Systemic Risk Measures and Macroeconomic shocks

Yan Li
School of Finance, Renmin University of China
Email: yan1731492846@163.com
59 Zhong Guan Cun Avenue, Hai Dian District, Beijing, China

and

Zongxin Qian (Corresponding Author)
School of Finance, Renmin University of China
Email: qianzx@ruc.edu.cn
Tel: +86-18610985881
59 Zhong Guan Cun Avenue, Hai Dian District, Beijing, China

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Highlights

- The paper asks the question whether more recently developed "new" measurements of systemic risk add valuable incremental information on future macroeconomic performance.
- More specifically, we ask whether aggregating those new measurements into existing aggregate index of systemic risk, which are constructed using "old" systemic risk measurements, leads to an improvement in forecasting ability on the future macroeconomic activities.
- The composite index aggregated using both the "new" and "old" measurements significantly outperform the aggregate index constructed using only the "old" measurements. The performance improvement is sizable, ranging from 44.40% to 180.57%.

Abstract

Previous studies have shown that the buildup of systemic risk in the financial sector could predict real economic activities in the US. This article collects and summarizes the systemic risk measures developed in recent years to investigate whether the inclusion of these "new" measures could improve the out-of-sample forecasting ability of existing aggregate index of systemic risk. We employ quantile regression and different dimension reduction methods to predict the economic downturns in the US and demonstrate that the "new" measurements could provide additional information about the future real macroeconomy and lead to an improvement in forecasting ability.

JEL classification: G10; G20; E37; C58

Keywords: Systemic risk, Quantile Regression, Dimension Reduction, Macroeconomy, Forecast

1 Introduction

The recent financial crisis of 2007-2009 has generated extensive interest in systemic risk, a term which is defined by the IMF as the risk of disruptions in the provision of key financial services that can have serious consequences for the real economy (IMF, 2009). Systemic events are intrinsically difficult to anticipate (IMF, 2010) and the spread of systemic risk would impair the capacity of the whole financial system, even the real economy. Extensive literature provided evidence about the large costs of implicit government subsidies and real economy welfare losses associated with the systemic event (Varotto and Zhao, 2018; Altunbas *et al*., 2017; Acharya and Yorulmazer, 2008; Hoggarth *et al.*, 2002; Claessens *et al*., 1999). Regulators from various countries have also been wrestling with the monitoring and measurement of systemic risk. As a result, a growing part of the literature focuses on the measurement of systemic risk, aimed at providing an early warning signal about the distressed economic condition.

However, given the endogenous and multidimensional nature of systemic risk, its measurement is a complex task (Allen *et al*., 2012; Morley, 2016; Caporin *et al.*, 2022) and many systemic risk measures lack a robust statistical association with macroeconomic downside risk individually (Giglio *et al*., 2016). The measurement noise may obscure the useful information contained in the measurement and a given systemic risk index may only capture one or several specific aspects of the systemic risk. Therefore, Giglio *et al*., (2016) employ dimension-reduction methods to extract the useful content from a large collection of systemic risk measures and find that principal component quantile regression (PCQR) and partial quantile regression (PQR) method could produce consistent forecasts for the distribution of the macroeconomic activity, especially the lower tail of macroeconomic shocks. Caporin *et al*. (2018) employ a more flexible targeted sparse systemic risk index (TASSYRI) method aggregating the risk measures to improve the forecasting performance. Compared with the individual measurements, the aggregate systemic risk measure could provide a more accurate warning signal to alert the regulators about the potential spillover risk to the real economy and contribute to the prevention of possible systemic risk events.

This paper further investigates the relationship between systemic risk measures and the distribution of real macroeconomic activities. Since the research of Giglio *et al*. (2016), the recent literature has constructed "new" systemic risk measures to monitor and predict the risk build-up in the financial sector in tranquil times. In this paper, we further collect and summarize the systemic risk measures developed in recent years and investigate whether these "new" systemic risk measures could improve the forecasting ability of real economic activities. Although the previous literature confirm that the aggregate index could improve the predictability compared with the individual one, it doesn't mean that the predictability would always be improved when we include more systemic risk measurements. When the information contained in the different measures is repetitive or even conflicting, aggregating more systemic risk measures could even worsen the forecasting performance. Thus, only if the new measurements could provide additional useful information related to future economic activities, could the predicting performance be improved.

In the first part of the paper, we examine all systemic risk measures individually to check whether these indicators could provide significant out-of-sample forecasting power individually. In the second part, we construct the composite risk index using different dimension-reduction methods and investigate whether the addition of "new" systemic risk measures to the composite index could improve the predictability. We further adopt the TASSYRI method proposed by Caporin *et al*. (2018), which excludes the possible redundant measures using the sparsity method and allows for a time-varying subset of the systemic risk measurements. The paper empirically extends that of Giglio *et al*. (2016), since we consider a much wider range of systemic risk indicators and a more flexible method to aggregate the composite risk index.

Our empirical results provide novel evidence. First, consistent with Giglio *et al*. (2016), the individual systemic risk measures lack a robust predicting ability to the macroeconomic downside risk. Some indicators such as CatFin, default spread, volatility, and turbulence are significantly informative out-of-sample. Some “newly” introduced measures, for example, Systemic Expected Shortfall (Acharya *et al*., 2017), $\widehat{\mathrm{CoVaR}}^{\mathrm{TENET}}$ (Härdle *et al*., 2016) and Component Expected Shortfall (Banulescu and Durnitrescu, 2015), also exhibit significantly stronger forecasting power than the unconditional quantile regression. Secondly, we present that the composite index constructed using “all” systemic measures by PCQR, PQR, and TASSYRI improves the forecasting performance by 44.40%, 87.97%, and 180.57% respectively compared to that relies on only the “old” measures in Giglio *et al*. (2016). These results suggest that these “new” measures contain useful information about the distribution of future real economic activities additionally. Thirdly, we focus on the forecasting horizon varying from 1 to 12 months and find that the predictive ability of the aggregated index declines after 8 months but remains positively significant up to 12 months.

The remainder of the paper proceeds as follows. Section 2 defines and provides a quantitative description of the selected systemic risk measures and macroeconomic shocks in the US. In Section 3, we introduce the dimension-reduction methods in detail. Section 4 examines the predicting performance of both the individual measure and the composite index for different quantiles of macroeconomic shocks and presents the forecasting ability over a longer horizon of up to 12 months. Section 5 concludes.

2 Data

Our research selects and summarizes 33 systemic risk measures. Detailed information could be found in Table 1. According to the different aspects these measures specified, we group them into the following five groups, institution-specific risk, connectedness and spillover, volatility and instability, liquidity and credit, and tail dependence. We first calculate the 19 commonly used measures outlined by the previous research. In line with Giglio *et al*., (2016), we construct these 19 measurements using the largest 20 financial institutions in each period, except for the size concentration index which we use 100 financial institutions. Apart from that, we then collect and summarize the systemic risk measures developed in the recent literature to the extent that we have access to enough time spans and relevant data for the index. In this paper, we call the measurements used in Giglio *et al*., (2016) the old measurements and additional measurements in this study as "new" measurements to facilitate discussions. Most risk measures are constructed on a daily basis[1] based on the 252-day rolling window and we compute each measure as the equally weighted average of the financial institutions. Detailed information on the measures can be found in the Appendix. We obtained all the US return data from CRSP and Yahoo Finance and the accounting data from Compustat. The macroeconomic variables are from the Federal Reserve Bank of St. Louis, Yahoo Finance, and Bloomberg database. To summarize, the systemic risk measures cover various information including stock market information, accounting information, bond market yields and the macroeconomic condition.

