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*Research article*

# Types of systemic risk and macroeconomic forecast: Evidence from China

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**Abstract:** The macroeconomic forecast is of great significance to the government macroeconomic policy formulation and micro-agent operational decisions. The individual systemic risk measurement has a certain scope of application and application conditions and, therefore, it is difficult for the individual indicator to reflect the systemic risk comprehensively. In this paper, the systemic risk is divided into four types: institution-specific risk, comovement and contagion, financial vulnerability, liquidity and credit. Next, the optimal combination is selected from multiple individual systemic risk indicators through dominance analysis to forecast the macroeconomic performance. The macroeconomic performance selects consumer price index (CPI), producer price index (PPI), industrial growth value (IVA), growth rate of broad money supply (M2) and gross domestic product (GDP) as proxies to compare the forecast effect of systemic risk, with the period considered spans from 2003M4 to 2022M7. The results of immediate forecasts of different macroeconomic performance proxies demonstrate the individual indicator cannot cover all the information of systemic risk, can only reflect the specific aspect of macroeconomic performance, or is only highly relevant in a given period. The contribution of systemic risk to the forecast of different macroeconomic performance proxies in different terms is diverse, and show various types of results. This paper uses the optimal combination of systemic risk to forecast the macroeconomic performance, which provides a valuable reference for improving the macro prudential supervision mechanism.

**Keywords:** systemic risk; macroeconomic performance forecast; dominance analysis; optimal combination

# 1. Introduction

## 1.1. Motivation

Since the global financial crisis in 2008, people have realized that systemic risks lead to a sharp decline in macroeconomics. Governments are eager to effectively identify the close relationship between them to cope with the adverse impact of systemic risks. The tight financial system junction will cause risk interconnection, and even seriously threaten the security and stability of the financial system. International Monetary Fund (IMF), Financial Stability Board (FBS) and Bank for International Settlements (BIS) pointed out that systemic risk refers to the risk that results from financial services that are interrupted due to the overall, or partial, destruction of the financial system, which has a potential negative impact on the real economy [1]. This means that while the systemic risk spreads rapidly in the financial market, it will also lead to the failure of the internal operating mechanism of financial institutions, and then cause a substantial adverse impact on macroeconomics. Countries all over the world have gradually realized that while financial globalization has strengthened the interaction between financial institutions and improved the efficiency of the financial system, it has also greatly increased the possibility of systemic financial crisis [2,3]. The level of systemic risk is not only affected by microcosmic factors, but also affected by the macroeconomic operation and government performance.

Macroeconomic forecasting research based on systemic risks is conducive to the "early identification, early detection and early disposal" of significant financial risk and response to macroeconomic changes. Macroeconomic forecast is of great significance to the government macroeconomic policy formulation and the micro-agent operational decisions. The government needs to judge the future macroeconomic situation to decide whether to adopt loose or tight fiscal and monetary policies. The micro-agent must be judged based on the future macroeconomic situation to decide whether to expand production and consumption decisions. The accumulation of systemic risks tends to aggravate the instability of the financial market and produce significant negative externalities on the macroeconomic [4]. The individual systemic risk indicator focuses on capturing the potential systemic risk in a certain aspect. Constructing a comprehensive indicator of systemic risk can further predict macroeconomics and provide a valuable reference for improving the macro prudential supervision mechanism [5,6]. Solving the following questions will enhance the forecasting effect of systemic risks on macroeconomic performance. How to choose from a large number of systemic risk indicators and build the optimal combination of systemic risk forecasting and macroeconomic performance? What are the differences between different types of systemic risk indicators in macroeconomic forecasting? What is the relationship between different macroeconomic proxies and systemic risk indicators?

## 1.2. Literature review and contribution

Many studies have shown an internal relationship between systemic risk and macroeconomic changes. Since the international financial crisis, the continuous advancement of global economic integration and cross-border transactions between institutions have become increasingly frequent, and the financial markets have become more closely related [7,8]. Research shows that economic globalization is conducive to the expansion of the scale of financial institutions, enhancing international competitiveness and diversifying income uncertainty, but it also dramatically increases the difficulty and urgency of risk prevention and control, making the systemic risk contagion problem expand from the national economic level to the international economic level [9]. The global pandemic of COVID-19 since 2020 has accelerated the evolution of these great changes. The downward pressure on the world economy and macroeconomic uncertainty continues to increase, aggravating the risk of sovereign debt default and systemic risk [10,11]. When a macroeconomic crisis occurs, there will be apparent systemic risk transmission between markets, and the risk spillover effect will increase significantly [12]. With the continuous strengthening of cross-border links in the global capital market, the significant linkage effect among countries further increases the possibility of systemic risks [13]. The international linkage between banks is closely related to the global spread of systemic risk [14]. During macroeconomic turbulence, the developed market is more influential than the emerging market, and in any period, the emerging market is more sensitive to the volatility impact than the developed market [15,16].

Regarding macroeconomic forecasts, scholars made predictions from different perspectives, including the following aspects. First, the most common is using credit spread indicators to forecast macroeconomics. In this way, it is generally believed that the spread curve contains much information about the future. By analyzing the changes in the slope, curvature and level of the spread curve, we can obtain important information about the changes in future economic activities [17–19]. In addition, the 2008 financial crisis has aroused people's interest in the impact of financial shocks on macroeconomics. On this basis, building a comprehensive financial condition index (FCI) to forecast macroeconomic performance has become their focus [20,21]. Similar to using a large number of indicators to construct the FCI, some scholars not only use financial related factors to forecast, but also select a large number of additional factors to forecast macroeconomics by extracting their main components [22]. In addition to the innovation of macroeconomic forecasts from indicators and perspectives, the macroeconomic forecast models are also constantly innovating. For example, solving the problem of over-identification to capture essential changes in forecast biases in different sequences, or develop new estimation processes to simplify models with many of the forecast indicators [23,24].

The systemic risk index is very valuable for forecasting macroeconomic performance. In recent years, there have been more and more pieces of literature on the impact of systemic risk on macroeconomic prediction, and the fields involved are also increasingly broad [25]. There are two primary reasons why systemic risk can predict macroeconomic. One is that systemic risk affects the coordinated operation within the financial system and the reasonable pricing of assets [26]. The second is that systemic risk affects the ability of finance to provide capital to the real economy [9,27]. Gilchrist et al. [17] shows that systemic risk related indicators contain abundant forward-looking information, so they have considerable prediction ability for economic activities. Giglio et al. [28] measured systemic risk and predicted multiple macroeconomic variables in European and American countries from 1950 to 2011. The results showed that the comprehensive indicators had good prediction ability outside the sample, especially for the rapid economic decline. Parker [29] introduced an implicit systemic risk measurement standard, which measures the coupling degree of the economic market, and can also be used to predict an economic recession. Klopotan et al. [30] developed a systemic risk early warning system and studied the role of early warning system in predicting and identifying adverse events, especially in the commercial, financial and economic fields. In addition, similar studies have shown that investor sentiment is a good indicator to predict the peak and trough of the business cycle [31,32].

In the past, many studies used a single systemic risk index to describe a particular aspect of the systemic risk, and it was challenging to include all the information comprehensively in the systemic risk. In terms of the inter-bank market, upper has made an in-depth analysis of the systemic risk formed by the direct connection network of the commercial interbank lending market [33]. In the stock market, Teply and Kvapilikova [34] used the wavelet analysis method to improve the CoVaR index and obtain the W-CoVaR index, which is used to measure the change of systemic risk in financial cycles of different lengths. The results show that the wavelet analysis method can improve the prediction effect of the CoVaR index on stock returns. In the bond market, Gilchrist et al. [28] used the transaction price of corporate bonds in the secondary market to construct a new credit spread index to predict economic activities. Some studies are based on the perspective of financial institutions. The measurement idea of most literature is similar to that of portfolio risk analysis, that is, to evaluate systemic risk by examining the contribution of individual institutions (or individual assets) to the risk of the financial system (or portfolio) [35,36]. For example, Acharya et al. [37] proposed the MES index, which estimates the marginal contribution of the individual institutions to the systemic financial risk by measuring the expected rate of return of individual institutions when the system returns are seriously reduced. At the same time, they constructed the SES index, which is regarded as a linear function of MES and institutional leverage ratio, and thus measured the extent of c individual institutions' capital loss when the system capital is seriously insufficient. Hwang et al. measured the systemic risk of each fund on the cross-section and found a significant positive correlation between the return of hedge funds and the systemic risk [38]. However, most of the previous studies focus on the financial market separately, less on the generation mechanism of systemic risk under the joint action of multiple correlations, and lack attention to forecasting the macroeconomic trend of systemic risk under different dimensions.

