Systemic Risk and Macroeconomic Forecasting: A Globally Applicable Copula-based Approach

Ghufran Ahmad*, Muhammad Suhail Rizwan*, Dawood Ashraf†

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Abstract

Financial markets are interconnected and fragile making them vulnerable to systemic contagion and measuring this risk is crucial for regulatory responsiveness. This study introduces a new set of measures for systemic risk using a copula-based (CB) estimation method with a focus on individual banks. Unlike most of the prevailing systemic risk measures, CB methodology relies on balance sheet data, instead of market price data, which makes it globally applicable. We compared CB measures with three existing measures of systemic risk which rely on market pricing data and find that CB measures outperform other measures, both in the short and medium-term, for systemic risk forecasting. The forecasting evaluation shows that CB measures perform consistently better than historical averages of macroeconomic indicators. By using out-of-sample predictive quantile regression, we ascertain that CB systemic risk measures can forecast the 20th percentile movements of different macroeconomic indicators up to 6 quarters in advance. We also find that systemic risk measures, existing as well as CB, are better predictors of financial sector performance while relatively less promising in predicting broader macroeconomic indicators such as industrial production or national activity indices.

Keywords: Systemic Risk, Macroeconomic Forecasting, Copula-Based Estimation, Quantile Regression

JEL Classification: G01; G21; G32; G17

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*NUST Business School (NBS), National University of Sciences & Technology (NUST), Pakistan. Corresponding author: suhail.rizwan@nbs.nust.edu.pk

†Senior Researcher, Islamic Research & Training Institute (IRTI), member of Islamic Developement Bank (IDB), KSA.

1 Introduction

Due to technological advancements and global networking, the global financial system has become highly interconnected and systemically fragile. The Global Financial Crisis (GFC) of 2007-09 and the current COVID-19 pandemic are examples of systemic fragility where macroeconomic and/or financial shock spills over and leads to systemic contagion. Regulators have to act promptly under such circumstances. For example, on March 20, 2020, the Basel Committee on Banking Supervision (BCBS) coordinated policy and supervisory responses to COVID-19 whereby, member jurisdictions have been advised to pursue a range of regulatory and supervisory measures.[1] As the pandemic is affecting both developed as well as developing economies, it is very crucial to have a consistent approach for systemic risk measurement that can be globally applicable. It may help both local and global regulators in devising prompt regulatory response to systemic shocks.

Empirical literature has responded to the GFC where practitioners and academicians developed different systemic risk measures to provide an early warning for systemic issues and alert regulators to take necessary actions and avoid systemic contagion (Acharya et al., 2016; Ahnert & Georg, 2018; Bisias et al., 2012). However, most of the proposed systemic risk measures either rely solely on market data or use a mix of market and balance sheet data for the estimation of systemic risk. The reliance on market data has certain inherent issues. For example, most models relying on market data in one way or the other, assume that equity and debt are fully tradable in the market and both assets and equity are non-negative. For most financial institutions, this may not be the case. In the U.S. only a small fraction of banks are listed and even for those banks, deposits, which are just like debt for the banks, are not tradable. Furthermore, an estimation of systemic risk measure using a limited number of listed banks only, may pose sample selection biases. This issue is even more concerning for developing and emerging economies where capital markets are less developed and only a small number of banks are listed. Moreover, issues in the market micro-structure, such as, noise (Black, 1986; Long et al., 1990; Shleifer & Summers, 1990), volatility (Bloom, 2009; Hazen, 1987; Shiller, 1981), under and over-reaction (Bondt & Thaler, 1985; Jegadeesh & Titman, 1993; Kent et al., 1998), investor sentiments (Baker & Wurgler, 2006, 2007), rumors (Schindler, 2007), limits to arbitrage (Barberis & Thaler, 2003), herding (Froot et al., 1992; Wermers, 1999), and illiquidity (Acharya & Pedersen, 2005; Amihud, 2002) may lead to deviations in market prices from fundamental values. Considering these concerns, the systemic risk measures that rely heavily on market data may provide false signals to the regulators regarding systemic stability which could potentially lead to inefficient regulatory actions.

To address these concerns, this study provides a set of systemic risk measures which rely solely on balance sheet data and use a copula-based (CB) methodology. In the recent literature, different variants of copulas have been used for systemic risk measurement and the resultant measures have provided very efficient results. For instance, Calabrese and Osmetti (2019) used bivariate Marshall-Olkin copula model on Type-1 censored data of three European countries, Germany, Italy and the UK, and show that their proposed censored model accurately estimated the systematic component of cross-boarder systemic risk. Clemente (2017) estimated the marginal contribution to systemic risk of a single financial institution by a CoVaR-model which is based upon copula functions and extreme value theory. Karimalis and Nomikos (2017) also used a copula CoVaR approach to measure systemic risk in the European banking sector. A copula approach

[1] https://www.bis.org/press/p200320.htm

has also been used on the Credit Default Swaps (CDS) spreads of European banks by Kleinow and Moreira (2016) from 2005 to 2014. Bernardi and Catania (2018) used switching generalized autoregressive score copula models to estimate systemic risk and conducted an empirical investigation on a panel of European regional portfolios. Their results show that the proposed CB model has the ability to explain and predict systemic risk over the period 1999-2015.

We utilized quarterly balance sheet data of U.S. Bank Holding Companies (BHCs) from 2000Q1 to 2018Q4. For forecasting evaluation, following Giglio et al. (2016), we used a quantile regression framework for out-of-sample forecasting of the 20th percentile variation of various macroeconomic indicators upto six quarters in advance. In addition, we compare the performance of our proposed measures with three existing measures, CATFIN and PQR from Giglio et al. (2016), and St. Louis Fed Financial Stress Index (StLFSI). Forecast evaluation shows that our proposed measures are able to outperform the historical 20th percentile of macroeconomic indicators, in both the short-term (up to four quarters in advance) and medium-term (five and six quarters in advance). Comparative analysis also shows superior forecasting performance of proposed measures compared to existing measures. Furthermore, in accordance with economic intuition, we find that systemic risk measures are better predictors of the financial sector as compared to broader macroeconomic indicators.

This study has policy implications for regulators especially from developing economies where either market data is not available or has market micro-structural issues. CB measures, introduced in this study, may provide valuable insight of the systemic stability of their financial system. Furthermore, global applicability of CB measures may enable relevant stakeholders to compare different financial systems by using a consistent set of measures.

The remainder of this paper is organized as follows: Section 2 proposes our systemic risk measures, Section 3 describes the estimation methodology used in this study, Section 4 explains the data, and discusses the results, and Section 5 concludes the paper.

2 An Overview of Systemic Risk Measures

As a response to the GFC, the regulatory paradigm shifted from micro-prudential to macro-prudential. It motivated practitioners and academicians to develop different systemic risk measures. Most of the proposed systemic risk measures either rely solely on market data or use a mix of market and balance sheet data for the estimation of systemic risk. Among others, Acharya et al. (2016) developed Systemic Expected Shortfall (SES) as a measure of systemic risk for an institution, i.e. the propensity of an individual financial institution to be under-capitalized when the system as a whole is under-capitalized. The authors determined that components of SES were able to predict the systemic shock during the GFC. Alongside SES, Acharya et al. (2016) measured Marginal Expected Shortfall (MES) of an institution that determines its tail losses based upon the losses of the whole financial system. MES is used extensively in the empirical literature investigating the drivers of systemic risk such as (Berger et al., 2019; Buch et al., 2019; Chang et al., 2018; Conlon & Huan, 2019; Kamani, 2018; Lee et al., 2019; Silva-Buston, 2019).

Another widely used systemic risk measure is conditional value at-risk (CoVaR) of the financial system introduced by Adrian and Brunnermeier (2016). CoVaR measures the systemic risk of financial system conditional on institutions being in distress. CoVaR captures institutional externalities such as “too big to fail”, “too interconnected to fail”, and crowded trade positions. Recent literature that explores the causes and effects of systemic risk, such as (Chang et al., 2018; Lee et al., 2019; Manguzvane & Mwamba, 2019), relies on CoVaR as a systemic risk measure.

Huang et al. (2009) proposed Stressed Insurance Premium (SIP) as an ex-ante systemic risk metric which represents a hypothetical insurance premium against systemic financial distress, defined as total losses that exceed a given threshold, say 15%, of total bank liabilities. Kritzman et al. (2011) proposed the Absorption Ratio (AR) measure, which is based upon a latent linear factor structure to study the time evolution of multidimensional system. It is the proportion of total system-level variance which is “absorbed” by a fixed number of factors and hence named “absorption ratio”. The authors find that before a turbulent period in the stock market, a significant shift in the the AR has been observed about 40 days in advance of the negative event. The authors, therefore, claim that the AR is a leading indicator of the U.S. housing market bubble.

With a critique on the micro-level measures of systemic risk, such as MES and CoVaR, L. Allen et al. (2012) proposed a macro-level measure of systemic risk which uses overall market indices data (referred as CATFIN) which measures the tail risk of the financial sector. The authors claim that their systemic risk measure is robust to different estimation methodologies and predict macroeconomic downturns six months in advance for the U.S. Gilchrist and Zakrajšek (2012) used micro-level data and constructed a Credit Spread (CS) index. The CS is decomposed into two components: one captures firm-specific information on expected defaults while the second captures the excess bond premium representing the cyclical changes in the relationship between default-risk and credit-spreads. The authors show that CS has considerable predictive power for macroeconomic indicators.

Billio et al. (2012), based upon principal-component analysis and Granger-causality networks, proposed several econometric measures of connectedness, and applied those measures to the monthly returns of hedge funds, banks, broker/dealers, and insurance companies. Their findings suggest that all four sectors have become highly interrelated and there exists asymmetry in the interconnectedness: “the returns of banks and insurers seem to have more significant impact on the returns of hedge funds and broker/dealers than vice versa” **(p.536)**. They argued that this increase in interconnectedness may have increased the level of systemic risk in the finance and insurance industries through a complex and time-varying network of relationships. Based upon out-of-sample tests, they claim that their measures can identify, quantify, and predict financial crisis periods.

Other measures include International Spillover Index by Diebold and Yilmaz (2009), who studied the interdependence of asset returns and/or volatility during crisis and non-crisis periods. By using the return-volaitility spillover analysis and data from 19 global equity markets, the authors find that return spillovers display a gradual increase in financial market integration while volatility spillovers, in contrast, provide readily-identified information about crisis events. Gradojevic and Caric (2016) used entropic indicators to predict systemic risk by using market signals coming from skewness premium and implied volatility of deepest out-of-the-money options during financial crisis of 2008. Their findings confirm the usefulness of their entropy setting in market risk management.

Brownlees and Engle (2016) introduced a measure, namely SRISK, that identifies the contribution of individual financial firms in overall systemic risk. Their methodology stems from the measurement of capital shortfall of a firm, conditional on severe market decline. Their model successfully identified major systemic risk contributors for the U.S. as early as 2005Q1. Moreover, the authors claim that an aggregate SRISK measure can provide early signals of distress in economic and financial indicators. M. Segoviano and Goodhart (2006) proposed a methodology which uses Consistent Information Multivariate Density Optimizing (CIMDO) methodology and defined the financial sector as a portfolio of individual financial firms in M. A. Segoviano and Goodhart (2009) and build the multivariate density of this portfolio, tail adjusted with the data from each institution, to estimate systemic risk. A similar approach has been adopted by Jin and de A. Nadal De Simone (2014) on European banking groups and provided systemic risk measures that performed well as early-warning measures of banks' systemic vulnerabilities.

