10.29	22.99
SP5EIND	5.9	13.9	50.5	104.62	23.5	42.35	10.86	7.95	8.2	10.83	12.27	3.67	15.01	9.9	16.59
SP5ETEL	4.15	11.55	40.89	58.91	7.27	8.26	4.39	3.42	2.3	7.18	5.24	2.95	10.73	7.96	10.29
SP5EMAT	7.38	20.2	72.69	105.42	22.36	49.24	11.28	8.71	9.17	11.95	14.13	3.66	13.34	8.65	16.92
SP5ECST	3.06	10.03	43.95	10.32	11.78	19.29	4.83	4.9	4.59	7.66	6.44	1.03	5.41	4.16	8.05
SP5EINT	6.56	14.59	61.31	81.55	19.89	38.18	10.84	6.66	8.1	11.24	12.4	4.28	19.03	13.75	18.07
SP5EUTL	2.77	8.31	45.4	16.3	13.26	18.52	2.31	3.8	2.31	4.67	4.44	1.61	3.14	2.97	7.03
OIL	11.44	13.58	48.86	41.4	13.43	20.75	9.97	7.63	7.33	28.42	27.83	9.31	12.67	13.89	19.02
ULSD	13.16	12.02	58.57	124.05	16.88	16.01	8.39	6.29	8.26	25.36	29.6	9.59	11.72	16.56	23.98
GAS	49.03	30.29	29.9	60.88	25.64	17.49	28.87	13.09	26.71	25.36	29.57	19.81	25.89	24.43	33.79
GOLD	6.67	5.18	23.15	45.57	6.11	10.52	11.37	11.32	3.93	4.21	6.06	2.66	2.08	2.52	6.67
SILVER	11.83	10.7	35.57	138.24	16.05	27.95	20.96	12.64	4.99	9.97	8.2	4.81	4.33	5.79	14.05
COPPER	16.8	14.64	51.01	92.9	13.55	16.41	10.81	6.12	3.35	6.8	6.11	4.61	5.71	4.36	12.25
WHEAT	10.21	11.69	28.29	15.71	15.17	17.69	11.74	5.61	7.64	10.06	8.33	9.84	9.78	7.91	10.06
COFFEE	10.67	9.8	16.7	15.36	12.6	13.38	11.67	9.14	15.75	13.96	11.3	8.82	9.07	12.16	15.87
COCOA	8.46	8.04	20.73	38.17	9.72	10.81	13.26	4.45	4.3	4.33	8.35	10.34	10.79	7.9	11.05
EUR	2	1.56	8.05	23.63	3.76	2.77	2.71	1.91	1.04	2.14	2.54	1.16	1.18	0.83	2.99
CHF	2.67	1.53	6.27	19.88	2.46	6.34	2.29	1.78	1.62	5.34	1.85	1.71	1.5	1.67	3.34
GBP	2.96	2.05	6.3	17.38	3.55	4.68	1.47	1.77	1.44	2.34	7.58	2.05	2.64	1.76	3.34
AUD	1.9	3.63	22.79	49	6.21	5.19	3.03	2.83	1.68	2.18	2.93	1.43	1.26	1.15	4.62
CAD	1.14	2.06	6.16	13.48	4.87	3.35	2.09	1.92	0.97	1.9	2.51	1.08	1.08	0.98	1.95
BMUS	0.34	1.85	6	2.58	2.2	2.15	1.57	0.92	0.58	1.09	1.83	1.13	0.53	1.25	1.39
BMBD	3.01	2.15	15.78	49.96	2.72	1.8	1.56	2.2	2.49	3.88	2.83	1.91	1.19	1.08	5.37
BMUK	2.02	1.63	3.52	13.38	1.98	1.55	1.31	1.72	1.12	1.75	5.16	1.87	0.96	1.1	2.67
BMJP	1.77	2.2	6.47	5.53	3.24	1.9	1.38	2.57	1.33	3.04	5.14	2.03	1.4	1.14	2.76
BMFR	2.96	1.55	16.38	49.64	2.08	2.25	1.92	2.19	0.9	2.67	2.72	1.82	1.18	0.95	4.91
Average (G1)	5.45	14.09	59.59	73.87	17.83	33.43	8.39	6.57	6.6	9.74	10.22	3.07	12.05	8.4	14.06
Average (G2)	15.36	12.88	34.75	63.59	14.35	16.78	14.11	8.48	9.14	14.28	15.04	8.87	10.23	10.61	16.3
Average (G3)	2.13	2.17	9.91	24.68	4.17	4.47	2.32	2.04	1.35	2.78	3.48	1.49	1.53	1.28	3.25
Average (G4)	2.02	1.88	9.63	24.22	2.44	1.93	1.55	1.92	1.29	2.49	3.54	1.75	1.05	1.1	3.42
Average (All)	7.36	9.55	34.7	53.64	11.74	17.84	7.94	5.58	5.57	8.7	9.4	4.37	7.77	6.6	11.06

value 0 50 100 150 200 250

FIGURE 6

Spillover risk in long and short terms

Figure 6 shows the heatmaps of long-term and short-term spillover risk. The long-term spillover risk is obtained by full-period data while the short-term spillover risk is obtained by annual panel. The x-axis and y-axis respectively indicate source and target, while the numbers marked in the axis represent the corresponding assets showed in Table 1.

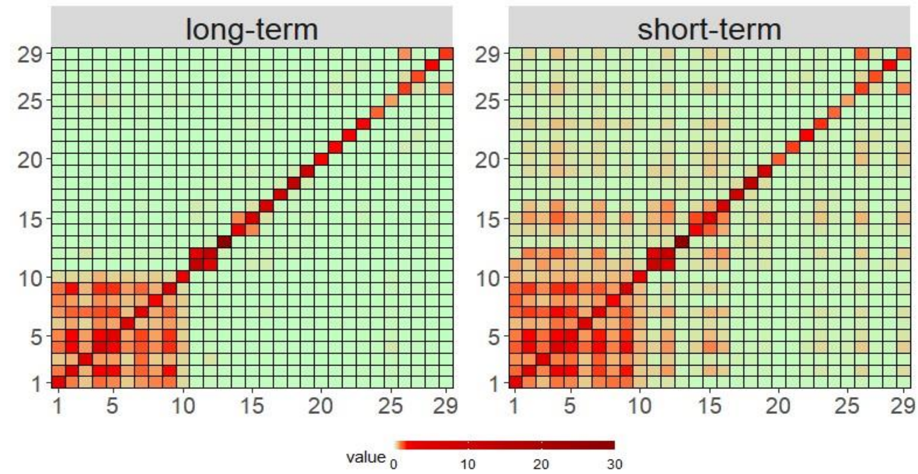
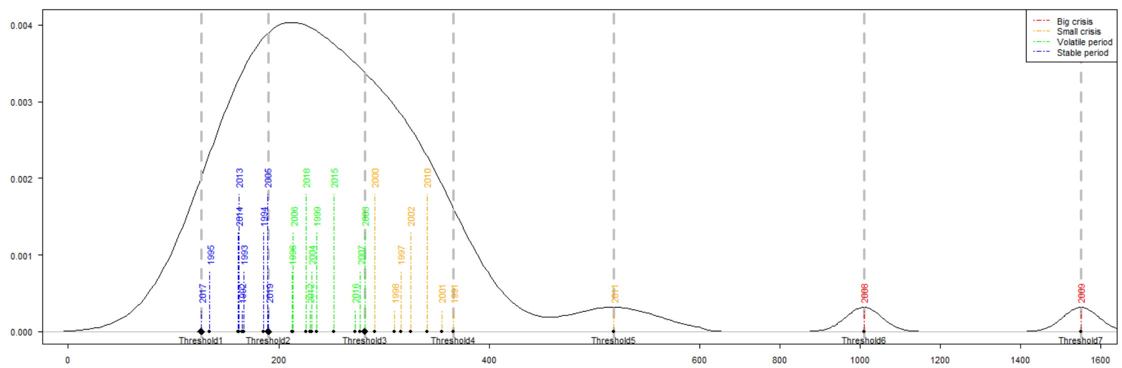


FIGURE 7

Periods classified by systemic risk score

In Figure 7, the periods of major crisis, mini crisis, volatile period and stable period are coloured by red, orange, green, blue. The classification is implemented by Fisher-Jenks clustering algorithm. The x-axis denotes the annual systemic risk score, obtained by equation (8), with annual panel adjacency matrices and daily VaR in q = 0.05 as composition level. The x-axis ticks higher than 600 are shrunk for a better visual effect. The y-axis denotes the density. The probability density curve is induced by kernel density estimation.



Appendix A Table and Figure

TABLE A1

Historically important events

Year	Event
1991	Persian Gulf war
1992	The GBP had a crash in 1992 "Black Wednesday"
1997-1998	Asian financial crisis
1999	The easing of credit in United States
2000	Dot-com bubble in United States
2001	September 11 attacks
2002-2003	Iraq War; Indices slid steadily in U.S. stock market
2004-2006	The oil price was raising
2007	United States bear market
2008	Global financial crisis
2009-2010	European sovereign debt crisis
2011	US stock markets fall in August 2011
2012	Commodities lower demand
2013	Indices hit record high in U.S. stock market
2014	Short-term interest rates near zero
2015-2016	Chinese stock market turbulence
2017	The S&P 500 and Nasdaq also had their best years since 2013
2018	Cryptocurrency crash.
2019	Indices climbing in U.S. stock market based on positive trade policy.