Looking far and wide at the current research results of emerging systemic risk, few scholars comprehensively compare and analyze the effectiveness and predictability of measurement methods in combination with China's actual economic conditions. Because the individual systemic risk measurement has a certain scope of application and application conditions, it is necessary to compare and analyze the forecast ability of various mainstream systemic risk indicators at this stage. It is difficult for the individual indicator to reflect the systemic risk comprehensively, still less to effectively explain the close relationship between the systemic risk and macroeconomic performance. Each measurement indicator can only capture the potential risk of a particular aspect, resulting in that it can only reflect macroeconomic changes in a specific term. Therefore, this paper may have the following marginal contributions. First of all, most of the previous articles on systemic risk indicators to study macroeconomic performance took developed countries with relatively mature financial markets as samples, and there was little research on developing countries. This paper took China, the largest developing country, as an example, effectively complementing the research results under different economies. Secondly, this paper uses dominance analysis to build a forecast combination of systemic risk indicators, which can effectively reveal the relationship between the individual systemic risk indicator and macroeconomic performance. In addition, the dominance analysis can effectively solve the contradiction between different indicators so that all information can be used more comprehensively. Finally, it further reveals the role of systemic risk types in macroeconomic performance forecasting and the reasons different systemic risk types dominate it in different terms.

The rest of the article is structured as follows. Section 2 is materials and methods, which introduces the selection and measurement of systemic risk, dominance analysis and forecast specification. Section 3 is the results of systemic risk combination and forecast, which shows the indicator combination and forecast results of different macroeconomic proxies under various terms.

Section 4 is the conclusion.

## 2. Materials and methods

### *2.1. Systemic risk measures*

In order to better observe systemic risk, a large number of systemic risk indicators have been proposed by many scholars. Since the measurement of individual systemic risk can only describe a particular aspect, some systemic risk indicators only work in a specific period. There are even contradictions between some systemic risk indicators, so it is essential to link many systemic risk indicators to measure the overall systemic risk better. In this paper, according to the standard classification of research, systemic risk is classified into "institution-specific risk", "composition and contagion", "financial vulnerability" and "liquidity and credit".

Institution-specific risk indicators are designed to capture the contribution or sensitivity of individual institutions to systemic risk in the economy as a whole. The indicators include: conditional value-at-risk (CoVaR), ΔCoVaR, marginal expected shortfall (MES). Adrian and Brunnermeier [39] proposed CoVaR, defining it as the predicted value of losses for the whole system based on the conditions of institution-specific losses, which can be a good measure of risk spillovers and is one of the effective indicators to measure systemic risk. In general, a larger value tends to imply that the financial system will go into distress along with individual institutions. At the same time, the indicator can also capture the importance of specific institutions in the whole system. Here, the DCC-GARCH model is used to calculate CoVaR, which better captures the conditional correlation between the time-varying changes of specific institutions and the whole system over time [40]. ΔCoVaR is more concerned with tail risk and is calculated from the difference in CoVaR between the predicament and the mean state. MES denotes the marginal expected gap, which represents the loss caused when a particular institution underperforms the increased risk to the overall economic system [37].

Indicators quantify the dependence between the stock returns of financial institutions in the comovement and contagion dimension, including absorption ratio (AR) and dynamic causality index (DCI). The AR responds to the degree of closeness between institutions, and the value of the total variance of asset returns is explained by a fixed number of eigenvectors [41]. Closer institutional linkages within the system imply a more fragile system, as any adverse shocks will spread faster and more widely across institutions. The DCI is defined as the number of causal relationships divided by the total number of possible causalities, which captures the network of relationships between institutions within the entire economic system through Granger causality, quantifying the interdependence of different institutions [42,43]. The increasing closeness of the relationships among the agents within the financial market has led to an increased contagion of risk events between other financial needs, showing a chain reaction of risk occurrence.

Financial vulnerability indicators measure the financial sector's volatility and instability, including volatility, turbulence and leverage. As a traditional measure of financial risk, volatility is caused by changes in macroeconomic factors and financial factors, which affect the realization of financial system functions and macroeconomic operations to varying degrees. Volatility is obtained by simply averaging the individual fluctuations of a certain number of institutions to the overall volatility of the system, with higher volatility implying a more unstable system [44]. Turbulence pays more attention to excessive volatility and reflects the unusual returns through a series of historical behavior models. Leverage measures systemic risk primarily in terms of institutional solvency, combining institutional book value and market value, and enormous leverage implies greater instability of the institution. Due to the particularity of financial institutions, there will be maturity mismatch, risk mismatch and other problems in the process of leverage in business activities.

The indicators of liquidity and credit, which reflect liquidity and credit conditions in financial markets, include the Treasury& SHIBOR spread (TSD) and term spread (TERM). In the capital flows channel, liquidity shocks appear at the heart of the current financial turmoil [45]. The TSD is expressed as the difference between the three-month SHIBOR rate and the yield to maturity of Treasury bonds, which reflects the tightness of liquidity and changes in investors' risk appetite. In general, when markets are relatively stable, investors demand lower risk compensation and the TSD shrinks, while when markets are unstable, investors demand higher risk compensation and the TSD widens. TERM refers to the difference between long-term and short-term interest rates, which is a significant predictor of future economic activity. The long-term interest rate is generally more significant than the short-term interest rate, and the term interest spread reflects the compensation for the term risk. The cycle of changes in the benchmark monetary rate is an essential determinant of the term spread, with a narrowing TERM during periods of stable benchmark monetary rates implying that investors are not optimistic about the economic prospects, while a widening spread indicates a positive economic future.

### *2.2. Methods*

#### 2.2.1. Dominance analysis

This paper draws on the technical approach of dominance analysis proposed by Israeli, Givoly et al. [46,47] to examine the intensity of systemic risk on macroeconomic factors. First, a cross-sectional regression model and its goodness-of-fit are examined.

$$Macro_t = a + \sum_{i=1}^{L} b_i x_{i,t} + \mu_t \tag{1}$$

In Eq (1), $L$is the total number of systemic risk indicators, $Macro$ denotes macroeconomic indicators, specifically including consumer price index (CPI), producer price index (PPI), industrial growth value (IVA), growth rate of broad money supply (M2) and gross domestic product (GDP). Under the assumption that the disturbance term is uncorrelated with the explanatory variable, the goodness-of-fit can decompose into the contribution degree of systemic risk to the macroeconomic performance. Generally, with $L$ systemic risk indicators, the degree of contribution of the $k$th indicator can be defined as $M_k$.

$$M_k = \frac{1}{L!}\left\{\begin{array}{c} R^2\left[Macro_t = a + \sum_{l \in S} b_l x_{l,t} + b_k x_{k,t} + \mu_t\right] \\ -R^2\left[Macro_t = a' + \sum_{l \in S} b'_l x_{l,t} + b_k x_{k,t} + \mu'_t\right] - R^2[Macro_t = a'' + \mu''_t] \end{array}\right\} \tag{2}$$

where $R^2[f(\cdot)]$ is goodness-of-fit, $S$ is the subset of all risk indicators other than the $k$th systemic risk indicator. The last term in the parentheses of Eq (2) is constant at 0. Since the goodness-of-fit represents the extent to which a set of systemic risk indicators changes in the macroeconomic performance, the difference in the goodness-of-fit due to the exclusion of a systemic risk indicator is the extent to which that systemic risk indicator contributes to the macroeconomic performance. On this basis, the dominance analysis can be judged by comparing the degree of each systemic risk indicator's contribution.

