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An Analysis of the "Belt and Road" Concept Index's Risk Alert Integrating Mixed-Frequency Macroeconomic Variables

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Abstract

The low-frequency macroeconomic variables are applied to the risk prediction of the "belt and road" concept index. Firstly, the time-varying parameter vector autoregressive model (TVP-VAR) is used to calculate the Risk Spillover Effect of the "belt and road" concept index, and the improved adaptive noise complete set empirical mode decomposition (ICEEMDAN) is used to decompose the Risk Spillover index; Secondly, combined with permutation entropy and extreme gradient lifting tree model with Shapley value (XGBOOST), the characteristics of monthly macroeconomic variables were screened and the dimension was reduced by factor analysis, and the macroeconomic factors were extracted; Then the empirical mode component terms of macroeconomic factors and Risk Spillover index decomposition are reconstructed by using the mixing sampling model (CARCH-MIDAS); Finally, the reconstructed data and technical data are combined to use the depth autocorrelation network model (AUTOFORMER) for prediction, and the error is compared with other benchmark models. The empirical results show that this model has a higher accuracy in predicting the risk trend of the "belt and road" concept index. Therefore, investors should pay attention to the impact of macroeconomic variables when preventing the risk of the "belt and road" concept index.

Keywords

Belt and Road, TVP-VAR, ICEEMDAN, AUTOFORMER

1. Introduction

Since 2013, China has advocated the strategic concepts of the "New Silk Road Economic Belt" and the "21st Century Maritime Silk Road" in an effort to create a new framework for international cooperation that fully utilizes the resource endowments and comparative advantages of the nations that make up the route. The success of regional economic and trade cooperation has been significantly boosted by this idea (Baniya et al., 2020). International trade protectionism, however, has grown more common in recent years. Additionally, a number of extreme financial events, like the Silicon Valley Bank bankruptcy, regional conflicts, like the Israel-Palestine conflict, and unexpected public health events, like the COVID-19 pandemic, have added uncertainty to the international financial environment and caused wild fluctuations in global stock markets. Furthermore, the Chinese financial market landscape is also rather intricate. Investor confidence in the financial market's upward trend has been shaken by significant events like the strengthening of real estate financial reform, the intensification of financial regulatory reform, and the restructuring of China's economic structure. As a result, it is now challenging to predict the market's future volatility and risk.

In the post-epidemic era, a spokesman for China's National Development and Reform Commission (NDRC) said China has signed more than 200 "Belt and Road" cooperation agreements with 32 international organizations and 147 countries. In addition to fostering China's economic openness and international cooperation, the Belt and Road Initiative has increased connectivity between China and the nations bordering its path. China's trade and economic cooperation with the nations along the route have expanded quickly, offering opportunities for collaboration in the areas of energy development, infrastructure building, and trade facilitation for the nations in the Belt and Road system. This has also improved regional peace and stability, boosted economic growth, and improved people's quality of life in many of the participating nations. The Belt and Road Initiative has expedited the process of RMB internationalization, facilitated the flow of international capital, and resulted in the development of a diverse investment and financing system based on the initiative and regional economic integration. The Belt and Road Initiative's unusual stock index swings and the effects of both internal and external financial risks on the Chinese stock market will have an impact on the steady growth of the Chinese financial system as a whole, given the current economic climate. In order to effectively respond to the financial risk spillover of the domestic market and improve risk supervision of the Belt and Road Initiative stock index, it is therefore possible to study the future risk dynamic changes of the index. In order for China to achieve macroeconomic development, facilitate the seamless growth of the financial market, encourage the flow of international capital, and boost investor confidence, this study is extremely important practically.

2. Literature Review

Accurate prediction of financial risk indicators is the key to building predictive risk models, and the commonly used risk prediction models are value-at-risk (VAR), conditional autoregressive value-at-risk by regression quantiles (CAVAR), autoregressive conditional heteroskedasticity (ARCH), etc. These risk prediction models can help financial regulators monitor the risk dynamics of the Belt and Road stock index and create more economic value for investors in the Belt and Road sector. Therefore, financial risk prediction has become an extensive research direction in the field of financial econometrics. Liu (2016) analyzed the risk of the "Belt and Road" sector stock index based on the MV-CAVaR model established by the conditional value at risk (CAVaR) and found that the "Belt and Road" sector and earnings volatility are the main factors affecting the tail risk and its linkage; Wu & Lu (2019) applied a GARCH-VaR model to calculate the stock index risk of eight countries participating in the Belt and Road Initiative before and after the initiative; Wang & Yang (2019) used Extreme Value Theory (EVT) and Dependence Function (Copula) to establish an EVT-Copula-CoVaR model and found that the Chinese stock market has bidirectional and asymmetric risk spillover effects with the stock markets of countries along the Belt and Road; Furthermore, Liu, Wu, & Kong (2021) studied the financial risk spillover and spillback effects of China on countries along the Belt and Road and found that the spillover and spillback effects of both markets were significant; Wang et al. (2022) used the TENET framework to measure the correlation and systematic risk in the banking industry along the Belt and Road and found that the risk spillover within the banking industry of the countries along the Belt and Road is stronger than the interregional risk spillover, and cross-border mergers and acquisitions and commodity trade exports are important factors driving the risk connectivity in this area; Unlike the above studies, Yang (2021) further developed a DCC-GARCH-CoVaR model based on the dynamic conditional correlation autoregressive conditional heteroskedasticity model (DCC-GARCH) to study the volatility and dynamic correlation of the "Belt and Road" concept index on the domestic stock market in the context of the new crown pneumonia epidemic; Niu & Dou (2022) used an ARMA-GARCH model combining autoregressive sliding average (ARMA) and GARCH to predict the logarithmic return of the CSI "Belt and Road" theme index. GARCH (1, 1) model with t-distribution as residuals can reflect its volatility trend; Geng & Guo (2022) applied a directed network constructed by VaR network analysis to characterize the exchange rate volatility of 15 countries along the Belt and Road route; Hsu & Chien (2022) used skew GARCH and asymmetric DCC models to estimate the dynamic conditional correlation between the Chinese stock market and related stock markets and showed that the volatility of the Chinese stock market and related stock markets increased after the launch of the Belt and Road Initiative. This positive shift leads to stronger volatility spillover effects when the Chinese stock market is more volatile. The prediction model in the conventional econometric approach can represent the trend of future financial market volatility. However, the model's long-term prediction effect is frequently not optimal due to its intricate nonlinear relationship.

The above is to build the time series forecasting model with the traditional econometric method. The establishment of this kind of model needs to assume that there is a certain linear relationship between the series, but there is a complex nonlinear relationship between the financial time series data, so the forecasting effect cannot reach the best state.