TABLE A2

Descriptive statistics and stochastic properties

Table 3 provides average descriptive statistics over four types of assets and the entire panel. For each asset, the total number of observations is 7,565. The sample period is from Jan 2, 1991 to Dec 31, 2019. Jarque-Bera test presents the test-statistics of the Jarque and Bera (1987) normality test. Q(20) and Q2 (20) corresponds to the test-statistics from Ljung-Box test for autocorrelation in returns and squared returns, respectively. ARCH(20) presents the statistics from Engle (1982) test of ARCH effects in the underlying series. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level respectively. ARCH(standardized residual) presents the statistics from Engle (1982) test of ARCH effects in the standardized residual induced from the best-fitting ARMA (3,3)-GARCH (3,3) model with Gaussian distribution.

	Stock	Commodity	Currency	Bond	All
Mean (%)	0.027	0.011	0.002	0.008	0.015
Std. Dev. (%)	1.290	2.028	0.755	0.663	1.319
Sharpe Ratio	-0.695	-0.481	-1.203	-1.393	-0.837
Maximum (%)	13.070	15.914	6.570	5.499	11.527
Minimum (%)	-11.618	-22.397	-7.306	-4.262	-12.951
Skewness	-0.136	-0.282	-0.110	0.041	-0.146
Kurtosis	8.930	8.666	9.529	3.054	7.938
Jarque-Bera	29289.003***	32414.547***	68373.537***	2989.488***	32463.313***
Q(20)	56.244***	46.012**	207.308***	33.200**	75.141***
Q2 (20)	5945.733***	1019.402***	2300.109*	732.225***	2889.435**
ARCH-LM(20)	1672.581***	533.593***	777.264*	401.571***	945.597**
ARCH-LM(standardized residual)	14.999	16.257	12.339	10.668	14.184

TABLE A3

Summary statistics of value-at-risk

Table 4 reports the average sector-wise summary statistics of value-at-risk for the underlying assets. The value-at-risk is calculated by q = 0.05 and conditional volatility that estimated by ARMA (3,3)-GARCH (3,3) model with Gaussian distribution, which is selected based on AIC and posttest of ARCH effect on standardized residual.

	Mean	Max	Min	SD	Median	Skewness	Kurtosis
Stock	1.836	9.429	0.801	0.914	1.580	2.995	14.373
Commodity	3.179	12.424	1.505	1.065	2.965	1.943	7.684
Currency	1.190	5.205	0.587	0.348	1.122	2.821	18.614
Bond	1.051	2.822	0.535	0.272	1.020	1.187	2.940

FIGURE A1

Price dynamics of sample assets

Note. The price dynamics of all assets from Jan 2, 1991 to Dec 31, 2019. For each asset, the total number of observations is 7,565.

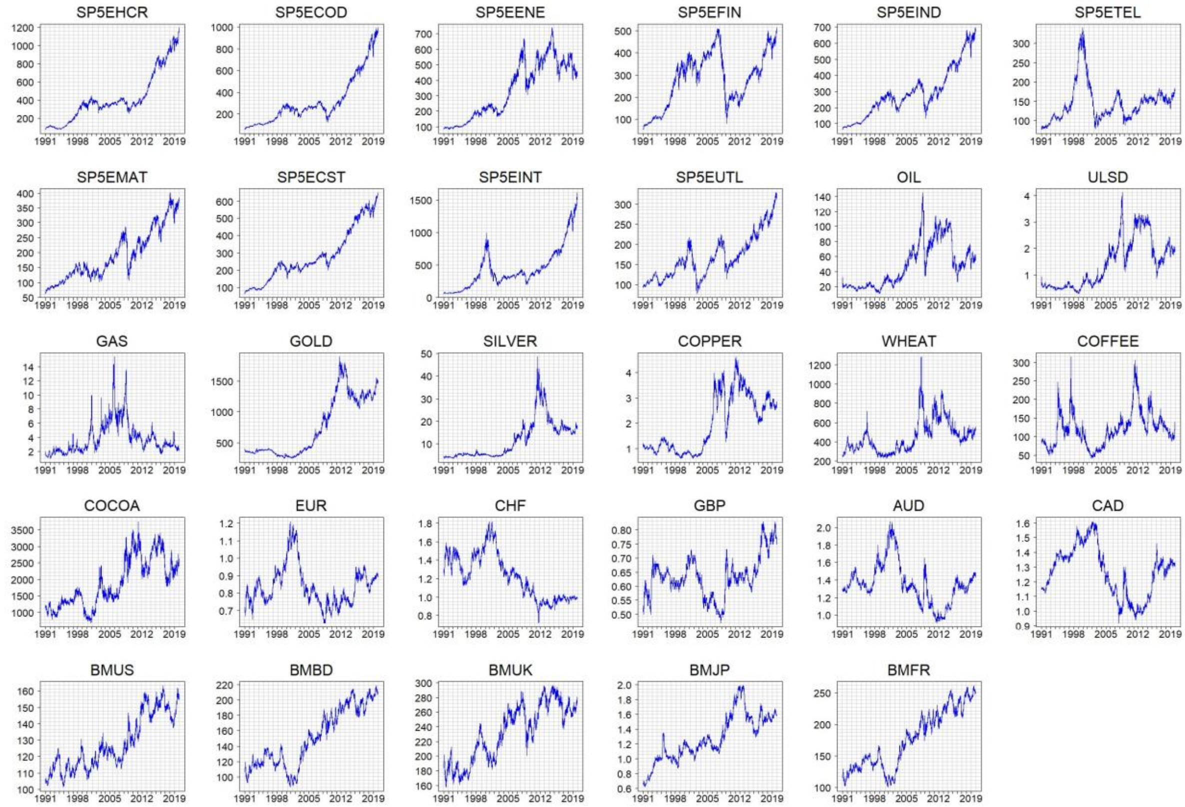


FIGURE A2

Conditional volatility by group

Note. The conditional volatility averaged by group. Based on the sample data, we utilize the best-fitting model ARMA (3,3)-GARCH (3,3) with Gaussian distribution and obtain the estimates of conditional volatility for all assets.

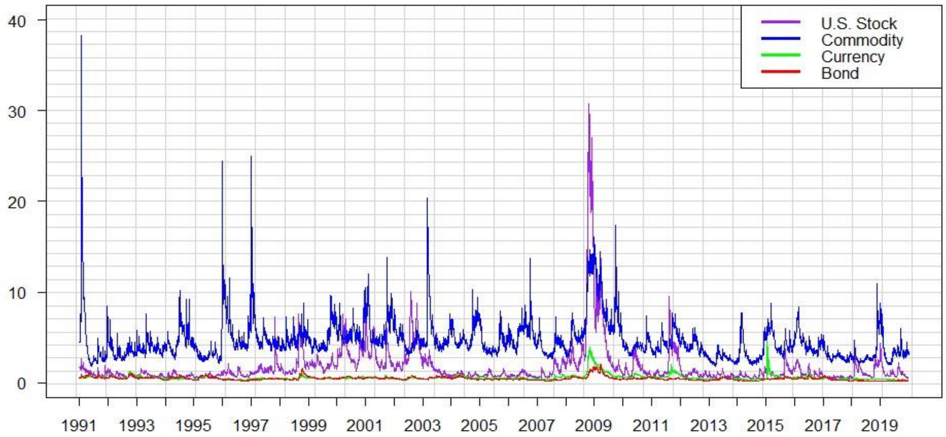


FIGURE A3

Value-at-risk

Figure A3 report the daily value-at-risk in q = 0.05. For each asset, the total number of observations is 7,565. The sample period is from Jan 2, 1991 to Dec 31, 2019. Based on the sample data, we utilize the best-fitting model ARMA (3,3)-GARCH (3,3) with Gaussian distribution and obtain the estimates of VaR for all assets.