### 2.2.2. Forecasting specification

We will expand the forecasting specification of Okimoto and Takaoka [19] to assess the information content of systemic risks on future macroeconomic performance. Our forecasting specification regresses the macroeconomic performance on systemic risk, to investigate whether systemic risk information can improve forecasts of macroeconomic performance in China. Specifically, the forecasting specification is given as follows:

$$\Delta^h Macro_{t+h} = \alpha + \sum_{i=1}^{L} \beta_i SRisk_{i,t} + \phi \Delta Macro_t + \varepsilon_{t+h} \tag{3}$$

where $h$ = 1, 3, 6, or 12 is the forecast horizon. We estimate the models (3) using ordinary least squares (OLS). For forecasting horizons h > 1, the overlapping observations imply that $\varepsilon_{t+h}$ has an MA(h-1) structure.

## *2.3. Data sources*

This paper examines the forecast effect of systemic risk on macroeconomic performance. Some indicators in this paper need to be calculated from existing data. Whenever the systemic risk measure is calculated at the level of individual enterprises, this paper estimates the measurement of financial system as the equal weighted average of 23 institutions, covering four major industries: banking, securities industry, insurance, and trust. Specifically: 000001.SZ, 600621.SH, 600837.SH, 600864.SH, 000617.SZ, 000627.SZ, 000666.SZ, 600783.SH, 000686.SZ, 000712.SZ, 600061.SH, 000776.SZ, 000728.SZ, 600095.SH, 000750.SZ, 000783.SZ, 600109.SH, 600155.SH, 600000.SH, 600016.SH, 600369.SH, 600036.SH, 600030.SH. This paper selected the daily closing prices of these 23 institutions from 2003M4-2022M7 to calculate their logarithmic returns [48]. We adopted the Shanghai Securities Composite Index as the market yield for convenience. Besides, we use the monthly average of the daily data, making the frequency consistent across all data. The macroeconomic data include three-month SHIBOR rate, the three-month Treasury maturity yield, 10-year Treasury maturity yield, CPI, PPI, IVA, M2, and GDP [49,50]. The data are obtained from Choice database and EPS database. The calculation method for each indicator is shown in Table 1.

**Table 1.** Variables and measurement methods.

| Major Indexes | Minor Indexes | Variable | Abbr. | Measurement Method |
|---|---|---|---|---|
| Systemic Risk | Institution-specific risk | Conditional Value-At-Risk | *CoVaR* | The system is based on VAR under loss conditions of specific institutions and calculated by DCC-GARCH model. |
| | | ΔConditional Value-At-Risk | Δ*CoVaR* | The difference between the value at risk of the financial system conditions corresponding to the financial institution in financial distress and the financial institution on average. It is calculated by DCC-GARCH model. |
| | | Marginal Expected Shortfall | *MES* | The expected institutional return rate is when the market return is lower than the critical value-calculated by DCC-GARCH model. |
| | Comovement and contagion | Absorption Ratio | *AR* | The total variance of a set of asset returns explained by a fixed number of eigenvectors. |
| | | Dynamic Causality Index | *DCI* | The fraction of statistically significant Granger causality among all financial institutions. |
| | Financial vulnerability | Volatility | *Volatility* | Volatility of financial institution's rate of return |
| | | Turbulence | *Turbulence* | Mahalanobis distance of return on assets |
| | | Leverage | *Leverage* | The ratio of book value to the market value of financial institutions |
| | Liquidity and credit | Term Spread | *TERM* | Difference between the yield to maturity of 10-year Treasury bonds and the yield to maturity of 3-month Treasury bonds. |
| | | Treasury& SHIBOR Spread | *TSD* | The difference between the 3-month SHIBOR interest rate and the Treasury bond maturity yield. |
| Macroeconomic Performance | - | Consumer Price Index | *CPI* | Choice database |
| | | Producer Price Index | *PPI* | Choice database |
| | | Industrial Growth Value | *IVA* | Choice database |
| | | Growth Rate of Broad Money Supply | *M2* | Choice database |
| | | Gross Domestic Product | *GDP* | EPS database |

### 2.3.1. Measurement and analysis of ΔCoVaR and MES

ΔCoVaR and MES are suitable measures of risk spillover effects, so it is necessary to select appropriate computational methods to assess systemic risk effectively [51]. This paper applies a DCC-GARCH model to capture the time-varying conditional correlation between financial institutions and financial markets. First, set the volatility equation, and use Eqs (4)–(7) to estimate the univariate GARCH model.

$$H_t = D_t R_t D_t \tag{4}$$

$$R_t = \left(diag(Q_t)\right)^{-1/2} Q_t \left(diag(Q_t)\right)^{-1/2} \tag{5}$$

$$D_t = diag\left(\sqrt{h_{11,t}}, \sqrt{h_{11,t}}, \ldots, \sqrt{h_{NN,t}}\right) \tag{6}$$

$$Q_t = (1-\eta-\omega)\bar{Q} + \omega Q_{t-m} + \eta \delta_{i,t-n}\delta_{j,t-n} \tag{7}$$

where $H_t$ is the conditional covariance matrix, $R_t$ is the dynamic correlation coefficient matrix, $D_t$ is the diagonal matrix consisting of the conditional standard deviation $\sqrt{h_{11,t}}$, and the conditional variance $h_{11,t}$ is fitted by a GARCH model of individual financial variable. $Q_t$ is the covariance matrix, $\bar{Q}$ is the unconditional covariance after residual normalization, $\eta$ is the standardized residual of lagged nth order coefficient, and $\omega$ is lagged-order conditional variance coefficient, which is non-negative and satisfy $\eta + \omega < 1$. Based on the parameter estimation of the univariate GARCH model, the dynamic conditional correlation coefficients between the two financial variables are then estimated, and the model is set as follows:

$$\rho_{ij,t} = \frac{(1-\eta-\omega)\bar{q}_{ij} + \omega q_{ij,t-1} + \eta \delta_{i,t-n}\delta_{j,t-n}}{\left[(1-\eta-\omega)\bar{q}_{ij} + \omega q_{ij,t-1} + \eta \delta_{i,t-n}^2\right]^{-1/2}\left[(1-\eta-\omega)\bar{q}_{ij} + \omega q_{ij,t-1} + \eta \delta_{j,t-n}^2\right]^{-1/2}} \tag{8}$$

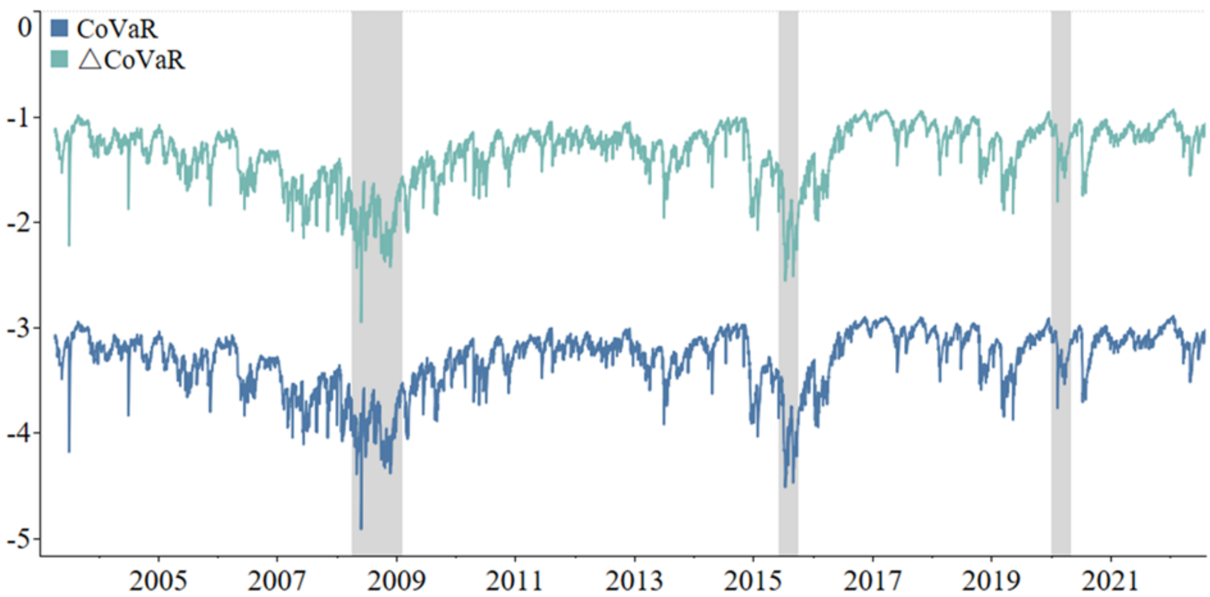



**Figure 1.** Calculation results of CoVaR and ΔCoVaR. Blue and cyan lines represent CoVaR and ΔCoVaR, respectively. The sample range is 2003M4-2022M7. The shaded areas indicate the three crisis events of the 2008 financial crisis, the 2015 Chinese stock market crash and the 2020 COVID-19 outbreak.

