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Systemic Risk Measurement and Its Economic Early Warning Ability: Based on Mixed-Frequency Dynamic Factor Model

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Abstract

As China's participation in the global market intensifies, the systemic risk arising from its expansive and interconnected economy becomes increasingly significant worldwide. The inherent complexity of systemic risk necessitates the integration of a wide array of information sources for its accurate assessment. In this context, our study utilizes the mixed-frequency dynamic factor model to develop a Systemic Risk Index (SRI) that effectively encapsulates. This model is adept at merging data indicators from varying frequencies, which is crucial for capturing the multifaceted nature of systemic risk. Moreover, the study further delves into the macroeconomic early warning capabilities of the SRI. Our findings demonstrate that the SRI is proficient in integrating and distilling information from diverse market dimensions, offering a more nuanced representation of China's economic and financial risks. Moreover, the SRI exhibits a robust capacity for economic foresight, outpacing macroeconomic indicators by a minimum of 12 months.

Keywords

Systemic Risk Index, Economic Warning, Mixed-Frequency Dynamic Factor Model

1. Introduction

The increasing interconnectedness of global financial markets underscores the critical role of systemic risk in emerging countries. The possibility of financial contagion means that a crisis in one nation could potentially jeopardize the entire global financial system, as evidenced by research from Kenourgios and Dimitriou (Kenourgios & Dimitriou, 2015) and Huang and Chen (Huang & Chen, 2020). Over the past two decades, the systemic significance of the Chinese market has grown, reflecting China's expanding role in global markets. Consequently, China's financial decisions now exert a substantial impact on the global economy. This interdependence is highlighted by Guo et al. (Guo et al., 2022), who note the mutual spillover effects of risks between China and international markets.

The ascent of China as a major economic and financial force is a key development of the 21st century. However, many emerging countries, including China, are susceptible to systemic risks due to factors such as underdeveloped regulatory frameworks, limited financial literacy among investors, and inadequate financial infrastructure, as per the World Economic Forum (WEF, 2014). These vulnerabilities make them more susceptible to macroeconomic and financial disturbances, both domestically and internationally. Therefore, identifying, monitoring, and managing systemic risk in China is not just a national concern but a global imperative. Effective management of systemic risk in China can help reduce the risk of financial contagion and economic upheaval, making it a matter of international importance.

However, systemic risk is complex and multi-dimensional, necessitating a comprehensive consideration of all contributing factors for proper identification and assessment. The International Monetary Fund (IMF), Financial Stability Board (FSB), and Bank for International Settlements (BIS) defined systemic risk in 2009 (IMF et al., 2009) as the risk of disruptions in the provision of financial services that seriously impact the real sector. Billio et al. (Billio et al., 2012) argue that the interconnectedness of financial institutions facilitates the spread of losses and risks, thereby creating systemic risk. Patro et al. (Patro et al., 2013) view systemic risk as the likelihood of a widespread collapse of the financial system triggered by systemic events, which profoundly affects financial markets and the real economy with significant negative externalities. Addressing systemic risk is an urgent challenge for all economic and financial entities, requiring an analysis that encompasses both real economic and financial risks.

Many studies have argued that economic and financial systems are interdependent (Allen et al., 2018; McMillan, 2021; Zabavnik & Verbič, 2021). Risks in a single sector of the economy can have repercussions and ripple effects across the rest of the system, and the interconnectedness of the real economy and finance may lead to systemic risk. Huang and Chen (Huang & Chen, 2020) note that a slight shock to the fundamentals of one market can lead to a financial crisis and spread to other markets. During an economic downturn, for example, businesses may be unable to pay their debts, and financial institutions may be exposed to heightened credit risk. Huang et al. (Huang et al., 2022) suggest that a single indicator cannot cover all information about systemic risk but can only reflect specific aspects of macroeconomic performance or has a high correlation only in a particular period. Thus, these characteristics require us to study and monitor the dynamic change process of systemic risk from the perspective of the whole economy-financial system rather than from a single market. Specific to the technical perspective, we need to fully use the rich information at the multidimensional market level and improve the frequency of monitoring. Compared with the high-frequency data of the stock and bond market, these low-frequency data from the real economy may be more indicative of the accumulation and development of systemic risk.

Remarkably, the data frequency varies significantly in different markets. For example, the stock market has many high-frequency data, but most of the data related to the real estate market only have a monthly frequency. Traditional research with the same frequency method cannot deal with the frequency mismatch of different market data, which may lead to neglecting important risk information. The mixed-frequency dynamic factor model proposed by Giannone et al. (Giannone et al., 2008) and Aruoba et al. (Aruoba et al., 2009) effectively overcomes this deficiency. The unique information content of multiple data sources with different frequencies can be extracted comprehensively, often used in constructing an economic or financial cycle. Based on this, we plan to use the mixed-frequency dynamic factor model to remove multi-source risk information from the Chinese stock market, real estate, banking, and local debt markets for building a more comprehensive and effective systemic risk index.

Meanwhile, most existing studies use linear models (such as multiple regression or impulse response) to study the impact of systemic risk on macroeconomics (e.g., Pagano & Sedunov, 2016). However, the effect tends to be non-linear. When the systemic risk stress exceeds a specific limit, the impact of SRI on the macroeconomy may change. Based on this, we introduce threshold regression, an effective means to study the nonlinear effect, to investigate the early warning ability of systemic risk stress on the macro economy.

This study makes the following contributions. Firstly, a new systemic risk index is constructed using multiple dimensions of market information. Unlike most previous studies, the index is not based on information from a single market. It covers essential information from the entire economic and financial system, reflecting relevant information from capital markets and the banking sector and using information from important markets such as real estate and local debt. In addition, different from the standard weighting method, we adopt the mixed-frequency dynamic factor model, which can effectively integrate and retain the rich information of a multi-dimensional market while avoiding the uncertainty interference of subjective judgment. The regression analysis results also confirm the validity of the new index which has good early warning capabilities. Secondly, it verifies the financial early warning ability of systemic risk pressure. The constructed systemic index leads the macroeconomic indicators for at least 12 months. Empirical research shows that SRI has a significant indicator and early warning ability for the future macroeconomic trend (using industrial added value and purchasing managers index as proxy variables), which has significant application value for prudential supervision and economic policy adjustment. Thirdly, with the increasing systemic importance of the Chinese market in the asset allocation of the global market, this paper constructs a systemic risk index for the representative of emerging markets using multiple market dimensions data and tests its effectiveness in macroeconomic forecasting. China's systemic risk increasingly impacts international markets as the global system becomes more interconnected. Thus, the result of this paper not only helps to provide a reference for other developing countries but is also conducive to protecting the financial stability of the global market.

2. Related Literature

Previous scholars have delved deeply into systemic risk measurement, predominantly utilizing financial market data. Key indices like Adrian and Brunnermeier's (Adrian & Brunnermeier, 2016) CoVaR, Acharya et al 's (Acharya et al., 2017) SES and MES, and Brownlees and Engel's (Brownlees & Engel, 2017) SRISK are based on the tail characteristics of asset returns in financial institutions, focusing on individual institutions' contributions to systemic risk. Other researchers, meanwhile, have approached financial risk from a broader systemic perspective, employing tools like the CatFin index and correlation measurements. Commonly, multivariate GARCH models are used to analyze the correlation between returns or volatility across different markets or institutions, as noted by Lin (Lin, 2013) and Li and Giles (Li & Giles, 2015). However, Barunik et al. (Barunik et al., 2016) argue that GARCH models may not fully capture the dynamic nature of systemic risks.