A few other studies attempted to aggregate outcomes of different standalone measures to develop a systemic risk index. Such studies include Giglio et al. (2016), who analyze 19 different systemic risk measures and study how these determine subsequent shocks to industrial production and other macroeconomic variables in the U.S. and Europe. They show that, among these 19 measures, CATFIN performs better in predicting shocks to macroeconomic variables. In addition, they used dimension reduction techniques to construct two additional estimators; namely, PQR and PCQR. They report PQR as their preferred estimator owing to its greater predictive power. Following Giglio et al. (2016), He et al. (2019) constructed a systemic financial risk index by using aggregated information from 15 systemic risk measures. Their results show that the aggregated index has successfully predicted the subsequent macroeconomic shocks to China's economy during 2005-2016. Guerra et al. (2016) used contingent claims and a complex networks approach to construct a systemic risk measure. Their method helps to identify Systemically Important Banks (SIBs) and can track the evolution of systemic risk over-time.

The review above shows the progression of systemic risk literature, specifically after the global financial crisis, towards proposing various systemic risk measures. These measures either rely solely on market data or use a mix of market and balance sheet data for the estimation of systemic risk. However, there are several concerns with the models relying on market data. All of these models, in one way or the other, assume that equity and debt are fully tradable and both assets and equity are non-negative. However, only a small fraction of banks are listed, and deposits, which are just like debt for banks, are not tradable. Furthermore, an estimation of systemic risk measure using a limited number of listed banks only may pose sample selection biases. This issue is even more concerning for developing and emerging economies where capital markets are less developed and only a small number of banks are listed. Moreover, issues in the market micro-structure, such as, noise (Black, 1986; Long et al., 1990; Shleifer & Summers, 1990), volatility (Bloom, 2009; Hazen, 1987; Shiller, 1981), under and over-reaction (Bondt & Thaler, 1985; Jegadeesh & Titman, 1993; Kent et al., 1998), investor sentiments (Baker & Wurgler, 2006, 2007), rumors (Schindler, 2007), limits to arbitrage (Barberis & Thaler, 2003), herding (Froot et al., 1992; Wermers, 1999), and illiquidity (Acharya & Pedersen, 2005; Amihud, 2002) may lead to deviations in market prices from fundamental values. Considering these concerns, the systemic risk measures that rely heavily on market data may provide false signals to the regulators regarding the systemic stability which could potentially lead to inefficient regulatory actions.

Keeping in view the limitations of the market model, this study proposes a set of systemic risk measures which relies solely on balance sheet data using a CB methodology. The methodology is developed in the next section.

3 Systemic Risk Measurement: A Copula-based Approach

Systemic risk is the possibility of some event leading to system-wide stress which may cause a financial system failure. In the context of BHCs, systemic risk would then refer to the possibility of instability in one or more BHCs which may spread to other BHCs, via interconnectedness, leading to a system-wide crisis. This suggests that we need to first identify stressed BHCs and then use those identified BHCs to measure systemic risk.

Consider an arbitrary time period t. Let B_t represent the set of all BHCs in period t. For any $i \in B_t$, let A_{it} and L_{it} represent assets and liabilities of the BHC i in period t, respectively. Then, equity of BHC i, in period t, can be stated as $E_{it} = A_{it} - L_{it}$. One potential choice for identification of a stressed BHC is whether it defaults in period t. Mathematically, we say that BHC i defaults in period t if $E_{it} \leq 0$. Then, the set of defaulted BHCs in period t can be defined as follows:

$$D_t = \{i \in B_t : E_{it} \leq 0\} \tag{1}$$

By using D_t as the definition of stressed BHCs in the financial system, we are inherently assuming that only defaulted BHCs stress the system. Arguably, the financial system can be stressed from a BHC which does not default but has very low equity levels. We refer to such BHCs as under-capitalized which can be defined, in period t, as:

$$UC_t = \{i \in B_t : E_{it} \leq \alpha A_{it}\} \tag{2}$$

That is, a BHC is considered as "under-capitalized" if its equity is lower than some fraction of its assets. In this study, we use $\alpha = 3\%$ which is defined under the Prompt Corrective Action (PCA) of the Federal Deposit Insurance Corporation Improvement Act (Congress, 1991) as "significantly under-capitalized" level of capital.

Mathematically, we would expect systemic risk measures based on UC_t to be more conservative as compared to those based on D_t, as long as $\alpha > 0$, because $E_{it} \leq \alpha A_{it}$ whenever $E_{it} \leq 0$ while the converse may not be true. In other words, a defaulted BHC is always under-capitalized but it is not necessary that an under-capitalized BHC defaults i.e. we expect $D_t \subset UC_t$.

Following Lehar (2005), we define systemic risk as the probability that the proportion of assets owned by defaulted BHCs to total assets of all BHCs exceeds some predetermined threshold θ. Formally, for any time period t, this can be given as:

$$SRD_t(\theta) = \Pr\left[\frac{\sum_{i \in D_t} A_{it}}{\sum_{i \in B_t} A_{it}} > \theta\right] \tag{3}$$

In equation (3), θ is some threshold e.g. $\theta = 5\%$, and $SRD_t(\theta)$ represents systemic risk, based on defaulted BHCs, in period t for threshold parameter θ. The corresponding measure for under-capitalized BHCs is denoted as $SRU_t(\theta)$ which can be obtained by replacing D_t with UC_t in equation (3). Then:

$$SRU_t(\theta) = \Pr\left[\frac{\sum_{i\in UC_t} A_{it}}{\sum_{i\in B_t} A_{it}} > \theta\right] \tag{4}$$

The choice of the threshold parameter θ is not straightforward. If θ is too small (large), the estimated number for systemic risk would be too large (small). In this manner, the systemic risk measures from equations (3) and (4) would be sensitive to the choice of threshold parameter θ. Arguably, an appropriate value of θ may not be the same for different economies or even across time. To avoid sensitivity of our results to the chosen value of θ, we estimate the systemic risk measures at four values of θ; 2%, 5%, 10%, and 15%.

It should be noted that for a given value of θ, the systemic risk measures of equations (3) and (4) do not consider the magnitude of stress on the financial system because these measures treat all events exceeding the threshold θ in an identical manner. For instance, with $\theta = 0.05$, the above measures treat events with proportion of defaulted BHCs assets to total BHCs assets of 6% and 20% identically without giving any importance to the additional stress that has been imposed on the system by the latter as compared to the former.

To avoid it, we propose another measure of systemic risk which is independent of a threshold parameter. An intuitive workaround is to consider the proportion of assets that are stressed within the system. By considering defaulted BHCs as the cause of stress to the system, then for time period t, the proportion of defaulted assets (PDA_t) can be stated as:

$$PDA_t = E\left(\frac{\sum_{i\in D_t} A_{it}}{\sum_{i\in B_t} A_{it}}\right) \tag{5}$$

Equation (5) calculates the expected value of the fraction of assets owned by defaulted BHCs in period t. We expect this measure to depict systemic risk because (1) $PDA_t \in [0, 1]$, (2) $PDA_t = 0$ if no BHC defaults in period t, (3) PDA_t increases with the increase in defaulted BHCs, and (4) $PDA_t = 1$ if all BHCs default in period t. The corresponding measure for under-capitalized BHCs can be calculated by replacing D_t in equation (5) with UC_t. We refer to this measure as the proportion of under-capitalized assets, denoted as PUA_t, formally defined as:

$$PUA_t = E\left(\frac{\sum_{i\in UC_t} A_{it}}{\sum_{i\in B_t} A_{it}}\right) \tag{6}$$

4 Estimation Methodology

In this section, we provide the methodology employed in the estimation of $SRD_t(\theta)$, $SRU_t(\theta)$, PDA_t, and PUA_t.

4.1 Copula Background

Copula is a statistical tool which is a multivariate probability distribution where each variable has a uniform marginal probability distribution. Copulas are able to maintain information on the dependence structure among the underlying variables after being applied to their univariate marginals. Therefore, these have applications in studying dependence and measuring association among variables Nelsen (1999) making these pertinent for a wide variety of financial problems

Jaworski (2010). Even though the theoretical basis of copulas are complex, its practical application is relatively straightforward compared to other simulation-based approaches proposed for modeling multivariate dependence structures Trivedi and Zimmer (2005).

Copula theory, to a significant extent, is based on Sklar's theorem which states that for an n-dimensional vector of random variables, $\boldsymbol{X} = (X_1, \cdots, X_n)$, there exists an n-dimensional copula function C such that:

$$F(x_1, \cdots, x_n) = C(F_1(x_1), \cdots, F_n(x_n)) \tag{7}$$

where $F(x_1, \cdots, x_n)$ is the joint cumulative distribution function (cdf), and $F_i(x_i)$ are the marginal cdfs for $i = 1, \cdots, n$ (Sklar, 1959). If the joint cdf is absolutely continuous and the marginal cdfs are strictly increasing continuous functions, the n-dimensional copula is uniquely defined. Additionally, the joint probability density function (pdf) of $F(x_1, \cdots, x_n)$ can be found as follows:

$$f(x_1, \cdots, x_n) = c(F_1(x_1), \cdots, F_n(x_n)) \times \Pi_{i=1}^{n} f_i(x_i) \tag{8}$$

where f_i are the marginal pdfs for $i = 1, \cdots, n$, and $c(F_1(x_1), \cdots, F_n(x_n))$ is the n-dimensional copula density function corresponding to the n-dimensional copula function C.

There are several families of copulas which can be broadly categorized as bivariate and multivariate. However, the class of copulas utilized for the multivariate case are limited (Czado, 2010). The Gaussian and Student's t copulas are most commonly used for multivariate cases. The Gaussian copula, for correlation matrix $R \in [-1, 1]^{n\times n}$, can be given as:

$$C(u_1, \cdots, u_n; R) = \Phi_R\left(\Phi^{-1}(u_1), \cdots, \Phi^{-1}(u_n)\right) \tag{9}$$

where Φ_R is the joint cdf of a multivariate normal distribution with zero mean and co-variance matrix of R, and Φ^{-1} is the inverse of standard normal cdf. The Student's t copula, for correlation matrix $R \in [-1, 1]^{n\times n}$, can be written as:

$$C(u_1, \cdots, u_n; \mathrm{df}, R) = t_{\mathrm{df},R}\left(t_{\mathrm{df}}^{-1}(u_1), \cdots, t_{\mathrm{df}}^{-1}(u_n)\right) \tag{10}$$

where $t_{\mathrm{df},R}$ is a multivariate Student's t cdf with correlation matrix R, t_{df}^{-1} is the inverse of univariate t cdf, and df is the degree of freedom.