The calculation results of CoVaR and ΔCoVaR are shown in Figure 1. The shaded areas indicate the three crisis events of the 2008 financial crisis, the 2015 Chinese stock market crash and the 2020 COVID-19 outbreak. We find that the measured CoVaR and ΔCoVaR strongly correlate with future economic activity and show relatively significant changes in all three crisis events. Meanwhile, both CoVaR and ΔCoVaR show more significant fluctuations during this period due to the weak domestic demand in 2018 caused by the massive demand stimulation and deleveraging efforts in the previous period, which resulted in a downward spiral in the Chinese economy. At the same time, the trade disputes between China and the United States have also increased in the volatility of systemic risk. The two are highly linearly correlated and given that ΔCoVaR is more concerned with tail risks, only ΔCoVaR is retained for the analysis of the two in the latter part.

The calculation results of MES are shown in Figure 2. The shaded area indicates what is consistent with the previous section, which shows that MES is more volatile overall than CoVaR and ΔCoVaR, and the overall trend is broadly consistent.

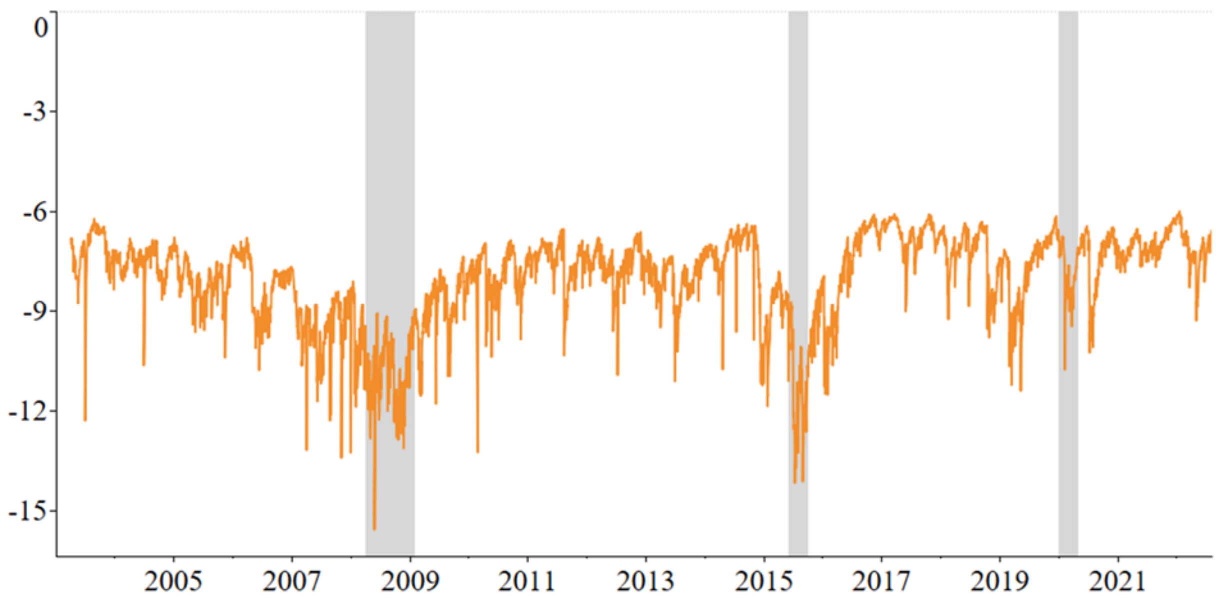



**Figure 2.** Calculation results of MES. Yellow line represents MES, respectively. The sample range is 2003M4-2022M7. The shaded areas indicate the three crisis events of the 2008 financial crisis, the 2015 Chinese stock market crash and the 2020 COVID-19 outbreak.

### 2.3.2. Descriptive statistics

Table 2 reports descriptive statistics for systemic risk indicators and macroeconomic performance proxy variables. The sample period is 2003M4-2022M7, where the available ranges for TSD and GDP data are 2006M10-2022M7 and 2003M4-2021M6, respectively.

It takes the selected systemic risk indicator ΔCoVaR as an example with the macroeconomic performance trend of proxy variables. Each indicator is standardized for comparison to eliminate the effect of the dimension. It can be seen from Figure 3 that ΔCoVaR remains broadly consistent with the trend of CPI and PPI. In contrast, the trend with the movement of IVA, M2 and GDP remains consistent only in some periods, which means such macroeconomic performance the relationship is not stable. It suggests that individual systemic risk indicators can only describe a particular aspect of systemic risk and that the relationship with proxies of macroeconomic performance is long-lasting only for a given period.

**Table 2.** Descriptive statistics.

| Variable | N | Mean | Std | Min | Max |
|---|---|---|---|---|---|
| *ΔCoVaR* | 232 | -1.34 | 0.27 | -2.25 | -0.96 |
| *MES* | 232 | -7.98 | 1.23 | -12.55 | -6.18 |
| *AR* | 232 | 0.92 | 0.04 | 0.80 | 0.98 |
| *DCI* | 232 | 0.10 | 0.05 | 0.00 | 0.35 |
| *Volatility* | 232 | 2.55 | 0.87 | 1.18 | 5.76 |
| *Turbulence* | 232 | 8866.25 | 8044.92 | 1045.28 | 46,309.96 |
| *Leverage* | 231 | 0.14 | 0.06 | 0.05 | 0.36 |
| *TERM* | 232 | 0.53 | 0.29 | -0.43 | 1.25 |
| *TSD* | 190 | 1.02 | 0.59 | 0.09 | 2.98 |
| *CPI* | 232 | 2.52 | 1.86 | -1.81 | 8.74 |
| *PPI* | 232 | 2.05 | 4.54 | -8.22 | 13.50 |
| *IVA* | 232 | 10.47 | 5.18 | -2.90 | 23.20 |
| *M2* | 232 | 14.43 | 4.87 | 8.00 | 29.74 |
| *GDP* | 219 | 100.02 | 1.30 | 85.49 | 103.03 |

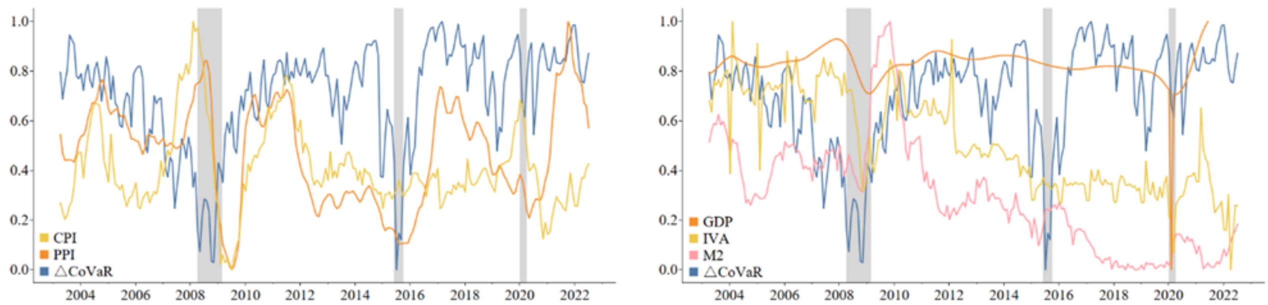



**Figure 3.** ΔCoVaR and macroeconomic performance. The CPI, PPI and ΔCoVaR are selected in the left figure for trend comparison. The GDP, IVA, M2 and ΔCoVaR are chosen in the right figure for trend comparison. The sample range is 2003M4-2022M7. The shaded areas indicate the three crisis events of the 2008 financial crisis, the 2015 Chinese stock market crash and the 2020 COVID-19 outbreak.