In response, alternative methods such as Diebold and Yilmaz's (Diebold & Yilmaz, 2012) information overflow index, Kritzman et al.'s (Kritzman et al., 2011) principal component analysis-based information absorption ratio, and Billio et al.'s (Billio et al., 2012) dynamic causal index using the Granger causal network have been proposed to analyze systemic risk spillovers more effectively. Innovations in these measurement techniques have been applied to study systemic risks in China's banking sector. For instance, Xu et al. (Xu et al., 2019) utilized LASSO-CoVaR to explore the interconnectedness and systemic risk of financial institutions, while Zou et al. (Zou et al., 2022) employed the maximum entropy method to construct a risk correlation network among Chinese banks, assessing systemic risk through network spillovers.

However, it's important to recognize that the financial market represents just one facet of China's vast economic system, which can be influenced by various factors including information content and efficiency, as highlighted by Carpenter et al. (Carpenter et al., 2021). Relying solely on financial data to gauge China's systemic risk is therefore insufficient and may not fully capture the economy's risk profile. To address this gap, our approach extends beyond typical financial data sources, incorporating real estate and local debt data. We employ the mixed-frequency dynamic factor model to assess China's systemic risks more comprehensively, providing an effective early warning for the economy and finance.

Real estate is a crucial component of the macroeconomic and financial system, representing a key systemic risk factor. Bubbles in the real estate sector can lead to systemic risks, as declining property values may significantly impair a country's overall economic performance, potentially triggering a major economic crisis. Research by Koetter and Poghosyan (Koetter & Poghosyan, 2010) reveals that substantial fluctuations in real estate collateral values can greatly increase bank credit risk, contributing to systemic financial risks. Capozza and Van Order (Capozza & Van Order, 2011) found that defaults in the real estate market are a primary cause of systemic financial risks. Understanding real estate's impact on systemic risk and developing preventive measures is therefore vital. The real estate sector's growth, particularly in China, has been increasingly linked to systemic risks, as shown in Han et al.'s (Han et al., 2021) analysis of the structural evolution of China's real estate industry between 2002 and 2017.

Additionally, local government debt in China plays a significant role in systemic risk, accounting for a large part of the country's economic activity. The introduction of the New Budget Law in 2015 led to improvements in local government debt transparency by transferring some implicit debts back to local governments' balance sheets. However, challenges persist, especially with economic slowdowns and the pandemic's impact straining local finances, as noted by Bo et al. (Bo et al., 2021). Mismanagement of local government debt could result in widespread economic distress, significantly affecting China's economy.

An effective way to fill in the gaps in these models for constructing a systemic risk index is through mixed-frequency dynamic factor models (MFDFM). The mixed-frequency dynamic factor model uses a weighting scheme to combine the indicators across frequencies and constructs a systemic risk index based on the identified common factors. Moreover, it combines both macroeconomic and financial data from different frequencies and attempts to identify common underlying factors or trends. These factors can then be used to construct a systemic risk stress index. This method is helpful for policymakers and financial institutions as it allows them to identify potential sources of systemic risk, even when the data is at different frequencies (Jiang et al., 2017; Algaba et al., 2023; Ding et al., 2022). By tracking and analyzing the model's output, policymakers and financial institutions can better understand the potential risks to the macroeconomic system and develop strategies to mitigate their impact.

Moreover, systemic risk is an important cause of significant changes in consumption, interest rates, currencies, and consumer confidence, which can often predict macroeconomic declines (Kambhu et al., 2007). The CatFin index proposed by Allen et al. (Allen et al., 2012) based on cross-sectional VaR can provide relatively adequate early warning for macro-economy. Kelly and Jiang's (Kelly & Jiang, 2014) study also reached a similar conclusion. Financial stress indexes based on macro-financial indexes (Cardarelli et al., 2011; Carlson et al.,

2014) are also commonly used to study the impact of systemic financial risks on the macroeconomy. Chen et al. (Chen et al., 2020) found that the systemic risk index has significant predictability on the subsequent impact of China's economic growth so it can be used as an early warning signal. Based on this, a comprehensive and accurate measurement of Chinese systemic risk has essential theoretical and practical significance for early macroeconomic warning and risk prevention.

To sum up, this section explores the measurement of systemic risk, primarily focusing on the integration of non-financial data like real estate and local government debt with traditional financial market data. It critiques existing indices like CoVaR, SES, MES, and SRISK for their limited focus on financial institutions and introduces the mixed-frequency dynamic factor model (MFDFM) as a more comprehensive approach. This model effectively combines macroeconomic and financial data across various frequencies to construct a systemic risk index. Emphasizing the broader economic impacts on systemic risk, this section underscores the importance of a multifaceted approach in assessing and predicting systemic risks in China's complex economic environment.

3. Methodology

3.1. Mixed-Frequency Dynamic Factor Model

Referring to Giannone et al. (Giannone et al., 2008) and Aruoba et al. (Aruoba et al., 2009), we adopted a mixed-frequency dynamic factor model to measure the systemic risk pressure. The model involves combining the power of low-frequency (e.g., quarterly) data with the advantages of high-frequency (e.g., daily) data, which helps find hidden connections between different economic and financial variables. In this paper, risk variables and implicit factors are set as monthly. There are only quarterly data in the last month of the quarter, and the remaining months are null. For annual data, only the last month of the year has data, and the rest of the month is null. The basic form of the model is shown in Equations (1)-(3):

$$\boldsymbol{y}_t = \boldsymbol{Z}_t \alpha_t + \Gamma_t \boldsymbol{w}_t + \varepsilon_t \tag{1}$$

$$\alpha_{t+1} = \boldsymbol{T} \alpha_t + R\eta_t \tag{2}$$

$$\varepsilon_t : (0, \boldsymbol{H}_t), \eta_t : (0, \boldsymbol{Q}) \tag{3}$$

$\boldsymbol{y}_t$ is the $N * 1$ dimension observation variable, and this paper contains many missing values for risks of different frequencies. α_t is the m * 1-dimensional state variable; $\boldsymbol{w}_t$ is an exogenous variable of the e * 1 dimension. Only constants and lag terms of dependent variables are considered in this paper. ε_t and η_t represent residuals and perturbations. The Kalman filtering method can process the structural equation model with missing values. Therefore, we use the Kalman filtering method to solve Equations (1)-(3), and the initial value is set as the mean value and covariance matrix of the observed variable sequence.