Bivariate copulas can also be used to model multivariate dependence structures via pair copula constructions (PCCs) by conditioning on a specific set of variables (Aas et al., 2009; Czado, 2010; Valle et al., 2016). This relies on the fact that conditional marginal density can be written as:

$$f_{X_i|\boldsymbol{z}}(x_i|\boldsymbol{z}) = c_{X_i,z_l|\boldsymbol{z_{-l}}}\left(F_{X_i|\boldsymbol{z_{-l}}}(x_i|\boldsymbol{z_{-l}}), F_{z_l|\boldsymbol{z_{-l}}}(z_l|\boldsymbol{z_{-l}})\right) \times f_{X_i|\boldsymbol{z_{-l}}}(x_i|\boldsymbol{z_{-l}}) \tag{11}$$

where $\boldsymbol{z}$ is the vector of conditioning variables, z_l is some component of $\boldsymbol{z}$, $\boldsymbol{z_{-l}}$ excludes z_l from $\boldsymbol{z}$, $F_{X_i|\boldsymbol{z_{-l}}}$ is the cdf of X_i conditional on $\boldsymbol{z_{-l}}$, and $c_{X_i,z_l|\boldsymbol{z_{-l}}}$ is the conditional bivariate copula density.

4.2 Estimating Systemic Risk

Previously, we defined equity for BHC i in period t as $E_{it} = A_{it} - L_{it}$ where A_{it} and L_{it} represent assets and liabilities, respectively. Similar to Valle et al. (2016), the expected value of equity for the BHC i at period t can be given as:

$$\mathrm{E}\left(E_{it}\right) = \int_0^\infty \int_0^\infty \pi_{i1}\left(A_{it}, L_{it}\right) g_{i1}\left(A_{it}, L_{it}\right) dA_{it} dL_{it} \tag{12}$$

where $\pi_{i1}\left(A_{it}, L_{it}\right) = A_{it} - L_{it}$ is the payoff function with density $g_{i1}\left(\cdot\right)$ for the BHC i. Based on Sklar's theorem, the above equation can be rewritten as:

$$\mathrm{E}\left(E_{it}\right) = \int_0^\infty \int_0^\infty \pi_{i1}\left(A_{it}, L_{it}\right) c\left(F_{A_{it}}, F_{L_{it}}\right) f_{A_{it}} f_{L_{it}} dA_{it} dL_{it} \tag{13}$$

where $c\left(\cdot\right)$ is a 2-dimensional copula density function, $F_{A_{it}}$, $F_{L_{it}}$ are the marginal cdfs, and $f_{A_{it}}$, $f_{L_{it}}$ are the corresponding marginal pdfs. However, for the main estimation, we decompose assets into current and long-term assets, and liabilities into current and long-term liabilities to account for the problem of maturity mismatching as implied by Valle et al. (2016). Therefore, the expected equity for BHC i in period t, based on the decomposed variables, can be given as:

$$\begin{aligned}\mathrm{E}\left(E_{it}\right) = \int_0^\infty \int_0^\infty \int_0^\infty \int_0^\infty & \pi_{i2}\left(CA_{it}, LA_{it}, CL_{it}, LL_{it}\right) \\ & \times g_{i2}\left(CA_{it}, LA_{it}, CL_{it}, LL_{it}\right) dCA_{it} dLA_{it} dCL_{it} dLL_{it}\end{aligned} \tag{14}$$

where CA_{it}, LA_{it}, CL_{it}, and LL_{it} denote current assets, long-term assets, current liabilities and long-term liabilities, respectively, and let $g_{i2}\left(\cdot\right)$ be the corresponding density function for $\pi_{i2}\left(\cdot\right)$ which is the payoff function for the decomposed data of the BHC i. The payoff function is as follows:

$$\pi_{i2}\left(CA_{it}, LA_{it}, CL_{it}, LL_{it}\right) = CA_{it} - CL_{it} + \beta_t\left(LA_{it} - LL_{it}\right) \tag{15}$$

where β_t is the risk-free discount factor in period t.[2] Applying Sklar's theorem allows decomposition of the density function $g_{i2}\left(\cdot\right)$ so that equation (14) can be rewritten as:

$$\begin{aligned}\mathrm{E}\left(E_{it}\right) = \int_0^\infty \int_0^\infty \int_0^\infty \int_0^\infty & \pi_{i2}\left(CA_{it}, LA_{it}, CL_{it}, LL_{it}\right) \\ & \times c_i\left(F_{CA_{it}}, F_{LA_{it}}, F_{CL_{it}}, F_{LL_{it}}\right) f_{CA_{it}} f_{LA_{it}} f_{CL_{it}} f_{LL_{it}} dCA_{it} dLA_{it} dCL_{it} dLL_{it}\end{aligned} \tag{16}$$

where $c_i\left(\cdot\right)$ depicts a 4-dimensional copula density function for BHC i, $F_{CA_{it}}$, $F_{LA_{it}}$, $F_{CL_{it}}$, $F_{LL_{it}}$ represent the marginal cdfs, and $f_{CA_{it}}$, $f_{LA_{it}}$, $f_{CL_{it}}$, $f_{LL_{it}}$ depict the corresponding marginal pdfs.

[2]For our main estimation, we take $\beta_t = 1$ for two reasons: (1) In deciding the solvency of a BHC, the regulator focuses on the balance sheet position which disregards time-value-of-money considerations, and (2) Long-term assets and liabilities are defined as items with maturity greater than 1 year i.e. $m \in (1, \infty)$ where m is the maturity. It is difficult to ascertain the representative discounting factor that can account for unknown maturities, m, within LA_{it} and LL_{it}.

Valle et al. (2016) use a D-vine decomposition to fit the copula density function $c_i(\cdot)$ which is then used to obtain simulated values of CA_{it}, LA_{it}, CL_{it}, and LL_{it}. These simulated values are then used to calculate the simulated value of E_{it} using a payoff function. Using the simulated values, Valle et al. (2016) approximate the function in equation (16), denoted as $\widetilde{E}_{it}$. Their probability-of-default, for operating and defaulted firms, is estimated for firm i in period t as $\Pr\left(\widetilde{E}_{it} \leq 0\right)$. Valle et al. (2016) argued that the copula estimation, by providing a joint multivariate distribution, embeds the dependence structure of the balance sheet components considered in the payoff function which is why it is better at predicting default than Altman's Z-score as the latter does not account for this dependence structure.

It should be noted that equation (14) shows that G_{i2}, the cdf corresponding to the density function g_{i2}, is the cdf of E_{it}. Then, equation (14) does not consider any linkages across different BHCs as it requires fitting of a copula density function, after application of Sklar's theorem, for each individual BHC. For a measure of systemic risk, it is imperative to consider the linkages across the financial institutions. To account for these linkages, the expected value of equity in period t can be calculated as:

$$\begin{aligned}\mathrm{E}(E_t) = &\int_0^\infty \int_0^\infty \int_0^\infty \int_0^\infty \pi_2(CA_t, LA_t, CL_t, LL_t) \\ &\times g_2(CA_t, LA_t, CL_t, LL_t)\, dCA_t dLA_t dCL_t dLL_t \end{aligned} \tag{17}$$

where $\pi_2(\cdot)$ is the payoff function with density function as $g_2(\cdot)$, and E_t, CA_t, LA_t, CL_t, and LL_t are $|B_t| \times 1$ vectors of equities, current assets, long-term assets, current liabilities, and long-term liabilities in period t of all the BHCs, respectively. Formally, these vectors can be represented as follows:

$$E_t = \begin{pmatrix} E_{1t} \\ \vdots \\ E_{|B_t|t} \end{pmatrix} \quad CA_t = \begin{pmatrix} CA_{1t} \\ \vdots \\ CA_{|B_t|t} \end{pmatrix} \quad LA_t = \begin{pmatrix} LA_{1t} \\ \vdots \\ LA_{|B_t|t} \end{pmatrix} \quad CL_t = \begin{pmatrix} CL_{1t} \\ \vdots \\ CL_{|B_t|t} \end{pmatrix} \quad LL_t = \begin{pmatrix} LL_{1t} \\ \vdots \\ LL_{|B_t|t} \end{pmatrix} \tag{18}$$

The expected value of equity in equation (17) relies on a joint multivariate distribution of different balance sheet components for all of BHCs rather than just using a joint multivariate distribution for the balance sheet components of an individual BHC as was the case in equation (14). Therefore, equation (17) accounts for the dependence structure within the different balance sheet components of a BHC and also its linkages, via the balance sheet components, with other BHCs unlike equation (14). After the application of Sklar's theorem, equation (17) can be rewritten as:

$$\begin{aligned}\mathrm{E}(E_t) = &\int_0^\infty \int_0^\infty \int_0^\infty \int_0^\infty \pi_2(CA_t, LA_t, CL_t, LL_t) \\ &\times c(F_{CA_t}, F_{LA_t}, F_{CL_t}, F_{LL_t})\, f_{CA_t} f_{LA_t} f_{CL_t} f_{LL_t}\, dCA_t dLA_t dCL_t dLL_t \end{aligned} \tag{19}$$

where $c(\cdot)$ depicts a $4|B_t|$-dimensional copula density function,[3] F_{CA_t}, F_{LA_t}, F_{CL_t}, F_{LL_t} represent the marginal cdfs, and f_{CA_t}, f_{LA_t}, f_{CL_t}, f_{LL_t} depict the corresponding marginal pdfs.

PCCs provide a flexible method for financial modeling of the multivariate structure as different bivariate copulas can be employed to construct the joint multivariate distribution (Aas et al., 2009; D. E. Allen et al., 2013; Bernard & Czado, 2012; de Melo Mendes et al., 2010; Dissmann et al., 2013; Min & Czado, 2010; Valle et al., 2016). However, for high dimensional distributions, the total number of possible PCCs is very high (Czado, 2010; Morales-Napoles, 2010). Specifically, in our case, for any period t, there are a total of $(4|B_t|)!$ distinct canonical and D-vines (Aas et al., 2009). This makes it extremely complicated (even infeasible) to choose an appropriate pair-copula decomposition because, for the sample period used in this paper, $|B_t|$, number of BHCs, ranges from 329 to 2219. This is especially the case because PCC is order-dependent where different order of variables lead to a different PCC (Valle et al., 2016). As such, for the sake of feasibility, we consider the Gaussian and Student's t copulas for generating the correlated samples of the balance sheet components for the BHCs.[4] However, for any period t, there are $4|B_t|$ variables which leads to linear independence violations when attempting to fit the Student's t copula density function to the data. Therefore, we rely on the Gaussian copula for the computation of the systemic risk measures proposed in Section 3.