3 Systemic Risk Measures

3.1.1 Institution-specific risk

The institution-specific risk mainly quantifies the contribution or sensitivity of the individual financial institution to the systemic risk. These measures include the CoVaR, ΔCoVaR (Adrian and Brunnermeier, 2010), the marginal expected shortfall (MES) (Acharya *et al*, 2010), and MES-BE proposed by Brownlees and Engle (2011). In this paper, we further include the SRISK, a conditional capital shortfall measure of systemic risk by Brownlees and Engle (2017), the component expected shortfall (CES) proposed by Banulescu and Durnitrescu (2015), which measures the firm's 'absolute' contribution to the ES of the financial system, and the systemic expected shortfall (SES) by Acharya *et al*. (2017). Apart from these measures, we further construct the State-Dependent Sensitivity Value-at-Risk (SDSVAR), which is based on the value-at-risk (VaR) measure, to obtain the direction and size of spillovers from one set of institutions to another (Adam *et al*. 2016). Härdle *et al* (2016) construct the $\widehat{\mathrm{CoVaR}}^{\mathrm{LASSO}}$ and $\widehat{\mathrm{CoVaR}}^{\mathrm{TENET}}$, the semi-parametric measures to estimate systemic interconnectedness

[1] Following Härdle et al. (2016), we calculate the $\widehat{\mathrm{CoVaR}}^{\mathrm{LASSO}}$ and $\widehat{\mathrm{CoVaR}}^{\mathrm{TENET}}$ based on the weekly data. Following Antonakakis et al. (2020) and Geraci and Gnabo (2018), we calculate TVP-VAR based on the monthly data.

across financial institutions based on tail-driven spillover effects in a high dimensional framework (Härdle *et al*. 2016). White *et al*. (2015) apply the multivariate, multi-quantile models to analyze the spillover effect in the values-at-risk (VaR).

3.1.2 Comovement and Contagion

The comovement and contagion capture the common risk exposure across the financial intuitions, which may be due to asset commonality, credit inter-linkages, etc. We first consider the Absorption Ratio and ΔAbs from Kritzman and Li (2010), the DCI from Billio *et al*. (2012), and the international spillover index from Diebold and Yilmaz (2009). Diebold and Yilmaz (2012) use a generalized vector autoregressive framework to characterize daily volatility spillovers across US stock, bond, foreign exchange, and commodities markets. We further take the connectedness index proposed by Diebold and Yilmaz among the sovereign bond markets into consideration, despite the relatively short time horizon. Following Geraci and Gnabo (2018), Gabauer and Gupta (2018), and Antonakakis *et al*. (2020), we measure the dynamic connectedness between financial institutions based on time-varying parameter vector autoregressions (TVP-VAR). Das (2016) and Chen (2018) propose the systemic risk score to quantify the aggregate risk in a network comprised of related entities based on the compromise level.

3.1.3 Volatility and instability

Volatility and instability represent the fluctuations and vulnerability of the financial system. We first construct the traditional volatility of the financial institutions' equity returns. The Turbulence index proposed by Kritzman and Li (2010) measures the long-term equity return volatility. Besides, the CatFin of Allen *et al*. (2012), the size concentration based on the Herfindal index in the financial sector, and the aggregate book leverage and market leverage are included in our analysis. All these metrics except the size concentration are calculated based on the largest 20 financial institutions during the given period. Mihoci *et al*. (2020) construct the Financial Risk Meter (FRM) based on the penalization parameters of the lasso regression to capture the potential changes in volatility.

Table 1.

Description of systemic risk measures and the sample start dates.

Indicator	*2.1.1 Institution-specific risk*	
"old"	CoVaR, ΔCoVaR	Adrian and Brunnermeier (2010)
	MES	Acharya *et al*. (2010)
	MES-BE	Brownlees and Engle (2012)
"new"	**SRISK**	Brownlees and Engle (2017)
	Component Expected Shortfall (CES)	Banulescu and Durnitrescu (2015)
	Systemic Expected Shortfall (SES)	Acharya *et al*. (2017)
	$\widehat{\mathbf{CoVaR}}^{\mathbf{LASSO}}$	Härdle *et al*. (2016)
	$\widehat{\mathbf{CoVaR}}^{\mathbf{TENET}}$	Härdle *et al*. (2016)
	SDSVAR	Adam *et al*. (2014)
	CAViaR	White *et al*. (2015)
	2.1.2 Comovement and Contagion	
"old"	Absorption ratio; ΔAbs	Kritzman and Li (2010)
	DCI	Billio *et al*. (2012)
	Intl. spillover	Diebold and Yilmaz (2009)
"new"	**Systemic risk score**	Das (2016); Chen (2018)
	TVP-VAR	Geraci and Gnabo (2018)
		Gabauer and Gupta (2018)
		Antonakakis *et al*. (2020)
	Overall Connectedness	Diebold and Yilmaz (2012)
	Sovereign bond Connectedness	Diebold and Yilmaz (2012)
	2.1.3 Volatility and instability	
"old"	Volatility	
	Turbulence	Kritzman and Li (2010)
	CatFin	Allen *et al*. (2012)
	Size conc.	
	Book leverage	
	Market leverage	
"new"	**Financial Risk Meter (FRM)**	Mihoci *et al*. (2020)
	2.1.4 Liquidity and credit	
"old"	AIM	Amihud (2002)
	Ted spread	
	Term spread	
	GZ spread	Gilchrist and Zakrajsek (2012)
	Default spread	
	2.1.5 Tail dependence	
"new"	**Asymptotic Dependence Rate (ADR)**	Balla *et al*. (2014)
	Average Chi (ACHI)	Balla *et al*. (2014)

3.1.4 Liquidity and credit

To measure the illiquidity across the financial institutions, we first calculate the AIM index developed by Amihud (2002). Besides, we construct the representative interest spreads, which are the Gilchrist and Zakrajsek (2012) credit spread measure (GZ), the default spread (BAA bond yield minus AAA bond yield), Term spread (10Y government rate minus 3M government bond rate) and Ted spread (3M LIBOR minus 3M government bond rate) to measure the credit conditions.

3.1.5 Tail dependence

Tail dependence is designed to capture the probability of extreme crisis coincidence. Balla *et al*. (2014) propose the Average Chi (ACHI) and Asymptotic Dependence Rate (ADR) to measure the prevalence and the strength of the asymptotic dependence among the US banking system.