Specifically, our model design is shown in Equations (4) and (5):

$$\begin{bmatrix} \tilde{y}_t^1 \\ \tilde{y}_t^2 \\ \tilde{y}_t^3 \\ \tilde{y}_t^4 \end{bmatrix} = \begin{bmatrix} \beta_1 & \beta_2 & \beta_3 & \beta_4 \\ 0 & 0 & \beta_3 & \beta_4 \\ 0 & 0 & \beta_3 & \beta_4 \\ 0 & 0 & 0 & \beta_4 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \beta_4 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} x_t \\ x_{t-1} \\ \vdots \\ x_{t-10} \\ x_{t-11} \\ u_t^1 \\ u_t^2 \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ \gamma_3 & 0 \\ 0 & \gamma_4 \end{bmatrix} \begin{bmatrix} \tilde{y}_{t-3}^3 \\ \tilde{y}_{t-12}^4 \end{bmatrix} + \underbrace{\begin{bmatrix} 0 \\ 0 \\ u_t^3 \\ u_t^4 \end{bmatrix}}_{\varepsilon_t} \tag{4}$$

$$\begin{bmatrix} x_{t+1} \\ x_t \\ \vdots \\ x_{t-9} \\ x_{t-10} \\ u_{t+1}^1 \\ u_{t+1}^2 \end{bmatrix} = \begin{bmatrix} \rho & 0 & \cdots & 0 & 0 & 0 & 0 \\ 1 & 0 & \cdots & 0 & 0 & 0 & 0 \\ 0 & 1 & \cdots & 0 & 0 & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & 0 & 0 & 0 & 0 \\ 0 & 0 & \cdots & 1 & 0 & 0 & 0 \\ 0 & 0 & \cdots & 0 & 0 & \gamma_1 & 0 \\ 0 & 0 & \cdots & 0 & 0 & 0 & \gamma_2 \end{bmatrix} \begin{bmatrix} x_t \\ x_{t-1} \\ \vdots \\ x_{t-10} \\ x_{t-11} \\ u_t^1 \\ u_t^2 \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ \vdots & \vdots & \vdots \\ 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} + \underbrace{\begin{bmatrix} e_t \\ \zeta_t^1 \\ \zeta_t^2 \end{bmatrix}}_{\eta_t} \tag{5}$$

$$\begin{bmatrix} \varepsilon_t \\ \eta_t \end{bmatrix} \sim N\left(\begin{bmatrix} \mathbf{0}_{4\times1} \\ \mathbf{0}_{3\times1} \end{bmatrix}, \begin{bmatrix} \boldsymbol{H}_t & \mathbf{0} \\ \mathbf{0} & \boldsymbol{Q} \end{bmatrix} \right)$$

$$\boldsymbol{H}_t = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & \sigma_3^2 & 0 \\ 0 & 0 & 0 & \sigma_4^2 \end{bmatrix}, \boldsymbol{Q} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \sigma_1^2 & 0 \\ 0 & 0 & \sigma_2^2 \end{bmatrix}$$

The value of the state variable obtained from Equations (4) and (5) is small. In order to observe the dynamic change trend of the systemic pressure index more intuitively, we scale it and finally construct the systemic pressure index as shown in Equation (6):

$$\text{SRI} = 100 \times x_t \tag{6}$$

We used the MARSS package of R language for data analysis. In order to speed up the running of the program, the BFGS quasi-Newton algorithm was adopted to solve the equation by referring to the research of Aruoba et al. (Aruoba et al., 2009).

3.2. OLS and Threshold Regression Model

By establishing the prediction model of macroeconomic variables, we can, on the one hand, test the early warning ability of systemic risk pressure indicators on macroeconomics and on the other hand, compare the differences and advantages and disadvantages between SRI and common systemic risk indicators (such as CoVaR). The basic OLS regression model is shown in Equation (7):

$$\text{Macro}_t = \alpha + \gamma \text{Risk}_{t-n} + \beta X_{t-n} + \varepsilon_t \tag{7}$$

Macro is the macroeconomic index (industrial added value and purchasing managers index are selected in this paper). Risk is the systemic risk index; n is the lag order; X is a series of control variables. Referring to the studies of other scholars, this paper selects the Wind All Share Index monthly yield (Ret), volatility (Vol), broad money supply (M2), Term spread (Term, 10-year Treasury bond yield - 1-year Treasury bond yield) and Credit spread (Credit, 10-year corporate bond yield - 10-year Treasury yield), etc.

Considering that there may be a threshold effect of systemic risk pressure on the macro-economy, that is, when the financial risk is low, the impact on the macro-economy is small; On the contrary, when financial risks are high, the impact on the macro economy will be significant. Therefore, we also established a threshold regression model to test this asymmetric effect. The specific model is shown in Equation (8):

$$\text{Macro}_t = \begin{cases} \alpha_1 + \gamma_1 \text{Risk}_{t-n} + \beta_1 X_{t-n} + \varepsilon_t, & \text{Risk}_{t-n} \le \text{Threshold} \\ \alpha_2 + \gamma_2 \text{Risk}_{t-n} + \beta_2 X_{t-n} + \varepsilon_t, & \text{Risk}_{t-n} > \text{Threshold} \end{cases} \tag{8}$$

Threshold indicates the threshold value. On the one hand, the non-linear early-warning ability of systemic risk to macro-economy can be investigated by threshold regression model. On the other hand, the performance difference between different systemic risk indicators and their merits and disadvantages can be judged.

3.3. Data

Unlike most scholars using stock market data to measure systemic risk (such as CoVaR, MES and SRISK, etc.), this paper also considers financial risks in banking, real estate, and local bond markets. Specifically, the stock market risk is measured by conditional value at risk (CoVaR). Based on Adrian and Brunnermeier's (Adrian & Brunnermeier, 2016) definition, CoVaR values of all listed financial institutions (including banking, insurance, and securities) are calculated by quantile regression. Moreover, take the mean on the cross-section to get the overall risk value (Giglio et al., 2016); And the banking risk calculated the default distance of each listed bank by the KMV model and converted it into default probability. The default probability was averaged on the cross-section to get the overall risk value; In addition, the ratio of house price to income measures the real estate market risk. The formula is housing price/resident annual income; Finally, the local government debt risk is measured by total local government debt/GDP. In terms of data frequency, the data frequency of local government debt risk is monthly, the data frequency of banking financial risk is quarterly, and the data frequency of local government debt financial risk is annual. The local government debt data comes from Chinabond, the official website of the Ministry of Finance, PRC, and the Local Statistical Yearbook. And the data on the stock market, banking and real estate are from the Wind database. The sample range is from January 2005 to December 2020, including 16 years, 64 quarters, and 192 months. The specific indicators are shown in **Table 1**.

Figure 1 shows the dynamic trend of the four risk indicators. It can be seen

Table 1. Variable description.