The Gaussian copula requires estimation of the linear correlation parameters in R of equation (9). These parameters consider: (1) the dependence structure among the different balance sheet components for each BHC, and (2) the linkages of each BHC with other BHCs. To formally show how this dependence structure is embedded in the joint multivariate distribution, consider any two BHCs i and j in period t. The linear correlation parameters for these two BHCs can be depicted as a 4×4 correlation matrix, say C_t^{ij}, as follows:

$$C_t^{ij} = \begin{pmatrix} \sigma_{11,t}^{ij} & \sigma_{12,t}^{ij} & \sigma_{13,t}^{ij} & \sigma_{14,t}^{ij} \\ \sigma_{21,t}^{ij} & \sigma_{22,t}^{ij} & \sigma_{23,t}^{ij} & \sigma_{24,t}^{ij} \\ \sigma_{31,t}^{ij} & \sigma_{32,t}^{ij} & \sigma_{33,t}^{ij} & \sigma_{34,t}^{ij} \\ \sigma_{41,t}^{ij} & \sigma_{42,t}^{ij} & \sigma_{43,t}^{ij} & \sigma_{44,t}^{ij} \end{pmatrix} \tag{20}$$

In the matrix C_t^{ij}, the rows 1, 2, 3, and 4 correspond to CA_{it}, LA_{it}, CL_{it}, and LL_{it} whereas columns 1, 2, 3, and 4 correspond to CA_{jt}, LA_{jt}, CL_{jt}, and LL_{jt}, respectively. Then, $\sigma_{rc,t}^{ij}$, for any $r, c \in \{1, 2, 3, 4\}$, represents the linear correlation of BHC i's r-th row variable with BHC j's c-th column variable. This means that based on the correlation matrix of equation (20), BHCs i and j are allowed to have linkages through 10 possible combinations of balance sheet components. Then, for the entire system of BHCs, the following matrix of linear correlation parameters is estimated:

$$C_t = \begin{pmatrix} C_t^{11} & \cdots & C_t^{1|B_t|} \\ \vdots & \ddots & \vdots \\ C_t^{|B_t|1} & \cdots & C_t^{|B_t||B_t|} \end{pmatrix} \tag{21}$$

[3]The copula density function is $4|B_t|$ dimensional because there are $|B_t|$ BHCs in period t and, for each BHC, 4 balance sheet components are considered in the payoff function.

[4]The Gaussian copula is tail independent whereas Student's t copula has identical upper and lower tail dependence. Admittedly, these two copulas are not the best choice but, considering the computational difficulties associated with having $(4|B_t|)!$ distinct canonical and D-vines, these present themselves as suitable alternatives.

For the Gaussian copula, the matrix of linear correlation parameters, C_t in equation (21), has been estimated by fitting the Gaussian copula to the data transformed to copula scale. The data observations of balance sheet components are then transformed to the copula scale using a kernel estimator of the cdf (Peter, 1985; Silverman, 1986). The matrix of linear correlation parameters of the Gaussian copula, $R = C_t$, is computed using maximum likelihood given as:

$$\max_{R} \ l(R) = \log\left[c\left(u_1, \cdots, u_{4|B_t|}; R\right)\right] \tag{22}$$

where $c(u_1, \cdots, u_n; R)$ is the Gaussian copula density function which can be written as:

$$c\left(u_1, \cdots, u_{4|B_t|}; R\right) = \frac{1}{\sqrt{\det R}} \exp\left[-\frac{1}{2}\begin{pmatrix}\Phi^{-1}(u_1)\\ \vdots \\ \Phi^{-1}\left(u_{4|B_t|}\right)\end{pmatrix}^T \cdot \left(R^{-1} - I\right) \cdot \begin{pmatrix}\Phi^{-1}(u_1)\\ \vdots \\ \Phi^{-1}\left(u_{4|B_t|}\right)\end{pmatrix}\right] \tag{23}$$

In equation (23), I is a $4|B_t| \times 4|B_t|$ identity matrix. After estimating R, $c\left(u_1, \cdots, u_{4|B_t|}; \widehat{R}\right)$ is used to generate correlated random numbers where $\widehat{R}$ denotes the estimated value of R using maximum likelihood presented in equation (22). The random numbers are converted to the original scale by using a kernel estimator of the inverse cdf which gives us simulated values of the balance sheet components. The k-th iteration of the simulated values of the balance sheet components for BHC i are denoted as $\widetilde{CA}_{it,k}$, $\widetilde{LA}_{it,k}$, $\widetilde{CL}_{it,k}$, and $\widetilde{LL}_{it,k}$. The simulated value of equity for the k-th iteration, denoted as $\widetilde{E}_{it,k}$, is calculated using the simulated values $\widetilde{CA}_{it,k}$, $\widetilde{LA}_{it,k}$, $\widetilde{CL}_{it,k}$, and $\widetilde{LL}_{it,k}$ in the payoff function provided in equation (15).

The set of defaulted BHCs for the k-th iteration of the simulated values in period t is determined as:

$$\widetilde{D}_{t,k} = \left\{i \in B_t : \widetilde{E}_{it,k} \leq 0\right\} \tag{24}$$

Let $\widetilde{A}_{it,k} = \widetilde{CA}_{it,k} + \widetilde{LA}_{it,k}$. Then, the estimated value of systemic risk from defaulted BHCs, in period t, is given as:

$$\widehat{SRD}_t = \frac{1}{N}\sum_{k=1}^{N} 1\left(\frac{\sum_{i\in\widetilde{D}_{t,k}} \widetilde{A}_{it,k}}{\sum_{i\in B_t} \widetilde{A}_{it,k}} > \theta\right) \tag{25}$$

where N is the number of simulations,[5] $1(\cdot)$ is an indicator function, and $\theta \in \{2\%, 5\%, 10\%, 15\%\}$. Additionally, the proportion of defaulted assets for period t is estimated as:

$$\widehat{PDA}_t = \frac{1}{N}\sum_{k=1}^{N} \left(\frac{\sum_{i\in\widetilde{D}_{t,k}} \widetilde{A}_{it,k}}{\sum_{i\in B_t} \widetilde{A}_{it,k}}\right) \tag{26}$$

Similarly, the set of under-capitalized BHCs in the k-th iteration for period t is given as:

$$\widetilde{UC}_{t,k} = \left\{i \in B_t : \widetilde{E}_{it,k} \leq \alpha \widetilde{A}_{it,k}\right\} \tag{27}$$

[5] We use 10,000 simulations.

Then, systemic risk from the under-capitalized BHCs is estimated as:

$$\widehat{SRU}_t = \frac{1}{N}\sum_{k=1}^{N} 1\left(\frac{\sum_{i\in \widetilde{UC}_{t,k}} \widetilde{A}_{it,k}}{\sum_{i\in B_t} \widetilde{A}_{it,k}} > \theta\right) \tag{28}$$

Finally, the proportion of under-capitalized assets in period t is estimated as:

$$\widehat{PUA}_t = \frac{1}{N}\sum_{k=1}^{N} \left(\frac{\sum_{i\in \widetilde{UC}_{t,k}} \widetilde{A}_{it,k}}{\sum_{i\in B_t} \widetilde{A}_{it,k}}\right) \tag{29}$$

5 Data, Results and Discussion

In this section, we explain variables and data sources, present our systemic risk measures and comparison with existing ones, and provide forecast evaluation of these measures using various macroeconomic indicators.

5.1 Data and Sources

We collected quarterly call report data of BHCs from the Federal Reserve Bank of Chicago. For the calculation of long and short-term components of assets and liabilities, we proceeded as follows:[6] First, we calculated total equity capital (Items: BHCK3210, BHCT3210, and BHCX3210) and subtracted it from total assets (Items: BHCK2170, BHC02170, BHC22170, BHC52170, BHC92170, BHCE2170, BHCKC244, BHCKC248, and BHCT2170) to calculate the total liabilities for each BHC. We calculated current liabilities (CL_{it}) as the sum of the portion of long-term debt that reprices within one year (item: BHCK 3298) and interest-bearing deposits that reprices within one year or mature within one year (item: BHCK 3296). We subtracted CL_{it} from total liabilities to calculate long-term Liabilities (LL_{it}). For estimations, we use only remunerative assets that are repriceable within one year or matures within one year (item: BHCK3197) as current assets (CA_{it}) and deducted these from total assets to calculate long-term Assets (LA_{it}).

For forecast evaluation, we use real macroeconomic shocks measured by innovations to Total Industrial Production (TIP_t), Financial Services Index (FSI_t), Chicago Fed National Activity Index ($CFNAI_t$) and its sub-components: Production and Income (PI_t), Employment, Unemployment, and Hours (EUH_t), Personal Consumption and Housing (CH_t), and Sales, Orders, and Inventory (SOI_t). The data of TIP_t and FSI_t was collected from Thomson Reuters DataStream Financial, while $CFNAI_t$ and its sub-components have been downloaded from the Federal Reserve Bank of Chicago. Our aim is to determine how well our measures of systemic risk explain the distribution of future macroeconomic shocks. The methodology for forecast evaluation is provided in Subsection 4.3.2.

We also compared our results with existing measures of systemic risk. We used the St. Louis Fed Financial Stress Index ($StLFSI_t$),[7] which has been widely used as a systemic risk measure in existing literature (Chiu et al., 2015; Kliesen,

[6] To form consistent time series from FR Y9-C, Consolidated Financial Statements for BHCs, we use the guidelines available at the Federal Reserve Bank of Chicago website.

[7] The StLFSI is a broad measure constructed via principal component analysis. The measure uses 18 different financial variables, including interest rates (effective federal funds rate, 2-year Treasury, 10-year Treasury, 30year Treasury, Baa-rated corporate, Merrill Lynch High-Yield Corporate Master II Index, and Merrill Lynch Asset-Backed Master BBB-rated), yield spreads (yield curve: 10-year Treasury minus 3-month Treasury, corporate Baa-rated bond minus 10-year Treasury, Merrill Lynch High-Yield Corporate Master II Index minus 10-year Treasury, 3-month London Inter-bank Offering Rate–Overnight Index Swap [LIBOR-OIS] spread, 3-month Treasury-Eurodollar [TED] spread, and 3-

Smith, et al., 2010; Ormerod et al., 2015; Sun et al., 2017). We downloaded this publicly available index from St. Louis Federal Reserve Bank website. We also compared our measures with two of the best performing measures of Giglio et al. (2016); namely, PQR_t and $CATFIN_t$. The data for these measures is available on the online data resource of the authors. [8]

5.2 Descriptive Statistics and Graphical Presentation of Systemic Risk Measures

Table 1 shows the descriptive statistics of our systemic risk measures for our overall sample period, and three subsample periods; Pre-Crisis (2000Q1 to 2007Q2), GFC (2007Q3 to 2009Q3), and Post-Crisis (2009Q4 to 2018Q4). Kruskal Wallis(Daniel, 1990) rank test compares the means of systemic risk measures between these three time-periods. Results show that all the measures show significantly high mean values during the GFC period. While, the Pre-Crisis period has significantly higher levels of systemic risk as compared to the Post-Crisis period. Overall, US financial system is stable in the Post-Crisis period.

Figure 1 shows progression of eight of our systemic risk measures over-time. Among these eight measures, PDA_t, $SRD02_t$, $SRD05_t$ and $SRD10_t$ are based on defaulted BHCs, while PUA_t, $SRU02_t$, $SRU05_t$ and $SRU10_t$ are based on under-capitalized BHCs. The shaded area shows the GFC time-period starting from 2007Q3, when market meltdown became global, Federal Reserve Bank slashed rates and the market crashed, to 2009Q3, when the G20 Summit pushed financial regulations, and U.S. banks stress-tested and showed positive results.