3.2 Macroeconomic data

Following Giglio *et al*. (2016), we focus on the real macroeconomic shocks measured by innovations to industrial production growth (IP) from January 1980 to December 2023. We obtain macroeconomic data from the Federal Reserve Board. We carry out the following autoregressive method for the growth rate of real industrial production growth (Y_t), we select the autoregressive order according to the Akaike Information Criterion (AIC). The macroeconomic shock is defined as the residual term of the following autoregressive model:

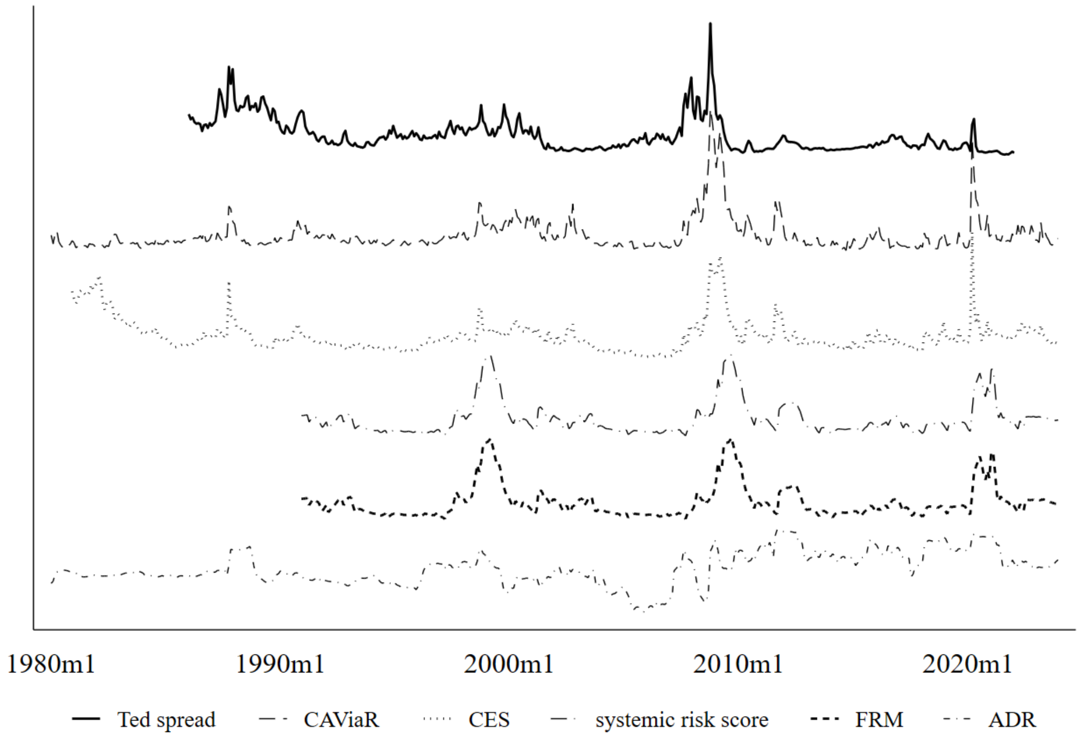
$$Y_t = c + \sum_{i=1}^{p} \alpha_i Y_{t-i} + U_t = c + \alpha_p(L) Y_t + U_t \quad (1)$$

where c and α_i are parameters, U_t is the error term.

3.3 Summary of comovement among systemic risk measures

Figure 1 plots the dynamic variations of selected measures in the US from 1980 to 2023. All the measures are standardized over the full sample. We could find significant spikes around 1990 and 2008, which corresponds to the oil crisis and global financial crisis. Many metrics also present unusual trends around 2020, which indicates that the COVID-19 pandemic impairs economic development significantly in the US.

Figure 1.
Dynamics of systemic risk measures. The figure plots the selected systemic risk measures[2]. All measures have been standardized to have equal variance for comparison.



The discrepancies between these indicators could be partly explained by the noise or the false signals and the multi-dimensional nature of the systemic risk. A single measurement may reflect one or several specific dimensions of systemic risk. Thus, it is necessary to extract useful information from those measurements to mitigate the impact of noises.

4 Methodology

The buildup of systemic risks in the financial sector has the potential spillover risk to the real economy. Thus, a useful systemic risk measure should provide regulators with an early warning signal of the possible downside risks of the real economy. We now focus on the out-of-sample predictive ability of the systemic risk measures on the left tail of macroeconomic activities. Following Giglio *et al*. (2016), we use the recursive quantile regression model given the nonlinear relationship between financial instability

[2] We only show a subset of the measures for readability and we could provide the descriptive statistics for all the measures if needed.

and the macroeconomy. The advantage of the quantile regression is that it is more flexible, with the coefficients varying across different quantiles.

4.1 Quantile Regression

The out-of-sample analysis is conducted based on the following quantiles regression.

$$Q_\tau(y_{t+h}|\mathbf{I}_t) = \beta_{\tau,0} + \boldsymbol{\beta}'_{\boldsymbol{\tau}}\boldsymbol{x_t} \quad (2)$$

where $Q_\tau(y_{t+h}|\mathbf{I}_t)$ is the conditional τ-quantile of the monthly shocks in the macroeconomic proxy, with horizon h ranging from 1 to 12 months, x_t is the monthly average of the daily systemic risk measures. We set τ equals to 20%, 50% and 80% following Giglio *et al*. (2016), where τ = 20% represents the left-tail of the macroeconomic shock, 50% is the median and 80% is the upper quantile.

The criteria used to judge the accuracy of the out-of-sample prediction is the R^2 based on the loss function ρ_τ. If the information contained in X_t could predict y_{t+h} more accurately than the unconditional quantile regression, the R^2 will be significantly positive and negative otherwise. The greater the R^2, the higher the predictive accuracy. R^2 can be expressed using the following equation.

$$R^2 = 1 - \frac{\frac{1}{T}\sum_t[\rho_\tau(y_{t+h} - \hat{\alpha} - \hat{\beta}X_t)]}{\frac{1}{T}\sum_t[\rho_\tau(y_{t+h} - \widehat{q_\tau})]} \quad (3)$$

where $\widehat{q_\tau}$ is the unconditional quantile of the regression. Following Clark and West (2007), we use the adjusted MSPE statistics to estimate the significance of the R^2.

$$f_{t+1} = (y_{t+h} - \widehat{q_\tau})^2 - \left[\left(y_{t+h} - \hat{\beta}_{\tau,0} - \hat{\beta}_{\tau,1}x_t\right)^2 - \left(\widehat{q_\tau} - \hat{\beta}_{\tau,0} - \hat{\beta}_{\tau,1}x_t\right)^2\right] \quad (4)$$

4.2 Dimension-reduction Methodology

In this section, we briefly introduce the methodologies adopted by the paper to extract latent factors, which could effectively aggregate useful information from a set of systemic risk measures.

We suppose that the macroeconomic shock y_{t+h} is a linear function of the unobserved latent factors f_t, conditional on the information set $\mathbf{I}_t$ and is expressed as a function of f_t.

$$Q_\tau(y_{t+h}|\mathbf{I}_t) = \alpha f_t \ (5)$$

The y_{t+h} is expressed as follows.

$$y_{t+h} = \alpha f_t + \eta_{t+h} \ (6)$$

where f_t is the unobserved latent factors and η_{t+h} is the residual of the quantile regression.

