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Modeling the Real-Time Transmission Effects of Economic Policies on Market Liquidity under a Time Series Analysis Framework

Xiaotong Liang[1,*]
[1] China National Gold Group Asset Management Corporation, Beijing, 100010, China
Corresponding authors: (e-mail: DL36359999@126.com).

Abstract Changes in market liquidity are of significant reference value to investors. This paper uses matrix processing of historical financial data to achieve a high-dimensional representation of time series. Combining the preprocessed data, a time convolution-Bayesian neural network (TCN-BNN) model is constructed to process financial time series data. Furthermore, through ensemble empirical mode decomposition (EEMD) and an improved multidimensional k-nearest neighbor (MKNN) algorithm, the financial market situation under changes in economic policy is predicted. The study shows that in the constructed financial time series model, with a time unit of 1 year, the autocorrelation range between financial markets and economic policies is -0.31 to 0.17, and the partial autocorrelation range is -0.23 to 0.18, indicating a high degree of correlation. The uncertainty of economic policies leads to significant fluctuations in financial markets during the 5th to 10th lag periods and time-varying periods.

Index Terms financial market liquidity, time series analysis, TCN-BNN, EEMD-MKNN, economic policy

I. Introduction

Liquidity is the foundation for the healthy and stable development of financial markets and serves as one of the key indicators for assessing market quality. Additionally, liquidity across different markets and tiers is mutually influential [1], [2]. Liquidity can span multiple dimensions—across markets, across time, or across assets. Therefore, when market liquidity experiences significant fluctuations or severe imbalances, such fluctuations or imbalances can spread across markets or tiers through liquidity linkage mechanisms, creating a liquidity cycle. In severe cases, this can further trigger a financial crisis [3]-[6]. Liquidity plays a crucial role in financial market stability. The 2007-2009 financial crisis was an unprecedented liquidity crisis, ultimately leading to a complete drying up of market liquidity and the outbreak of the crisis [7], [8]. Currently, due to the incomplete development of financial markets, policy changes can significantly impact market participants' expectations and investment behavior, thereby affecting liquidity across various financial submarkets. The interconnectivity of liquidity across these submarkets further amplifies such impacts, increasing systemic financial risks and potentially causing market turmoil or triggering a financial crisis [9]-[12].

As financial markets continue to develop, economic policies are needed to control and adjust them, especially given the rapid development of the financial economy. Policies must improve, supervise, and perfect the financial markets from two aspects: monetary policy and fiscal policy. Only under the influence of macroeconomic policies can financial markets meet the development needs of the market [13]-[15]. In China, since 2012, with the slowing of GDP growth, the economy has entered a phase of overlapping three stages. With the initial success of structural reforms in the economic sector and the transition of financial market “deleveraging” to “stable leverage,” the financial cycle appears to be gradually approaching its bottom, with signs of recovery emerging [16]-[18]. However, due to significant changes in the monetary policy environment under the new normal and in the reformed financial markets, the objective difficulty of formulating economic policies has increased [19]. Starting in 2016, the People's Bank of China signaled a policy orientation toward financial deleveraging, and financial market liquidity gradually shifted toward tightening alongside a series of stringent financial regulatory measures [20], [21]. Since 2018, the central bank has implemented six rounds of reserve requirement ratio cuts, injecting a certain amount of liquidity into the market. Speculation about reopening the floodgates to support the economy has intensified, leading to significant divergence among economists in their assessments of future financial policy [22], [23]. These changes in policy direction and measures, while adjusting economic development, have also brought uncertainty shocks to financial markets. The impact of these shocks on various financial submarkets and intermarket liquidity is closely related to the prevention of systemic financial risks [24], [25]. Therefore, at the current stage, studying how economic policies affect intermarket liquidity holds important practical significance for preventing systemic financial risks and maintaining financial market stability.