Notable spikes can be observed during the 2001-02 period where the U.S. economy experienced a mild recession along with other developed countries (Karnizova & Li, 2014). We have also observed a considerable volatility in the systemic environment till GFC. Each of the eight measures shows the highest peak during the GFC period which is not surprising considering the severity of the crisis. The measures based on under-capitalized BHCs show a leading trend as compared to the measures based on defaulted BHCs suggesting that the former may have leading capability and, therefore, may provide early warning signals. It is also worth noting that after the GFC period, all the measures show a sharp decline suggesting recovery of the U.S. financial system. Notable spikes have also been observed during the 2013-14 period which might be due to the decline in output in the U.S. at an annual rate of 2.9% in 2014Q1.[9] However, in the most recent time, we have observed historically low levels of systemic risk indicating a stable systemic environment in the U.S. financial system which has also been the conclusion of a recent work by Engle and Ruan (2019) who measured systemic risk through SRISK.

month commercial paper minus 3-month Treasury bill), and other indicators (J.P. Morgan Emerging Markets Bond Index Plus, Chicago Board Options Exchange Market Volatility Index [VIX], Merrill Lynch Bond Market Volatility Index [1-month], 10-year nominal Treasury yield minus 10-year Treasury Inflation Protected Security yield, and Vanguard Financial Exchange-Traded Fund). Furthermore, the index is built by using principal component analysis to extract the factors responsible for the co-movement of a group of variables.

[8]Giglio et al. (2016) online data resource.

[9]Bureau of Economic Analysis.

Table 1: Descriptive Statistics

Time Period	Whole Sample		Pre-Crisis (1)		Crisis (2)		Post-Crisis (3)		K-Wallis Test		
Measure	Mean	SD	Mean	SD	Mean	SD	Mean	SD	(1) vs (2)	(2) vs (3)	(1) vs (3)
PDA	0.0099	0.0102	0.0115	0.0052	0.0271	0.0094	0.0033	0.0043	18.2***	26.2***	27.2***
PUA	0.0333	0.0284	0.0432	0.0116	0.0785	0.0153	0.0123	0.0160	20.6***	26.0***	28.6***
SRD02	0.1891	0.2036	0.2258	0.1261	0.5109	0.1245	0.0609	0.1253	18.2***	27.4***	24.4***
SRU02	0.5719	0.4486	0.8648	0.1289	0.9840	0.0302	0.2483	0.4124	9.5***	18.7***	17.7***
SRD05	0.0452	0.0886	0.0368	0.0488	0.1871	0.1318	0.0047	0.0206	15.0***	35.0***	27.8***
SRU05	0.2674	0.3389	0.2678	0.2097	0.8616	0.1343	0.0744	0.2003	20.3***	29.4***	28.3***
SRD10	0.0074	0.0216	0.0069	0.0165	0.0174	0.0307	0.0044	0.0207	4.0**	18.5***	5.9**
SRU10	0.0441	0.0803	0.0492	0.0605	0.1468	0.1294	0.0074	0.0228	8.4***	29.8***	23.4***
SRD15	0.001	0.0041	0.0011	0.0050	0.0040	0.0067	0.0000	0.0000	6.4**	20.6***	4.8**
SRU15	0.0077	0.0215	0.0066	0.0161	0.0321	0.0404	0.0006	0.0022	9.9***	32.4***	16.7***

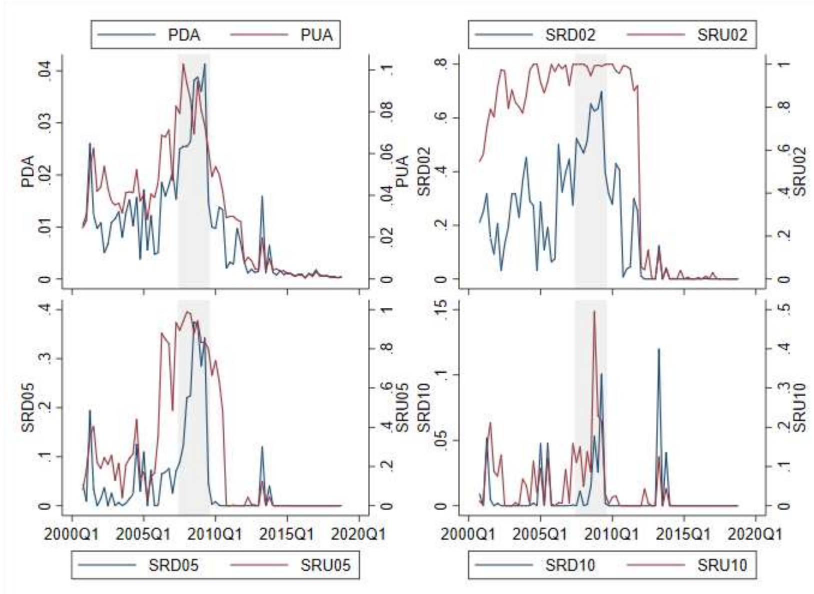

Figure 1: Estimates of the proposed systemic risk measures over-time.

5.3 Comparison with Existing Measures and Forecast Evaluation

5.3.1 Graphical Comparison

Figure 2 and Figure 3 show progression of $CATFIN_t$ and PQR_t,[10] respectively, along with four of our proposed systemic risk measures, namely, PDA_t, PUA_t, $SRD05_t$ and $SRU05_t$. We observe a similar progression pattern, however, there are notable differences in terms of peaks. PDA_t and $SRD05_t$, show highest peaks in synchronicity with $CATFIN_t$ and PQR_t, but PUA_t and $SRU05_t$ show peaks a bit earlier. Futhermore, PDA_t, PUA_t, and $SRU05_t$ started an upward movement before the start of the GFC period (grey-shaded region). However, both $CATFIN_t$ and PQR_t started an upward movement during the GFC. This suggests the leading nature of our measures.

[10]Since PQR_t has negative values, to graph a comparable pattern, we use its absolute values. Furthermore, $CATFIN_t$ and PQR_t data is only available till 2011Q4. Therefore, 5.3.1 and 5.3.1 show comparison during this period only.

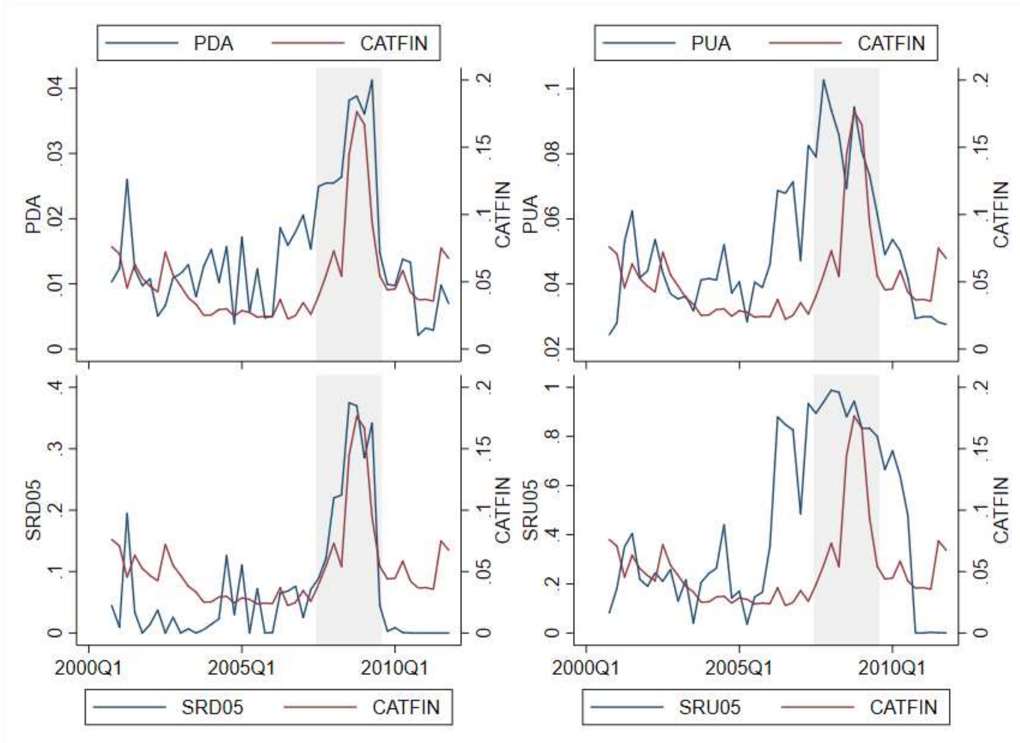

Figure 2: Comparison of PDA_t, PUA_t, $SRD05_t$ and $SRU05_t$ with $CATFIN_t$.

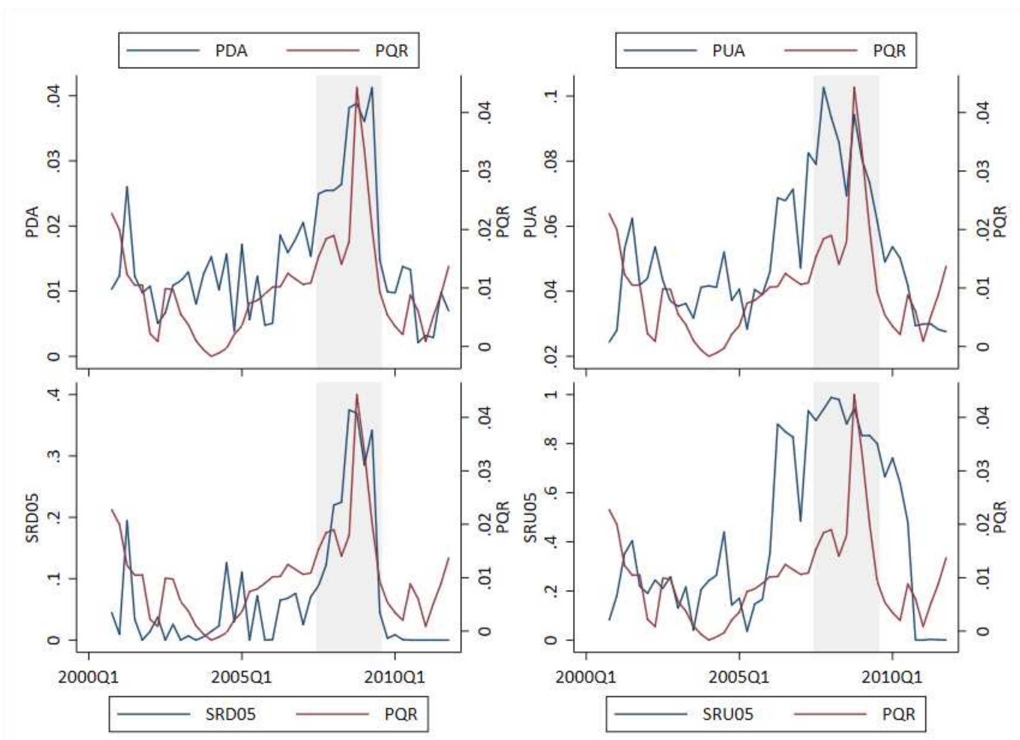

Figure 3: Comparison of PDA_t, PUA_t, $SRD05_t$ and $SRU05_t$ with PQR_t.

Figure 4 shows the progression of $StLFSI_t$ along with our proposed measures for the full sample. A similar pattern has been observed among $StLFSI_t$, PDA_t, and $SRD05_t$. However, we observe that PUA_t and $SRU05_t$ show a leading behavior in terms of the upward movement right before the GFC as well as during the crisis peak. Overall, graphical comparison with already established systemic risk measures suggests a pro-active nature of our proposed measures.