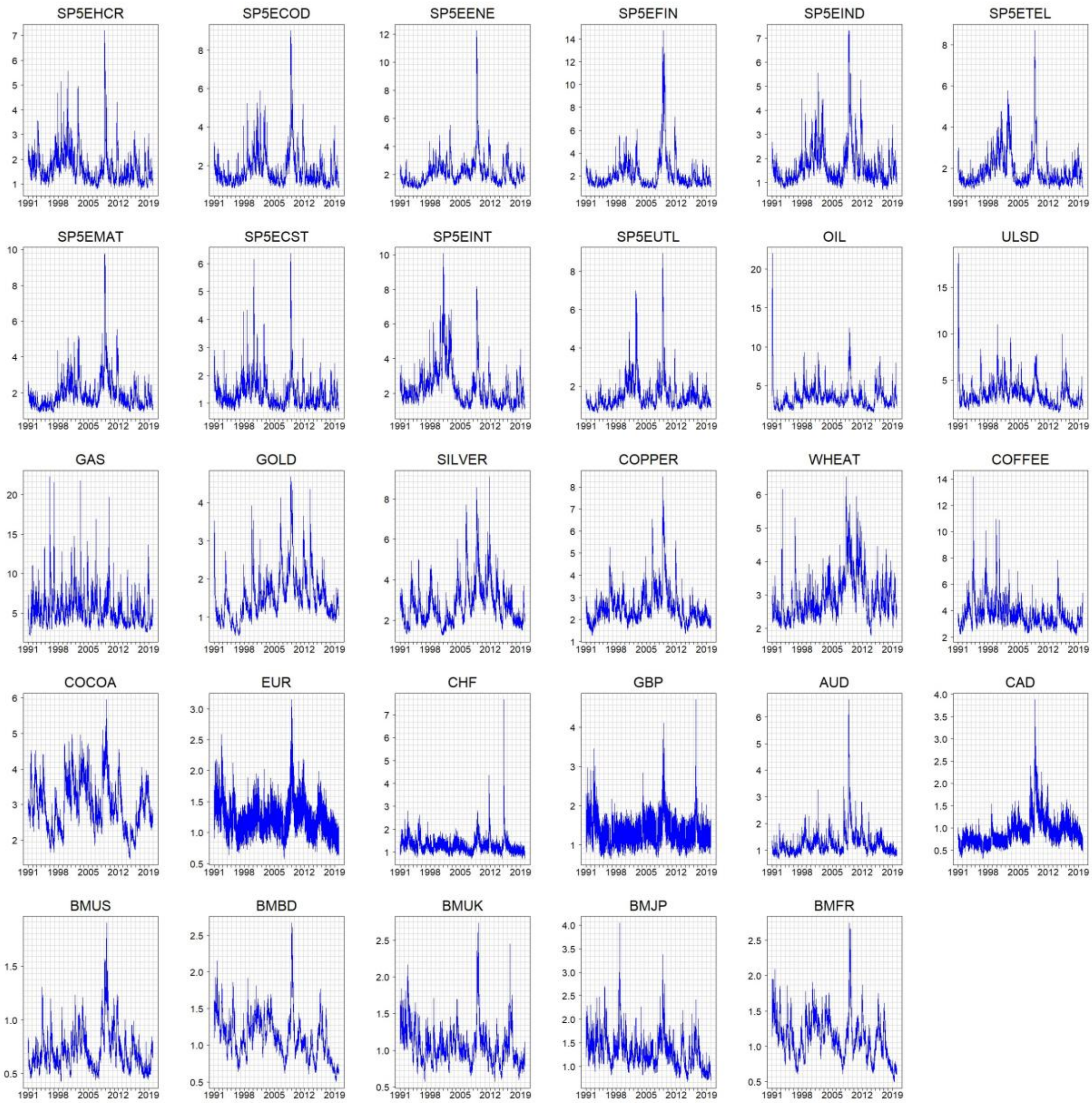


FIGURE A4

Connectedness in long and short terms

The heatmaps in Figure A4 show the connectedness among assets in short and long terms. The x-axis and y-axis respectively indicate source and target, while the number marked in the axes represent the corresponding asset showed in Table 1. The long-term results of connectedness are calculated by generalized variance decomposition in equation (6-7), estimated by full sample panel of zero-mean log conditional volatility, with T = 7,565, P = 1, H = 12, lambda = (19.531, 8750.000). The short-term heatmap is the averaged result over sample period, estimated by annual sample panel of zero-mean log conditional volatility, with T = 252, P = 1, H = 12, and lambda = (1.221, 78.125). The darker color of entry indicates a higher value of connectedness.

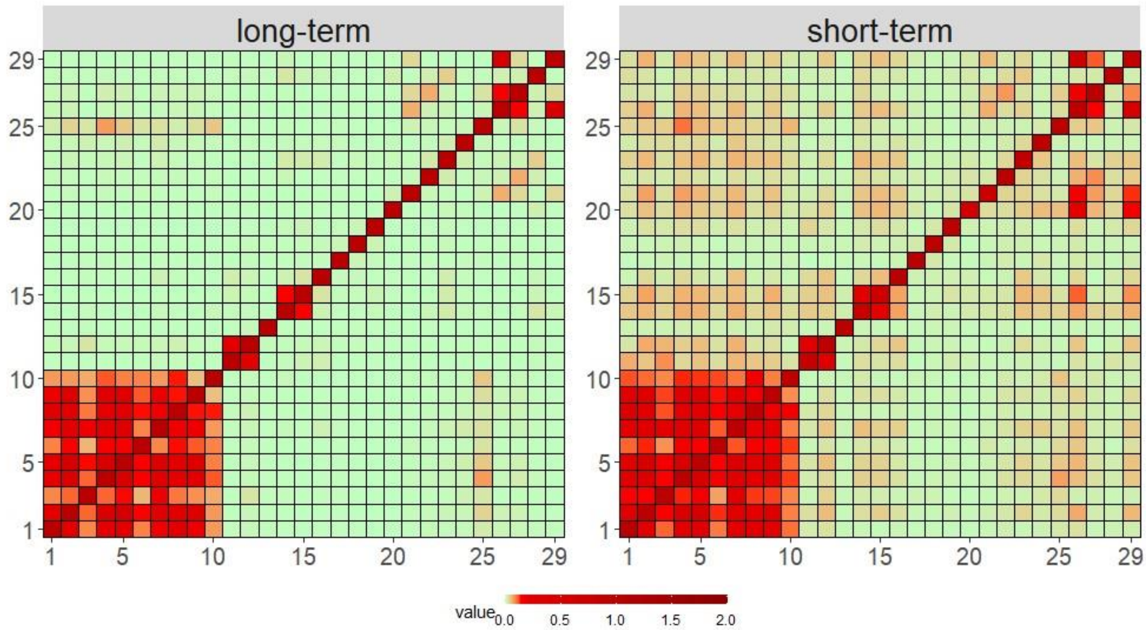
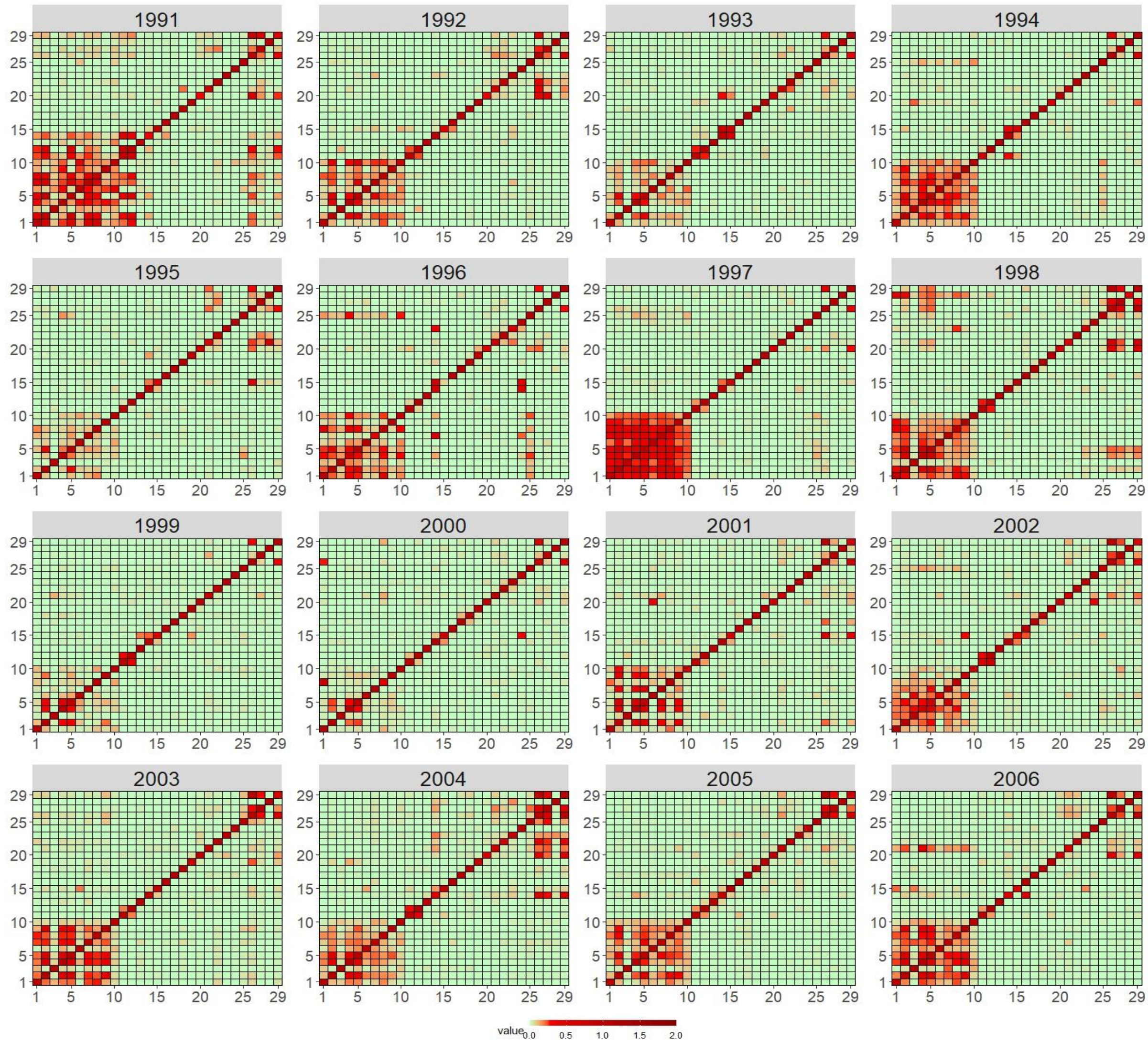


FIGURE A6

Annual heatmaps of connectedness

In the heatmaps of Figure A6, the x-axis and y-axis respectively indicate source and target, while the numbers marked in the axis represent the corresponding assets showed in Table 1. The results of connectedness are calculated by generalized variance decomposition in equation (6-7), estimated by annual sample panel of zero-mean log conditional volatility, with T = 252, P = 1, H = 12, and lambda = (1.221, 78.125). The darker color of entry indicates a higher value of connectedness.