We use vector $\boldsymbol{x_t}$ to represent the systemic risk measures which is a function of the latent factor f_t.

$$\boldsymbol{x_t} = \Lambda F_t + \varepsilon_t \equiv \varphi f_t + \psi g_t + \varepsilon_t \ (7)$$

where ε_t refers to the idiosyncratic measurement errors. The vector $\boldsymbol{x_t}$ is comprised of the two parts, one is the latent factor f_t which contains the useful content about the macroeconomy h months later, the other is the irrelevant information g_t, uncorrelated to the macroeconomic distribution. F_t represents the first K principal components and Λ is the eigenvectors of first K eigenvalues of $\sum_{t=1}^{T} \boldsymbol{x_t x_t'}$.

4.2.1 Principal components quantile regression (PCQR)

The PCQR estimator mainly consists of two parts. In the first stage, we extract the common factor F_t from the systemic risk measures $\boldsymbol{x_t}$.

$$\hat{F}_t = (\Lambda'\Lambda)^{-1}\Lambda'\boldsymbol{x_t}(8)$$

In the second stage, we forecast the macroeconomy by quantile regression of y_{t+h} on the $\hat{F}_t$ and a constant.

$$Q_\tau(y_{t+h}|\mathbf{I}_t) = \alpha'\boldsymbol{\hat{F}}_t(9)$$

When the number of the predictors and the time length become large, the PCQR could get the consistent estimation through the quantile regression of y_{t+h} (Giglio *et al.*, 2016).

$$\forall t, when\ N, T \to \infty, \alpha'\hat{F}_t - \alpha' f_t \xrightarrow{p} 0(10)$$

4.2.2 Partial quantile regression (PQR)

The second estimator is the partial quantile regression (PQR) following Giglio *et al.* (2016). Different from PCQR which condenses the cross-section according to covariance within the predictors, PQR condenses each predictor's covariance on the cross-sectional level, which typically uses fewer factors than PCQR.

In the first stage, we regress y_{t+h} on each $x_{i,t}$ and a constant to get the slope coefficient $\hat{\varphi}_i$, then calculate the cross-sectional covariance between $\hat{\varphi}_i$ and $x_{i,t}$ at each time to get the common factor $\widehat{f}_t$, the latent factor determined by the slope coefficient $\hat{\varphi}_i$. Then in the prediction stage, we obtain the macroeconomic forecast by quantile regression of y_{t+h} on the $\widehat{f}_t$ and a constant. The PQR predictor is a consistent estimation by choosing a linear combination of the measures.

$$\forall t, when\ N, T \to \infty, \hat{\alpha}\hat{f}_t - \alpha f_t \xrightarrow{p} 0 \quad (11)$$

4.2.3 Targeted Sparse Systemic Risk Index (TASSYRI)

Following Caporin *et al*. (2018) and Shen and Huang (2008), we adopt the TASSYRI as our third estimator to forecast the macroeconomy. We briefly introduce the TASSYRI below and refer readers to Shen and Huang (2008) for additional details. The SPCA method proposed by Shen and Huang (2008) is based on the close connection between PCA and singular value decomposition (SVD). The SVD of the matrix M is as follows,

$$M = UDV' \quad (12)$$

where $U = [u_1 \quad \cdots \quad u_r]$ is the left singular vector of M, $V = [v_1 \quad \cdots \quad v_r]$ contains the right singular vectors and $D = diag\{d_1 \quad \ldots \quad d_r\}$ is the diagonal matrix. The matrix $Z = UD$ are the Principal Components (PCs) and the columns of V is the corresponding loadings.

Shen and Huang (2008) mainly focus on the following minimization problem,

$$min_{\tilde{v}\in\mathbb{R}^p} \left[\left| |M - \tilde{u}\tilde{v}'| \right|_F^2 + \lambda P(\tilde{v}) \right] \quad (13)$$

where $\tilde{u} = [u_1 \quad \cdots \quad u_l]$ and $\tilde{v} = [v_1 \quad \cdots \quad v_l]$ with $l \leq p$ representing the first rank l approximations of the U and V. λ is a tuning parameter, and $P(\tilde{v})$ is the penalty function defined over the loadings. $\left| \left| M - \tilde{u}\widetilde{v'} \right| \right|_F^2 = tr\{(M - \tilde{u}\tilde{v}')(M - \tilde{u}\tilde{v}')\} = \sum_{i=1}^{n} \sum_{j=1}^{p} (x_{ij} - \tilde{u}_i\tilde{v}_i)^2$ represents the squared Frobenius norm.

The optimal solution is chosen by a LASSO penalty as follows,

$$\tilde{v}^{s} = sign(X'^{\tilde{u}})(|X'^{\tilde{u}}| - \lambda)_{+} \quad (14)$$

Then we could obtain the first l sparse principal components as $\hat{Z} = M\hat{x}^{s}$, where $\hat{x}^{s}$ is the standardized optimal parameter's vectors in the above function.

5 Systemic risk measures and the macroeconomy

5.1 Empirical evaluation of the individual systemic risk index

Table 2 presents the recursive out-of-sample results for the 20th percentile of the IP shocks. The out-of-sample forecasting starts in January 1990 and January 2000[3]. Following Giglio *et al*. (2016), we choose January 1990 as our first out-of-sample start date and we also choose January 2000 as our second out-of-sample start date as the robustness test of our results because we want to expand our training sample and test the performance of our composite index during the dot-com crisis and financial crisis. The result is consistent with that of Giglio *et al*. (2016). Some systemic risk measures demonstrate significant forecasting power compared to the unconditional quantile regression. CatFin, default spread, volatility, and turbulence are significantly predictive concerning different split dates. Among the "new" measures, $\widehat{\mathrm{CoVaR}}^{\mathrm{TENET}}$, component expected shortfall and systemic expected shortfall provide significant out-of-sample predictability for the lower tail of the IP shocks. Some indicators perform worse than the unconditional quantile regression, with negative R^2. However, this doesn't mean that the information contained in the measures are useless. The index may only reflect one or several dimensions of the systemic risk, which may not result in a full-blown financial crisis. However, the results are not that robust in every specification.

As shown by Table 3 and Table 4, the systemic risk measures present relatively weaker forecasting power in the median and 80$^{\mathrm{th}}$ percentiles shock, with few measures performing well. Only CatFin, default spread, CAViaR and $\widehat{\mathrm{CoVaR}}^{\mathrm{TENET}}$ exhibits significantly positive R^2 for the prediction of the median IP shock.

[3] We adopt the recursive out-of-sample method, which means that the independent variable for T= t+1 is estimated based on the training sample T=1 to T=t.

Figure 2.

IP growth shocks and predicted 20th percentiles. Fitted values for the 20th percentile of one-quarter-ahead IP growth shocks. “historical” is the in-sample (1980–2023) 20th percentile of IP growth shocks shown as black dots. “PCQR” is the out-of-sample 20th percentile forecast based on PCQR.