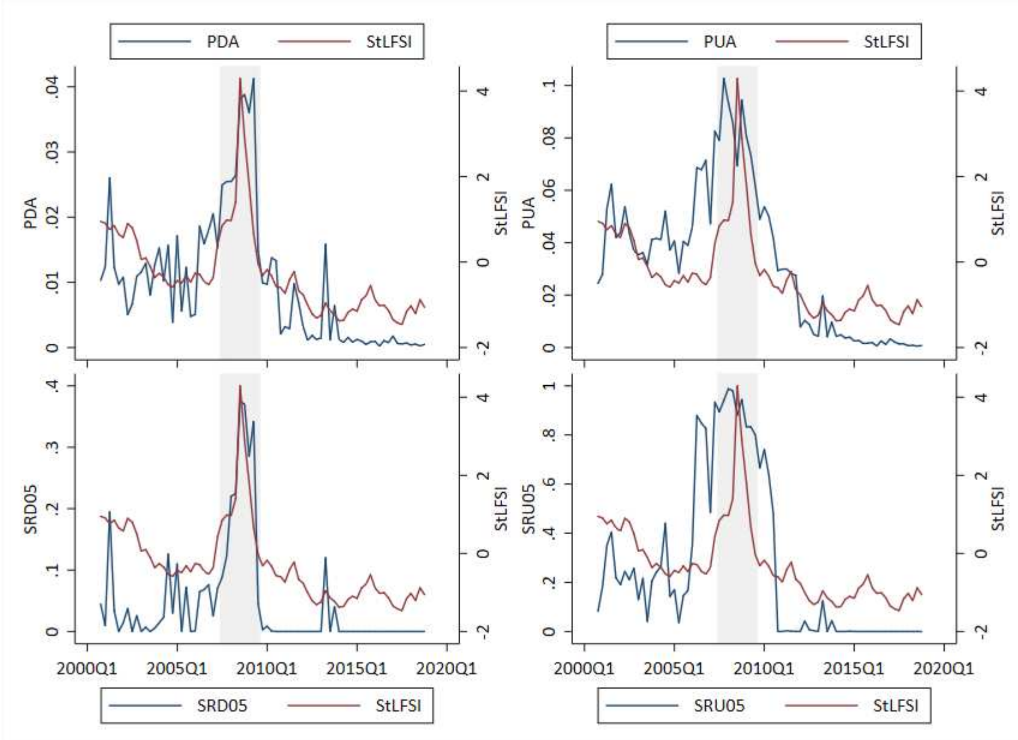

Figure 4: Comparison of PDA_t, PUA_t, $SRD05_t$ and $SRU05_t$ with $StLFSI_t$

5.3.2 Forecast Evaluation of the Systemic Risk Measures

Following Giglio et al. (2016), we rely on the relevance of the various systemic risk measures in forecasting shocks to different macroeconomic indicators as the evaluation criterion. Our methodology of forecast evaluation is presented below.

Let Y_t denote a macroeconomic indicator of interest. The shocks to Y_t are constructed from the following autoregressive model:

$$Y_t = a_0 + \sum_{m=1}^{p} a_m Y_{t-m} + \varepsilon_t \tag{30}$$

In equation (30) the number of lags, p, are selected to minimize the Akaike Information Criterion (AIC). The estimation of equation (30) removes the variation of Y_t explained from its own lags. This is a conventional approach in the macroeconomic forecasting literature (Bai & Ng, 2008; Stock & Watson, 2012). Similar to Giglio et al. (2016), the forecasted residual at time $t+\tau$, from the estimation of equation (30), is taken as the quarterly shock to Y_t in period $t+\tau$; these are denoted as $\eta_{t+\tau}$ where $\eta_{t+\tau} = \widehat{\varepsilon}_{t+\tau}$.[11] Therefore, forecasts of the macroeconomic shock, $\eta_{t+\tau}$, are constructed only with the data available till time period t. For the forecast evaluation of the different systemic risk measures, we take $\tau \in \{1, 2, \cdots, 6\}$. In doing so, we ascertain the relevance of the different systemic risk measures in explaining various macroeconomic shocks up to six quarters into the future.

Following Giglio et al. (2016), we rely on quantile forecasts to ascertain relevance of the different systemic risk measures.

[11]The equation (30) is estimated recursively using out-of-sample predictions following Giglio et al., 2016.

This is accomplished by the estimation of the following quantile regression:

$$Q_{\lambda}\left(\eta_{t+\tau}|\mathcal{I}_t\right) = b_0 + b_1 X_t \tag{31}$$

where X_t, in equation (31), represents a measure of systemic risk.[12] Considering that, Giglio et al. (2016) shows that systemic risk measures are able to explain the 20th percentile of shocks to the macroeconomic variables in period $t+\tau$, our estimation focuses on $\lambda = 0.2$. The forecasting accuracy of the systemic risk measure X_t is evaluated using the following:

$$R_{\tau}^2 = 1 - \frac{\sum_t \left[\rho_{\lambda}\left(\eta_{t+\tau} - \hat{b}_0 - \hat{b}_1 X_t\right)\right]}{\sum_t \left[\rho_{\lambda}\left(\eta_{t+\tau} - \hat{q}_{\lambda}\right)\right]} \tag{32}$$

In equation (32), $\rho_{\lambda}(\cdot)$ is the quantile loss function. The R_{τ}^2 from equation (32) compares the losses in the explanation of the shock $\eta_{t+\tau}$ by the systemic risk measure X_t with those from the historical unconditional quantile $\hat{q}_{\lambda}$. Note that R_{τ}^2 will be negative (positive) if the historical unconditional quantile performs better (worse) than X_t as a forecast. Since $\eta_{t+\tau}$ is the forecasted residual from the estimation of equation (30), we rely on block-bootstrap with 1,000 replications to compute statistical significance of R_{τ}^2 in a robust manner.

Table 2 Panel A reports out-of-sample predictive statistics of our eight systemic risk measures for six forward time-periods, F1 to F6, starting from time-period 2007Q3 against three macroeconomic indicators; TIP_t, FSI_t, and $CFNAI_t$. The results are very promising especially in the case of TIP_t. Among the systemic risk measures which were based on defaulted BHCs, PDA_t consistently shows significant forecasting power in all six forward quarters while $SRD02_t$ ($SRD05_t$) shows significant forecasting power in all forwards except for F3 (F4) and F6. However, $SRD10_t$ and $SRD15_t$ remain insignificant except for $SRD15_t$ showing significance in F2. Among four of the systemic risk measures based on under-capitalized BHCs, PUA_t shows significant forecasting power except for F1 and F4, $SRU02_t$($SRU05_t$) also shows significance in all forwards except F1, and F4 (F1, F4 and F5). $SRU10_t$ shows consistent results for the first three forwards while $SRU15_t$ has significance for only F1 and F3. Overall, we have observed that CB systemic risk measures are significantly informative for out-of-sample predictions of TIP_t.

Results of forecasting evaluation are even more promising for FSI_t. PDA_t, PUA_t, $SRD02_t$, and $SRU05_t$ show significant forecasting power for all six forward quarters while $SRU02_t$ show forecasting power in all forwards except F3. $SRD05_t$ and $SRU15_t$ show predictability in the first forward while $SRU10_t$ has predictability in F1, F2 and F6. It is worth-mentioning that FSI_t represents the performance of the financial sector and, therefore, is more relevant to the analysis of systemic risk. As shown in Table 2, our proposed measures have performed exceptionally well in forecasting shocks to FSI_t.

With regards to $CFNAI_t$, PUA_t ($SRU02$), shows significant results for all forward quarters except for F1 (F1 and F2) while $SRU05_t$ shows significance for F2, F3, F5, and F6. On the other hand, PDA_t, and$SRD02_t$, also show significant results in multiple forwards. However, $SRD05_t$, $SRD10_t$, $SRD15_t$, $SRU10_t$, and $SRU15_t$ do not show promising results in forecasting shocks to $CFNAI_t$.

[12]The systemic risk measure X_t is constructed using data till period t.

For the sake of comparison, Panel B of Table 2 reports out-of-sample ability of $StLFSI_t$ in forecasting shocks to the three macroeconomic indicators. The index performs well and shows significant forecasting power especially for FSI_t where the results are significant for all forward quarters. In the case of TIP_t, F1 and F6 are insignificant while in $CFNAI_t$ we find insignificance in F4 and F5. If we compare the results of $StLFSI_t$ with our CB systemic risk measures, we can see that in the case of TIP_t, PDA_t outperforms $StLFSI_t$ in terms of consistency while PUA_t shows competitive results. In case of FSI_t, three of our measures, PDA_t, PUA_t, and $SRU05_t$ are as consistent as $StLFSI_t$, while $CFNAI_t$, PDA_t, and PUA_t show competitive results with $StLFSI_t$. Overall, we observe that $StLFSI_t$ is a very effective measure for forecasting the lower quantile movements in macroeconomic indicators and three of our measures - PDA_t, PUA_t, and $SRU05_t$ - are as good as $StLFSI_t$. It is worth mentioning that $StLFSI_t$ is one of the most comprehensive measures of systemic risk generated using the data from 18 different financial market variables. It cannot possibly be estimated in less developed financial systems due to data limitations. Our systemic risk measures, which performed as good as $StLFSI_t$, rely solely on balance sheet data and, hence, are globally applicable.

To further investigate the forecasting ability of the systemic risk measures, we extend our analysis on four sub-components of $CFNAI_t$; namely, PI_t, EUH_t, CH_t, and SOI_t. Panel A of Table 3 provides results of our CB measures against each of these components while Panel B reports results of $StLFSI_t$. Overall, we observe that PDA_t, PUA_t, $SRD02_t$, and $SRU05_t$ provide promising results in forecasting shocks to the sub-components of $CFNAI_t$. For PI_t, PUA_t, and $SRU05_t$ show significance in F2, F3, and F6, while PDA_t is significant in F2 and F6. Even better results have been observed for EUH_t where PDA_t and $SRD02_t$ show consistent results for the first five forward quarters, while PUA_t shows consistent performance for the last five forward quarters. For CH_t, PDA_t show significant results in F1, F2, F4 and F6; PUA_t is significant in F1, F2, F5, and F6; $SRU05_t$ is significant in F1, F2, F3, and F5 while $SRD05_t$ and $SRU10_t$ show consistent results for the first two forwards. For SOI_t, $SRU05_t$ shows significance for the last four forward quarters, $SRD02_t$ is significant from F2 to F4 and PUA_t is significant in F2, F3, F5, and F6. However, PDA_t, $SRD05_t$, $SRU10_t$ and $SRU15_t$ show significance occasionally whereas $SRD10_t$, and $SRD15_t$ do not show significance in any of the forward quarters.

In comparison, as shown in Panel B of Table 3, $StLFSI_t$ also shows significant results for the first three forwards for PI_t, first five forwards for EUH_t, first two and last two forward quartersfor CH_t, and second and third forwards for SOI_t. Overall, we find that PDA_t, PUA_t, and $SRU05_t$ show competitive results for forecasting shocks to the sub-components of $CFNAI_t$.