Machine learning has advanced significantly in recent years, and it is now capable of accurately predicting the evolution of trends in financial risk data as well as capturing the nonlinear relationship between noisy financial time series. Some researchers have combined machine learning and econometric models to create hybrid models, which have the benefits of linear and nonlinear models, respectively, lessen the disturbances caused by linear models, and significantly enhance forecasting performance. For instance, a hybrid ANN-GARCH model, was used by Liang, Guo, & Wan (2022) to forecast stock market indices in Mexico, Brazil, and Chile. The outcomes demonstrate that artificial neural networks (ANN) can enhance the GARCH (1, 1) model's forecasting performance; To create the LSTM-RV-EVT risk management VAR model, Liu, Wu, & Kong (2021) combined LSTM and semi-parametric extreme value theory (EVT). The empirical findings demonstrated that, in comparison to the conventional VAR model, the lstm-rv-evt model significantly improved prediction accuracy; Yi & Yan (2023) modeled the low-frequency and high-frequency data decomposed from the original data using the moving average autoregressive (ARIMA) model and GRU, respectively. The findings demonstrated that the ARIMA-GRU model performed well in both short- and long-term foreign trade risk prediction and was superior to single models like LSTM and GRU; The online public opinion index was included in the time-varying parameter vector autoregressive model (TVP-VAR) and LSTM model by Ouyang, Lu, & Zhou (2022). The findings demonstrated that the online public opinion index's financial risk early warning system can accurately capture changes in China's financial risks. Researchers have discovered a nonlinear relationship between macroeconomic variables and financial risk information in recent years; By combining ANN and BP neural networks, Huang, Qiu, & Li (2021) were able to create a dynamically weighted financial condition index and an early warning system for financial risks. The dynamic weighted financial condition index can accurately reflect China's current financial situation, according to the results, and changes in interest rates, home prices, and stock prices must be taken into account; Zolfaghari & Gholami (2021) developed models combining Adaptive Wavelet Transform (AWT), LSTM, ARIMAX and GARCH series to predict stock indices and combining AWT, LSTM, and Variable Autoregressive series to predict volatility of US stock indices, respectively. The results indicated that AWT-LSTM-ARMAX-FIEGARCH outperforms the benchmark model in predicting stock indices, and AWT-LSTM improves the ability of HAR(3)X-RV in predicting real stock volatility; In order to forecast three historical stock market data sets, Peng, Khan, Khan, Shaikh, Yonghong, Ullah, & Ullah (2021) used multilayer perceptrons (MLP), recurrent neural networks (RNN), and ARIMA. The results showed that the hybrid model displayed greater robustness in forecasting than the individual ARIMA, MLP, and RNN models. Additional studies conducted in recent years have discovered a nonlinear relationship between macroeconomic factors and information on financial risk as well; Zhang & Chen (2022) combined the isolated forest and the deep autocorrelation network model (Autoformer), and used the low-frequency data with high reliability to build the financial risk early warning system of China's banking industry. The system can effectively detect which factors have the most impact on the systematic financial risk of China's banking industry. By combing and drawing on the above literature, it is found that the sample indices of the study have experienced significant fluctuations, which can be attributed to the fact that the fluctuations of the conceptual index of "Belt and Road" are closely related to China's trade economy and financial investment, indicating that there is a non-linear causal relationship between the domestic macroeconomic environment and the financial risk of the conceptual index of "Belt and Road". This can be attributed to the fact that the fluctuation of the "Belt and Road" conceptual index is closely related to China's trade economy and financial investment, indicating that there is a non-linear causal relationship between the domestic macroeconomic environment and the financial risk of the "Belt and Road" conceptual index. Therefore, adding macroeconomic variables to the prediction model can improve its prediction effect. Since there are many macroeconomic variables and most of them are low-frequency data, when choosing macroeconomic variables, the mixed-frequency part needs to be further screened and processed. At present, there are many studies on the financial risk of the "Belt and Road", but there are still deficiencies:

1) Most studies on the financial risks of the Belt and Road have been conducted using traditional econometrics, which has limitations in predicting data with complex linear relationships;

2) Most financial risk prediction models are designed to forecast long-term time series. However, these models incorporate various time-dependent features with complex relationships, making it difficult for deep learning models to derive accurate temporal dependencies directly from long-term time series data, ultimately reducing the performance of these models. As a result, further research is necessary to enhance the performance of these models by exploring alternative methods for modelling complex temporal relationships among time-dependent features in financial risk analysis;

3) Macro-economic variables and financial risk factors exhibit non-linear relationship. However, most macro-economic variables belong to low-frequency data, while original financial risk data is often high-frequency, leading to the problem of uneven frequency in raw data.

To address the aforementioned shortcomings, this paper employs Time-Varying Parameter Vector Autoregressive Model (TVP-VAR) to compute the risk spillover effects of four "Belt and Road" concept indices, and then examines the correlation between macroeconomic variables and the risk of "Belt and Road" concept indices. Furthermore, a financial risk forecasting model is established using an Autoformer model based on hybrid-frequency reconstruction.

The main contributions of this paper are as follows:

1) The application of the TVP-VAR model on the systematic risk analysis of "Belt and Road" concept indices, utilizing an Improved Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (ICEEMDAN) and fuzzy entropy feature recognition for decomposition reconstruction to separate the components with different frequency features, thus enhancing the model's prediction accuracy.

2) Introducing low-frequency macroeconomic variable factors, selecting variables with significant correlation with the risk of "Belt and Road" concept indices through an Extreme Gradient Boosting Tree Model (Xgboost) with Shapley Value and Permutation Entropy, extracting dimensionality-reduced variables, and utilizing the hybrid-frequency forecasting model combined with high-frequency empirical modes to generate feature components with macroeconomic characteristics, harboring significant economic implications.

3) The "Belt and Road" sector's systemic risk is the first to be addressed using the Autoformer model, and the empirical analysis of the "Belt and Road" concept index risk is important in reducing systemic risk in the "Belt and Road" sector. Preventing the market impact of systemic risk on the "Belt and Road" sector is crucial.

3. Methodology

3.1. Time-Varying Parametric Vector Autoregressive Model

The time-varying spillover index is calculated in the present research by applying a time-varying parameter vector autoregressive model with a forgetting factor in the Kalman filter. First, the TVP-VAR model is expressed as (1) and (2),

$$y_t = A_t z_{t-1} + \varepsilon_t \qquad \varepsilon_t \mid \Omega_{t-1} \sim N\left(0, \Sigma_t\right), \tag{1}$$

$$vec\left(A_t\right) + vec\left(A_{t-1}\right) + \xi_t \qquad \xi_t \mid \Omega_{t-1} \sim N\left(0, \Xi_t\right), \tag{2}$$

where Ω_{t-1} stands for all information that was known before $t-1$, y_t and ε_t represent $m \times 1$ vectors, ξ_t is a $m^2 p \times 1$ vector, and $vec\left(A_t\right)$ is a vectorized $m^2 p \times 1$ matrix. Time-varying coefficients include $A'_T = \left(A_{1t}, A_{2t}, A_{3t}, \cdots, A_{pt}\right)^{\mathrm{T}}$ and $z_{t-1} = \left(y_{t-1}, y_{t-2}, y_{t-3}, \cdots, y_{t-p}\right)$, while time-varying variance-covariance matrices Σ_t and Ξ_t are also included.

As a result, it is expected that the variable x_i will be affected at time *t*. Additionally, x_i represents the impact on the variable in accordance with its prediction error variance share after forecasting H previously.