(a) 1991 to 2006



(b) 2007 to 2019

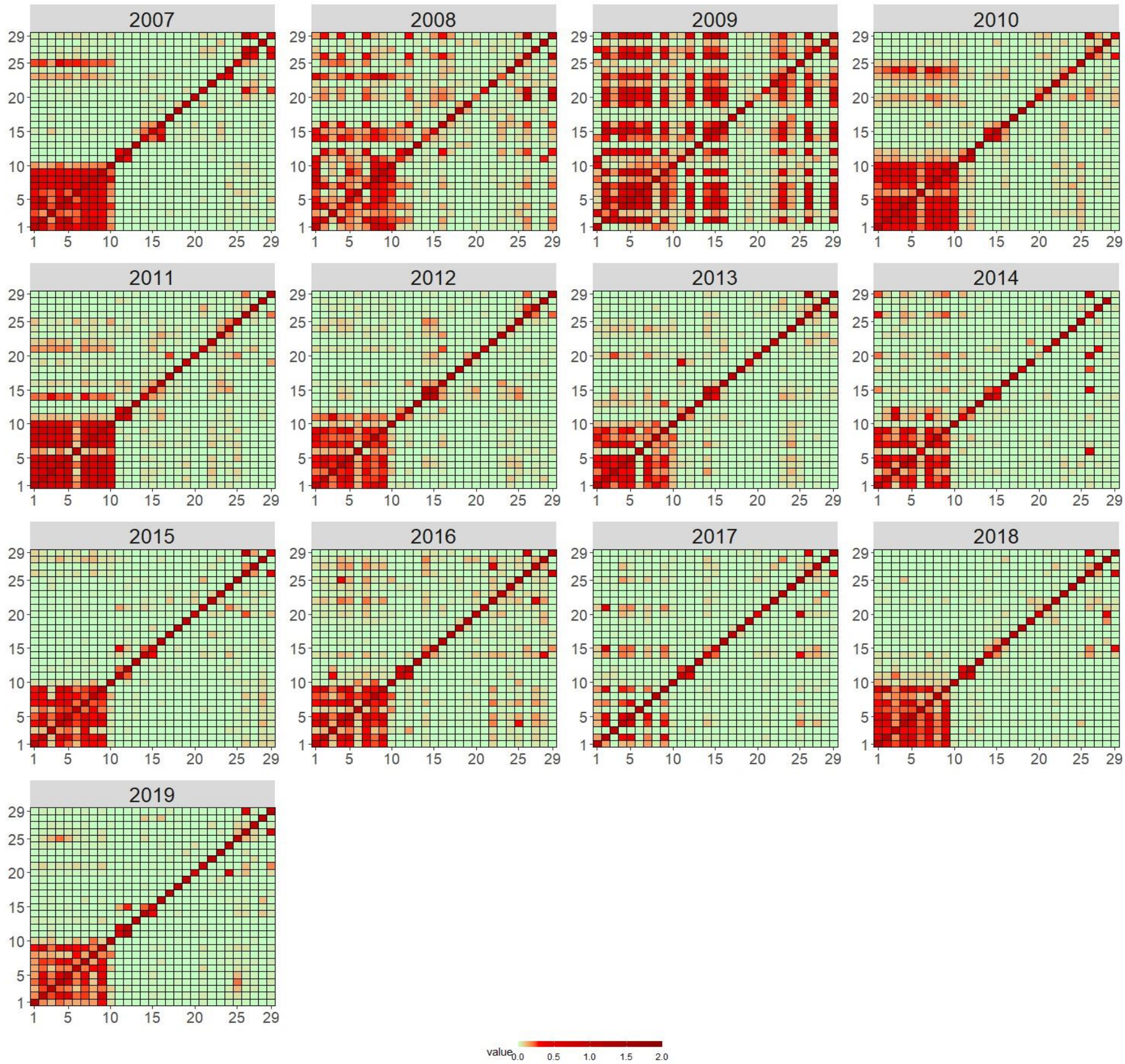
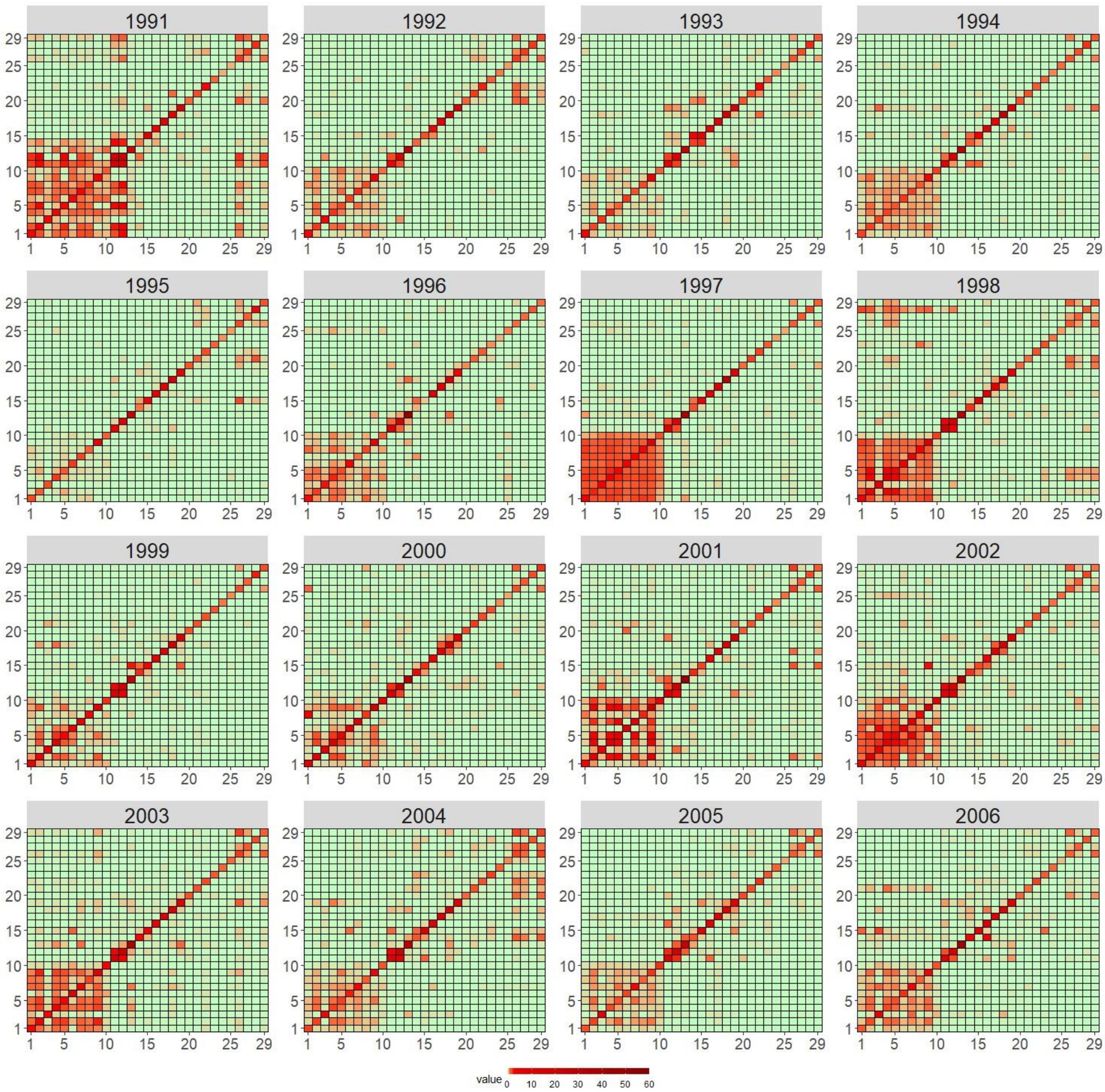


FIGURE A7

Annual heatmaps of spillover risk

Figure A7 shows the spillover risk in each year. The x-axis and y-axis respectively indicate source and target, while the numbers marked in the axis represent the corresponding assets showed in Table 1. The results are estimated from annual panel of zero-mean log conditional volatility. The calculation of risk spillover follows equation (11). The darker color of entry indicates a higher value of spillover risk.