## 3. Results of systemic risk combination and forecast

### *3.1. Indicator combination selection*

Firstly, the optimal combination of predictors of different systemic risk indicators on macroeconomic performance proxies is selected based on dominance analysis. The indicator combinations are chosen separately for different forecast periods (h = 1, 3, 6, 12) and the regression results are shown in Table 3. Table 3 reports the contribution of different systemic risk indicators to macroeconomic performance forecasts, and the top indicators with a cumulative contribution of more than 80% are selected for the combination.

In the case of a very short-term (h = 1) forecast, all four systemic risk indicators are included in the construction of the CPI forecast, with liquidity and credit making the main contribution to forecasting the future trend of the CPI in the very short-term, and the TSD making the immense contribution among the individual indicators. Constructing the PPI forecast portfolio includes six systemic risk indicators, among which institution-specific risk accounts for the main contribution to predicting the future trend of very short-term. The PPI, and the MES contributes the most in the individual indicators. Meanwhile, six systemic risk indicators are included in the construction of the IVA forecast, of which liquidity and credit are the main contributors to forecasting the future trend of the IVA in the very short term, and the AR is the most significant contributor among the individual indicators. Building the M2 forecast portfolio includes five systemic risk indicators, with liquidity and credit making the main contribution to forecasting the future trend of the M2 in the very short term, and the AR contributes the most among the individual indicators. Only three types of three systemic risk indicators are included in the construction of the GDP forecast, with liquidity and credit making the main contribution to forecasting the future trend of the GDP in the very short term, and the TSD making the enormous contribution among the individual indicators.

In the case of a short-term (h = 3) forecast, all five systemic risk indicators are included in the construction of the CPI forecast, with liquidity and credit making the main contribution to forecasting the future trend of the short-run CPI, and the TSD making the immense contribution among the individual indicators, but decreasing compared to the very short-run forecast. Building the PPI forecast portfolio includes five systemic risk indicators. Among them, institution-specific risk accounts for the main contribution to predicting the future trend of short-term the PPI, and the MES contributes the most among the individual indicators. Constructing the IVA forecast portfolio includes six systemic risk indicators, of which liquidity and credit is the main contributor to the forecast of the short-term IVA's future trend. At the same time, the AR contributes the most among the individual indicators. Building the M2 forecast portfolio includes six systemic risk indicators. I shift from liquidity and credit to institution-specific risk significantly contributes to forecasting the future trend of the M2 in the short term, and the AR makes an immense contribution among the individual indicators. Only three types of three systemic risk indicators are included in the construction of the GDP forecast, with liquidity and credit making the main contribution to forecasting the future trend of the short-term GDP and the TSD making the enormous contribution among the individual indicators.

In the case of medium-term (h = 6) forecast, all six systemic risk indicators are included in the CPI forecast indicator construction, with the transformation from liquidity and credit to financial vulnerability accounting for the main contribution to forecasting the future trend of the CPI in the medium term, and the shift to the AR making the most considerable contribution among the individual indicators. Constructing the PPI forecast portfolio includes five systemic risk indicators, among which the change from institution-specific risk to liquidity and credit makes the main contribution to forecasting the future trend of the PPI in the medium term. In contrast, the change to the TERM contributes the most among individual indicators. Constructing the IVA forecast portfolio includes five systemic risk indicators, among which the shift from liquidity and credit to financial vulnerability makes the most considerable contribution to forecasting the future trend of the IVA in the medium term. At the same time, the AR contributes the most among the individual indicators, higher than the short-term forecast. Constructing the M2 forecast portfolio includes five systemic risk indicators, among which institution-specific risk makes the main contribution to forecasting the future trend of the M2 in the medium term. Meanwhile, AR contributes the most among the individual indicators. Constructing the GDP forecast portfolio only includes three systemic risk indicators. In comparison, the shift from liquidity and credit to financial vulnerability is the main contribution to forecasting the future GDP trend in the medium term, and the transformation to the AR has an immense contribution among the individual indicators.

In the case of the long-term (h = 12) forecast, all six systemic risk indicators are included in the CPI forecast, with the shift from financial vulnerability to liquidity and credit making the main contribution to forecasting the future trend of the long-term CPI. The transformation to the TSD contributes the most significantly among the individual indicators. Constructing the PPI forecast portfolio only includes three systemic risk indicators of two types, where the shift from liquidity and credit to institution-specific risk contributes the most to forecasting the future long-term PPI trend. At the same time, the transformation to the TSD makes an immense contribution among the individual indicators. Building the IVA forecast portfolio only includes four systemic risk indicators of three types, where financial vulnerability makes the main contribution to forecasting the future trend of long-term IVA. Besides, the shift to leverage makes an enormous contribution among individual indicators. Building the M2 forecast portfolio only includes six systemic risk indicators, where institution-specific risk makes the main contribution to forecasting the future M2 trend in the long-term. In contrast, the shift to the ΔCoVar makes the most considerable contribution among the individual indicators. Building the GDP forecast portfolio only includes three systemic risk indicators of a single type, that is, financial vulnerability accounts for the main contribution to the forecast of long-term GDP future trends. Meanwhile, the shift to turbulence is the most significant contributor among the individual indicators.

In summary, it is not difficult to see that various types of systemic risk perform differently in predicting macroeconomic performance proxies. The forecast of financial vulnerability on the consumer price index (CPI) and institution-specific risk on producer price index (PPI) are relatively stable under different terms. In the forecast of industrial growth value (IVA) by various systemic risk indicators, liquidity and credit have the highest contribution in the short-term. In contrast, financial vulnerability has the highest contribution in the medium- and long-term. Among the different systemic risk indicators for the growth rate of the broad money supply (M2) forecast, liquidity and credit have the largest contribution only in the very short-term, and it shows the most considerable contribution of institution-specific risk in the subsequent most extended-term. The gross domestic product (GDP) forecast across different systemic risk indicators is consistent with the IVAs. In the case of individual systemic risk indicators forecasting proxies for macroeconomic performance, the maximum contribution indicators of the five proxy variables of macroeconomic performance are relatively stable in the short term, with Treasury& SHIBOR spread (TSD) and absorption ratio (AR) performing optimally. In contrast, the contribution of individual indicators in the medium and long run shows instability. It further suggests that some systemic risk indicators play a role in forecasting macroeconomic performance only in specific terms. In addition, this forecast indicator selection procedure exhibits a decrease in the required indicators with the extension of the forecast term for PPI and IVA. While the CPI shows an increase in the required indicators, M2 and GDP broadly remain the same.