After being normalized such that each row adds up to 1, the variance shares of the variances are then divided by the total number of variables that jointly explain the variable x_i, resulting in a prediction error variance of 100%. The standardized variance matrix for the $GFEVD\left(\tilde{\phi}_{ij,t}\left(H\right)\right)$ prediction error variance is (3):

$$\tilde{\phi}_{ij,t}(H)=\frac{\phi_{ij,t}(H)}{\sum_{j=1}^{m}\phi_{ij,t}(H)} \quad \phi_{ij,t}(H)=\frac{\sigma_{ii,t}^{-1}\sum_{h=0}^{H-1}\left(e_i' B_{h,t}\Sigma_{u,t}e_j\right)^2}{\sum_{h=0}^{H-1}\left(e_i' B_{h,t}\Sigma_{u,t}B_{h,t}' e_j\right)^2}, \tag{3}$$

$\sigma_{ii,t}^{-1}$ is the *i* elements on the diagonal of $\Sigma_{u,t}$. $\Sigma_{u,t}$ is the time-varying covariance matrix of the perturbing variable u_t. e_j denotes that the *j-th* element is 1 and all remaining elements are 0. *H* denotes the number of prediction steps, and *h* denotes the number of lags *h* orders of the perturbing variable. The standardized prediction error covariance variance matrix also condition (4),

$$\sum_{j=1}^{m}\tilde{\phi}_{ij,t}(H)=1 \quad \sum_{i,j=1}^{m}\tilde{\phi}_{ij,t}(H)=m. \tag{4}$$

Further define the risk-taking effect $C_{i\leftarrow j}^{from}$ and the risk spillover effect $C_{i\rightarrow j}^{to}$ of x_i at moment *t* to be calculated as (5),

$$C_{i,t}^{from}=\sum_{\substack{j=1\\ i\neq j}}^{m}\tilde{\phi}_{ij,t} \quad C_{i,t}^{to}=\sum_{\substack{i=1\\ i\neq j}}^{m}\tilde{\phi}_{ij,t}. \tag{5}$$

The net spillover effect $C_{i,t}$ of x_i at moment *t* is denoted as (6),

$$C_{i,t}=C_{i,t}^{to}-C_{i,t}^{from}. \tag{6}$$

Finally, the denominator of the total risk spillover index represents the cumulative effect of all shocks, while the numerator represents the cumulative effect of shocks in x_i. Based on the standardized variance matrix of forecast errors, the constructed total risk spillover index is (7):

$$C_t(H)=\frac{\sum_{i,j=1,i\neq j}^{m}\tilde{\phi}_{ij,t}(H)}{\sum_{i,j=1}^{m}\tilde{\phi}_{ij,t}(H)}\times 100=\frac{\sum_{i,j=1,i\neq j}^{m}\tilde{\phi}_{ij,t}(H)}{m}\times 100. \tag{7}$$

3.2. Autoformer Model

The Autoformer model consists of a deep decomposition architecture, a sequence decomposition unit, an Auto-Correlation mechanism, and the corresponding encoder and decoder.

3.2.1. Deep Decomposition Architecture

$$\chi_t=AvgPool\left(Padding(\chi)\right) \quad \chi_s=\chi-\chi_t, \tag{8}$$

while (8) are the trend and period terms, respectively, and χ is the hidden variable to be decomposed, and we embed the aforementioned serial decomposition unit between Autoformer layers, indicated as (9),

$$\chi_t,\chi_s=SeriesDecomp(\chi). \tag{9}$$

The primary function of the deep decomposition architecture is to integrate the sequence decomposition unit module as a model internal unit into the encoder and decoder. The trend and period factors are separated from the hidden variables to accomplish asymptotic decomposition by having the model alternate between prediction result optimization and sequence decomposition during the prediction phase.

3.2.2. Auto-Correlation Mechanism

When sequences are observed for their periodicity, it is discovered that similar phases across various periods typically show similar sub-processes. In order to achieve sequence-level connectedness and explain the complexity, an Auto-Correlation mechanism based on stochastic process theory can be built based on this periodicity. These are the Auto-Correlation coefficients, indicated as (10):

$$\Re_{\chi\chi}(\tau) = \lim_{L\to\infty}\frac{1}{L}\sum_{t=0}^{L-1}\chi_t\chi_{t-\tau}. \tag{10}$$

In the case when the χ_t sequence is a genuine discrete time process and $\chi_{t-\tau}$ signifies the delay τ latency of the χ_t sequence and the aforementioned autocorrelation coefficient denotes the similarity of the time delay between them, we can use $\Re(\tau)$ to denote the degree of confidence with period length τ.

The Auto-Correlation mechanism requires information aggregation of similar sub-processes, whereby the cycle terms of the sequence can be separated. The same as the self-attentive mechanism, the inputs here are query, key, and value. first, the most likely k cycle lengths are selected, and then the autocorrelation coefficients corresponding to the τ delay are brought into the *Softmax* function. Here $Roll(\cdot)$ means that the part of the time delay is successively followed by the subprocess, and finally $Roll(\cdot)$ is multiplied with the corresponding *Softmax* result and weighted to sum up, and calculated is (11), (12) and (13),

$$\tau_1,\cdots,\tau_k = \underset{\tau\in\{1,\cdots,L\}}{argTopk}\left(\Re_{Q,K}(\tau)\right), \tag{11}$$

$$\hat{\Re}_{Q,K}(\tau_1),\cdots,\hat{\Re}_{Q,K}(\tau_k) = Softmax\left(\hat{\Re}_{Q,K}(\tau_1),\cdots,\hat{\Re}_{Q,K}(\tau_k)\right), \tag{12}$$

$$AutoCorrelation(Q,K,V) = \sum_{i=1}^{k} Roll(V,\tau_k)\hat{\Re}_{Q,K}(\tau_k). \tag{13}$$

3.2.3. Encoder and Decoder

The trend components are gradually removed in the encoder section. In the Decoder, these trend components are summed. In addition, based on the periodicity of the sequence, an embedded autocorrelation mechanism is used to combine related subprocesses from different time periods to achieve information aggregation. This process is expressed as (14),

$$\begin{cases} \mathcal{S}_{\mathrm{en},-}^{l,1} = SeriesDecomp\left(AutoCorrelation\left(\mathcal{X}_{\mathrm{en}}^{l-1}\right)+\mathcal{X}_{\mathrm{en}}^{l-1}\right) \\ \mathcal{S}_{\mathrm{en},-}^{l,2} = SeriesDecomp\left(FeedForward\left(\mathcal{S}_{\mathrm{en}}^{l,1}\right)+\mathcal{S}_{\mathrm{en}}^{l,1}\right) \end{cases}. \tag{14}$$

In the Decoder, the trend components and the period components are modeled independently. For the period components, the autocorrelation mechanism uses the periodic nature of the series to aggregate subsequences with similar processes in different cycles; for the trend components, we use a cumulative approach to gradually extract the trend information from the predicted hidden variables. This process is expressed as (15),

$$\begin{cases} \mathcal{S}_{de}^{l,1}, \Gamma_{de}^{l,1} = SeriesDecomp\left(AutoCorrelation\left(\mathcal{X}_{de}^{l-1}\right) + \mathcal{X}_{de}^{l-1}\right) \\ \mathcal{S}_{de}^{l,2}, \Gamma_{de}^{l,2} = SeriesDecomp\left(AutoCorrelation\left(\mathcal{S}_{de}^{l,1}, \mathcal{X}_{en}^{N}\right) + \mathcal{S}_{de}^{l,1}\right) \\ \mathcal{S}_{de}^{l,3}, \Gamma_{de}^{l,3} = SeriesDecomp\left(FeedForward\left(\mathcal{S}_{de}^{l,2}\right) + \mathcal{S}_{de}^{l,2}\right) \\ \Gamma_{de}^{l} = \Gamma_{de}^{l-1} + W_{l,1} * \Gamma_{de}^{l,1} + W_{l,2} * \Gamma_{de}^{l,2} + W_{l,3} * \Gamma_{de}^{l,3} \end{cases}. \tag{15}$$