(a) 1991 to 2006



(b) 2007 to 2019

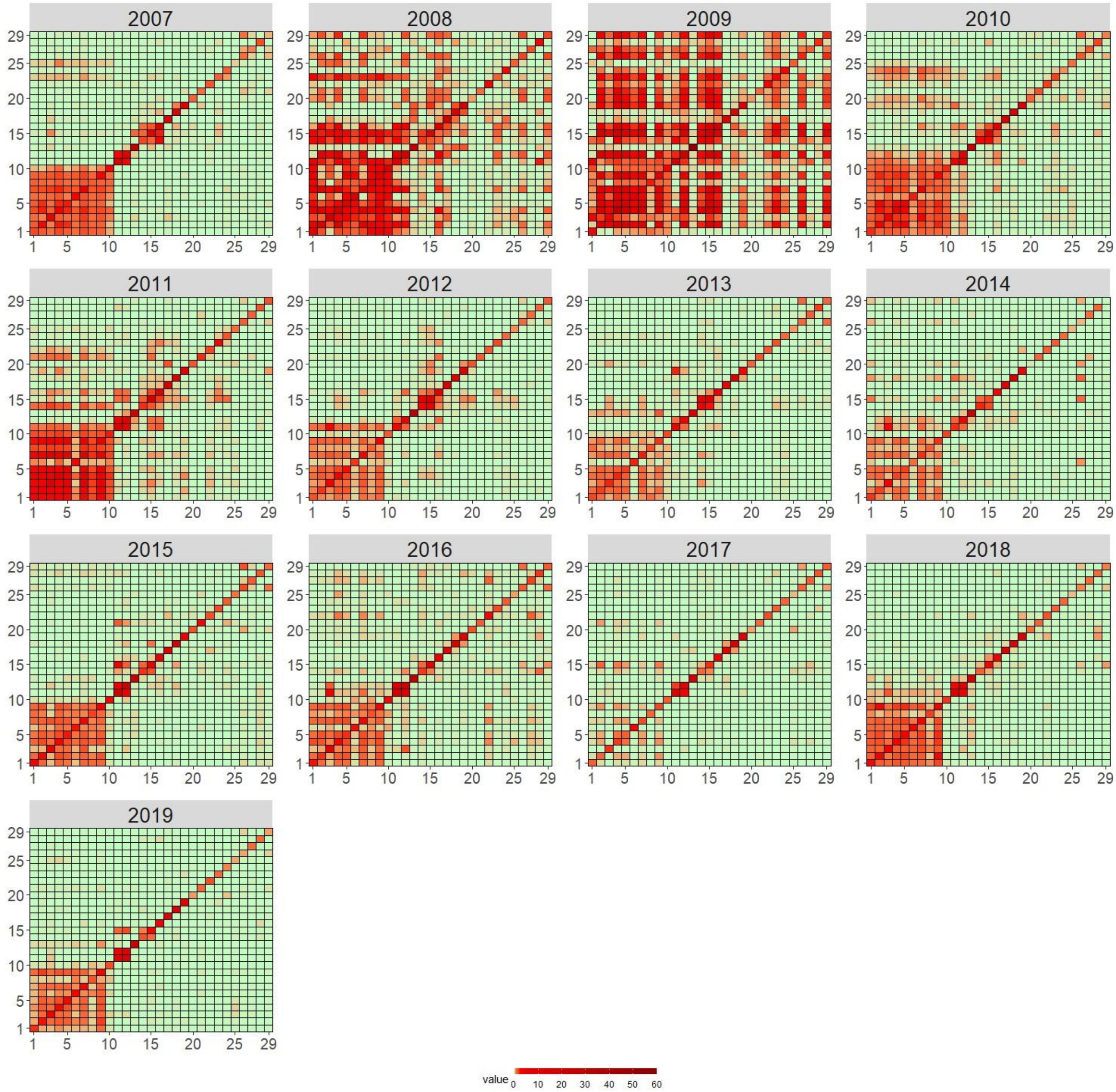
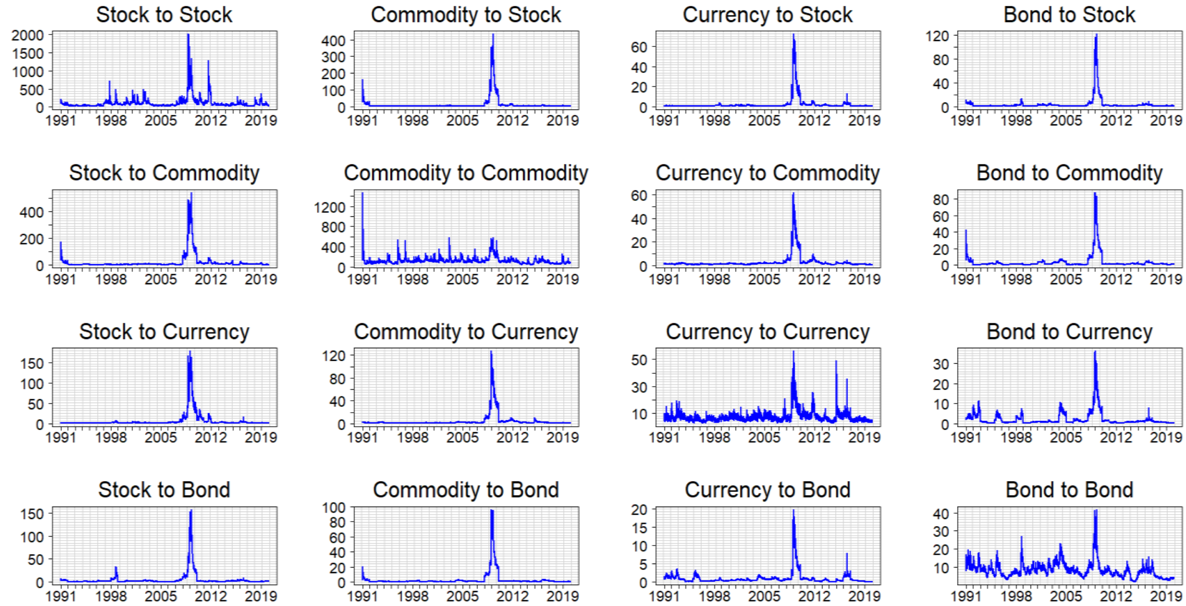


FIGURE A8

Intergroup spillover risks

Figure A8 shows the intergroup spillover risks obtained based on equation (12), where daily VaR is used as comprise loading, and the adjacency matrices are induced by annual panel.



Appendix B Period classification results in detail

A. Major Crisis

As shown in Figure 7, the years of 2008-2009 are identified as major crisis, corresponding to the well-known Global Financial Crisis. The Global Financial Crisis started from the announcement of the bankruptcy of Lehman Brothers in 2008, which follows the U.S. bear stock market that started in October 9, 2007. The vulnerability of the financial system was exposed with large decline of asset prices after the collapse in mortgage market. This crisis generated the reflections of government support and regulatory action in systemic risk management (IMF, 2009).

According to our empirical results, the Global Financial Crisis of 2008-2009 is featured by the concurrent of high idiosyncratic risk, strong connectedness and long-term evolutionary process.

Firstly, high idiosyncratic risk is a basic feature for the Global Financial Crisis. As shown in Figure A1, during 2008-2009, the asset price experienced a crash for the majority of assets. Falling asset prices bring pessimistic investment return expectations. Investors are more likely to get a negative return on assets by investing at this time, which means a higher investment risk. It is corresponding to the result shown in Figure 1, where the value of idiosyncratic risk peaked in 2008-2009 for each asset.

The second crucial feature of Global Financial Crisis is the strong connectedness among all asset classes. From the perspective of asset market operation, when the prices of some assets crashed, the prices of other assets also fell due to the strong connectedness. Whatever investors invested in asset market, were more likely to get a negative rate of return. Due to the wide-spread connectedness among the asset market, there appeared to be a loss confidence for the whole asset market which resulted in a flight away from these markets. Fire sale caused a further decline of asset prices, because of the plummeting demand and the sudden increase in assets supply. Along with the continuous risk contagion, the scope of the crisis is constantly expanded, thus forming the huge scale of the GFC. The Figure 3 provides the sum of connectedness, from which we can find the 2008-2009 reached the historic high from 1991. As shown in Figure A6a, compared with the years before and after the crisis, the heatmaps in 2008 and 2009 have stronger connectedness coloured by red. In 2008, apart from the highly self-connected U.S. stock market, some assets in other asset classes such as commodity, currency and bond also have strong connectedness with each other. In 2009, all four asset classes are connected with each other in a stronger and a wider extent. All assets acted as linkage importers, including currencies and some commodities that did not output risk from others. Stocks, bonds and part of commodities were the targets of strong connectedness. In total, the connectedness of asset market in Global Financial Crisis in 2008-2009 is unprecedentedly close and widespread.