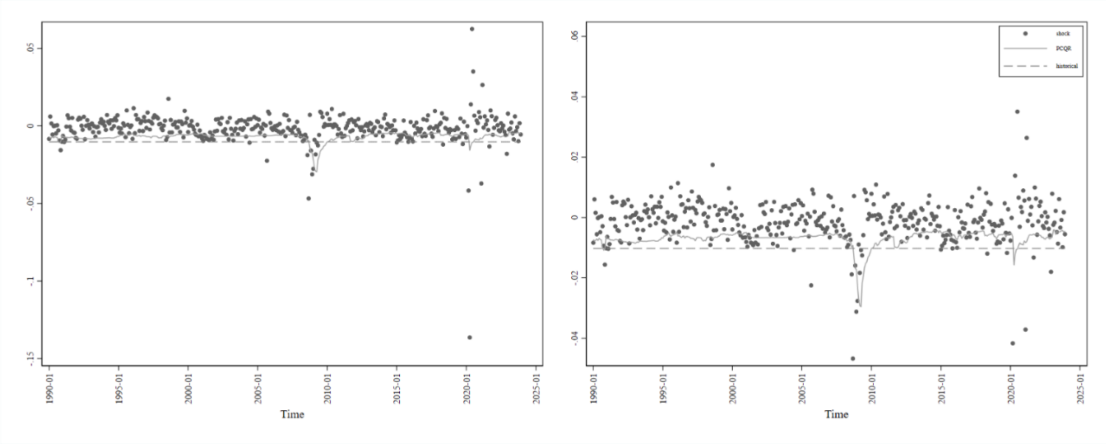


Table 2.
Monthly 20th Percentile Quantile Regression Results

Systemic risk measures and the macroeconomy (Individual Systemic Risk Measurement)		
	US	
Out-of-sample start	1990	2000
Absorption_ratio	-0.0100***	-0.0265***
AIM	-0.0282***	-0.0150***
Book_leverage	-0.0078***	-0.0206
CatFin	0.0493**	0.0575**
CoVaR	0.0017	0.0033
DCI	-0.0059***	-0.0265***
Def_sprs	0.0648***	0.0470***
Delta_Absorption	-0.0017***	-0.0170***
Delta_CoVaR	-0.0081	-0.0090
gz	0.1884	0.2223
intl_spillover	0.1030	0.0717
MES	-0.0057	-0.0101
MES-BE	0.0447	0.0666
Market_ leverage	0.0152***	-0.0254*
Vol	0.0545*	0.0674*
Size_con	-0.0408***	-0.0389***
Ted_spr	0.0072***	-0.0215***
Term_spr	0.0032***	-0.0122***
Turbulence	0.0793***	0.0820*
CAViaR	0.0401	0.0617
Systemic_risk_score	-0.0074	-0.0104
SDSVAR	0.0186	0.0177
ACHI	-0.0336***	-0.0156***
ADR	-0.0161	-0.0178
TVP-VAR	-0.0044***	-0.0084***
SRISK	-0.0213	-0.0043
SES	0.0365***	0.0389***
$\widehat{\mathrm{CoVaR}}^{\mathrm{TENET}}$	-	0.0210***
$\widehat{\mathrm{CoVaR}}^{\mathrm{LASSO}}$	-	-0.0220***
CES	0.0673***	0.0628*
FRM	-	-0.0336

Note: Table reports out-of-sample quantile prediction R^2 for the regression horizons h = 1 for the corresponding quantiles of IP shock. Out-of-sample start date is noted for each column. Statistical significance at 10%, 5%, and 1% levels are denoted by $*$, $**$, and $***$, respectively. Samples are monthly from January 1980 to December 2023. "-" Indicates insufficient data for estimation in a given sample.

Table 3.

Monthly 50th Percentile Quantile Regression Results

Systemic risk measures and the macroeconomy (Individual Systemic Risk Measurement)		
	US	
Out-of-sample start	1990	2000
Absorption_ratio	-0.0029	-0.0034
AIM	-0.0041	-0.0018
Book_leverage	-0.0051	-0.0115
CatFin	0.0105*	0.0146*
CoVaR	-0.0064	-0.0052
DCI	0.0000	-0.0005
Def_sprs	0.0276***	0.0298**
Delta_Absorption	-0.0050	-0.0017
Delta_CoVaR	-0.0062	-0.0070
gz	0.1874***	0.2225***
intl_spillover	0.0790	0.0238*
MES	-0.0083	-0.0093
MES-BE	0.0162	0.0216*
Market_ leverage	-0.0022***	-0.0133**
Vol	0.0072	0.0157
Size_con	-0.0145	0.0005
Ted_spr	-0.0123*	-0.0229*
Term_spr	0.0078	0.0126
Turbulence	0.0164	0.0278
CAViaR	0.0102*	0.0175*
Systemic_risk_score	-0.0055*	-0.0053*
SDSVAR	0.0157	0.0207
ACHI	-0.0106	-0.0027*
ADR	-0.0082	-0.0071
TVP-VAR	-0.0088	-0.0044
SRISK	-0.0186***	-0.0049**
SES	0.0292*	0.0411*
$\widehat{\text{CoVaR}}^{\text{TENET}}$	-	0.0066*
$\widehat{\text{CoVaR}}^{\text{LASSO}}$	-	-0.0128
CES	0.0176	0.0222
FRM	-	-0.0039

Note: Table reports out-of-sample quantile prediction R^2 for the regression horizons h = 1 for the corresponding quantiles of IP shock. Out-of-sample start date is noted for each column. Statistical significance at 10%, 5%, and 1% levels are denoted by $*$, $**$, and $***$, respectively. Samples are monthly from January 1980 to December 2023. "-" Indicates insufficient data for estimation in a given sample.

Table 4.

Monthly 80th Percentile Quantile Regression Results

Systemic risk measures and the macroeconomy (Individual Systemic Risk Measurement)		
	US	
Out-of-sample start	1990	2000
Absorption_ratio	-0.0062**	-0.0054***
AIM	-0.0047***	0.0015***
Book_leverage	-0.0055***	-0.0100***
CatFin	0.0019	0.0018
CoVaR	-0.0046***	-0.0063***
DCI	-0.0025**	-0.0021
Def_sprs	0.0030	0.0007
Delta_Absorption	-0.0042	-0.0014
Delta_CoVaR	-0.0019***	-0.0033***
gz	0.1780***	0.1931***
intl_spillover	0.1570**	0.1552**
MES	0.0005***	0.0018***
MES-BE	-0.0036**	-0.0029**
Market_ leverage	-0.0075*	-0.0033*
Vol	-0.0004*	-0.0012*
Size_con	-0.0102	-0.0084***
Ted_spr	-0.0027***	-0.0171*
Term_spr	0.0023*	0.0055**
Turbulence	-0.0151*	-0.0163*
CAViaR	-0.0043**	-0.0048**
Systemic_risk_score	0.0055***	0.0072***
SDSVAR	0.0002**	0.0007**
ACHI	-0.0055	-0.0107
ADR	-0.0033	-0.0066
TVP-VAR	-0.0075***	-0.0141***
SRISK	-0.0358***	-0.0300***
SES	0.0348	0.0380*
$\widehat{\mathrm{CoVaR}}^{\mathrm{TENET}}$	-	-0.0169**
$\widehat{\mathrm{CoVaR}}^{\mathrm{LASSO}}$	-	-0.0098***
CES	0.0015	-0.0001
FRM	-	-0.0055***

Note: Table reports out-of-sample quantile prediction R^2 for the regression horizons h = 1 for the corresponding quantiles of IP shock. Out-of-sample start date is noted for each column. Statistical significance at 10%, 5%, and 1% levels are denoted by $*$, $**$, and $***$, respectively. Samples are monthly from January 1980 to December 2023. “-” Indicates insufficient data for estimation in a given sample.