Literature [26] analyzes the relationship between return volatility and liquidity volatility, finding that their spillover effects have increased post-financial crisis. Literature [27] confirms that national financial market liquidity is significantly positively influenced by financial openness, GDP, inflation rate, market value, the ratio of foreign exchange assets to GDP, and the ratio of foreign direct investment to GDP. Literature [28] demonstrates that during the implementation of the central bank's large-scale asset purchase mechanism (quantitative easing policy), market liquidity premiums were lower than expected, indicating that the policy is conducive to enhancing market liquidity. Literature [29] reviews that, from a macroeconomic perspective, monetary policy plays a key role in stock market liquidity in emerging market economies, and this role varies across different time periods. Literature [30] uses high-frequency data to explore the impact of monetary policy announcements on liquidity in the gold and silver markets. Liquidity disappears directly within the first 5 minutes before the announcement and recovers within 10–20 minutes afterward. Literature [31] employs a panel threshold method model to investigate the relationship between economic policy uncertainty and stock market liquidity, finding that stock market liquidity decreases as policy uncertainty increases. Literature [32] points out that under unexpected changes in tight monetary policy, stock returns in the stock market exhibit a negative response, while unexpected changes in expansionary monetary policy lead to a positive response in stock returns, primarily through their impact on entities facing financial and liquidity constraints. Literature [33] analyzes the Nigerian foreign exchange market, finding that exchange rates influence foreign exchange market liquidity, and calls for the formulation of relevant exchange rate policies to enhance foreign exchange market liquidity. Literature [34] uses autoregressive distributed lag techniques to analyze the impact of macroeconomic policies on liquidity in the Nigerian stock market, finding that the dual effects of fiscal and monetary policies have a long-term relationship with stock market trading ratios. Time series analysis demonstrates that economic policies have a high degree of adaptability to financial market liquidity.

This paper introduces the theory of financial friction into macroeconomic research to analyze the impact of economic policy uncertainty on investors' willingness to invest in financial markets. Historical time series data from financial markets are represented using high-dimensional tensor representations, and a Time Convolution-Bayesian Neural Network (TCN-BNN) model is constructed to predict the direction of financial data. The improved multi-dimensional mode vector K-nearest neighbor algorithm (EEMD-MKNN) is introduced, considering the similarity of time series data trends to enhance the accuracy of financial market liquidity predictions. The stock market is used as a representative of financial markets, and empirical research and analysis are conducted to test the practical effectiveness of the proposed method.

II. Time series-based financial market analysis techniques

II. A. Theoretical Basis Analysis

II. A. 1) Financial Friction Theory

Incorporating financial friction theory into macroeconomic models to study macroeconomic fluctuations. Financial friction manifests in two ways: first, constraints on borrowers' balance sheets. When borrowers seek financing, creditors typically require collateral or guarantees to mitigate risk. However, any loss in the value of collateral or guarantees will significantly impact a firm's ability to secure financing. In situations of rising economic policy uncertainty, the probability of firms being required to provide collateral or guarantees when seeking external financing increases, potentially leading to a contraction in their balance sheets. This can reduce the value of collateral, thereby delaying investment. The second manifestation is constraints on banks' balance sheets. As the primary creditors, banks face deteriorating firm balance sheets, leading them to adopt a more cautious approach to lending. When economic policy uncertainty rises and bank loans are an important source of investment funds for businesses, this increases the cost of investment or reduces the scale of investment. Therefore, the financial friction theory is considered the primary theoretical basis for how economic policy uncertainty affects business investment.

II. A. 2) Theory of Information Asymmetry

The theory of information asymmetry has become one of the key theoretical frameworks for studying market failures and related areas. It posits that in market economic activities, economic entities cannot fully possess equivalent information. This asymmetry can lead to those with information advantages seeking greater benefits, thereby causing losses for those with information disadvantages. Information asymmetry may occur before or after the signing of a contract. In reality, due to the higher degree of information asymmetry and its significant impact, the efficiency of resource allocation through market mechanisms is affected. This results in the party with information advantages obtaining more surplus in transactions compared to other parties lacking such advantages, leading to an imbalance in interest distribution due to significant information disparities, particularly in corporate investment and financing. Therefore, it is argued that under conditions of rising economic policy uncertainty, the existence of information asymmetry affects the strength of corporate financing constraints, thereby influencing corporate financialization investments.