Market	Variable	Frequency	Description
Stock market	CoVaR	Monthly	The cross-sectional mean of financial institutions' CoVaR of daily returns
Banking	EDF	Quarterly	The cross section mean of bank default probability calculated by KMV model
Real estate	House	Monthly	Housing price/Household income
Local government debt	Debt/GDP	Annual	Total local government debt/GDP

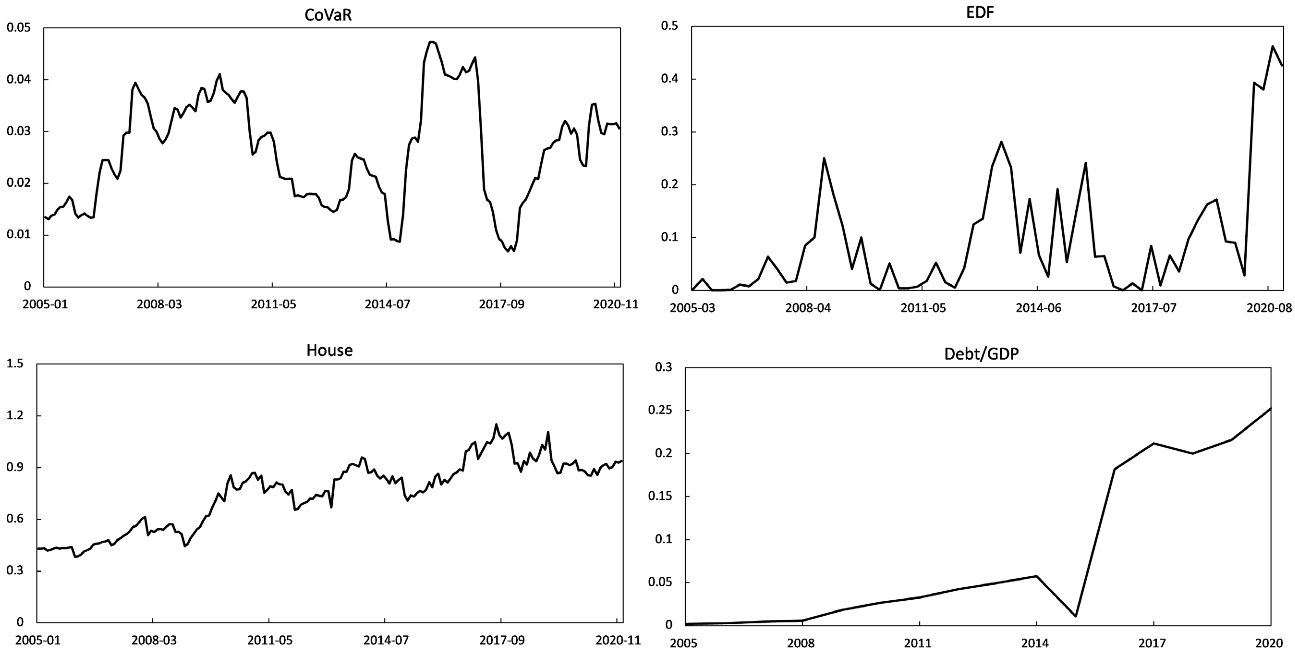

Figure 1. Dynamic trend of risk indicators (Data sourced from Chinabond, the official website of the Ministry of Finance, PRC, the Local Statistical Yearbook, and the Wind Database).

that the trend difference among the four indicators is significant: CoVaR reached a stage peak at the beginning of 2009 and the end of 2015. In 2009, it was affected by the fermentation of the US subprime crisis. 2015 was a challenging year for the Chinese economy. GDP growth was 6.91%, falling below 7% for the first time since 1991. Affected by the COVID-19 outbreak in March 2020, the index rose sharply again. The bank default probability reached its peak after September 2008, June 2013, September 2015, and March 2020, respectively, which overlapped with the peak of CoVaR, corresponding to the subprime mortgage crisis, European debt crisis, economic downturn, and stock market crash in 2015, and the COVID-19 epidemic in 2020 respectively. In particular, the default probability reached a historical peak after March 2020, which confirmed the severe economic setback caused by the novel coronavirus pandemic. Financial risks in the real estate and local government bond markets have been rising, consistent with the high bubble in China's real estate market and high local government debt. In conclusion, there are specific differences in the information delivered by different financial risk indicators. CoVaR and default distance fluctuate wildly, and the ratio of housing price to income and local debt has an apparent upward trend.

4. Results

4.1. SRI Index Construction and Analysis

Firstly, the four risk indicators were de-averaged, and then the systemic risk index was obtained using the mixed-frequency dynamic factor model. The dynamic trend of SRI is shown in Figure 2, and the correlation coefficients between SRI and each sub-index are shown in Table 2. Firstly, by observing the correlation between the sub-indicators, it can be found that the correlation coefficient between the ratio of housing price to income and the ratio of local debt is as high as 0.78; the correlation value between CoVaR and the other three indicators is small; although the correlation coefficient between default probability and the other three indicators is significantly positive, it does not exceed 0.4, indicating that there are specific differences in the risk information reflected by the four indicators. Therefore, the mixed-frequency dynamic factor model for integrating the risk information of four indicators can be used to measure systemic

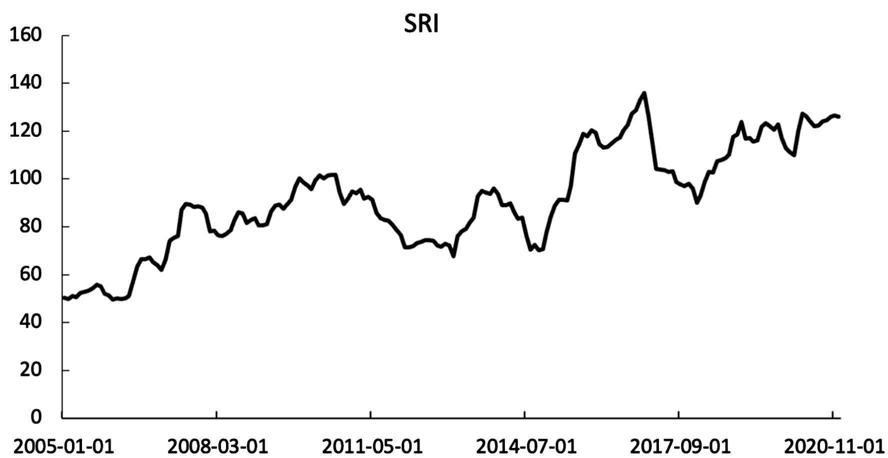

Figure 2. Dynamic trend of SRI.

Table 2. Correlation coefficient matrix.

	SRI	CoVaR	EDF	House	Debt/GDP
SRI	1				
CoVaR	0.5789***	1			
EDF	0.3644***	0.1400**	1		
House	0.7672***	0.0093	0.3214***	1	
Debt/GDP	0.7533***	−0.0387	0.3869***	0.7794***	1

Note: *, ** and *** are significant at the level of 10%, 5% and 1% respectively.

risk pressure systemically and comprehensively. SRI strongly correlates positively with CoVaR, EDF, House, and Debt/GDP. The correlation coefficients are up to 0.58, 0.36, 0.77, and 0.75, respectively, indicating that SRI can better extract the implied systemic risk pressure of the four indicators.

As can be seen from **Figure 2**, from 2005 to 2020, China's systemic risk pressure continued to rise in the turbulence, with several local highs appearing successively in 2007, 2010, 2013 and 2016. As we all know, the US subprime mortgage crisis originated in 2007. In that year, subprime mortgage lenders went bankrupt in the US, rating agencies downgraded subprime mortgage bonds, and several hedge funds were on the verge of collapse. The bankruptcy of Lehman Brothers in 2008 further pushed the subprime mortgage crisis to its climax. At the end of 2009, the world's three major rating companies downgraded Greece's sovereign rating. Since 2010, other European countries have also started to fall into crisis, and the European debt crisis has swept the world. China's economy was also greatly affected by the two crises, as evidenced by the continuous rise of SRI in recent years and the successive highs.