5.2 Empirical evaluation of the aggregate systemic risk index

Table 5 shows that the composite index provides robust out-of-sample predictive information for future macroeconomic shock prediction in the 20th percentile and report results for out-of-sample start dates of 1990 and 2000. The R^2 reaches around 7% for the PCQR method, which is much higher than that of the individual index. Apart from that, The PCQR estimator constructed by all the measures is 44.40% significantly higher than that constructed using only the "old" ones, indicating that our "new" measures could provide useful content related to the future macroeconomy. Also, the PQR estimator aggregated by all the measures exhibits stronger forecasting power than that of the "old" measures, which further confirms the informativeness of the "new" measures. The overall predictive performance of the PCQR estimator is better than that of the PQR.

Figure 2 plots the out-of-sample fitted values of the quantile regression since 1980. The dots represent the real macroeconomic shocks, and the solid line is the PCQR predicted value of the 20th percentile regression. The dotted line is the unconditional 20th percentile of economic shocks. We could find obvious downshifts around 1990, 2008, and 2020, corresponding to the oil crisis, global financial crisis, and the COVID-19 pandemic. Also, we could observe that the quantile regression fitted values shift down a bit earlier than that of the macroeconomic shocks around the three crises, which could be viewed as an early warning signal to the real economy.

The classical PCA approach serves as a special case of the sparse PCA we introduced in section 3 for the classical one always takes all the systemic risk measures into consideration. In case the classical PCA may include conflicting or even wrong information contained in the measures to obscure our results, we further apply the TASSTRI method proposed by Caporin *et al.* (2018) to exclude the redundant and useless information. Also, the TASSTRI method is much more flexible because of the time-varying components. The results demonstrate that the "new" measures are informative about the future economic activities and the aggregate index could be viewed as a robust out-of-sample predictor of the left tail of the macroeconomy.

Table 5.

Aggregate systemic risk measures and the macroeconomy (20th percentile)

	US	
Out-of-sample start	1990	2000
PCQR2-all index	0.0699***	0.0787**
PCQR2-old index	0.0564***	0.0545**
PQR-all index	0.0434***	0.0297**
PQR-old index	0.0197***	0.0158*
TASSTRI2-all index	0.0633***	0.0592***
TASSTRI2-old index	0.0425***	0.0211***

Note: Table reports out-of-sample quantile prediction R^2 for the regression horizons h = 1 for the corresponding quantiles of IP shock. Out-of-sample start date is noted for each column. Statistical significance at 10%, 5%, and 1% levels are denoted by $*$, $**$, and $***$, respectively. Samples are monthly from January 1980 to December 2023.

Table 6.

Aggregate systemic risk measures and the macroeconomy (50th percentile)

	US	
Out-of-sample start	1990	2000
PCQR2-all index	0.0620***	0.0750**
PCQR2-old index	0.0071*	0.0080*
PQR-all index	0.0339***	0.0428**
PQR-old index	-0.0039*	0.0155*
TASSTRI2-all index	0.0509**	0.0602**
TASSTRI2-old index	-0.0027**	-0.0065**

Note: Table reports out-of-sample quantile prediction R^2 for the regression horizons h = 1 for the corresponding quantiles of IP shock. Out-of-sample start date is noted for each column. Statistical significance at 10%, 5%, and 1% levels are denoted by $*$, $**$, and $***$, respectively. Samples are monthly from January 1980 to December 2023.

Table 7.

Aggregate systemic risk measures and the macroeconomy (80th percentile)

	US	
Out-of-sample start	1990	2000
PCQR2-all index	0.0072**	0.0051**
PCQR2-old index	-0.0016**	-0.0041**
PQR-all index	-0.0087*	-0.0110*
PQR-old index	-0.0212	-0.0230
TASSTRI2-all index	0.0052***	0.0050***
TASSTRI2-old index	-0.0109***	-0.0106***

Note: Table reports out-of-sample quantile prediction R^2 for the regression horizons h = 1 for the corresponding quantiles of IP shock. Out-of-sample start date is noted for each column. Statistical significance at 10%, 5%, and 1% levels are denoted by $*$, $**$, and $***$, respectively. Samples are monthly from January 1980 to December 2023.

As for the central tendency of macroeconomic shocks shown in Table 6, it is apparent that the forecasting ability of the aggregated index using "all" measures improves a lot, which means that our composite index is also informative on the median of the macroeconomic shocks. The predictability of the upward movements of the macroeconomic shocks shown in Table 7 is not evident in contrast to the 20th percentile and the median.

5.3 Further Analysis

In this section, we further examine the predictability of our composite index comprised of all the measures over a longer term, with the forecasting horizon ranging from 1 to 12 months. As presented in Table 8, the aggregated index exhibits strong predictive power for up to 8 months in the left tail of the macroeconomic shocks, with R^2 decreasing afterward. The results indicate that our composite index contains useful information for future macroeconomic activities over a longer horizon. Apart from that, it is notable that the composite index using all the systemic risk information provides much more accurate forecast up to 10 months, which confirms the previous evidence. The results also demonstrate that the "new" systemic risk measures could provide additional useful information over a longer forecasting horizon.

Table 8.

Aggregate systemic risk measures and the macroeconomy

	Aggregate systemic risk measures (PCQR)					
	all index			old index		
	20th	50th	80th	20th	50th	8th
h=2	0.0958***	0.0710***	-0.0105***	0.0800***	0.0242**	0.0009**
h=3	0.0814***	0.0739***	0.0032***	0.0750***	0.0263***	0.0010**
h=4	0.0695***	0.0707***	-0.0010**	0.0580***	0.0101**	-0.0054
h=5	0.0772***	0.0795***	-0.0010**	0.0451***	0.0126**	-0.0015
h=6	0.0494***	0.0623***	-0.0197	0.0312***	0.0058*	-0.0141
h=7	0.0607***	0.0699***	-0.0280	0.0551***	0.0123**	-0.0090
h=8	0.0626***	0.0550***	-0.0334	0.0551***	0.0123**	-0.0090
h=9	0.0552***	0.0590***	0.0018	0.0501***	0.0286***	0.0033*
h=10	0.0351***	0.0659***	-0.0081**	0.0329***	0.0237**	-0.0059

h=11	0.0542***	0.0682***	-0.0059***	0.0622***	0.0438***	0.0006***
h=12	0.0546***	0.0434***	-0.0110**	0.0549***	0.0180**	-0.0053***

Note: Table reports out-of-sample quantile prediction R^2 for the regression horizons h = 2 to 12 months for the corresponding quantiles of IP shock. Statistical significance at 10%, 5%, and 1% levels are denoted by $*$, $**$, and $***$, respectively. Samples are monthly from January 1980 to December 2023. Out-of-sample forecasts start in January 1990.