3.3. Construction of the TVP-VAR-Autoformer Model

The TVP-VAR-Autoformer model proposed in this paper combines TVP-VAR, Xgboost-shap, fuzzy entropy and alignment entropy, ICEEMDAN, mixed-frequency data processing ideas, and Autoformer. This paper uses the TVP-VAR model to measure the "Belt and Road Concept Index" and the risk spillover between the "Belt and Road Concept Index" and calculate the total risk spillover index. Then uses ICEEMDAN and alignment entropy to perform the modal decomposition of the total risk spillover index; and also combines Xgboost-shap and alignment entropy to perform the feature screening of the mixed-frequency data. In addition, factor analysis and confounding sampling models are applied in dimensionality reduction to extract the main information and reconstruct the confounding with the information after the modal decomposition to improve the prediction accuracy of the main variables and the prediction performance of the whole model. The model can be divided into three steps.

3.3.1. Risk Spillover Index Decomposition Integration

First, let the *i*-th "One Belt, One Road" daily concept index be $x_i\left(i=1,2,\cdots,m\right)$, and then use the TVP-VAR model to calculate the two-two risk spillover between index x_i and the *j-th* index $x_j\left(j=1,2,\cdots,m\right)$ at time *t* and express it as $\tilde{\phi}_{ij,t}$. Then further calculate the risk tolerance effect $C_{i,t}^{from}$ and the risk spillover effect $C_{i,t}^{to}$ of index x_i at time *t*. Then, the net spillover effect $NET_{i,t}$ and the total risk spillover index $BARCS_t$ of each index at time *t* are defined, and **Table 1** shows the risk spillover table of the daily concept index of "One Belt, One Road".

Second, the total risk spillover index $BARCS_t$ is empirically modally decomposed, and the corresponding components and residuals are decomposed. Meanwhile, ICEEMDAN can well solve the problems of noise residuals and spurious modalities, reduce many unnecessary components, improve the accuracy of decomposition, and ensure that each modal component has good stability and regularity. The frequency characteristics of the decomposed modal components are also different, while the components are independent and do not affect each other. Therefore, the fuzzy entropy of the modal components is used to reflect the frequency characteristics of each modal component and classify them. The larger the fuzzy entropy value of the modal components, the greater the complexity of the time series, and the classification of the modal components based

Table 1. Risk overflow table.

	Index 1	Index 2	Index 3	…	Index m	Intake
Index 1	$\tilde{\phi}_{11,t}$	$\tilde{\phi}_{12,t}$	$\tilde{\phi}_{13,t}$	…	$\tilde{\phi}_{1m,t}$	$C_{1,t}^{from}$
Index 2	$\tilde{\phi}_{21,t}$	$\tilde{\phi}_{22,t}$	$\tilde{\phi}_{23,t}$	…	$\tilde{\phi}_{2m,t}$	$C_{2,t}^{from}$
Index 3	$\tilde{\phi}_{31,t}$	$\tilde{\phi}_{32,t}$	$\tilde{\phi}_{33,t}$	…	$\tilde{\phi}_{3m,t}$	$C_{3,t}^{from}$
…	…	…	…	…	…	…
Index m	$\tilde{\phi}_{m1,t}$	$\tilde{\phi}_{m2,t}$	$\tilde{\phi}_{m3,t}$	…	$\tilde{\phi}_{mm,t}$	$C_{m,t}^{from}$
Output	$C_{1,t}^{to}$	$C_{2,t}^{to}$	$C_{3,t}^{to}$	…	$C_{m,t}^{to}$	
Net Spillover	$NET_{1,t}$	$NET_{2,t}$	$NET_{3,t}$	…	$NET_{m,t}$	$BARCS_t$

on the fuzzy entropy value can be divided into three categories:

1) Short-term IMF term: The short-term IMF term's component features are more frequent and volatile, resulting in a more complex short-term risk spillover index series with less reliable data.

2) Medium-term IMF term: The medium-term IMF term's features are less frequent and volatile than those of the short-term IMF term, but they may still show a definite regularity. These medium-term components make up the majority of the reliable data in the risk spillover index series.

3) Long-term IMF term: The long-term IMF term mainly contains the long-term periodicity and regularity of the risk premium index and primarily displays the long-term trend of the risk premium index, which is characterized by low-frequency amplitude fluctuations that are not small and are least complex.

3.3.2. Dimensionality Reduction and Reconstruction of Macro Impact Factors

The main content of the task presented in this subsection is the efficient information extraction of high-dimensional monthly macroeconomic variables and the reconstruction with the three IMF terms in 1.3.2 for mixing frequencies. The risk premium index is sensitive to the macroeconomic environment, and screening out the relevant monthly macroeconomic variables can improve the effectiveness of the model.

First, the high-dimensional monthly macroeconomic variables are subjected to permutation entropy calculation, and the variables with small permutation entropy values are removed to reduce the dimensionality of macroeconomic variables. Then, the processed macroeconomic variables in the Xgboost-Shap model are subjected to feature screening, using the size ranking of both contribution and Shap value to eliminate variables with a small correlation and obtain macroeconomic variables with a strong correlation with the risk spillover index. The dimensionality of macroeconomic variables is still high after elimination, so in order to improve the computational performance of the model, it is necessary to further reduce the dimensionality of macroeconomic variables by using factor analysis methods to extract macroeconomic factors that retain the most useful information.

Second, the macroeconomic factors are combined with the IMF terms with different characteristic frequencies in step 1. The frequencies of the extracted macroeconomic factors are monthly, but the short-term, medium-term, and long-term IMF terms are daily data. The GARCH-MIDAS model can handle mixed frequency data by transforming the monthly data into daily data through frequency pairing. The macro-short-term IMF term, macro-medium-term IMF term, and macro-long-term IMF term are obtained as macro-factor variables and input to the forecasting model.

3.3.3. Autoformer Model Prediction with Mixed Frequency Data

The task presented in this subsection is to input technical indicators and macro-factor variables as covariates and risk spillover indices as primary variables into the Autoformer model, and then to divide the input data into a training set, a validation set, and a test set. The training set is used to train the model, the validation set is used to find the optimal parameters, and the test set is used to verify the model training results. Second, the Autoformer model gradually separates the trend and period terms of the input sequences based on the deep decomposition architecture and uses the autocorrelation mechanism to solve the problem of being able to solve the complexity of temporal patterns in long sequences, making it possible to calculate excellent prediction results in long-term prediction. Finally, different prediction lengths are set for error comparison with other models, and the error evaluation index is used to evaluate the final effect of the summary prediction model.