II. A. 3) Preventive savings theory

The precautionary savings theory posits that, given consumers' risk-averse nature, they will save to mitigate potential financial risks. The life cycle theory suggests that people save to maintain their standard of living after retirement. However, another important motivation is to prepare for potential future income declines. The precautionary savings theory argues that, in the face of increased income uncertainty, consumers will base their consumption on current income. Simultaneously, as uncertainty and risk increase, precautionary savings will also increase. From a corporate perspective, the precautionary savings theory refers to the practice of investing idle funds into assets with stable income when facing greater future risks. When economic policy uncertainty rises and future cash flows become unstable, companies increase holdings of liquid, low-risk, and relatively stable assets to prevent liquidity shortages.

II. B. Time series construction based on TCN-BNN

II. B. 1) Analysis of the financial time series forecasting process

Financial time series forecasting refers to the use of historical financial data for analysis and modeling to predict future trends in financial data. Financial time series forecasting is an important tool for financial analysis and investment decision-making, as it helps investors assess investment risks and returns and develop more reasonable investment strategies. To facilitate the discussion of the issue, we first provide the following necessary definitions. Time series TS (TS is a series of data points or observations arranged in chronological order. A time series can be represented as $TS=\{vt_1, vt_2, \dots, vt_i, vt_{i+1}, \dots, vt_n\}$).

where vt_i denotes the data value corresponding to the time attribute of the time series at time i. We refer to this time point as a time series point. In our experiments, the dataset is represented in the form of a time series, where vt_i denotes the closing price (CP) at time t, and n denotes the time span of the time series. For time-series data or online systems, n can be represented as an infinite number. Therefore, our objective is to determine the value of vt_{i+1} at time $t+1$ using the historical data $\{vt_1, vt_2, \dots, vt_i\}$.

Figure 1 shows the TCN-BNN network structure:

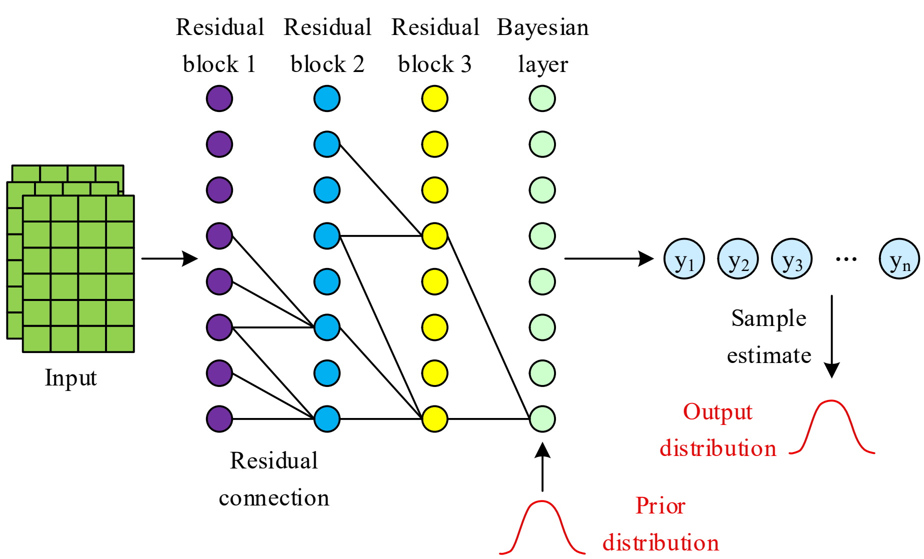


Figure 1: TCN-BNN arctechlure

The structure proposed in this paper is based on time convolution networks and Bayesian neural networks, aiming to combine the training speed advantages and accuracy of TCNs with the strong generalization performance of Bayesian neural networks. The output results are probability distributions containing uncertainty, enriching the form and content of the output and providing reference value for subsequent research.

II. B. 2) Processing financial time series data sets

Financial time series data is typically represented as a two-dimensional matrix, where each row represents a point in time and each column represents a feature. For example, stock price time series data can be represented as daily stock prices as features, with each trading day as a row. However, due to the rapid development of modern detection technology and computing power, in time series analysis, we often need to consider data from multiple time steps, such as data from the past few hours, days, weeks, or months. Therefore, to account for these different time steps, we need to represent time series data as a high-dimensional tensor, where each dimension represents a time step. This results in time series data exhibiting high dimensionality.