6 Conclusion

This article collects and summarizes the systemic risk measurements developed after Giglio *et al*. (2016) and examines the forecasting ability of the individual index and the composite index on the distribution of economic activities. Our paper complements and extends the literature on the relationship between systemic risk measurements and macroeconomy since we consider a much wider set of systemic risk measurements. Our findings show that the composite measure of systemic risk provide a much more accurate prediction after including the “new” measures, indicating that these newly introduced measures are informative on future economic activities. The composite index could serve as an early warning signal for future economic downturns since it exhibits significant forecasting ability over a relatively long horizon.

Acknowledgements

We would like to thank Zeno Adams, Jun Ma, Jennie Bai, Tommaso Belluzzo and David Gabauer for providing the relevant codes.

Appendix

This appendix briefly describes the technical details of the systemic risk measures. We do not include those measures used in Giglio *et al*. (2016) since readers could refer to that paper for the details.

Systemic Risk Measures

SRISK (Brownlees and Engle (2017)) SRISK is defined as the expected capital shortfall conditional on a systemic event.

$$SRISK_{it} = E_t(CS_{i\,t+h} | R_{m\,t+1:t+h} < C) \text{ (A1)}$$

where $R_{m\,t+1:t+h}$ is the multi-period arithmetic market equity return between period $t+1$ and $t+h$ and the systemic event is defined as $\{R_{m\,t+1:t+h} < C\}$. In this paper, we set the threshold C to be -10%.

SRISK is a function of the size of the firm, its degree of leverage, and its expected equity devaluation conditional on a market decline.

$$\begin{aligned} SRISK_{it} &= kD_{i\,t} - (1-k)W_{i\,t}(1 - LRMES_{i\,t}) \\ &= W_{i\,t}[kLVG_{i\,t} + (1-k)LRMES_{i\,t} - 1] \text{ (A2)} \end{aligned}$$

where $LVG_{i\,t}$ denotes the quasi-leverage ratio $(D_{i\,t} + W_{i\,t})/W_{i\,t}$ and $LRMES_{i\,t}$ is Long Run MES, the expectation of the firm equity multi-period arithmetic return conditional on the systemic event, that is,

$$LRMES_{i\,t} = -E_t\big((R_{i\,t+1:t+h} | R_{m\,t+1:t+h} < C)\big) \text{ (A3)}$$

where $R_{i\,t+1:t+h}$ is the multiperiod arithmetic firm equity return between period $t+1$ and $t+h$. In estimating SRISK, the LRMES prediction is constructed using a DCC-GARCH model by Engle (2002, 2009).

Systemic Expected Shortfall (Acharya et al. (2017)) The measure represents the expected amount a bank is undercapitalized in a future systemic event in which the overall financial system is under-capitalized.

$$SES^i \equiv E\big[za^i - w_1^i \big| W_1 < zA\big] \text{ (A4)}$$

where w_1^i is the bank i's equity, W_1 represents the aggregate banking capital, z represents the required level of assets a^i and aggregate assets A.

Component Expected Shortfall (Banulescu and Durnitresc，2015) The Component Expected Shortfall (CES) of a financial institution measures the firm's 'absolute' contribution to the Expected Shortfall (ES) of the financial system. Formally, CES corresponds to the product of Marginal Expected Shortfall (MES) and the weight of the institution in the financial system.

$$CES_{it} = w_{it}\frac{\partial ES_{m,t-1}(C)}{\partial w_{it}} = -w_{it}E_{t-1}(r_{it}|r_{mt} < C) \text{ (A5)}$$

$$CES_{it}(C) = -w_{it}[\sigma_{it}\rho_{it}E_{t-1}\left(\varepsilon_{mt}\middle|\varepsilon_{mt} < \frac{C}{\sigma_{mt}}\right) + \sigma_{it}\sqrt{1-\rho_{it}{}^2}E_{t-1}\left(\xi_{it}\middle|\varepsilon_{mt} < \frac{C}{\sigma_{mt}}\right) \text{ (A6)}$$

where ε_{mt} are market return shocks, ξ_{it} is the individual firm return and C is set to 2 following Brownlees and Engle (2011).

SDSVAR (Adam *et al.*, 2014) The State-Dependent Sensitivity Value-at-Risk (SDSVAR) captures the response of institutions to shocks in another institution changes with the state of the market (tranquil, normal, and volatile). SDSVAR is based on the fitted values $\widehat{VaR}$ of four major financial institutions as commercial bank, insurance company, investment bank and hedge fund.

$$\widehat{VaR_m} = \hat{\mu}_{m,t} + z\hat{\sigma}_{m,t} \text{ (A7)}$$

$$\widehat{SDSVAR}_{\{i|j,k,l\},t,\theta} = \hat{\alpha}_\theta + \hat{\beta}_{1,\theta}\widehat{VaR_{j,t}} + \hat{\beta}_{2,\theta}\widehat{VaR_{k,t}} + \hat{\beta}_{3,\theta}\widehat{VaR_{l,t}} + \hat{\beta}_{4,\theta}\widehat{VaR_{\iota,t-1}} \text{ (A8)}$$

where $\hat{\mu}_{m,t}$ is the mean of institution m at time t and $\hat{\sigma}_{m,t}$ is the conditional standard deviation extracted from the GARCH model.

CAViaR (VAR for VaR) (White *et al.* (2015)) VAR for VaR denotes the Value at risk (VaR) estimated by a vector autoregressive (VAR) model. The dependent variables are the VaR of the financial institutions, which are dependent on (lagged) VaR and past shocks. For each of equity return series, we estimate a bivariate VAR for VaR where one variable is the market return and the other variable is the return on the single financial institution. For a given level of confidence $\theta \in (0,1)$, the quantile q_{it} at time t for random variables Y_{it} $i = 1,2$ conditional on $\mathcal{F}_{t-1}$ is

$$\Pr[Y_{it} < q_{it} | \mathcal{F}_{t-1}] = \theta, \;\; i = 1,2 \text{ (A9)}$$

$$q_{1t} = X_t' \beta_1 + b_{11} q_{1t-1} + b_{12} q_{2t-1} \text{ (A10)}$$

$$q_{2t} = X_t' \beta_2 + b_{21} q_{1t-1} + b_{22} q_{2t-1} \text{ (A11)}$$

where X_t represents predictors belonging to $\mathcal{F}_{t-1}$ and typically includes lagged values of Y_{it}.