The actual flow chart of the TVP-VAR-Autoformer model is in Figure 1.

4. Empirical Analysis

4.1. Data Selection and Processing

In this paper, the daily returns of CSI One Belt & One Road lndex (399991), CSI SWS One Belt and One Road lndex (930620), SSE One Belt & One Road Index (000160), and CSI SOE Belt and Road Index (000859) indexes are selected as the Belt and Road concept index samples. The data source is RISE database, which covers a wide range of financial data. The "Belt and Road" had a major breakthrough after 2015, so the trading days between 2015/11/2-2022/9/30 were selected and supplemented by interpolation. Technical indicators must also be included as covariates. A total of eight indicators, including the daily closing index and the daily gain/loss of each index, are chosen in this case. The trend of each index is shown is Figure 2.

The daily return trends of the four sample indices are plotted and analyzed for the sample period. First, the daily returns of the indices selected for the study sample all experienced significant volatility from the end of 2015 to the first half of 2016, which can be attributed to the introduction of programs such as "Belt and Road" planning and construction and the official establishment of the Asian

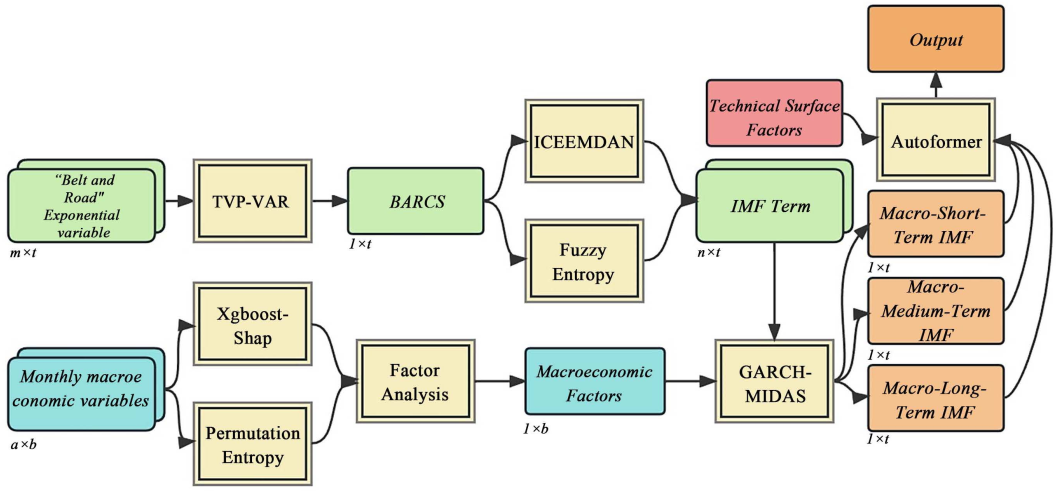

Figure 1. Model logic diagram.

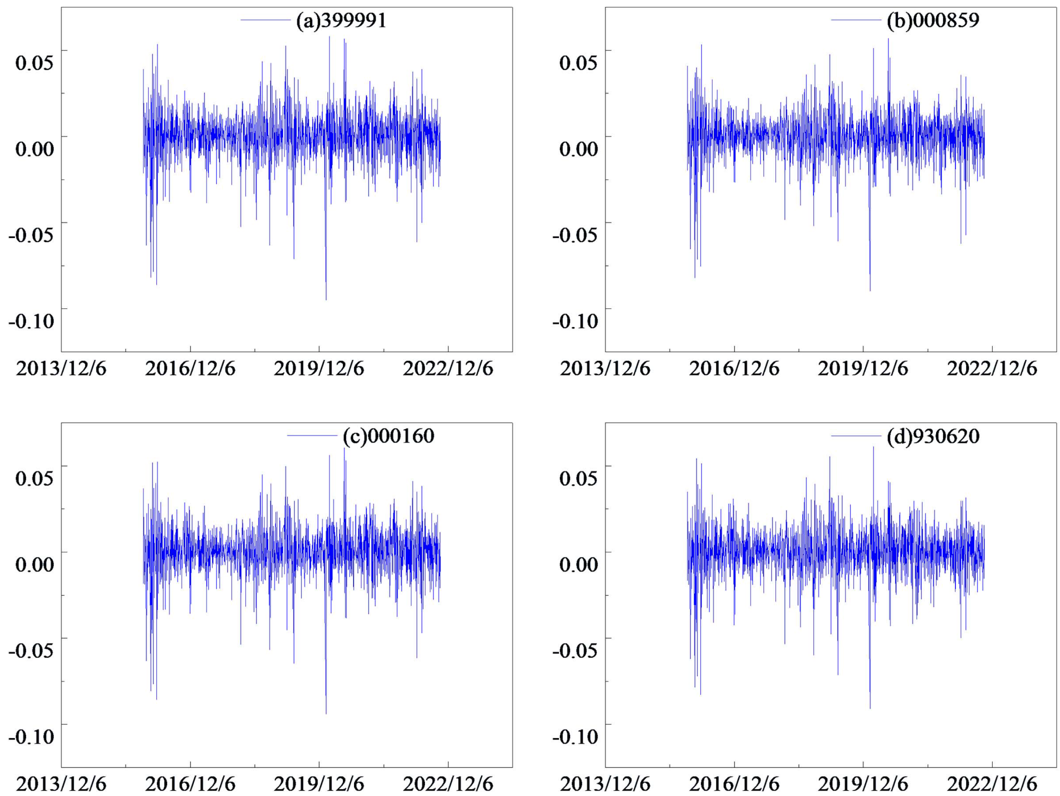

Figure 2. Trend chart of daily yield of four indexes.

Infrastructure Investment Bank, as well as domestic interest rate reduction policies, "deleveraging," and large financial capital inflows into domestic financial markets. Events such as "deleveraging" and large financial capital inflows have stimulated the growth of systemic risk in the "Belt and Road" index. Second, from the end of 2017 to the beginning of 2019, the daily yields of the indexes did not experience less volatility, and then the systemic risk to be borne had to increase accordingly. The reason is that in 2018, more than 60 countries participated in the Belt and Road Initiative, and the first International Import Expo was held in that year, which promoted China's further opening to the world market, and more foreign capital flowed into the domestic investment market, which increased the systemic risk. Third, from the beginning of 2020 to the beginning of 2022, the daily return of each index was subjected to a more severe shock in the beginning of 2020, although the daily return of each index had a brief counter-trend to rebound, but then the daily return fell and the fluctuation range gradually narrowed, and the daily return of each index began to stabilize at the end of 2021. Fourth, the fluctuations in the daily returns of the four data differ very little, which suggests that the four indices are exposed to similar systemic risk intensity. The smallest magnitude is found in the 000859 index, which suggests that SOEs are more resilient to systemic risk.