**Table 3.** Contribution of systemic risk to macroeconomic forecast in various periods.

| h = 1 | (1) $CPI_{t+1}$ | (2) $PPI_{t+1}$ | (3) $IVA_{t+1}$ | (4) $M2_{t+1}$ | (5) $GDP_{t+1}$ |
|---|---|---|---|---|---|
| $\Delta CoVar$ | 8.26 | 20.22 | 7.87 | 13.88 | 2.45 |
| *MES* | 6.55 | 23.72 | 6.53 | 10.89 | 2.65 |
| *AR* | 1.68 | 7.06 | 22.82 | 24.7 | 26.23 |
| *DCI* | 6.64 | 8.13 | 0.84 | 1.87 | 1.59 |
| *Volatility* | 4.12 | 7.82 | 6.36 | 6.65 | 6.11 |
| *Turbulence* | 3.41 | 6.31 | 9.45 | 5.4 | 9.52 |
| *Leverage* | 9.62 | 5.73 | 13.77 | 5.48 | 4.57 |
| *TERM* | 1.81 | 15.16 | 16.02 | 18.67 | 0.91 |
| *TSD* | 57.92 | 5.85 | 16.33 | 12.46 | 45.97 |
| h = 3 | (1) $CPI_{t+3}$ | (2) $PPI_{t+3}$ | (3) $IVA_{t+3}$ | (4) $M2_{t+3}$ | (5) $GDP_{t+3}$ |
| $\Delta CoVar$ | 7.52 | 18.7 | 8.42 | 15.91 | 3.49 |
| *MES* | 6.73 | 23.38 | 6.86 | 12.43 | 3.34 |
| *AR* | 6.63 | 2.53 | 25.18 | 24.42 | 27.57 |
| *DCI* | 1.27 | 7.19 | 0.89 | 0.95 | 4.69 |
| *Volatility* | 3.53 | 9.22 | 6.32 | 7.28 | 12.39 |
| *Turbulence* | 3.56 | 8.22 | 10.1 | 5.57 | 15.75 |
| *Leverage* | 24.88 | 4.29 | 15.74 | 9.44 | 1.28 |
| *TERM* | 5.91 | 22.72 | 14.39 | 12.67 | 1.3 |
| *TSD* | 39.97 | 3.75 | 12.09 | 11.33 | 30.17 |
| h = 6 | (1) $CPI_{t+6}$ | (2) $PPI_{t+6}$ | (3) $IVA_{t+6}$ | (4) $M2_{t+6}$ | (5) $GDP_{t+6}$ |
| $\Delta CoVar$ | 4.1 | 12.31 | 5.63 | 18.63 | 5.04 |
| *MES* | 4.5 | 16.18 | 4.76 | 14.62 | 5.22 |
| *AR* | 19.26 | 3.59 | 28.76 | 22.59 | 29.65 |
| *DCI* | 3.49 | 1.8 | 0.38 | 0.96 | 2.33 |
| *Volatility* | 10.74 | 8.51 | 7.78 | 7.89 | 10.6 |
| *Turbulence* | 17.43 | 10.96 | 14.08 | 5.49 | 22.89 |
| *Leverage* | 16.14 | 5.1 | 23.81 | 14.88 | 3.06 |
| *TERM* | 13.61 | 25.74 | 10.85 | 4.58 | 1.09 |
| *TSD* | 10.73 | 15.82 | 3.95 | 10.36 | 20.11 |
| h = 12 | (1) $CPI_{t+12}$ | (2) $PPI_{t+12}$ | (3) $IVA_{t+12}$ | (4) $M2_{t+12}$ | (5) $GDP_{t+12}$ |
| $\Delta CoVar$ | 3.02 | 3.33 | 12.51 | 23.41 | 5.93 |
| *MES* | 3.3 | 3.88 | 8.94 | 18.17 | 6.59 |
| *AR* | 15.48 | 2.86 | 13.77 | 13.67 | 6.13 |
| *DCI* | 10.54 | 1.72 | 0.41 | 5.17 | 3.42 |
| *Volatility* | 6.59 | 3.55 | 4.22 | 9.05 | 14.63 |
| *Turbulence* | 15 | 5.96 | 7.24 | 6.04 | 40.15 |
| *Leverage* | 8.55 | 1.92 | 51.05 | 14.18 | 27.39 |
| *TERM* | 15.79 | 12.28 | 5.6 | 1.52 | 0.2 |
| *TSD* | 21.73 | 64.51 | -3.74 | 8.8 | -4.44 |

The reasons for the difference in the relatively dominant indicators of contribution to forecasting macroeconomic performance may be as follows. First, financial liquidity is closely related to residential consumption, and the tightness of financial liquidity and changes in investor risk appetite will affect the consumption decisions of residents and consumer prices. The increased financial market liquidity leads to excess volatility and hedging capabilities [52]. Second, financial institutions can provide producers with resources to address their financial needs. Since financial institutions are too closely linked or banks are susceptible to systemic risk, which is closely related to the capital acquisition cost of producers and the risk of financial chain breakage. Third, as an essential source of capital, credit is one of the crucial factors of industrial growth. If the demand gap for wealth is not relieved for a long time will have a severe impact on industrial growth. The investment demand of the real economy will affect industrial growth. The liquidity and credit conditions in the financial market in the short-term, and the volatility and instability of the financial sector are essential factors affecting credit in the long term. Fourth, in order to avoid inflation, the money supply is bound to be affected by market liquidity and credit conditions [53]. The stability mechanism between the long-term money supply and financial institutions is the policy basis to ensure the smooth operation of finance. The potential cost and risk of managing the risks on individual financial institutions are enormous, and the monetary authorities will carefully consider their impact on the financial institutions' risk-taking in the formulation of policies. Fifth, good development of financial markets can lead to economic growth, dominated by liquidity and credit conditions in the short-term, and volatility and instability in the long-term.

### *3.2. In-sample analysis*

We combine the systemic risk indicators selected above in a forecasting regression for the five proxies of macroeconomic performance according to Eq (3), and the results are shown in Table 4. Since the systemic risk indicators selected and the order may vary across forecast terms, the indicators are referred to in the text using $Compo_i$ ranked by contribution.

**Table 4.** The forecast of systemic risk to macroeconomic forecast in various periods.

| One Month Ahead Forecasting Horizon (h = 1) | | | | | |
|---|---|---|---|---|---|
| | $CPI_{t+1}$ | $PPI_{t+1}$ | $IVA_{t+1}$ | $M2_{t+1}$ | $GDP_{t+1}$ |
| $Compo_1$ | -0.097<br>(-1.200) | 0.760*<br>(1.898) | -12.694*<br>(-1.952) | -1.396<br>(-0.432) | 0.262*<br>(1.635) |
| $Compo_2$ | -2.159<br>(-1.135) | -2.207<br>(-1.216) | 0.425*<br>(1.736) | 0.157<br>(0.708) | -4.209*<br>(-1.816) |
| $Compo_3$ | 0.233*<br>(1.639) | 0.906***<br>(3.079) | 1.086**<br>(2.013) | -2.340<br>(-1.037) | -0.000<br>(-1.162) |
| $Compo_4$ | 1.038<br>(1.168) | -1.977*<br>(-1.736) | 3.485<br>(0.831) | -0.036<br>(-0.271) | -<br>- |
| $Compo_5$ | -<br>- | -0.016<br>(-0.099) | -0.000<br>(-0.469) | 0.357<br>(0.783) | -<br>- |
| $Compo_6$ | -<br>- | -3.936*<br>(-1.720) | 0.037<br>(0.026) | -<br>- | -<br>- |
| N | 189 | 231 | 189 | 189 | 176 |
| $R^2$ | 0.913 | 0.961 | 0.846 | 0.967 | 0.323 |
| F | 375.692 | 748.246 | 124.844 | 690.178 | 36.287 |

*Continued on next page*

| Three Month Ahead Forecasting Horizon (h = 3) | | | | | |
|---|---|---|---|---|---|
| | $CPI_{t+3}$ | $PPI_{t+3}$ | $IVA_{t+3}$ | $M2_{t+3}$ | $GDP_{t+3}$ |
| $Compo_1$ | -0.363*** | 2.632*** | -28.298*** | -7.485* | 0.213 |
| | (-2.821) | (2.751) | (-3.028) | (-1.624) | (1.035) |
| $Compo_2$ | -6.095** | 2.544*** | 9.778* | -1.844 | -1.794 |
| | (-2.501) | (3.645) | (1.824) | (-0.492) | (-0.941) |
| $Compo_3$ | -0.466 | -10.119** | 1.146* | -0.415 | -0.001*** |
| | (-0.235) | (-2.417) | (1.671) | (-1.182) | (-2.856) |
| $Compo_4$ | 0.618 | 0.272 | 0.337 | 0.072 | 0.720** |
| | (1.555) | (0.450) | (0.735) | (0.096) | (2.109) |
| $Compo_5$ | -19.482*** | -0.000 | -0.000 | -0.112 | - |
| | (-5.786) | (-1.089) | (-0.700) | (-0.607) | - |
| $Compo_6$ | - | - | 0.182 | 17.206*** | - |
| | - | - | (0.105) | (3.130) | - |
| N | 187 | 229 | 187 | 187 | 174 |
| $R^2$ | 0.760 | 0.763 | 0.742 | 0.909 | 0.269 |
| F | 94.577 | 132.048 | 67.160 | 175.367 | 8.979 |
| Six Month Ahead Forecasting Horizon (h = 6) | | | | | |
| | $CPI_{t+6}$ | $PPI_{t+6}$ | $IVA_{t+6}$ | $M2_{t+6}$ | $GDP_{t+6}$ |
| $Compo_1$ | -11.971*** | 3.491*** | -18.425** | -14.300* | -3.700 |
| | (-2.862) | (3.680) | (-2.370) | (-1.932) | (-1.175) |
| $Compo_2$ | -0.000*** | 0.097 | 11.910*** | -7.714 | -0.001*** |
| | (-3.211) | (0.064) | (3.332) | (-1.388) | (-2.869) |
| $Compo_3$ | -6.907 | -2.112*** | -0.001* | 33.360*** | 0.183 |
| | (-1.582) | (-5.709) | (-1.863) | (4.193) | (0.705) |
| $Compo_4$ | 1.151*** | 0.828 | 0.577 | 0.889 | 0.440* |
| | (4.097) | (0.126) | (0.736) | (0.807) | (1.953) |
| $Compo_5$ | 1.025** | -0.001** | 1.015 | 0.203 | - |
| | (2.195) | (-2.083) | (1.194) | (0.790) | - |
| $Compo_6$ | -0.442*** | - | - | - | - |
| | (-2.660) | - | - | - | - |
| N | 184 | 184 | 226 | 184 | 171 |
| $R^2$ | 0.510 | 0.503 | 0.656 | 0.813 | 0.126 |
| F | 19.194 | 43.900 | 89.713 | 83.723 | 5.969 |
| Twelve Month Ahead Forecasting Horizon (h = 12) | | | | | |
| | $CPI_{t+12}$ | $PPI_{t+12}$ | $IVA_{t+12}$ | $M2_{t+12}$ | $GDP_{t+12}$ |
| $Compo_1$ | -0.006 | -4.500*** | 34.444*** | -32.890*** | -0.001* |
| | (-0.030) | (-8.616) | (7.182) | (-3.278) | (-1.655) |
| $Compo_2$ | 1.788*** | 2.697*** | -2.611 | 5.143** | 3.469*** |
| | (4.380) | (2.818) | (-0.274) | (2.323) | (2.845) |
| $Compo_3$ | -15.810*** | -0.001*** | -25.867*** | 31.045*** | 0.623 |
| | (-3.618) | (-3.689) | (-3.079) | (4.222) | (1.361) |