In the first half of 2013, there was downward pressure on China's economic growth. Industrial added value, fixed asset investment, and export growth in April and May have declined somewhat. A large amount of capital outflow trapped the People's Bank of China. The rate at which banks lend to each other overnight hit an annualized 25% on June 20^{th}, compared with 6% in America on the day Lehman Brothers collapsed in 2008. In **Figure 2**, SRI also began to climb in 2013 and reached a phased peak in July 2013. In 2015, China suffered a spectacular stock market crash, with 1000 shares falling by the daily limit and frequent index circuit breakers. The Shanghai Composite Index fell by nearly half from a high of 5178 in June 2015 to 2638 points in early 2016, leading to sharp declines in stock markets worldwide. In addition, 2015 was a relatively complex year for China's economy. CPI in January was much lower than market expectations, reaching the lowest level since November 2009. PPI dropped 4.3% year-on-year, the most significant drop since 2009. China's property market also faces the risk of a hard landing, with prices starting to decline in the second half of 2014; For the whole of 2015, GDP growth was 6.91 percent, falling below 7 percent for the first time since 1991. As can be seen from **Figure 2**, SRI began to climb from the beginning of 2015, and there were two peaks at the end of 2015 and 2016, coinciding with China's high economic and financial risks. Since then, there has been a significant decline in SRI, but overall, it has remained high, surpassing its 2010 high. In March 2020, SRI showed a slight jump because the global economy was nearly stagnant due to the COVID-19 incident. China's GDP growth rate plummeted to −6.8% in the first quarter, which brought about a slight rise in risks in the financial sector.

Therefore, SRI can better reflect China's economic and financial risk situation since 2005. Meanwhile, compared with CoVaR and other single indicators, SRI's overall upward trend is more consistent with China's current situation of high systemic risk. It is a more comprehensive indicator to measure the pressure of systemic risk.

4.2. SRI's Macroeconomic Early Warning Capability

In order to test the early warning ability of SRI to macro-economy and to verify that SRI can measure systemic risk better than CoVaR (CoVaR is more commonly used to measure systemic risk than the other three indicators, and CoVaR is relatively higher frequency), In this part, we used cross-correlation coefficient analysis, linear regression analysis, and threshold regression analysis to test the impact of SRI on macroeconomic.

4.2.1. Cross-Correlation Coefficient Analysis

We choose two common indicators to characterize the macroeconomy: industrial value-added (IVA) and purchasing managers index (PMI). IVA is the consistent index of the macroeconomy, while PMI has a specific lead for the macroeconomy. By combining these two indicators, the impact of systemic risk on the macroeconomy can be judged more effectively. Figure 3 reports the cross-correlation coefficients between two risk indicators and macroeconomic indicators. The left figure is the correlation coefficient between risk indicators and IVA, and the correct figure is the correlation coefficient between risk indicators and PMI. The solid line is the correlation coefficient of SRI, and the dashed line is the correlation coefficient of CoVaR. The horizontal coordinate represents the order of the risk index leading the macroeconomic index; for example, "−12" means the risk index leading the macroeconomic index for 12 months, and "0" means the risk index and macroeconomic index in the same period. The ordinate represents the correlation coefficient. In order to better display the results, we present the ordinate in reverse order. As can be seen from the figure, no matter IVA or PMI, the absolute value of the correlation coefficient of SRI is more significant than 0.4, which is significantly higher than that of CoVaR. The significance test shows that the correlation coefficient of SRI is significant at any leading order, while CoVaR is not significant at any order. In

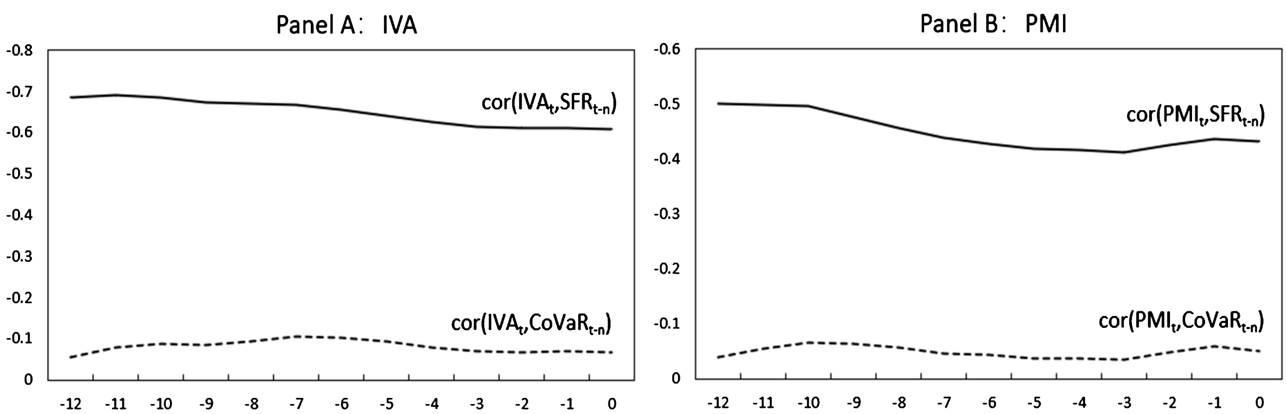

Figure 3. Cross-correlation coefficient analysis.

summary, SRI has a more significant ability to predict the future trend of the macroeconomy. In absolute terms, the macro economy will likely decline when the systemic risk is higher.

4.2.2. OLS Regression Analysis

Furthermore, we use a regression model to test the prediction ability of systemic risk to macroeconomic indicators. The dependent variables are IVA and PMI, the independent variables are SRI and CoVaR, and the control variables are Wind All Share Index monthly yield (Ret), volatility (Vol), broad money supply (M2), Term spread (term, 10-year Treasury bond yield - 1-year Treasury bond yield) and Credit spread (Credit, 10-year corporate bond yield - 10-year Treasury bond yield). All independent and control variables in the regression equation are taken with a lag of one period. To keep the dimensions of the variables the same, we divide SRI by 100 and multiply CoVaR by 100.

Table 3 reports the regression results. Panel A and B are regression results of IVA and PMI as dependent variables, respectively. Models (1) and (4) are regression results using SRI as independent variables; models (2) and (5) are

Table 3. OLS regression results.