4.2. "Belt and Road" Index Risk Spillover Model

4.2.1. Statistical Descriptive Analysis

As can be seen from **Table 2**, first, the fluctuations of the four data daily returns do not differ much, and the smallest fluctuation range is the 000859 index, which indicates that the four indices face similar systematic risk intensity. The "Belt and Road" index risk calculated by the four indices can represent the systemic risk faced by the "Belt and Road" industry sector, which is represented by the four indices. Second, the mean values of the four sample indices are negative, the mean value of the 930620 index is negative, and the absolute and maximum values of the mean values are the largest, while the mean values of the other three indices are positive, indicating that the 930620 index is likely to face the greatest risk compared to the other three indices, and at the same time, the return can be greater. Thirdly, the skewness of the four index indicators is less than 0, indicating that the four return distributions are left-skewed, and the kurtosis is greater than 3, showing a peak that is steeper than the normal distribution and more susceptible to extreme risk, indicating that the "Belt and Road" Index is prone to extreme fluctuations in risk fluctuations.

The TVP-VAR model was used to calculate the risk of the Belt and Road Index and to analyze the overall time-varying trend of the Belt and Road industry sector:

As shown in **Figure 3**, the risk value of the Belt and Road concept index fluctuates between 65 and 75 from the end of 2016 to September 2022. There are significant increases and decreases in the risk of the Belt and Road concept index at the end of 2015, 2017, 2019, and around November 2021. At the end of 2015 and until the first half of 2016, the introduction of the "Belt and Road" implementation plan, the establishment of the ADB, the domestic interest rate reduction policy, deleveraging and a large amount of financial capital into the domestic financial market caused the "Belt and Road" concept index The risk of rapid increase. From 2016 to the end of 2017, due to the continuous expansion of the three transportation routes of the "Belt and Road" by sea, land and air, the "Belt and Road" land steadily advanced, the "Belt and Road" index risk gradually declined.

Table 2. Descriptive statistical table of index.

Index code	399991	000859	000160	930620
samples	1687	1687	1687	1687
Range of fluctuations	0.1529	0.1464	0.1544	0.1520
minimum	−0.0949	−0.0896	−0.0940	−0.0909
maximum	0.0580	0.0568	0.0604	0.0611
Mean	0.000021	0.000018	0.000005	−0.000148
standard deviation	0.0139875	0.0130398	0.0137124	0.0136634
Skewness	−0.872	−0.894	−0.797	−0.806
kurtosis	5.674	5.856	5.658	5.210

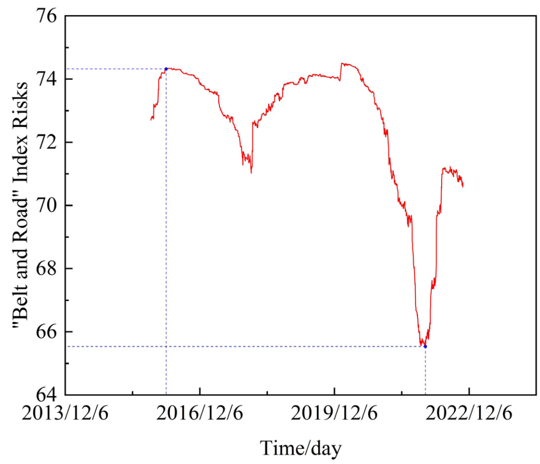

Figure 3. "The Belt and Road" Index Risk Map.

"From the end of 2017 to the end of 2019, the "Belt and Road" entered a period of rapid development, more than 60 countries joined the "Belt and Road" in 2018, and the first International Import Expo was successfully held. In early 2020, the outbreak of the new crown epidemic affected the entire domestic financial market. The risk of the "Belt and Road" index increased rapidly and reached a peak. After the domestic stabilization, the epidemic is rapidly spreading abroad, domestic production is resuming, and the global economy is recovering through the "Belt and Road" route. The risk of the "Belt and Road" concept index is also decreasing. At the end of 2021, China formally applied to join the Digital Economy Partnership Agreement, and the Regional Comprehensive Economic Partnership Agreement (RCEP) officially came into force on January 1, 2022, so the "Belt and Road" industrial sector is attracting a lot of attention. The "Belt and Road" concept index risk is rapidly increasing. It can be seen that the impact of international and domestic events on the "Belt and Road" industrial sector will make the "Belt and Road" concept index risk exposure to the systemic risk spillover both positive and negative.

4.2.2. Decomposition and Reconstruction of the "Belt and Road" Concept Index Risk

Using ICEEMDAN, the standardized "Belt and Road" concept index risk series is decomposed, and a total of eight IMF modal components is produced, of which IMF8 is the residual term. Based on the fuzzy entropy value and ICEEMDAN decomposition diagram to classify the IMF components, the fuzzy entropy values of IMF1 to IMF4 are larger than 0.006, which can be classified as short-term IMF terms, the complexity of this class of IMF components is higher, the fluctuations are large, and the periodicity is smaller. The decomposition diagram is shown in **Figure 4**.

Based on the fuzzy entropy value and the ICEEMDAN decomposition diagram for classifying the IMF components, IMF1 to IMF4 fuzzy entropy values are all greater than 0.006, which can be classified as short-run IMF terms, and the IMF components of this class have higher complexity, large fluctuations, and less periodicity. IMF5–IMF7 are all less than 0.006 and greater than 0.001, which can be classified as mid-term IMF conditions. The IMF components of this class clearly show regularity, and these mid-term components contain most of the valid information. IMF8 has the lowest complexity and mainly contains the long-term trend results of the risk spillover index. **Table 3** shows the detailed IMF classification.

4.3. Extraction of High-Dimensional Macroeconomic Variables

The monthly macroeconomic variables associated with the risk of the "Belt and Road" concept index are screened using the alignment entropy algorithm and the Xgboost-Shap model. Here, 47 monthly macroeconomic variables are selected from the China Macroeconomic Database and the China Financial Database with the time interval of 2015/11/2-2022/9/30, and the data source is the EPS database.

The ranking entropy parameter takes the value: the embedding dimension is 7 and the time delay is 1. Based on the ranking entropy results, variables with a ranking entropy value of 0 are removed. The remaining macroeconomic variables and the "Belt and Road" concept index risk are input into the Xgboost-Shap model, and the parameters are tuned to obtain the characteristic contributions. Then, using the average of the absolute value of the shap value of each macroeconomic variable characteristic as the importance of that characteristic. The bar graph plotting of the contribution of macroeconomic variables based on SHAP values is shown in **Figure 5**.

Macroeconomic variables with small shap values were further removed, and the final screened macroeconomic variables were. The filtered macroeconomic variables are downscaled using factor analysis to obtain five macroeconomic factors, and then the total macroeconomic factors are further calculated using the rotated contribution rates as weights. After processing, the total macroeconomic factors are still monthly data, but the risk of the "Belt and Road" concept index is daily data, so the GARCH-MIDAS model is used here to process the