The upshot of the concurrent of high idiosyncratic risk and strong connectedness is that risk spillovers are market-wide, shown as the heatmaps in Figure A6a with time marked as 2008 and 2009. The evidence shows that most assets imported risk from other assets. During the GFC, with the two requirements above fullfilled, the spillover risk naturally achieved high value and spread across the entire asset market. Compared with the years before and after the crisis, Figure A8 provides the group-level spillover risk, spillover between each two classes are extremely high during this crisis. Figure 5 provides the risk contribution of all asset classes. With benchmark of average contribution in the last column, all asset classes contributed to the crisis period by exacerbating systemic risk. The Figure 4 shows that in 2009 the systemic risk reached historic high from 1991, which is the consequence of all the above factors.

The third feature of the Global Financial Crisis is a relatively long duration. From the beginning of the collapse, an evolutionary process is required. The strong connectedness in the Global Financial Crisis and the impacts of subsequent macroeconomic downturn, which is the reason for financial losses in such a widespread range. If a crisis causes macroeconomic downturn, it will back to impact the asset and intensify the connectedness (IMF, 2009; Giglio et al., 2016; Adrian et al., 2019). From the empirical result of Figure A6a and A7a, the increase of connectedness shows that impacts between asset classes gradually replaced the impacts within asset classes. Note the U.S. bear stock market started around October 9, 2007 and the start point of Global Financial Crisis is reorganized as Lehman Brothers' bankruptcy on 15 September 2008. In 2007, the results show the close connectedness within U.S. stocks. Then in 2008, the non-stock assets became more closely linked. Non-stock assets including commodities, currencies, and bonds formed homogeneity in 2008, in terms of their strong connectedness with each other. In 2009, strong connectedness in the asset classes further intensified because bonds, stocks and commodities exported more serious impacts to all asset classes. The large-scale spread of the crisis takes a long time, often more than a year. The underlying reason is that the amplification mechanism (see, Cifuentes et al., 2005; Brunnermeier and Pedersen, 2009; Glasserman and Young, 2015) and continuous strengthening of connectedness require a relatively long duration.

B. Mini Crisis

In this section we focus on mini crises. As shown in Figure 7, the years classified as mini crisis include the 1991, 1997-1998, 2000-2002, 2010, and 2011. We start from the backgrounds of each year and provide empirical analysis, then summarize the features of all mini crises.

1. Persian Gulf War (1991)

The features in the year of 1991 can be summarized as high idiosyncratic risk of energy commodities, connectedness between stocks and energy commodities, some safe-haven investments, and limited range and short duration of impacts.

When geopolitical environment in the Middle East or other oil-rich regions of the world flared up and created conflicts, causing an increase in the price of energy as a result, as shown in Figure A1 in year 1991, just by virtue of the risk of supply being disrupted, or transportation being disrupted, such as a canal or pipeline or workers going on protest. The fall in oil production caused energy price to increase. From Figure A3, we can notice the high idiosyncratic risk of oil and ULSD in 1991.

The year 1991 is the tightest period in end of 20th century, as the sum value of connectedness reached a high point, even higher than 1997, seeing Figure 3. The internal linkages of U.S. stocks are very strong, and their idiosyncratic risks have increased at the same time (shown in Figure 1), causing the risk contagion inside the U.S. stock market. Evidences show that the 1990-1991 Gulf War has a wider range of impact than Iraq war. The Figure A6a shows that connectedness between stocks and energy commodities reached a high level in 1991. The strong connectedness between stock and energy is not surprising as many literatures have proved their dependencies (Maghyereh et al., 2016; Mensi et al., 2017; Kilian and Park, 2009; Du and He, 2015; Creti et al., 2013). The intensified connectedness about energy and stock, as well as the increased idiosyncratic risk of commodities simultaneously cause the fluctuation of systemic risk. As shown in the Figure 14, in year of 1991, there are serious spillover risk between U.S. stock market and energy commodities. In Figure 5, the systemic risk of 1991 constituted mainly by the spillover risk and idiosyncratic risk related to oil, ULSD and U.S. stock market. While in 2003, the shocks of oil price have small impacts on other assets. The connectedness between stocks and energy commodities existed as well, but the connectedness is relatively weak than that in 1991.

During Gulf war, there are various safe-haven strategies adopted. As shown in Figure A1, the price of l0-year treasury bond decreased, perhaps due to the investors moving to short-term assets as a safe investment to maintain liquidity during uncertain times. From

Figure A6a, we can notice the strong connectedness among bonds of various nations, such as German, UK, and France bonds, leading to relatively big systemic risk contributed by bonds. The German bond exported strong connectedness to U.S. stocks, while both France and German import connectedness from U.S. stocks. On the other hand, precious metal of gold or silver imported connectedness from stocks. But due to the high stability of bonds, they seldom acted as the main systemic risk contributor, as shown in Figure 5.

Finally, the shock caused by Gulf war had a short duration and a fast recovery speed. The systemic risk increased during Persian Gulf war quickly declined after the war. The main reason is that the influence of regional war is rarely strong enough to leading up to the widening of crisis. As can be seen in Figure 3, in 1991, the commodities mainly acted as the importer of connectedness, while the role of exporter is relatively small. The asymmetric connectedness accounted for a considerable portion of the limited widening of the financial destruction. Another reason for only parts of the market involved is that the crises were stopped by policies' positive signals. The 1990-1991 Gulf war was followed by the 1990s economic boom in the United States.

2. Asian Financial Crisis (1997-1998)

While in the 1997-1998 Asian Financial Crisis, from Figure A1 and A2, we notice that the U.S. stocks had increased price and high value of conditional volatility. The Figure 1 shows that from 1997, the U.S. stock market entered into a high-risk period, which could be related to the increased U.S. interest rates and hot money inflows. The UK bond and U.S. bond witness an upward trend of VaR during this period, as shown in Figure A3.

From the Figure A6a, there is a strong connectedness inside U.S. stock market in 1997, which is in line with the homogeneous upward trend of stock prices for all sectors. In 1998, as shown in Figure 3, the connectedness outputted and inputted by bonds intensified.

Specifically, the U.S. financial and industrials sectors have high values of connectedness with bonds; the Euro, Swiss Franc have a high value of connectedness with bonds; the connectedness among U.S. and European bonds intensified as well. This could be attributed to the risk-aversion activity when there is a high volatility in the global financial market.

In the case of systemic risk, seeing Figure 4 and Figure 5, one can find that the systemic risk contributed by stocks often reach in a high level, from Asian Financial Crisis, and until the year of 2003 after the dotcom bubble and Iraq war.

To sum up the above results, the Asian Financial Crisis 1997-1998 was a period of prosperity for the U.S. stock market (Radelet et al., 1998; Radelet and Sachs, 2000). In order to obtain greater investment income, hot money from Asia flows to the U.S. financial markets. The volatility of the global financial market has made international bonds an ideal investment target for some investors. The high systemic risks in the U.S. financial market is caused by the simultaneous stimulation of the private capital inflows.

3. Dotcom Bubble Crash and September 11 Attacks (2000-2002)

During 2000–2002 when dotcom and internet-based businesses soared causing a rapid escalation in asset prices (Hill, 2018), the S&P 500 sector of information technology achieved a relatively high value of VaR. From Figure A6a, the connectedness outputted from S&P 500 sector of information technology intensified during 2000 to 2002, while the connectedness inside U.S. stock market grew simultaneously.

As shown in Figure 3, the sum value of all connectedness increased gradually during this period, but the sum value is lower than the level of 1997 Asian Financial Crisis and Global Crisis, which is in line with our perception that dotcom bubble crash is a less influential crisis. Another finding is that apart from Japanese bond, the international bonds witnessed an increased connectedness during this period. The price for almost all bonds in Figure A1 presents homogeneous fluctuations during this period. From the Figure A6, the spillover risk from stock to currency is witnessed with a relatively high value during this dotcom bubble crash. The homogeneity of bonds and the spillover from stock to bonds could attributed to the portfolio rebalancing that shorts U.S. stocks in the bubble market and longs international bonds.

For the September 11 attacks of 2001, as shown in Figure 1, the idiosyncratic risk of stocks and commodities experienced significant jumps in the short-run but recovered quickly afterwards. Figure A6a shows that, the terrorist attack in 2001 did not play a significant role in the gradual increase of connectedness between assets in comparison to the dotcom bubble crash of 2000–2002. From the Figure 5, we see that the sector of consumer discretionary and the sector of industrials contributed a higher value to the systemic risk than other years. This may be related to the regional and sectoral impact of the terrorist attack, which is in line with the finding of Nikkinen et al. (2008).

4. European Sovereign Debt Crisis (2010)

The European debt crisis is a multi-year crisis which started at the end of 2009 and have a long bailout period[7]. During 2009-2014, there are considerable quantity of financial shocks and influential factors, such as Greece debt crisis of 2009, the fear of Greece's default of 2010, U.S. stock market crash of 2011, the recovery of Global Financial Crisis, and U.S. quantitative easing of 2008-2014.