	Panel A: IVA			Panel B: PMI		
	(1)	(2)	(3)	(4)	(5)	(6)
SRI (−1)	−7.8152***		−9.8114***	−0.8012		2.4203**
	(1.0013)		(1.9484)	(0.5576)		(1.0533)
CoVaR (−1)		−1.2469***	0.4759		−0.3431***	−0.7681***
		(0.2178)	(0.3987)		(0.1119)	(0.2155)
Ret (−1)	−3.2733	−2.6379	−3.3997	1.1209	1.137	1.3249
	(2.5187)	(2.6747)	(2.5181)	(1.4027)	(1.3746)	(1.3613)
Vol (−1)	−0.9543	4.2737	−2.9512	−4.0496**	−2.6093	−0.827
	(3.1048)	(3.4246)	(3.5236)	(1.7291)	(1.76)	(1.9049)
M2 (−1)	0.56***	0.7469***	0.5086***	0.2186***	0.2428***	0.3016***
	(0.0654)	(0.0662)	(0.0782)	(0.0364)	(0.034)	(0.0423)
Term (−1)	−1.1181*	−1.1088*	−1.1612*	0.0779	0.1346	0.1475
	(0.5894)	(0.6275)	(0.5898)	(0.3282)	(0.3225)	(0.3189)
Credit (−1)	−1.6075***	−1.9947***	−1.5262***	−1.236***	−1.2517***	−1.3672***
	(0.2696)	(0.2785)	(0.2778)	(0.1501)	(0.1431)	(0.1502)
Cons_	13.9731***	7.6086***	15.3878***	2.2811***	1.917***	−0.0019
	(1.3505)	(0.9739)	(1.7956)	(0.7521)	(0.5005)	(0.9707)
Adj−R^2	0.6819	0.6406	0.6827	0.556	0.5728	0.5825
F value	68.89	57.45	59.39	40.65	43.46	38.87
Observations	191	191	191	191	191	191

Note: Values in brackets are standard errors; *, ** and *** are significant at the level of 10%, 5% and 1% respectively.

regression results using CoVaR as independent variables; models (3) and (6) are regression results using both SRI and CoVaR as independent variables. As seen from Panel A, both SRI and CoVaR have significant damaging prediction abilities for IVA. When SRI and CoVaR are included in the regression equation simultaneously, only the regression coefficient of SRI is significantly harmful.

In contrast, the coefficient of CoVaR becomes positive and insignificant. It shows that SRI has a more vital prediction ability for IVA than CoVaR because SRI can measure systemic risks more comprehensively. As seen from Panel B, the prediction ability of SRI to PMI is insignificant. PMI is a leading indicator of the macroeconomy. When systemic risk (especially SRI) is only one stage ahead, the prediction ability of PMI is not strong. However, it may have long-term forecasting ability for PMI (when the systemic risk is 12 periods ahead in Table 4, it is found that SRI has significant forecasting ability for PMI). In control variables, M2 can significantly positively affect the macroeconomy; Credit can substantially negatively affect the macroeconomy. At the same time, the Wind All Share Index, volatility, and term spread have insignificant or unstable influences on the macro economy.

Table 4. OLS regression results.

	Panel A: IVA			Panel B: PMI		
	(1)	(2)	(3)	(4)	(5)	(6)
SRI (−12)	−6.9165*** (0.9607)		−10.1941*** (1.8398)	−1.4366** (0.6525)		−3.2582** (1.2546)
CoVaR (−12)		−0.9625*** (0.2025)	0.753** (0.3618)		−0.1298 (0.1297)	0.4185* (0.2467)
Ret (−12)	1.9646 (2.298)	2.7427 (2.4596)	1.6739 (2.2805)	0.3372 (1.5607)	0.5172 (1.5751)	0.1756 (1.5552)
Vol (−12)	1.4367 (2.8386)	5.4058* (3.1721)	−1.7568 (3.2029)	−0.4859 (1.9278)	0.0286 (2.0314)	−2.2607 (2.1843)
M2 (−12)	0.3274*** (0.0604)	0.4703*** (0.0632)	0.2484*** (0.0708)	0.103** (0.041)	0.13*** (0.0405)	0.0591 (0.0483)
Term (−12)	1.4453*** (0.5488)	1.5076** (0.5893)	1.3637** (0.545)	0.4204 (0.3727)	0.421 (0.3774)	0.375 (0.3717)
Credit (−12)	−1.7841*** (0.2455)	−2.1565*** (0.2541)	−1.6439*** (0.2523)	−1.1313*** (0.1667)	−1.2172*** (0.1627)	−1.0533*** (0.1721)
Cons_	13.6755*** (1.2228)	8.1477*** (0.8971)	15.9663*** (1.6365)	3.4379*** (0.8304)	2.2121*** (0.5745)	4.7111*** (1.116)
Adj-R^2	0.7341	0.6944	0.7392	0.4391	0.4267	0.4451
F value	83.38	68.78	73.46	24.36	23.2	21.51
Observations	180	180	180	180	180	180

Note: Values in brackets are standard errors; *, ** and *** are significant at the level of 10%, 5% and 1% respectively.

To further analyze the long-term forecasting ability of systemic risk indicators in the macro economy, we lag all independent variables by 12 orders to investigate the forecasting ability of systemic risk in the macro economy one year later. Table 4 reports the regression results. It can be seen that, for IVA, both SRI and CoVaR have significant long-term prediction abilities. However, only SRI shows important damaging prediction ability after the two indicators are included in the regression equation. SRI has an important damaging predictive ability for PMI, while CoVaR has no significant predictive power. After both are included in the equation, only SRI has an important damaging predictive power. SRI's leading macroeconomic indicators have been at least 12 months and have more significant economic forecasting ability than CoVaR.

4.2.3. Threshold Regression Analysis

Systemic risk may have a threshold effect on the macroeconomy; when the financial risk is low, the impact on the macroeconomy is small. On the contrary, when financial stakes are high, the effect on the macro economy will be significant. Therefore, this part adopts a threshold regression model for further analysis. Table 5 reports the threshold regression results, among which Panel A and

Table 5. Threshold regression results.

	Panel A: IVA		Panel B: PMI	
	SRI (−1)	CoVaR (−1)	SRI (−1)	CoVaR (−1)
Risk < Threshold	−3.2174 (3.7677)	3.0249** (1.5199)	1.8284 (3.6917)	−0.0642 (0.4642)
Risk > Threshold	−10.898** (4.3635)	−4.9982*** (1.185)	−7.5424** (3.4738)	−0.6934 (0.9807)
Ret (−1)	−3.3253 (3.0813)	−2.0721 (3.4339)	1.2076 (1.6954)	0.9679 (1.5813)
Vol (−1)	−2.4192 (3.3758)	3.9692 (4.1739)	−4.8283*** (1.874)	−2.9815 (2.2083)
M2 (−1)	0.4934*** (0.0592)	0.7565*** (0.0485)	0.1788*** (0.0414)	0.2472*** (0.0335)
Term (−1)	−0.8054 (0.5956)	−1.3022** (0.5594)	0.2437 (0.3559)	0.1295 (0.3389)
Credit (−1)	−2.0303*** (0.3933)	−2.1462*** (0.257)	−1.4893*** (0.1752)	−1.2612*** (0.1319)
Con	12.2855*** (2.4403)	1.5665 (1.8405)	1.3403 (2.3562)	1.4027* (0.7953)
Threshold	0.9486	1.765	0.9858	2.8648
Threshold test value	7.538***	20.262***	10.925***	3.138
Observations	191	191	191	191

Note: Values in brackets are standard errors; *, ** and *** are significant at the level of 10%, 5% and 1% respectively.

Panel B are regression results using IVA and PMI as dependent variables, the first and third columns are the results when SRI is used to measure systemic risk, the second and fourth columns are the results when CoVaR is used to measure systemic risk. All independent variables lag by one order. In SRI regression, the original data is still divided by 100.