	F1	F2	F3	F4	F5	F6
Panel A: Copula-based systemic risk measures						
Total Industrial Production (*TIP*)						
PDA	0.1149*	0.1701**	0.0893*	0.0946*	0.0630*	0.0601*
PUA	0.0864	0.1428**	0.1609**	0.1214	0.1007*	0.0954**
SRD02	0.1673*	0.1214**	0.1103	0.0978*	0.1068**	0.0413
SRD05	0.2044*	0.2157**	0.1043*	0.1023	0.0968*	0.0357
SRD10	0.0406	0.0313	0.0095	0.0709	0.0002	0.0587
SRD15	0.0205	0.0833*	0.1108	0.0493	0.0328	0.0198
SRU02	0.0195	0.1519**	0.1506*	0.1469	0.1265*	0.1092*
SRU05	0.1105	0.1837**	0.1756**	0.1598	0.1117	0.0991*
SRU10	0.0817*	0.0939*	0.1351**	0.0451	0.0839	0.0224
SRU15	0.1512*	0.1456	0.2320*	0.0675	0.0194	0.0159
Financial Services Index (*FSI*)						
PDA	0.2610**	0.2798**	0.2036**	0.2456**	0.2188*	0.1563*
PUA	0.3218***	0.2409**	0.2779**	0.2737**	0.2847*	0.2558**
SRD02	0.279**	0.2225*	0.1945*	0.2346*	0.2117*	0.2426*
SRD05	0.2078*	0.1399	0.1043	0.0982	0.1296	0.0675
SRD10	0.0023	-0.0328	0.1088	0.0850	0.0410	0.0536
SRD15	0.0334	-0.0355	0.0394	0.0204	0.1128	0.0284
SRU02	0.1986***	0.1774*	0.2008	0.1785*	0.1646*	0.1405**
SRU05	0.3611**	0.2420**	0.3199**	0.2333**	0.2649*	0.2593**
SRU10	0.1834*	0.0979*	0.0916	0.1175	0.1296	0.0645*
SRU15	0.1331*	0.1217	0.1287	0.0748	0.0942	0.0473
Chicago Fed National Activity Index (*CFNAI*)						
PDA	0.2035	0.2388**	0.0415	0.2169	0.1719*	0.1767*
PUA	0.1528	0.3248***	0.2761**	0.3454*	0.3225*	0.1882*
SRD02	0.1615**	0.2396**	0.0906	0.2235*	0.1264*	0.1618
SRD05	0.1458	0.1414*	-0.0066	0.1289	0.0394	0.0390
SRD10	0.0237	-0.0068	0.0693	0.0141	0.0298	0.0145
SRD15	0.0227	0.0193	0.1156	0.0700	0.0420	0.0211
SRU02	0.1576	0.2328	0.2125**	0.2028**	0.2305**	0.1655*
SRU05	0.0799	0.1957*	0.1743*	0.2531	0.1631*	0.1979*
SRU10	0.0033	0.0726	0.0533	0.1777	0.0991	0.0353
SRU15	0.0448*	0.1808	0.2326	0.1436	0.0340	0.0698
Panel B: St. Louis Fed's Financial Stress Index (*StLFSI*)						
TIP	0.1842	0.1858*	0.1313*	0.1092*	0.1053*	0.0655
FSI	0.3234**	0.3667**	0.2356*	0.1679*	0.1197*	0.0545*
CFNAI	0.3608***	0.3028**	0.1606*	0.1453	0.0696	0.1276*

Table 2: 20th percentile TIP_t, FSI_t, and $CFNAI_t$ shock forecasts. This table reports out-of-sample quantile forecast R^2 (in fractions) relative to the historical quantile model. $*$, $**$, and $***$ show statistical significance at the 10%, 5%, and 1% levels, respectively. The sample is from 2000Q1–2018Q4. The out-of-sample start date is 2007Q3.

	F1	F2	F3	F4	F5	F6
Panel A: Copula-based systemic risk measures						
Production and Income (PI)						
PDA	0.0825	0.1859*	0.0620	0.1084	0.0914	0.1311*
PUA	0.0633	0.2416**	0.2187**	0.2679	0.1612	0.1041*
SRD02	0.0592	0.2041**	0.0783	0.1531	0.0765	0.0918
SRD05	0.1062	0.1477	0.0522	0.0768	0.0482	0.0401
SRD10	0.0208	-0.0044	0.0255	0.0212	0.0323	0.0094
SRD15	0.0186	0.0541	0.1714	0.0908	0.0245	0.0169
SRU02	0.1215	0.1043	0.1248**	0.104*	0.1472	0.0347
SRU05	0.0580	0.1424*	0.1461*	0.1995	0.1438	0.1617*
SRU10	0.0097	0.0918	0.0875	0.1467	0.1020	0.0151
SRU15	0.0370	0.2031	0.2856	0.1668	-0.0155	0.0401
Employment, Unemployment, and Hours (EUH)						
PDA	0.2045*	0.1287**	0.1319*	0.1606*	0.1892*	0.0912
PUA	0.0363	0.1956**	0.1746**	0.1616**	0.1171*	0.1640*
SRD02	0.2122*	0.0937**	0.1086*	0.0892*	0.1261*	0.0834
SRD05	0.1742	0.0902*	0.0528*	0.0685	0.1203	0.0387
SRD10	0.0006	0.0062	0.0286	0.0304	0.0034	0.0046
SRD15	0.0175	0.0323	0.0465	0.1044	0.0302	-0.0036
SRU02	-0.0299	0.1464	0.1227	0.1176	0.1062*	0.1163*
SRU05	0.1146	0.1796*	0.1864*	0.1431*	0.0726	0.1339*
SRU10	-0.0680	-0.0032	0.0822	0.1363	0.0949	0.0956
SRU15	0.0659	0.1799	0.1070	0.1255	-0.0028	0.0494
Personal Consumption and Housing (CH)						
PDA	0.2003***	0.1019**	0.1154	0.1211*	0.1258	0.2064*
PUA	0.2434***	0.2211***	0.2307	0.1514	0.1794**	0.1139*
SRD02	0.235***	0.1327**	0.2126**	0.164**	0.1013*	0.1695
SRD05	0.0804*	0.0716*	0.0756	0.0494	0.0855	0.0304
SRD10	0.0107	0.0240	0.0680	0.0306	0.0702	0.0156
SRD15	-0.0131	0.0398	0.0450	0.0311	0.0474	0.0460
SRU02	0.175**	0.1946	0.1343	0.1992**	0.1253*	0.1548
SRU05	0.2740***	0.2424***	0.1952*	0.2010	0.1899*	0.0930
SRU10	0.1396**	0.0654*	-0.0280	0.0805	0.0270	0.0386
SRU15	0.0741*	0.0687	0.1015	0.0813	0.0187	-0.0155
Sales, Orders, and Inventory (SOI)						
PDA	0.1614	0.2989**	0.0510	0.1991*	0.0414	0.0796
PUA	0.1763	0.3281*	0.269*	0.1861	0.1676*	0.1694*
SRD02	0.0843	0.2208*	0.118**	0.1848*	0.1399	0.0814
SRD05	0.1533*	0.1749*	0.0998	0.0762	0.0029	0.0599
SRD10	0.0519	0.0500	0.0473	0.0729	-0.0064	0.0306
SRD15	0.0521	0.0550	0.0684	0.0476	0.0267	-0.0286
SRU02	-0.0598	0.025	0.0418	0.0245	0.1223	0.0687
SRU05	0.0956	0.1765	0.1447*	0.2157*	0.1371**	0.1567*
SRU10	0.1489*	0.0476	0.0910	0.0563	0.0502	0.0101
SRU15	0.1285*	0.0767	0.1920	0.0765	0.0244	0.0191
Panel B: St. Louis Fed's Financial Stress Index ($StLFSI$)						
PI	0.2085**	0.1214**	0.1292*	0.1226	0.0685	0.0389
EUH	0.3002**	0.1835**	0.093**	0.1644*	0.0784*	0.1150
CH	0.2139***	0.1727***	0.1088	0.0684	0.0486*	0.0813*
SOI	0.1373	0.1627*	0.1566*	0.0780	0.0723	0.0071

Table 3: 20th percentile PI_t, EUH_t, CH_t and SOI_t (sub-components of $CFNAI_t$) shock forecasts: This table reports out-of-sample quantile forecast R^2 (in fractions) relative to the historical quantile model. $*$, $**$, and $***$ show statistical significance at the 10%, 5%, and 1% levels, respectively. The sample is from 2000Q1–2018Q4. The out-of-sample start date is 2007Q3.

For comparison purposes, we used the two best performing measures of Giglio et al. (2016); namely, PQR_t and $CATFIN_t$. As these measures were available on monthly basis, we used a three-month average to convert these to quarterly frequency.[13] Moreover, these measures are only available till 2011Q4. Thus, we show results of forecasting ability of these measures starting from 2007Q3 till 2011Q4.

Results, as provided in Table 4, show that for TIP_t, PDA_t shows significant forecasting power in F2, F4, and F6 while PUA_t has significance in F2 and F3. $SRD05_t$ shows consistent results in first three forward quarters while $SRD02_t$ is significant for first two forward quarters. Similar results have been shown by $SRD15_t$, $SRU05_t$, and $SRU10_t$. In contrast, PQR_t has no significant forecasting power except for the F3; $CATFIN_t$ is significant in F2, F4, and F5 while $StLFSI_t$ is significant in F2, F3, and F5. Once again, our proposed measures have shown competitive results with $CATFIN_t$ and $StLFSI_t$ while outperforming PQR_t.

When considering FSI_t, results are even more promising where $SRU05_t$ shows very consistent results in all six forward quarters while PUA_t also shows significance in all forwards except for F4. PDA_t is significant except for the F2 and F6. In comparison, PQR_t shows significant results only for F5 while $CATFIN_t$ is significant only in F5 and F6. $StLFSI_t$ turned out to be insignificant in all forward quarters. In case the of $CFNAI_t$, PUA_t shows significance for F2 and F3; $SRU05_t$ shows significance in F2, F3, and F6; and $CATFIN_t$ is significant in F3 and F4. For $CFNAI_t$, PQR_t and $StLFSI_t$ remain insignificant for all forward quarters. Our measures provide better results as compared to the already established measures of systemic risk. It is also worth mentioning that the time-period used for the forecasting evaluation presented in Table 3, 2007Q3 till 2011Q4, corresponds to the GFC. During this period, the existing measures of systemic risk have shown their inability to forecast shocks to the macroeconomic indicators, while the CB measures provide significant results.

Table 5 reports results of the four sub-components of $CFNAI_t$. Overall, we find that during this time-period all the measures provide relatively less promising results in forecasting shocks to the sub-components of $CFNAI_t$. In case of PI_t, among our measures, $SRU05_t$ provides significant results in F2 and F3 while PUA_t provides significant results in F3 only. Among the existing measures, $StLFSI_t$ shows significance in F1 and F2 while $CATFIN_t$ is significant in F2 only. For EUH_t, $SRD02_t$ performs best among all measures and shows consistent results in the first five forward quarters. PDA_t is significant for F1 and $SRU05_t$ is significant in F2, while $StLFSI_t$ and PQR_t are significant in F5 and F4, respectively. $CATFIN_t$ shows significant forecasting ability in F4 and F5. PUA_t and $SRU05_t$ show relatively consistent performance by providing significance in F1 and F2 for CH_t while $SRU10_t$ shows significance in F1. For the existing measures, $StLFSI_t$ is significant in F1, PQR_t in F1 and F5, while $CATFIN_t$ is significant in F5. $SRU05_t$ outperforms the existing measures in forecasting the shocks to SOI_t where it significantly forecasts SOI_t in F3, F4, F5, and F6. PDA_t is significant in F2 and F4; $SRD02_t$ is significant in F2 and F3, PUA_t is significant in F3; while $SRD05_t$ is significant for F1. The existing measures are insignificant in all forward quarters for SOI_t. Overall, we have observed that during the GFC, our measures, PDA_t, PUA_t, and $SRU05_t$ outperform the already established measures of systemic risk.