Figure 1, indicates that there was increased idiosyncratic risks for all asset classes with the anticipation of the "fear of Greece's default" in 2010. The idiosyncratic risk in other

[7] The European debt crisis started at the end of 2009 around European Union because of having difficulties in refinancing government debts or repayments of loans to Eurozone countries, European Central Bank
(ECB) and International Monetary Fund (IMF).

times except these two timepoints is relatively low. Figure A6b and A7b, suggests that the precious metal contributed some strong connectedness and spillover risk, which could be attributed to the safe-haven investment activity. The currencies contributed to a relatively higher systemic risk during the European debt crisis, which reflect the impact of European shocks to U.S. market.

The dynamics of connectedness and spillover risk during this period suggests that this crisis has not evolved into a global crisis or seriously impacted U.S. financial market. This could perhaps be due to the fact that the sovereign state bailout/precautionary programmes launched by EFSF/ESM as well as the U.S. bull stock market stimulated by quantitative easing policy that contribute towards decreasing the idiosyncratic risk as well as connectedness.

5. U.S. Stock Market Crash (2011)

The stock market crash of 2011, featured the downgrading America's credit rating by Standard & Poor's, and then the sharp drop in stock prices which occurred in international stock market.

Figure 1 state that the surge of volatility and idiosyncratic risk in stocks and bonds occurred firstly, followed by the increase risk of currencies and commodities. It can be also noticed from Figure A6b that the stocks exported strong connectedness mainly to gold and Swiss Franc. The Figure A1 shows the increased price of safe-haven assets (see, Baur and McDermott, 2010; Bredin et al., 2015), such as gold and silver. The direction of connectedness from stock to currency is in line with the lead lag relationship in the price drops of foreign stock markets, which is also proved by Jayech (2016).

The Figure 3 shows the highest value of connectedness inside stock class during our sample period, which is even higher than the value in Global Financial Crisis. The values of outputted and inputted connectedness between stocks and non-stock assets in 2011 are relatively low, indicating the limited impacts of this crash.

The dynamic systemic risk in Figure 4 shows that those shocks in Europe have smaller impacts to U.S. financial asset market than the U.S. stock market crash of 2011. The Figure 5 and A7b have indicate that the impacts of this crash is limited in U.S. stocks and for safe-haven precious metals. Crises of 2011 was followed by the quantitative easing policies that stimulated the economy and employment. The crisis did not lead to a huge damage to the real economy, so it did not evolve into a wide-range crisis.

6. Features of Mini Crisis

The mini crisis can be summarized by three features as follows. Firstly, a minority of assets might have high value of idiosyncratic risk. Like major crisis, high idiosyncratic risk is also a basic requirement for a mini crisis. The Figure 1 show that, during mini crisis periods, parts of groups have high idiosyncratic risk in mini crisis periods, such as the commodities' risk in 1990-1991, and the U.S. stocks' risk in 2011-2012. Compared with major crisis, the idiosyncratic risk of mini crisis is milder than major crisis. The amplitude of price drop is relatively smaller, and there are fewer high-risk assets. For domestic shock, U.S. stocks downward co-movement and increased VaRs are typical features. For foreign shock, the dropped price and increased risk can be also witnessed in specific asset.

The second feature of mini crisis is that strong connectedness exists among parts of asset classes, as shown in Figure A6a. Assets facing high financial losses are connected to other assets, which will cause risks to spillover to these assets, causing crises in particular segments. It is worth noting that in those periods with no crisis, such as in 2012 and 2014, the connections were sometimes strong as well, but because the idiosyncratic risk was low, the two requirements for risk contagion were not met simultaneously. By studying among Figure 3, A6a, and A7a, we discover several frequently occurring situations in mini crises. First of all, the internal linkages of U.S. stocks are very strong, and their independent risks have increased at the same time, causing the risk contagion inside the U.S. stock market. Second, prices of energy commodities, i.e., crude oil, ULSD, and gas commodity, acted as the main systemic risk contributors. As commodities with similar functions, there are natural correlations between their prices. Affected by events such as the Gulf War, energy prices always fluctuate rapidly. For these reasons, the internal spillover risk among energy commodities frequently reaches high value. In addition, as shown in the Figure A7a, in year of 1991, the U.S. stock market has serious impacts to energy commodities. Moreover, during crises, there are strong connections among bonds of various nations, which may be related to the safe-haven activities. But due to the high stability of bonds, they seldom acted as the main systemic risk contributor.

Finally, mini crises always have a short duration, a limited impact range, and a fast recovery speed. Unlike the global financial crisis, the mini crises always occurred in parts of asset classes and market segments. From the dynamics of connectedness and spillover risk during this period, one can find that this crisis has not evolved into a global crisis or seriously impacted U.S. financial market for various reasons, such as economic growth or bailout programmes. The main reason for only parts of the market to be affected is that the crises was stopped by policies' and positive signals. For example, the 1990-1991 Gulf war was followed by the 1990s economic boom in the United States. Crises of 2011 were followed by the quantitative easing policies that stimulated the economy and employment. The crisis did not cause a huge damage to the real economy, so it did not adversely affect other assets.

C. Volatile period

The volatile period has higher systemic risk than stable period, and lower systemic risk than crisis period. As Figure 7 shows, the classified volatile periods include 1996, 1999, 2003-2004, 2006-2007, 2012, 2015-2016, and 2018. Specifically, there are two characteristics of volatile period: (1) the transitional period between stable period and crisis period; (2) shock events, while the crisis management is handled by regulation and policies.

1. Transitional Period Between Stable Period and Crisis

The first transitional period is the year of 2007, which is the pre-crisis period before GFC. Note the U.S. bear stock market started in October of 2007 and the start point of Global Financial Crisis is reorganized as Lehman Brothers' bankruptcy on 15 September 2008. The characteristic of 2007 is that systemic risk was accumulating, but accompanied by risk hedging. Some assets were stagnated, but other assets were increasing in price. Investors can make substitutions among multiple assets without exiting the asset market. The government could regulate the systemic risk by using policy such as quantitative easing, bid of investment, encouragement of domestic trade, etc. The positive expectation of economic and asset market defused the fire sales, and boosted the investment demand in asset markets. Alternatively, in short-term, the appropriate emergency policy is to falter the first requirement, e.g., rescuing financial institutions that are on the verge of bankruptcy, so that the idiosyncratic risk of institutions decrease.

The second transitional period is the year of 2012, which is the post-crisis period after U.S. stock market crash (2011). As shown in Figure 4, the systemic risk in 2012 was decreasing, and the years of 2013-2014 are assessed as stable period. In this period, the Federal Reserve kept interest rates at the lowest level in two centuries to stimulate economic growth. And, meanwhile, the dollar declined from 2012, helping exports and boosting economic growth. If the expected rate of return is positive, the probability of loss will naturally decrease, with the idiosyncratic risk decreases. The strong connections are the catalyst for crisis years, but in the presence of bull market and economic growth, with the lack of first qualifying condition of high idiosyncratic risk, this situation cannot be classified as drastic. From Figure A6a and A7a, we find that there are many strong connections filled in the heatmap of 2012, while the spillover risk remained in low level. In the initial stage of crisis recovery, the risk of all asset decreased simultaneously, which could be due to the strong connectedness in 2012. Looking at the Figure A6, all intergroup spillover risks were declined. Thus, although the strong connected structure was apparent in the assets market, the downtrend and low level of idiosyncratic risk takes the market out of danger. From 2012, the healing process continued with the low idiosyncratic risk maintained, until U.S. Federal Reserve ended quantitative easing in the Oct. 2014.

2. Regulated Shock

There are some volatile periods accompanied by small eventful shocks, such as 1999 Argentina crisis, 2015–2016 stock market selloff, energy price shocks in 1996 and 2003-2006, and cryptocurrency crash in 2018. The events mentioned above caused the idiosyncratic risk, which resulted to the fluctuation of asset market, but the influence of oil market, technological stocks, and cryptocurrency is rarely strong enough to cause a crisis. We find the common ground of these years are: (1) a few of assets have high idiosyncratic risk; (2) the connectedness is not as strong as crisis.

As shown by the dynamic of oil price in Figure 1, oil price shocks happened in 1996 and 2000-2006. The idiosyncratic risk of stocks declined while the connectedness intensified, causing that stocks' high contribution continues. The weak influence of oil market can be proved by the result of Figure A6a and A7a. As can be seen, the commodities of oil, gas and ULSD mainly acted as the importer of connections and spillover risk, while the role of exporter is relatively nonsignificant. On the other hand, in 2003, precious metal of gold or silver imported connectedness from stocks. But due to the high stability of bonds, they seldom acted as the main systemic risk contributor, as shown in Figure 5. Gas contributed strong systemic risk in 2003. While after the Iraq war, the U.S. stock indices have a slow steady growth during 2003 to 2007, which limited the generation of a crisis.