$\widehat{CoVaR}^{LASSO}$ and $\widehat{CoVaR}^{TENET}$ (Härdle *et al.* (2016)) The $\widehat{CoVaR}^{TENET}$ builds up a risk interdependence network based on nonlinear Single Index Model (SIM) for quantile regression with variable selection. Compared with $CoVaR$ by Adrian and Brunnermeier (2016), $\widehat{CoVaR}^{TENET}$ could not only include the asset returns of other firms estimated and the macro variables, but the company specific characteristics like leverage, maturity mismatch, market-to-book and size included in the paper. Following Härdle *et al*. (2016), we use the weekly historical data and choose $n = 48$ as the rolling window.

$$X_{j,t} = g\left(\beta_{j|R_j}^{\mathrm{T}} R_{j,t}\right) + \varepsilon_{j,t} \text{ (A12)}$$

$$\widehat{CoVaR}^{TENET} \stackrel{\text{def}}{=} \hat{g}\left(\hat{\beta}_{j|\tilde{R}_j}^{\mathrm{T}} \tilde{R}_{j,t}\right) \text{ (A13)}$$

Where $R_{j,t} \stackrel{\text{def}}{=} \{X_{-j,t}, M_{t-1}, B_{j,t-1}\}$, $X_{-j,t}$ are the returns of all financial institutions except for a financial institution j, $B_{j,t-1}$ are the firm characteristics calculated from their balance sheet information. M_{t-1} is a vector of macro state variables.

The $\widehat{CoVaR}^{LASSO}$ is based on the linear quantile LASSO models. $\beta_{j|R_j}^{\mathrm{T}}$ and $\hat{\beta}_{j|\tilde{R}_j}^{\mathrm{T}}$ are estimated by using linear quantile regression with variable selection.

$$X_{j,t} = \alpha_{j|R_j} + \beta_{j|R_j}^{\mathrm{T}} R_{j,t} + \varepsilon_{j,t} \text{ (A14)}$$

$$\widehat{CoVaR}^{L} \stackrel{\text{def}}{=} \hat{\alpha}_{j|\tilde{R}_j} + \hat{\beta}^{\mathrm{T}}_{j|\tilde{R}_j}\tilde{R}_{j,t} \text{ (A15)}$$

Systemic Risk Score (Das, 2016) Systemic risk score for the aggregate system accounts for the connections between institutions and the level of individual compromise at each node in the network.

$$S(\mathbf{C}, \mathbf{E}) = \sqrt{\mathbf{C}^{\mathbf{T}}\mathbf{E}\mathbf{C}} \text{ (A16)}$$

Scalar S is a function of the compromise level vector $\mathbf{C}$ for all nodes and the connections between nodes, given by adjacency matrix $\mathbf{E}$. The individual risk contributions sum up to the total systemic score S. In this paper, we choose the expected loss measure for a financial institution as the measure of compromise used by Acharya *et.al* (2011).

$$S = \sum_{i=1}^{N} S_i = \frac{\partial S}{\partial C_1}C_1 + \frac{\partial S}{\partial C_2}C_3 + \cdots + \frac{\partial S}{\partial C_N}C_N \text{ (A17)}$$

TVP-VAR (Geraci and Gnabo (2018) and Antonakakis *et al.* (2020)) In this paper, we enhance the dynamic connectedness measures originally introduced by Diebold and Yilmaz (2012, 2014) with a time-varying parameter vector autoregressive model to estimate the dynamic network of financial spillover effects. Following Diebold and Yilmaz (2014), the total connectedness index is constructed as follows,

$$C_t(H) = \frac{\sum_{i,j=1,i\neq j}^{m} \tilde{\phi}_{ij,t}(H)}{\sum_{i,j=1}^{m} \tilde{\phi}_{ij,t}(H)} * 100 = \frac{\sum_{i,j=1,i\neq j}^{m} \tilde{\phi}_{ij,t}(H)}{m} * 100 \text{ (A18)}$$

where $\tilde{\phi}_{ij,t}(H)$ represents the pairwise directional connectedness from j to i and illustrates the influence variable j has on variable i in terms of its forecast error variance share.

Asymptotic Dependence Rate and Average Chi (Balla *et al.*, 2014) Asymptotic Dependence Rate (ADR) is defined as the proportion of asymptotically dependent financial institution pairs to the total number of financial institution pairs in our sample, thus measuring the prevalence of asymptotic dependence between financial institutions based on the extremal dependence measure χ.

$$\chi = \lim_{q \to 1} \Pr\left(L_1 > L_{1,q} \middle| L_2 > L_{2,q}\right) \text{ (A19)}$$

where L_1, L_2 stand for two loss variables and $L_{1,q}$, $L_{2,q}$ stand for their respective marginal q th quantiles. If $\chi = 0$, L_1 and L_2 are said to be asymptotically independent. If $\chi > 0$, L_1 and L_2 are said to be asymptotically dependent and χ measures the strength of the asymptotic dependence.

$$AsympDep_{ij,t} = \begin{cases} 1 & if\ \chi_{ij,t} > 0 \\ 0 & if\ \chi_{ij,t} = 0 \end{cases} \text{ (A20)}$$

$$AsympDepRate_t = \frac{\sum_i \sum_{j \neq i} AsympDep_{ij,t}}{N \times (N-1)} \text{ (A21)}$$

Average Chi (ACHI) is defined as the average strength of asymptotic dependence across all pairs of financial institutions. This measure can provide insights regarding the strength of extremal dependence in the financial system.

$$AvgChi_t = \frac{\sum_i \sum_{j \neq i} \chi_{ij,t}}{N \times (N-1)} \text{ (A22)}$$

Financial Risk Meter (Mihoci *et al.*, 2020) Financial Risk Meter (FRM) is defined as the average over the series of selected penalization term λ_j^* of the quantile lasso regression model of the companies under consideration. The Linear Quantile Lasso Regression Model is defined as below,

$$X_{j,t}^s = \alpha_j^s + A_{j,t}^{s\ \mathrm{T}} \beta_j^s + \varepsilon_{j,t}^s \text{ (A23)}$$

where $A_{j,t}^s = \begin{bmatrix} M_{t-1}^s \\ X_{-j,t}^s \end{bmatrix}$, M_{t-1}^s represents the m dimensional vector of macro variables, $X^s_{-j,t}$ is the $p-m$ dimensional vector of the returns of all other firms except firm j at time t, and α_j^s is a constant term. The moving window s is chosen to be 252 days.

The regression is performed using L_1-norm quantile regression proposed by Li and Zhu (2008), which is defined as:

$$\min_{\alpha_j^s, \beta_j^s} \left\{ n^{-1} \sum_{t=s}^{s+(n-1)} \rho_\tau \left(X_{j,t}^s - \alpha_j^s - {A_{j,t}^s}^{\mathrm{T}} \beta_j^s \right) + \lambda_j^s \parallel \beta_j^s \parallel_1 \right\} \text{ (A24)}$$

where λ_j^s is the penalization parameter. The FRM is defined as the average lambdas over the set of k firms for all windows.

$$FRM \stackrel{\text{def}}{=} \frac{1}{k} \sum_{j=1}^{k} \lambda_j^* \text{ (A25)}$$

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