*Continued on next page*

| Twelve Month Ahead Forecasting Horizon (h = 12) | | | | | |
|---|---|---|---|---|---|
| | $CPI_{t+12}$ | $PPI_{t+12}$ | $IVA_{t+12}$ | $M2_{t+12}$ | $GDP_{t+12}$ |
| $Compo_4$ | -0.001*** | - | 4.977*** | 8.904 | - |
| | (-3.914) | - | (2.830) | (1.107) | - |
| $Compo_5$ | 7.540*** | - | - | 0.128 | - |
| | (3.145) | - | - | (0.221) | - |
| $Compo_6$ | 13.994*** | - | - | 1.843*** | - |
| | (3.536) | - | - | (5.894) | - |
| N | 178 | 178 | 220 | 178 | 207 |
| $R^2$ | 0.322 | 0.405 | 0.591 | 0.720 | 0.173 |
| F | 9.940 | 33.673 | 77.565 | 74.614 | 16.247 |

Notes: This table reports the regression coefficients and T values. *, **, *** represent significant at 10, 5 and 1% level, respectively.

The in-sample regression can obtain several interesting results from the results. First, the type of systemic risk indicator is constructed by dominance analysis in forecasting different proxy variables for macroeconomic performance behaves differently under various terms. In combining systemic risk indicators under multiple terms to forecast CPI, institution-specific risk types indicators are only significant in the very short-term forecast. In contrast, the remaining types of indicators are effective outside the very short-term forecast. In the forecast of PPI at different terms, the systemic risk type of liquidity and credit contribute the most and are significant except in the very short term. Besides, the systemic risk type of institution-specific risk is significant only in the short-term, and the systemic risk type of financial vulnerability is significant only in the medium- to long-term. In IVA, the systemic risk type that dominates changes from liquidity and credit to financial vulnerability as the terms increase, and the coefficient is all significant in the periods in which they dominate the contribution. In the forecast of M2, it can be seen that none of the types is significant in the very short-term, and the institution-specific, risk-specific risk dominates the contribution with the extension of the term, but is significant only in the long-term. With the extension of the GDP forecast term, the contribution of financial vulnerability is increasing, and only this indicator type is substantial.

Second, the four types of systemic risk indicators behave differently for forecasting proxy variables of macroeconomic performance at different terms. All four types of systemic risk indicators are included in the forecast of proxy variables, but as the forecast term increases, the type of systemic risk indicator required for the forecast will decrease. It is further shown that specific risk indicators are only predictive at a given horizon and that systemic risk indicators must be dynamically adjusted over time to better forecast macroeconomic performance on different terms. In addition, we note that systemic risk indicators tend to be less effective in forecasting proxy variables of macroeconomic performance, such as M2, which are greatly influenced by the direct regulation of policymakers, is often not as good as other proxy variables.

### *3.3. Out-of-sample forecast comparison*

We test in out-of-sample forecasts whether the systemic risk indicators combination constructed from the dominance analysis improves the forecasting of macroeconomic performance, as compared to the forecast of the first three individual indicators alone. In order to verify whether the forecast effect of the systemic risk combination constructed in this paper on the macroeconomic performance proxies is better or not, the forecast effect of the constructed systemic risk indicators is tested by referring to Diebold and Mariano [54], who verify the forecast ability of the comparative model by the loss function.

$$E(d_t) = E\left(g(e_{i,t}) - g(e_{j,t})\right) \tag{9}$$

$$\bar{d} \sim N\left(0, \hat{V}(\bar{d})\right), \; DM = \frac{\bar{d}}{\sqrt{\hat{V}(\bar{d})}} \sim N(0,1) \tag{10}$$

where $e_{i,t}$ and $e_{j,t}$ denote the forecast errors of models $i$ and $j$, and $g(\cdot)$ denotes the loss function. If two models have the same forecast ability then the loss function has the same expected value $E(d_t)$ is 0. If the DM is not significantly different from 0, it means that the two models have equal predictive ability. If the DM is significantly positive, it means that the loss of the model $i$ function is significantly larger than the model $j$, then the model $j$ has better predictive power. Here, the model $i$ is set as the forecast combination constructed in this paper, and the model $j$ is set as the forecast model of an individual systemic risk indicator, and the results are shown in Table 5.

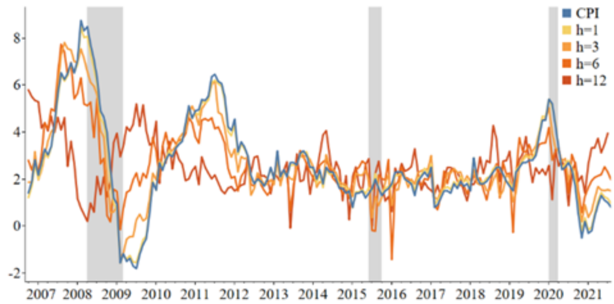
**Table 5.** Out-of-sample predictability.

| | h = 1 | | | | h = 3 | | |
|---|---|---|---|---|---|---|---|
| | $Compo_1$ | $Compo_2$ | $Compo_3$ | | $Compo_1$ | $Compo_2$ | $Compo_3$ |
| $CPI_{t+1}$ | -7.494*** | -7.751*** | -7.496*** | $CPI_{t+3}$ | -6.04*** | -6.686*** | -6.205*** |
| $PPI_{t+1}$ | -13.19*** | -13.41*** | -11.88*** | $PPI_{t+3}$ | -9.864*** | -9.472*** | -10.18*** |
| $IVA_{t+1}$ | -9.74*** | -9.24*** | -11.02*** | $IVA_{t+3}$ | -8.564*** | -9.192*** | -9.393*** |
| $M2_{t+1}$ | -7.349*** | -9.412*** | -7.472*** | $M2_{t+3}$ | -7.446*** | -7.19*** | -8.313*** |
| $GDP_{t+1}$ | -2.367* | -2.72*** | -2.636*** | $GDP_{t+3}$ | -2.914*** | -3.076*** | -2.548** |
| | h = 6 | | | | h = 12 | | |
| | $Compo_1$ | $Compo_2$ | $Compo_3$ | | $Compo_1$ | $Compo_2$ | $Compo_3$ |
| $CPI_{t+6}$ | -4.538*** | -4.229*** | -4.585*** | $CPI_{t+12}$ | -3.454*** | -2.708*** | -3.445*** |
| $PPI_{t+6}$ | -6.756*** | -6.662*** | -6.854*** | $PPI_{t+12}$ | -2.545** | -4.975*** | -7.095*** |
| $IVA_{t+6}$ | -8.095*** | -8.217*** | -11.33*** | $IVA_{t+12}$ | -5.783*** | -7.834*** | -9.323*** |
| $M2_{t+6}$ | -6.641*** | -6.865*** | -6.859*** | $M2_{t+12}$ | -6.048*** | -6.546*** | -5.827*** |
| $GDP_{t+6}$ | -2.54** | -3.681*** | -3.222*** | $GDP_{t+12}$ | -2.277** | -1.778* | -1.715* |