[13]Results of end-period values have also been estimated and, overall, found to be similar.

	F1	F2	F3	F4	F5	F6
Total Industrial Production (*TIP*)						
PDA	0.2127	0.3512**	0.2159	0.2274*	0.1342	0.1179*
PUA	0.1809	0.3193**	0.4585**	0.4001	0.2910	0.2014
SRD02	0.3171*	0.2774**	0.2524	0.2297	0.2053*	0.0802
SRD05	0.3704*	0.4105**	0.2012*	0.1920	0.1588	0.0656
SRD10	0.0679	0.0877	0.0249	0.0962	-0.0125	0.0939
SRD15	0.0364	0.1492*	0.2067*	0.0866	0.0498	0.0363
SRU02	0.0114	0.2341	0.2827	0.2464	0.1899	0.1578
SRU05	0.2103	0.3384**	0.3198**	0.3456	0.2352	0.1964
SRU10	0.1368	0.1843**	0.2576**	0.0907	0.1159	0.0552
SRU15	0.2728	0.2633	0.4229*	0.1204	0.0303	0.0318
PQR	0.2940	0.1947	0.2221*	0.1294	0.0451	0.0885
CATFIN	0.2057	0.2728*	0.0736	0.1123*	0.0482*	0.1037
StLFSI	0.3542	0.3334*	0.2661*	0.1837	0.1764*	0.0804
Financial Services Index (*FSI*)						
PDA	0.2327*	0.2423	0.1396*	0.1918*	0.1944*	0.1206
PUA	0.3462**	0.1694*	0.2478*	0.2135	0.3499*	0.2441*
SRD02	0.2171*	0.1632	0.1134	0.1566	0.1684	0.1656
SRD05	0.1901*	0.1022	0.1048	0.0861	0.1505	0.0787
SRD10	-0.0087	-0.1080	0.1844*	0.1494	0.0508	0.0805
SRD15	0.0653*	-0.1130	0.0712	0.0371	0.1190	0.0057
SRU02	-0.0354	0.0272	0.1105	0.0338	0.0923	-0.0049
SRU05	0.3925**	0.2245*	0.3403**	0.1960*	0.2477*	0.2769*
SRU10	0.1539	0.0082	0.0743	0.1435	0.1258	0.0616
SRU15	0.1048	0.1035	0.1635*	0.0677	0.0593	0.0601
PQR	0.1921	0.1125	0.1071	0.1228	0.1270*	0.0787
CATFIN	0.1877	0.0369	0.1103	-0.0067	0.1275*	0.0881*
StLFSI	0.2516	0.2877	0.1711	0.0429	0.0919	0.0226
Chicago Fed National Activity Index (*CFNAI*)						
PDA	0.0955	0.0969	-0.0433	0.0534	0.0723	0.0296
PUA	-0.0602	0.1557*	0.1384*	0.2155	0.1879	0.0445
SRD02	-0.0088	0.117	0.0189	0.0685	-0.0723	-0.0288
SRD05	0.0868	0.0763	0.0042	0.1710	0.0454	0.0377
SRD10	0.0156	-0.0167	0.0931	0.0116	0.0425	0.0208
SRD15	0.0381	0.0402	0.1891	0.0751	0.0068	0.0155
SRU02	-0.0218	0.027	0.0291	0.038	0.0246	0.0041
SRU05	-0.0353	0.0887*	0.0874*	0.1284	0.0408	0.0811*
SRU10	-0.0453	-0.0296	0.0473	0.0743	0.0735	0.0329
SRU15	0.0157	0.1626	0.2747	0.1029	-0.0151	0.1262
PQR	-0.0205	0.0159	-0.0061	-0.0245	0.0368	0.0127
CATFIN	0.0203	0.1448	0.0680*	0.0717*	0.0746	0.1454
StLFSI	0.2378	0.1163	0.0465	0.0637	0.0163	0.0912

Table 4: 20th percentile TIP_t, FSI_t and $CFNAI_t$ shock forecasts, comparison with PQR_t, $CATFIN_t$, and $StLFSI_t$: This table reports out-of-sample quantile forecast R^2 (in fraction) relative to the historical quantile model. $*$, $**$, and $***$ show statistical significance at the 10%, 5%, and 1% levels, respectively. The sample is from 2000Q1–2011Q4. The out-of-sample start date is 2007Q3.

	F1	F2	F3	F4	F5	F6
Production and Income (PI)						
PDA	0.0370	0.1522	0.0245	0.0426	0.0573	0.0744
PUA	-0.0122	0.2083	0.1981*	0.2553	0.1349	0.0450
SRD02	-0.0224	0.1677**	0.0344	0.1117	0.025	0.024
SRD05	0.0664	0.1378	0.0403	0.072	0.0284	0.0277
SRD10	0.0383	-0.0209	-0.0009	0.0277	0.0364	0.0133
SRD15	0.0291	0.0380	0.1993	0.1233	0.0201	0.0023
SRU02	0.008	0.005	0.041	0.0537	0.0959	-0.025
SRU05	0.0050	0.1033*	0.1296*	0.1817	0.1229	0.1245
SRU10	0.0343	0.0408	0.0661	0.1274	0.0851	0.0133
SRU15	0.0157	0.1804	0.3300	0.1642	-0.0495	0.0467
PQR	0.0311	0.0001	0.0115	-0.0130	0.0129	0.0252
CATFIN	0.1217	0.1012**	0.0836	0.0745	0.0694	0.1153
StLFSI	0.1745*	0.0618*	0.0851	0.0915	0.0467	0.0414
Employment, Unemployment, and Hours (EUH)						
PDA	0.2188*	0.0911	0.1011	0.1282	0.1814	0.0609
PUA	-0.1240	0.1609	0.1830	0.1986	0.0911	0.1576
SRD02	0.2122*	0.0937**	0.1086*	0.0892*	0.1261*	0.0834
SRD05	0.2245	0.0772	0.0501	0.0881	0.1543	0.0285
SRD10	0.0365	-0.0109	0.0754	0.0627	0.0161	0.0239
SRD15	0.0397	0.0517	0.0682	0.1412	0.0333	-0.0205
SRU02	-0.0762	0.0192	0.0552	0.0462	0.0238	0.0405
SRU05	0.0473	0.152*	0.1835	0.1182	0.0208	0.1012
SRU10	-0.0510	-0.0519	0.0946	0.1487	0.0711	0.1178
SRU15	0.0721	0.2479	0.1443	0.1605	-0.0201	0.0730
PQR	0.0020	0.0909	0.054	0.0618*	0.1033	0.0622
CATFIN	0.052	0.1106	0.1405	0.1081*	0.1006*	0.2010
StLFSI	0.3259	0.1385	0.0670	0.1266	0.0715*	0.1634
Personal Consumption and Housing (CH)						
PDA	0.1497	-0.0271	0.0248	0.0575	0.0744	0.1843
PUA	0.2496*	0.2249*	0.2123	0.214	0.2335	0.0590
SRD02	0.2244**	0.0181	0.1636*	0.1148*	0.0232	0.1299
SRD05	0.0600	0.0732	0.1039	0.0328	0.0549	0.0312
SRD10	0.0075	0.0649	0.1126	0.0614	0.1186	0.0348
SRD15	-0.0565	0.1066	0.0944	0.0482	0.0271	0.0678
SRU02	0.0272	0.003	-0.0116	0.0729	0.0323	0.0431
SRU05	0.2892*	0.2439*	0.1359	0.1952	0.1500	0.0329
SRU10	0.1912*	0.801	-0.0351	0.1132	-0.0367	0.0344
SRU15	0.1063	0.0730	0.1320	0.0871	0.0039	-0.0092
PQR	0.0693*	0.0220	-0.0190	0.0562	0.0307*	0.0932
CATFIN	0.0498	0.1691	0.1002	0.0753	0.1547*	0.1351
StLFSI	0.1675*	0.1451	0.0957	0.0156	-0.0076	0.0222
Sales, Orders, and Inventory (SOI)						
PDA	0.1160	0.2827**	-0.0197	0.2154*	-0.0437	0.0638
PUA	-0.0617	0.3357	0.2913*	0.1548	0.0782	0.0989
SRD02	0.0145	0.1922**	0.1038**	0.1979	0.0758	0.0784
SRD05	0.1027*	0.1923	0.1191	0.1370	0.0127	0.1238
SRD10	0.0850	0.1141	0.0559	0.1070	-0.0110	0.0446
SRD15	-0.0176	0.1724	0.0775	0.0752	0.0019	-0.0541
SRU02	-0.102	-0.0376	-0.0469	0.0307	-0.0487	0.0137
SRU05	-0.0379	0.2031	0.1637*	0.2544*	0.0689*	0.1456*
SRU10	0.0343	0.0408	0.0661	0.1274	0.0851	0.0133
SRU15	0.1072	0.0062	0.2480	0.0873	-0.0485	0.0543
PQR	0.0359	0.0736	0.0801	0.0891	-0.0756	0.0472
CATFIN	-0.1428	-0.0393	-0.0758	0.0476	-0.0195	0.1720
StLFSI	-0.0122	0.1069	0.1145	0.0325	0.0146	0.0311

Table 5: 20th percentile PI_t, EUH_t, CH_t, and SOI_t (the sub-components of $CFNAI_t$) shock forecasts, comparison with $StLFSI_t$, PQR_t, and $CATFIN_t$: This table reports out-of-sample quantile forecast R^2 (in fractions) relative to the historical quantile model. $*$, $**$, and $***$ show significance at the 10%, 5%, and 1% levels, respectively. The sample is from 2000Q1–2011Q4. The out-of-sample start date is 2007Q3.

6 Conclusion

Motivated by the need to have globally applicable systemic risk measures, this paper proposes a set of CB systemic risk measures. For global applicability, our measures use only balance sheet data of financial institutions as existing measures mainly rely on market data which poses limitations on their application in less developed markets. By using CB methodology, we estimated ten different systemic risk measures and, by using a quantile regression framework, we conducted a comprehensive forecasting evaluation. Our proposed measures have shown a high level of systemic risk during the GFC. Furthermore, our measures also show quite elevated levels leading to the GFC. Arguably, these elevated levels before the GFC shows the ability of these measures to provide early-warnings. Results of out-of-sample forecasting analysis of our measures with macroeconomic indicators show the ability of our measures to forecast macroeconomic shocks as early as six quarters. We further compared the performance of our proposed measures with already established market data based systemic risk measures. Comparative analysis shows the superior performance of our measures. Looking forward, an application of our methodology in less developed economies, to estimate systemic risk and its determinants, presents a natural direction for further research.

Data Availability Statement: The data that support the findings of this study are available from the corresponding author upon reasonable request.

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