From the threshold test value, the threshold effect of CoVaR on PMI regression is insignificant. The regression threshold effect of CoVaR on IVA was significant, and its threshold value was 1.765 (the maximum value of CoVaR was 4.45, which did not belong to the extreme risk area). SRI has a very significant threshold effect on IVA and PMI regression; the threshold values are 0.9486 and 0.9858, respectively (corresponding to the original SRI index of 94.86 and 98.58 the maximum SRI is 127). When it is greater than the threshold, it belongs to the high-risk area, indicating that relative to CoVaR, the economics of SRI thresholds are stronger.

For IVA regression, the regression coefficient is insignificant when SRI is less than 94.86, and when SRI exceeds 94.86, the regression coefficient reaches −10.898 and is significant at 1%. Using PMI as a dependent variable, the regression coefficient is insignificant when SRI is less than 98.58. And when SRI exceeds 98.58, the regression coefficient reaches −7.5424 which is significant at the 5% level. In summary, the threshold effect of CoVaR on the macroeconomy is insignificant. When the SRI value is low (i.e., the systemic risk is low), the impact on the macroeconomy is weak; however, when the SRI value is high (i.e., the systemic risk is high), the negative impact on the macroeconomy is highly significant.

Also, we tested the threshold effect of systemic risk with a lag of 12 periods on the macro economy, and **Table 6** reported the regression results. Results similar to **Table 5** can be obtained. SRI has a more significant threshold effect than CoVaR. When SRI is low, it has a negligible impact on the macroeconomy, while when SRI is high, it significantly impacts the macroeconomy. Combined with the research results of **Figure 3**, **Table 3** to **Table 6**, SRI can predict the macroeconomy more significantly. When SRI is higher, its impact on the macroeconomy is more significant, which is more consistent with the impact mechanism of systemic risk on the macroeconomy and the essential characteristics of systemic risk. Therefore, it can be shown that, compared with CoVaR, SRI can measure systemic risks more accurately and effectively.

5. Conclusion and Discussion

5.1. Conclusion

In this paper, we apply the mixed-frequency dynamic factor model (MFDFM) to effectively measure systemic risk, drawing on multi-dimensional and multi-source information. This innovative approach allows for the integration of data from various sectors such as the stock market, banking industry, real estate, and local debt markets, culminating in the development of a comprehensive systemic risk

Table 6. Threshold regression results.

	Panel A: IVA		Panel B: PMI	
	SRI (−12)	CoVaR (−12)	SRI (−12)	CoVaR (−12)
Risk < Threshold	5.8586* (2.9875)	3.9397*** (1.3193)	−6.8007*** (2.5500)	2.0236 (1.4138)
Risk > Threshold	−13.8318** (3.0423)	−5.3336*** (0.9492)	−10.6128*** (2.7449)	−2.2606 (2.2020)
Ret (−12)	1.4266 (2.7980)	3.3168 (2.997)	0.7488 (1.9764)	0.6273 (2.3181)
Vol (−12)	0.0691 (3.3606)	5.3413 (3.9034)	1.6275 (2.0375)	0.0088 (2.193)
M2 (−12)	0.2951*** (0.0616)	0.4772*** (0.0629)	0.169*** (0.0412)	0.1325*** (0.0382)
Term (−12)	1.7783*** (0.6386)	1.2432* (0.655)	0.097 (0.442)	0.3085 (0.4022)
Credit (−12)	−1.9716*** (0.3117)	−2.2231*** (0.1982)	−0.6954*** (0.2140)	−1.2179*** (0.1530)
Con	1.9038 (1.881)	1.626 (1.8836)	5.5326*** (1.6146)	−0.4776 (1.6553)
Threshold	0.6193	1.5412	0.8936	1.3755
Threshold test value	5.2571**	16.5900***	17.9900***	4.0702
Observations	191	191	191	191

Note: Standard error in brackets; *, ** and *** are significant at the level of 10%, 5% and 1% respectively.

index (SRI). The SRI, underpinned by the MFDFM, showcases a forward-looking nature and a robust early warning capability, accurately reflecting China's economic and financial risks since 2005. It outperforms traditional single indicators like CoVaR in capturing the dynamic development and changes in China's systemic risks, offering valuable insights for emerging economies in shaping economic and financial policies.

5.2. Discussion

The paper concludes that systemic risk is a global phenomenon that cannot be comprehensively understood through single-market indicators alone. Our use of the MFDFM in analyzing multiple markets like stock, banking, real estate, and local bond markets provides a more holistic view of systemic risk assessment. Despite a decrease from its peak in 2016, systemic risk in China is on an upward trend, indicating ongoing macroeconomic pressure and the imperative for high-quality development, economic transformation, and financial risk mitigation. This is particularly pertinent given the rising financial risks in China's real estate and local debt markets, which are crucial to residential rights and government operations. For emerging countries like China, addressing issues like housing bubbles and local government debt is crucial in averting systemic risks. The paper also underscores the importance of enhanced risk management systems, improved financial transparency, and stricter oversight of financial institutions and markets to effectively mitigate systemic risk.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

Acharya, V., Pedersen, L., Philippon, T., & Richardson, M. (2017). Measuring Systemic Risk. *Review of Financial Studies, 30,* 2-47. https://doi.org/10.1093/rfs/hhw088

Adrian, T., & Brunnermeier, M. K. (2016). CoVaR. *American Economic Review, 106,* 1705-1741. https://doi.org/10.1257/aer.20120555

Algaba, A., Borms, S., Boudt, K., & Verbeken, B. (2023). Daily News Sentiment and Monthly Surveys: A Mixed-Frequency Dynamic Factor Model for Nowcasting Consumer Confidence. *International Journal of Forecasting, 39,* 266-278. https://doi.org/10.1016/j.ijforecast.2021.11.005

Allen, F., Bartiloro, L., Gu, X., & Kowalewski, O. (2018). Does Economic Structure Determine Financial Structure? *Journal of International Economics, 114,* 389-409. https://doi.org/10.1016/j.jinteco.2018.08.004

Allen, L., Bali, T., & Tang, Y. (2012). Does Systemic Risk in the Financial Sector Predict Future Economic Downturns? *Review of Financial Studies, 25,* 3000-3036. https://doi.org/10.1093/rfs/hhs094

Aruoba, S. B., Diebold, F. X., & Scotti, C. (2009). Real-Time Measurement of Business Conditions. *Journal of Business & Economic Statistics, 27,* 417-427. https://doi.org/10.1198/jbes.2009.07205

Barunik, J., Kocenda, E., & Vacha, L. (2016). Asymmetric Connectedness on the U.S. Stock Market: Bad and Good Volatility Spillovers. *Journal of Financial Markets, 27, 55-78.* https://doi.org/10.1016/j.finmar.2015.09.003

Billio, M., Getmansky, M., Lo, A. W., & Pelizzon, L. (2012). Econometric Measures of Connectedness and Systemic Risk in the Finance and Insurance Sectors. *Journal of Financial Economics, 104,* 535-559. https://doi.org/10.1016/j.jfineco.2011.12.010

Bo, L., Yao, H., & Mear, F. (2021). New Development: Is China's Local Government Debt Problem Getting Better or Worse? *Public Money & Management, 41,* 663-667. https://doi.org/10.1080/09540962.2021.1881273

Brownlees, C., & Engle, R. (2017). SRISK: A Conditional Capital Shortfall Measure of Systemic Risk. *Review of Financial Studies, 30,* 48-79. https://doi.org/10.1093/rfs/hhw060