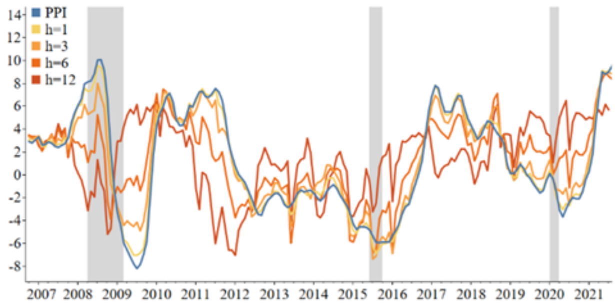
Notes: *, **, *** represent significant at 10, 5 and 1% level, respectively.

It can be seen from the results in Table 5 that the DM value of the systemic risk combination prediction indicator constructed in this paper is significantly negative under different terms. The result indicates that the prediction performance of the systemic risk combination is better than that of the prediction model of individual systemic risk indicators.

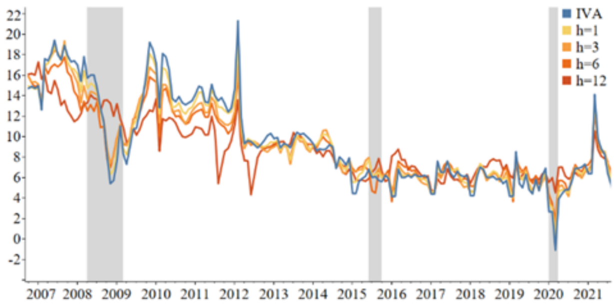
Figure 4 reports the forecast of the systemic risk combination on the macroeconomic performance proxies. The shaded areas indicate the three crisis events of the 2008 financial crisis, the 2015 Chinese stock market crash and the 2020 COVID-19 outbreak. The blue represents the actual value of macroeconomic performance proxies, and the other colors represent the forecast value of the systemic risk combination in different terms. Although, the amplitude of the forecast curve is smaller than the actual value in extremis, the overall performance is basically consistent.



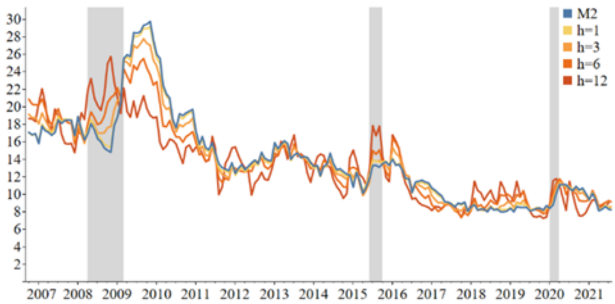

(a) Actual CPI and forecast results in different periods



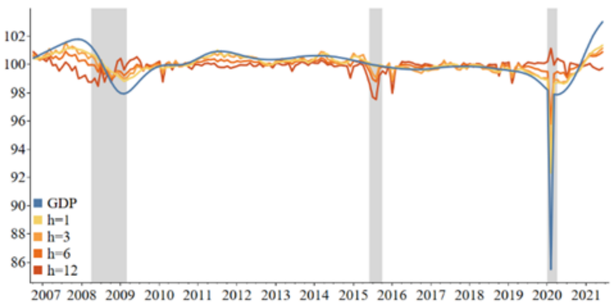

(b) Actual PPI and forecast results in different periods




(c) Actual IVA and forecast results in different periods




(d) Actual M2 and forecast results in different periods




(e) Actual GDP and forecast results in different periods

**Figure 4.** Forecast results of macroeconomic performance.

## 4. Conclusions

Accurately judging future economic activities' tendencies is crucial for developing daily production activities and formulating economic policies. There is a close relationship between systemic risk and macroeconomic performance. Many systemic risk indicators have been proposed and verified well. However, individual systemic risk indicators can only describe a specific aspect of systemic risk, and it is difficult to give full play to the forecast function of systemic risk on macroeconomic performance. Whenever the systemic risk measure is calculated at the level of individual enterprises, this paper estimates the measurement of the financial system as the equal-weighted average of 23 institutions, covering four major industries: banking, securities, insurance and trust. The SHIBOR and Treasury bond relevant data are used to calculate other systemic risk indicators. The macroeconomic performance selects the consumer price index (CPI), producer price index (PPI), industrial growth value (IVA), the growth rate of broad money supply (M2) and the gross domestic product (GDP) to compare the forecast ability of systemic risk on various proxies, with the period considered spans from 2003M4 to 2022M7. In this paper, the systemic risk indicators are divided into four types, and then the optimal combination of the different macroeconomic performance proxies and the systemic risk indicators is captured through the dominance analysis. Subsequently, we further forecast the macroeconomic performance proxies according to the constructed systemic risk portfolio.

First of all, the individual systemic risk indicator cannot cover all the information of systemic risk, can only reflect the specific aspect of macroeconomic performance, or is only highly relevant in a given period. In different terms, the contribution of systemic risk to the forecast of different macroeconomic performance proxies is diverse. In the case of the individual systemic risk indicator for forecasting macroeconomic performance proxies, the leading contribution indicators of the five proxy variables of macroeconomic performance are relatively stable in the short term, with Treasury& SHIBOR spread (TSD) and absorption ratio (AR) performing optimally. In contrast, the contribution of individual indicators in the medium and long run shows instability. From the quantitative macroeconomic performance forecast, the optimal combination of systemic risk indicators, with the extension of the forecast term, the number of PPI and IVA decreases, the number of CPI increases, and the number of M2 remains basically unchanged. The difference in the relatively dominant indicators of contribution to forecasting is the closeness of macroeconomic performance proxies and financial conditions reflected by individual systemic risk indicators.

Secondly, the types of systemic risk indicators included in the optimal forecasting portfolio of different macroeconomic performance proxies are diverse. Overall, the four types of systemic risk indicators will be included in the forecast of macroeconomic performance proxies. However, with the increase of the forecast term, the types of systemic risk indicators required for forecast will decrease. Financial vulnerability is included in the optimal forecast combination of systemic risk most often, while institution-specific risk is the least. The financial stability is closely related to various macroeconomic performance proxies. From the perspective of multiple systemic risk indicator types for forecasting macroeconomic performance proxies, financial vulnerability and institution-specific risk indicators play a more significant role in predicting long-term macroeconomic performance. As a proxy indicator of macroeconomic performance directly controlled by policymakers, such as M2, the forecast effect of systemic risk indicators is often not as good as other macroeconomic performance proxies. Based on the results of the out-of-sample forecast comparison, we can know that the forecast performance of the systemic risk combination constructed in this paper is better than that of individual systemic risk. Although the predicted macroeconomic performance in extremis is not as violently as the actual situation, the economic trend in the whole forecast term is basically consistent.

Finally, according to the above research results, this paper tries to give the following policy recommendations. On the one hand, there is a complex and changeable relationship between systemic risk and various macroeconomic performance proxies, so the optimal systemic risk forecast combination should be constructed by the actual economic situation of different countries. Blind selection of abundant systemic risk indicators to forecast the macroeconomic not only increases the challenge forecast, but also decreases the forecast effect due to the contradiction between some indicators. On the other hand, China should constantly strengthen the weak links of risk prevention and control in the financial system, and reduce the financial institutions' vulnerability. Financial stability is closely related to the various macroeconomic performance proxies. The regulatory authorities should improve their ability to forecast risks and adjust policies on time to ensure the financial market's smooth operation and to avoid adverse impacts on the macroeconomics caused by excessive fluctuations in the financial market due to emergencies.

## Conflict of interest

The authors declare there is no conflict of interest.

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