During the 2015–2016 stock market selloff[8], when the stock price declined in Chinese stock market, as shown in Figure 1 and 2, the U.S. stock price witnessed a jump of idiosyncratic risk and high level of volatility. A strong connectedness is shown in the heatmap of Figure A6b inside the U.S. stock market. While the Figure 3 shows that the bond exported and imported more connectedness with others in 2016. In view of the sharp rise in bond yields in early 2016, and 2016 being classified as the worst year for IPOs in America since 2003, we can infer that the increased bond yields may intensify the linkage between bond and other assets. Another interesting finding is that the energy commodities, i.e., gas, crude oil, and ULSD, contributed considerable systemic risk during 2015 to 2016, which could be related to the crash of their price (shown in Figure A1), high idiosyncratic risk (shown in Figure 1), and the connectedness inside energy commodities (shown in Figure A6b). From Figure 4, we see that the years of 2015-2016 have a relatively high level of systemic risk than 2012-2014. There was already a big potential to evolve into a mini crisis, however, the idiosyncratic risk decreased at the end of 2016. The evolution of this shock was interrupted by resurgent economic growth and booming stock market resulted by the blockbuster corporate profits from sweeping tax. Along with new president elect, the U.S. indices increased through the end of the year, as investors bid up stocks in anticipation of deregulation, lower taxes, inflation and infrastructure spending. In contrast, in 1997 and 2007, the government did not intervene the two requirements

[8] The 2015–2016 stock market selloff was the period of globally decline in stock prices that occurred between June 2015 to June 2016. It includes the 2015–2016 Chinese stock market turbulence, in which the Shanghai Composite Index fell 43% in just over 2 months from June 2015 to August 2015. Chinese stock market turbulence caused a fall in petroleum prices, the Greek debt default in June 2015, the effects of the end of quantitative easing in the United States in October 2014.

and let the spillover risk drift. In 2017, the idiosyncratic risk returned to a low level, and the strong connectedness subsided. In addition, the events of volatile period were always happened in a sector with lower systemic influence, such as Argentina crisis, Chinese stock market selloff, and cryptocurrency crash, there are normal limitations to spillover and evolve into a crisis. Thus, there is a rationale for controlling the risk connectedness beforehand that the vulnerability increases when spillover risk channels are strong.

D. Stable Period

As shown in Figure 7, the years of 1992-1995, 2005, 2013-2014, 2017 and 2019 are assessed as stable period. One can find that the stable period does not mean a lifeless economy without vitality, but the best period with economic growth or bull stock market. The idiosyncratic risk and connectedness in the stable period are extremely low.

During 1992-1995, United States had an economic boom[9] began after the end of the early 1990s recession in March 1991, and ended in March 2001 with the Dot-com bubble crash (2000–2002). As shown in Figure A1 during 1991-2000, the price of U.S. stocks witnessed moderate, steady, continuous uptrend. The moderate uptrend of stock price is accelerated by finance-driven technology and R & D development (Brown et al., 2009; Galbraith, 2015), economic growth (Levine and Zervos, 1998), and investment boom (Tevlin and Whelan, 2003). As shown in Figure 1, the idiosyncratic of asset remained in a low level without rapid fluctuations during 1992-1995. As shown in Figure 4, the years of 1992-1995 have very low value of systemic risk.

[9] Resulted from the ended Cold War, rapid technological developments and sound monetary policy, in 1990s, United State experienced a long economic expansion with steady job creation, low inflation, rising productivity, economic boom, and a surging stock market in 1990s.

In the year of 1992, when the British government was forced to withdraw the British Pound from the European Exchange Rate Mechanism (ERM), there was a high idiosyncratic risk for British Pound, see in Figure 1. The connectedness heatmap in 1992 shows the Euro, Swiss Franc, and several bonds have been exposed to the impact of the shock of British Pound. We can notice from Figure A7a and 12 that bonds outputted a relatively high value of risk to currencies, while the opposite direction has a lower spillover risk. From Figure 1, we find related drops of price for currencies (Euro, Swiss Franc and British Pound) and bonds (German, UK and France bonds). It also in line with the connectedness from bonds to currencies shown in Figure A6a. These results can be explained by that the British Pound's impact on the price of bonds firstly, and then, the alternative investments to the foreign bonds caused international capital flow and the shocks of exchange rate. But as reported in the connectedness heatmaps of Figure A6a, the U.S. stocks had very weak connectedness with British Pound. From the dynamics of risk score presented in Figure 4, the Black Wednesday occurred on 16 September 1992 only caused a slight increase of systemic risk, with a fast recovery speed. The risk contribution in Figure 5 reflects the result that the British Pound had not contributed a high systemic risk to U.S. financial market. It reflects that the moderate uptrend of U.S. stock price accelerated by steady economic growth of 1990s might be difficult to interrupt by separate incidents occurred in the foreign financial market.

Now we explore the underlying relation between bull stock market and low systemic risk. From Figure 3 and 12, it is obvious that connectedness in 1992-1996 and 1999-2000 have relatively low value. Comparing the period 1992-1995 with 1999-2000 which is another low connectedness period, we can detect that both periods have similar level of connectedness, while 1992-1995 experienced a steady bull stock market with lower value of idiosyncratic risk, which leads to low systemic risk contribution of U.S. stocks shown in Figure 5. The idiosyncratic risk had lower value than other periods, which is precisely the achievement of economic growth. When the driving force of economic growth is strong, the asset market also enters a bull market because of the expected increase in investment returns. The high rate of asset return reduces the possibility of loss, that is, the idiosyncratic risk is reduced.

It can be noticed that the connectedness measurements show that the average connectedness in 1990s is lower than that in 2000s before Global Financial Crisis. While after the Global Financial Crisis, the average level of connectedness is higher than the previous years and has not got back to the pre-crisis level until 2017. The strong spillover risk among various classes of assets might be a result of the increase of assets global integration and increase in global leverage (Eichengreen, 2010; Mendoza et al., 2009; Fratzscher, 2012; Broner and Ventura, 2016; Caballero, 2016; Devereux and Yu, 2020). In heatmaps of Figure A6a, one can find that the linkages between stocks and non-stock assets are relatively not obvious in 1990s. As we can see, although there were a series of shocks, such as Black Wednesday of British Pound in 1994, Mexico in 1995, Asia in 1997, Russia in 1998, and Argentina in 1999, the financial stability of U.S. asset market in 1990s was only disturbed significantly by 1997-1998 Asian Financial Crisis.

After the Global Financial Crisis, various stimulus policies have appeared in turn, such as quantitative easing, trade tariff policies, and changes in crude oil production, all of which are continuously stimulating the U.S. stock market. The stable periods of 2013-2014, 2017 and 2019 are related to these policies. The quantitative easing, including QE1 announced in November 2008, QE2 in November 2010, QE3 in September 2012, and QE4 started in September 2019, were targeted to maintain the financial stability (Krishnamurthy and Vissing-Jorgensen, 2011; Joyce et al., 2012). As shown in Figure 4, the systemic risk was decreasing after the end of U.S. stock market crash of 2011 and reach a low level after QE3 in 2012. Then the years of 2013-2014 can be assessed as stable period with the average risk contribution shown in Figure 5 lower than 6.0. In this period, the Federal Reserve kept interest rates at the lowest level in two centuries to stimulate economic growth. And, meanwhile, the dollar declined from 2012, helping exports and boosting economic growth. With the positive economic expectations, the expected rate of return relatively high, and the probability of loss will naturally decrease, which is in line with the decreased idiosyncratic risk reported in Figure 1. In 2017, there was another resurgent economic growth and booming stock market caused by the blockbuster corporate profits from tax concessions. The idiosyncratic risk returned to low level, so there is no significant systemic risk.

Strong connectedness provide the channel and mechanism for crisis evolution (Hautsch et al., 2015; Jayech, 2016; Demirer et al., 2018). However, we find that in the presence of bull markets and economic growth to control the idiosyncratic risk, strong connectedness is not very bad. From Figure A6a and A7a, we find that there is a strong connectedness in 2010, while the spillover risk remained at a low level. In the initial stage of crisis recovery, the risk of all asset decreased simultaneously, which is the reason of the strong connectedness in 2010. Looking at the Figure A6, all intergroup spillover risks were declined. Thus, although the strong connected structure happened to the assets market, the downtrend or low level of idiosyncratic risk takes the market out of danger. This is in line with our findings in previous sections, i.e., the impact of stock market crash of 2011 and European debt crisis are limited by the U.S. bull stock market stimulated by quantitative easing policy, and bailout/precautionary programmes from EFSF/ESM.

The implication of stable period can be summarized as follows. When the asset market is confronted with various shocks, the positive policies and the bull market are firewalls to prevent risk contagions and systemic crises. The government can regulate the systemic risk by using policy such as quantitative easing, bid of investment, encouragement of domestic trade, etc. The positive expectation of economic and asset market will defuse the fire sales, and boost the investment demand in asset markets. Alternatively, in short-term, the appropriate emergency policy, e.g., rescuing financial institutions that are on the verge of bankruptcy, ensured that the idiosyncratic risk of institutions decrease.

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