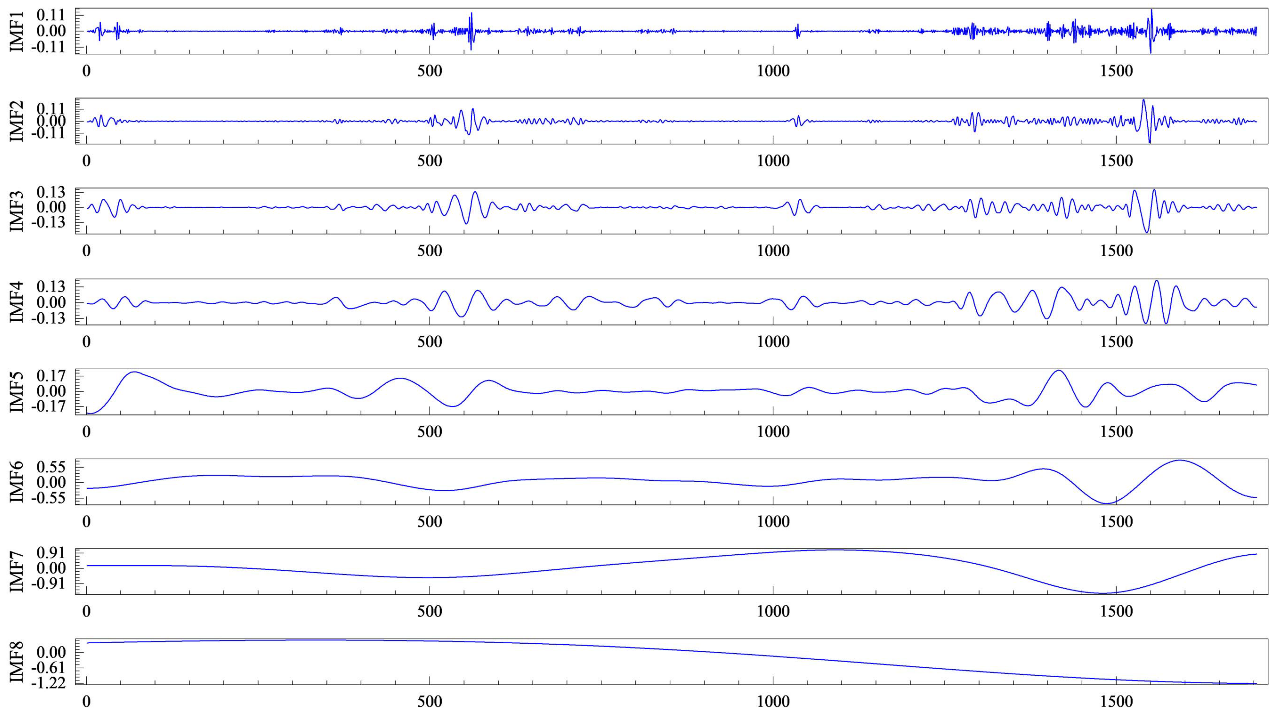

Figure 4. ICEEMDAN exploded view.

Table 3. IMF term fuzzy entropy table.

IMF	IMF1	IMF2	IMF3	IMF4
Fuzzy entropy	0.00818	0.01031	0.01176	0.00987
Reconstruction results		Short		
IMF	IMF5	IMF6	IMF7	IMF8
Fuzzy entropy	0.00563	0.0045	0.00228	0.00032
Reconstruction results		Mid		Long

mixed-frequency data. The total macroeconomic factor is combined with the decomposed short-term IMF term, medium-term IMF term, and long-term IMF term, and at this time, in order to make the model results more accurate, the parameter K value is taken as 1, the November 2015 forecast value is not considered, and the macro-short-term IMF term, macro-mid-term IMF term, and macro-long-term IMF term are predicted, and then further combined with the technical indicators for the next forecast.

4.4. Prediction and Analysis of the Autoformer Model

The predicted macro-short-term IMF term, macro-medium-term IMF term, macro-long-term IMF term, daily closing index and daily range of each index as the main variable of the Belt and Road concept index risk and covariates are inputted into the Autoformer model. In the modeling process, the data is split into training set, validation set and test set in the ratio of 8:1:2. The parameters are set as itr = 1, epochs = 10, batch = 32, learning rate = 0.0001, and activation

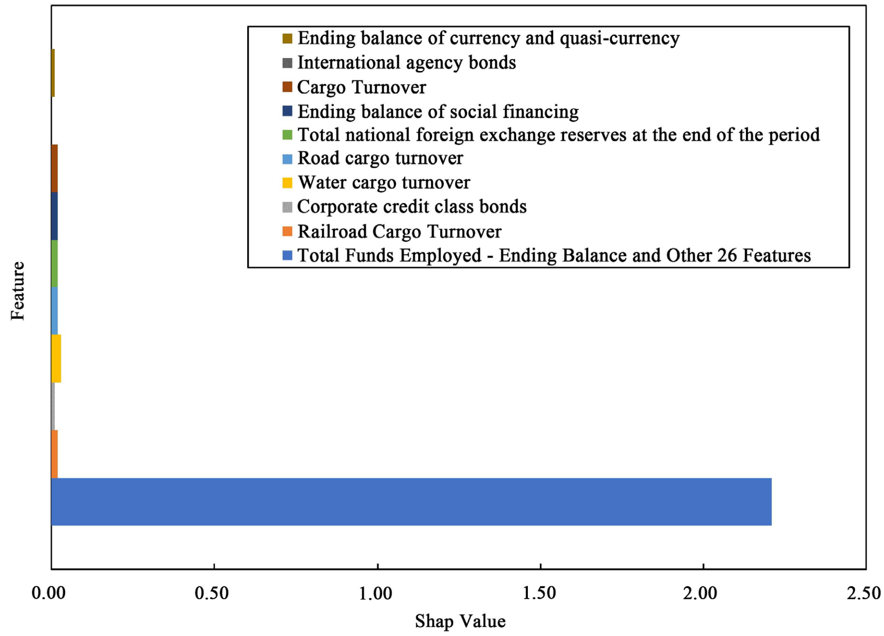

Figure 5. Shap contribution diagram.

function is gelu. The prediction error metrics are selected as, Root Mean Square Error (16), Mean Absolute Error (17), Mean Squared Percentage Error (18), and Mean Squared Error (19) were selected for judgment, and the smaller the value of the four error indicators, the better the model prediction result,

$$\mathrm{RMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\widehat{x_i}-x_i\right)^2}, \tag{16}$$

$$\mathrm{MAE}=\frac{1}{n}\sum_{i=1}^{n}\left|\widehat{x_i}-x_i\right|, \tag{17}$$

$$\mathrm{MAPE}=\frac{1}{n}\sum_{i=1}^{n}\left(\frac{x_i-\widehat{x_i}}{x_i}\right)^2, \tag{18}$$

$$\mathrm{MSE}=\frac{1}{n}\sum_{i=1}^{n}\left(\widehat{x_i}-x_i\right)^2. \tag{19}$$

In order to verify the superiority of this paper's model, a comparative model experiment is considered to test the difference between this paper's model and other benchmark models. The selection of the benchmark model is mainly divided into two types of models, one part of which considers the Transformer class of models, e.g., Transformer, Informer, Reformer. The other part is the forecasting model after reconstruction with macroeconomic factors. In addition, the model errors of different forecast lengths are further compared to test the performance of the model for long-term forecasting, and the forecast lengths are selected as 12, 24, 48, and 96.

Here we select the prediction results with a prediction length of 96 (Table 4) for comparison, thanks to the advantages of the Autoformer model's own

Table 4. Model comparison results for predicted length 96.