Capozza, D., & Van Order, R. (2011). The Great Surge in Mortgage Defaults 2006-2009: The Comparative Roles of Economic Conditions, Underwriting and Moral Hazard. *Journal of Housing Economics, 20,* 141-151. https://doi.org/10.1016/j.jhe.2011.04.005

Cardarelli, R., Elekdag, S., & Lall, S. (2011). Financial Stress and Economic Contractions. *Journal of Financial Stability, 7,* 78-97. https://doi.org/10.1016/j.jfs.2010.01.005

Carlson, M., Lewis, K., & Nelson, W. (2014). Using Policy Intervention to Identify Financial Stress. *International Journal of Finance & Economics, 19,* 59-72.

https://doi.org/10.1002/ijfe.1482

Carpenter, J. N., Lu, F., & Whitelaw, R. F. (2021). The Real Value of China's Stock Market. *Journal of Financial Economics, 139,* 679-696. https://doi.org/10.1016/j.jfineco.2020.08.012

Chen, G., Liu, Y., & Zhang, Y. (2020). Can Systemic Risk Measures Predict Economic Shocks? Evidence from China. *China Economic Review, 64,* Article 101557. https://doi.org/10.1016/j.chieco.2020.101557

Diebold, F. X., & Yilmaz, K. (2012). Better to Give than to Receive: Predictive Directional Measurement of Volatility Spillovers. *International Journal of Forecasting, 28,* 57-66. https://doi.org/10.1016/j.ijforecast.2011.02.006

Ding, L., Zhao, Z., & Wang, L. (2022). Probability Density Forecasts for Natural Gas Demand in China: Do Mixed-Frequency Dynamic Factors Matter? *Applied Energy, 312,* Article 118756. https://doi.org/10.1016/j.apenergy.2022.118756

Giannone, D., Reichlin, L., & Small, D. (2008). Nowcasting: The Real-Time Informational Content of Macroeconomic Data. *Journal of Monetary Economics, 55,* 665-676. https://doi.org/10.1016/j.jmoneco.2008.05.010

Giglio, S., Kelly, B., & Pruitt, S. (2016). Systemic Risk and the Macroeconomy: An Empirical Evaluation. *Journal of Financial Economics, 119,* 457-471. https://doi.org/10.1016/j.jfineco.2016.01.010

Guo, W., Tang, J., Zhu, H., & Ma, X. (2022). Time-Frequency Spillover Effect of Domestic and Foreign Commodity Markets on China's Price Levels. *Emerging Markets Finance and Trade, 58,* 4207-4217. https://doi.org/10.1080/1540496X.2022.2106212

Han, Y., Zhang, H., & Zhao, Y. (2021). Structural Evolution of Real Estate Industry in China: 2002-2017. *Structural Change and Economic Dynamics, 57,* 45-56. https://doi.org/10.1016/j.strueco.2021.01.010

Huang, W., & Chen, Z. (2020). Modelling Contagion of Financial Crises. *The North American Journal of Economics and Finance, 54,* Article 100793. https://doi.org/10.1016/j.najef.2018.06.007

Huang, Y., Gui, W., Jiang, Y., & Zhu, F. (2022). Types of Systemic Risk and Macroeconomic Forecast: Evidence from China. *Electronic Research Archive, 30,* 4469-4492. https://doi.org/10.3934/era.2022227

IMF, FSB, & BIS (2009). *Guidance to Assess the Systemic Importance of Financial Institutions, Markets, and Instruments: Initial Considerations*. Report to the G-20 Finance Ministers and Central Bank Governors, International Monetary Fund, Financial Stability Board, and Bank for International Settlements. https://www.bis.org/publ/othp07.pdf

Jiang, Y., Guo, Y., & Zhang, Y. (2017). Forecasting China's GDP Growth Using Dynamic Factors and Mixed-Frequency Data. *Economic Modelling, 66,* 132-138. https://doi.org/10.1016/j.econmod.2017.06.005

Kambhu, J., Schuermann, T., & Stiroh, K J. (2007). Hedge Funds, Financial Intermediation, and Systemic Risk. *Economic Policy Review, 3,* 1-18. https://doi.org/10.2139/ssrn.995907

Kelly, B., & Jiang, H. (2014). Tail Risk and Asset Prices. *The Review of Financial Studies, 27,* 2841-2871. https://doi.org/10.1093/rfs/hhu039

Kenourgios, D., & Dimitriou, D. (2015). Contagion of the Global Financial Crisis and the Real Economy: A Regional Analysis. *Economic Modelling, 44,* 283-293. https://doi.org/10.1016/j.econmod.2014.10.048

Koetter, M., & Poghosyan, T. (2010). Real Estate Prices and Bank Stability. *Journal of*

Banking & Finance, 34, 1129-1138. https://doi.org/10.1016/j.jbankfin.2009.11.010

Kritzman, M. P., Li, Y., Page, S. B., & Rigobón, R. (2011). Principal Components as a Measure of Systemic Risk. *The Journal of Portfolio Management, 37,* 112-126. https://doi.org/10.3905/jpm.2011.37.4.112

Li, Y., & Giles, D. E. (2015). Modelling Volatility Spillover Effects between Developed Stock Markets and Asian Emerging Stock Markets. *International Journal of Finance & Economics, 20,* 155-177. https://doi.org/10.1002/ijfe.1506

Lin, P.-T. (2013). Examining Volatility Spillover in Asian REIT Markets. *Applied Financial Economics, 23,* 1701-1705. https://doi.org/10.1080/09603107.2013.848023

McMillan, D. G. (2021). When and Why Do Stock and Bond Markets Predict US Economic Growth? *The Quarterly Review of Economics and Finance, 80,* 331-343. https://doi.org/10.1016/j.qref.2021.03.004

Pagano, M. S., & Sedunov, J. (2016). A Comprehensive Approach to Measuring the Relation between Systemic Risk Exposure and Sovereign Debt. *Journal of Financial Stability, 23,* 62-78. https://doi.org/10.1016/j.jfs.2016.02.001

Patro, D. K., Qi, M., & Sun, X. (2013). A Simple Indicator of Systemic Risk. *Journal of Financial Stability, 9,* 105-116. https://doi.org/10.1016/j.jfs.2012.03.002

WEF (2014). *The Global Risks Report 2014*.

Xu, Q., Li, M., Jiang, C., & He, Y. (2019). Interconnectedness and Systemic Risk Network of Chinese Financial Institutions: A LASSO-CoVaR Approach. *Physica A: Statistical Mechanics and its Applications, 534,* Article 122173. https://doi.org/10.1016/j.physa.2019.122173

Zabavnik, D., & Verbič, M. (2021). Relationship between the Financial and the Real Economy: A Bibliometric Analysis. *International Review of Economics & Finance, 75,* 55-75. https://doi.org/10.1016/j.iref.2021.04.014

Zou, J., Fu, X., Yang, J., & Gong, C. (2022). Measuring Bank Systemic Risk in China: A Network Model Analysis. *Systems, 10,* Article 14. https://www.mdpi.com/2079-8954/10/1/14 https://doi.org/10.3390/systems10010014