Model	Index			
	MSE	MAE	RMSE	MSPE
Transformer	9.4961	4.7481	10.1567	1.6681
Informer	6.1651	3.0826	8.1556	1.4161
Reformer	7.1561	3.5781	6.1561	1.5492
ICEEMDAN-Xgboost-Transformer	8.1569	4.5785	11.1652	1.9634
ICEEMDAN-Xgboost-Informer	7.1525	5.0781	7.1561	1.9261
ICEEMDAN-Xgboost-Reformer	5.1224	6.0608	9.1647	1.4428
ICEEMDAN-Xgboost-Autoformer	**0.2792**	**0.1390**	**1.1568**	**0.1118**

structure, the four error results obtained by the model proposed in this paper are the smallest compared with other models, and the largest error is obtained by the Transformer. Then, the prediction model reconstructed with the addition of the macroeconomic factors is compared with that without reconstruction, and the MSE, MAE, and MSPE errors of the model reconstructed with the addition of macroeconomic factors are smaller. The MSE, MAE, and MSPE errors of the reconstructed model with macroeconomic factors are all smaller. However, after adding macroeconomic factors to Informer and Reformer, their errors also become larger. It shows that the Informer and Reformer are not improved after adding macroeconomic factors and then decomposing and reorganizing them in the long-term forecasting. However, for the ICEEMDAN-Xgboost-Autoformer model, there is a clear advantage in all comparisons. In terms of long-term forecasting, the ICEEMDAN-Xgboost-Autoformer model has better stability and robustness and can be combined with macroeconomic factors to improve the forecasting accuracy, which is able to predict the long-term changes in the risk of the Belt and Road concept index.

4.5. Ablation Experiments

In order to verify the influence of each module on the model results, the experiments are divided into three groups for comparison by adding modules step by step: Autoformer, ICEEMDAN-Autoformer, and ICEEMDAN-Xgboost-Autoformer. The Autoformer is the single model without adding any modules, while the ICEEMDAN and Autoformer are the model that decomposes and reorganizes the samples without adding macroeconomic factors. The comparison results are shown in **Table 5**. The ablation experiments demonstrate that adding the ICEEMDAN module improves the error accuracy of MSE, MAE, and MSPE. Furthermore, adding macroeconomic factors further improves the error accuracy of RMSE.

4.6. Comparison of Different Forecast Lengths

As can be seen from the **Table 6**, the errors of Transformer, Informer,

Table 5. Comparative results of ablation experimental models.

Model	Index	Error
Autoformer	MSE	5.7792
	MAE	1.6213
	RMSE	3.4503
	MSPE	1.7321
ICEEMDAN-Autoformer	MSE	1.7931
	MAE	1.3962
	RMSE	2.4277
	MSPE	1.4324
ICEEMDAN-Xgboost-Autoformer	MSE	**0.2792**
	MAE	**0.1390**
	RMSE	**1.1568**
	MSPE	**0.1118**

Table 6. Comparative results for different prediction lengths.

Model	Index	Long			
		12	24	48	96
Transformer	MSE	4.4984	7.1566	8.1651	9.4961
	MAE	2.2492	3.5783	4.0826	4.7481
	RMSE	3.4986	5.1562	6.4896	10.1567
	MSPE	0.249	0.4892	0.8126	1.2681
Informer	MSE	2.4961	2.6891	5.4891	6.1651
	MAE	1.2481	1.3446	2.7446	3.0826
	RMSE	1.7864	2.7985	4.1966	8.1556
	MSPE	0.1898	0.1916	0.2489	0.4161
Reformer	MSE	2.1415	3.4156	5.4165	7.1561
	MAE	1.0708	1.7078	2.7083	3.5781
	RMSE	2.7891	2.9816	5.1695	6.1561
	MSPE	0.2417	0.3465	0.4977	0.5492
ICEEMDAN-Xgboost-Transformer	MSE	6.3489	9.1562	10.419	13.1569
	MAE	3.1745	4.5781	5.2095	6.5785
	RMSE	5.4961	7.1566	10.1516	11.1652
	MSPE	0.549	0.7892	1.518	1.9634
ICEEMDAN-Xgboost-Informer	MSE	4.4156	5.1596	7.9196	10.1561
	MAE	2.2078	2.5798	3.9598	5.0781
	RMSE	2.5498	2.8161	6.1561	7.1561
	MSPE	0.2916	0.4894	0.5713	0.9261

Continued

ICEEMDAN-Xgboost-Reformer	MSE	3.1651	5.4196	9.1652	12.1216
	MAE	1.5826	2.7098	4.5826	6.0608
	RMSE	4.1296	7.1682	7.6316	9.1647
	MSPE	0.3728	0.5741	0.9119	1.4428
ICEEMDAN-Xgboost-Autoformer	MSE	1.2498	2.4695	1.5685	**0.2792**
	MAE	0.6249	1.2348	0.7843	**0.1390**
	RMSE	0.4753	0.9278	1.5586	**1.1568**
	MSPE	1.8987	0.641	0.936	**0.1118**

ICEEMDAN-Xgboost-Transformer, ICEEMDAN-Xgboost-Informer, and ICEEMDAN-Xgboost-Reformer models under different prediction lengths are gradually getting larger. This indicates that as the prediction length increases, the prediction ability of the model is gradually weakened. The error of ICEEMDAN-Xgboost-Autoformer model under different prediction lengths shows up and down fluctuation, although the error increases with the increase of prediction length, the overall error is still kept in an acceptable smaller range.

5. Conclusion

With the deepening cooperation between China and other Belt and Road countries, the interaction between the domestic economy and foreign Belt and Road construction has increased. Therefore, it is important to consider economic stability from the perspective of systemic risk spillover, both theoretically and practically. Based on the results of the empirical analysis, the following conclusions can be drawn:

1) The error of the autoformer model with the addition of the decomposed and reconstructed macroeconomic factors is smaller than that of the autoformer model without the addition, which indicates that the macroinformation has a significant impact on the error of the risk prediction model. In addition, the macro characteristics filtered by the Xgboost-shape model and alignment entropy are more correlated with the risk of the "Belt and Road" index.

2) Low-frequency macroeconomic variables are used as confounding covariates of the high-frequency risk of the Belt and Road Index. The GARCH-MIDAS model reconstructs the macroeconomic factors and the risk decomposition term of the "One Belt, One Road" index to maximize the retention of the original information of the macroeconomic variables and regresses them with the IMF term of the "One Belt, One Road" index risk, which makes the macroeconomic information more suitable for predicting the long-term risk and improves the accuracy of the model.

3) The autoformer model is smaller than other transformer models in terms of prediction error. In the comparison experiments of predicting long-term risk, it is obvious that the error of the Autoformer model increases with the growth of length, but the increase is smaller and the overall error remains in a smaller range,

indicating that the Autoformer model has good reliability in predicting long-term risk.

Finally, we believe that in order to effectively prevent the financial risk of the Belt and Road Index, the regulator should not only pay attention to the volatility and risk spillover of the Belt and Road Index but also consider the changes in related macroeconomic indicators to facilitate the study of "the correlation between the Belt and Road financial risk index and macroeconomic indicators". In addition, the impact of the Belt and Road concept risk index on the industries represented by the Belt and Road concept index should be considered. This includes various industries such as energy, transportation, agriculture, finance, etc. Then, regulators need to consider the actual development status, risk tolerance, and risk transfer capacity of industries related to the Belt and Road construction and formulate different anti-risk policies for different industries to achieve the sustainable and healthy development of the national economy.

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Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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