The dataset used in this paper was first crawled from the Y Finance website for the OHLC data of the studied stocks, and then multiple technical indicators were calculated using existing technical indicator calculation methods to generate technical indicator time series for financial analysis and prediction. These indicators, based on historical price and volume data, can help investors identify market trends caused by economic policies, assess price movements, quantify risks, and develop trading strategies.

Exponential Moving Average (EMA), Moving Average Convergence Divergence (MACD), and Bollinger Bands (BBAND) are common technical indicators for financial time series. EMA helps identify price trends, where the fast line is the short-term EMA minus the long-term EMA, and the slow line is the moving average of the fast line. The MACD column represents the difference between the fast line and the slow line, used to display price changes and trend conditions. Bollinger Bands utilize moving averages and the standard deviation of prices to display the range of price fluctuations. When prices approach the upper band, it indicates the market may be overbought; when prices approach the lower band, it indicates the market may be oversold. Bollinger Bands can also be used to identify price trends and volatility. Through preprocessing, the input dataset is transformed from a 5286×4 two-dimensional matrix to a 5286×10 two-dimensional matrix. The input dataset is constructed using a sliding window approach, with the moving window spanning 28 trading days.

II. C.EEMD-MKNN liquidity prediction method

The KNN algorithm is often used to predict stock indices. The original KNN method only uses the nearest values to predict future values, ignoring the similarity of trend changes. The improved KNN method, which introduces pattern vectors, takes this into account and improves prediction accuracy. Based on this, the multi-dimensional pattern vector K nearest neighbor algorithm (MKNN) is proposed.

The following shows a simple example of a two-dimensional MKNN model. Consider two time series $\{X = x_1, x_2, \ldots, x_n\}$ and $\{Y = y_1, y_2, \ldots, y_n\}$, where n is the number of sample points in the sequence, and x_n and y_n represent the current state. First, we find the nearest neighbor values for the current states x_n and y_n. Then, based on these nearest neighbors, we predict x_{n+1} and y_{n+1}. Taking these two time series $\{X = x_1, x_2, \ldots, x_n\}$ and $\{Y = y_1, y_2, \ldots, y_n\}$ as examples, the definition of the sequence difference matrix is:

$$Q = \begin{pmatrix} q_{n-l}^x & q_{n-l+1}^x & \cdots & q_n^x \\ q_{n-l}^y & q_{n-l+1}^y & \cdots & q_n^y \end{pmatrix} \tag{1}$$

where $l\left(1 \le l \le n-1\right)$ is the pattern scale, $q_i^x = x_{i+1} - x_i$, $n-l \le i \le n-1.0$, $q_j^y = y_{j+1} - y_j$, $n-l \le j \le n-1.0$. These differences are mapped to three-valued variables to define the direction of change:

$$d_i = \begin{cases} -1.0, & q_i < 0 \\ 0.0, & q_i = 0 \\ 1.0, & q_i > 0 \end{cases} \tag{2}$$

The pattern matrix of the current state of the time series can be represented as:

$$P_d = \begin{pmatrix} d_{n-l}^x & \cdots & d_n^x \\ d_{n-l}^y & \cdots & d_n^y \end{pmatrix} \tag{3}$$

Assumption:

$$\begin{aligned} X &= \left(x_{n-4}, x_{n-3}, x_{n-2}, x_{n-1}, x_n\right) = \left(10, 8, 6, 4, 2\right) \\ Y &= \left(y_{n-4}, y_{n-3}, y_{n-2}, y_{n-1}, y_n\right) = \left(9, 7, 5, 3, 1\right) \end{aligned} \tag{4}$$

For two current state vectors, their pattern scale is $l = 4.0$. The pattern matrix is:

$$P_d = \begin{pmatrix} -1.0 & 1.0 & -1.0 & 0.0 \\ -1.0 & 1.0 & 0.0 & -1.0 \end{pmatrix} \tag{5}$$

The steps of MKNN are as follows:

1) Select the minimum number of nearest neighbors k;

2) Select the minimum pattern scale l;

3) Form the pattern matrix $P_d = \begin{pmatrix} d_{n-l}^x & \cdots & d_n^x \\ d_{n-l}^y & \cdots & d_n^y \end{pmatrix}$ of the current state of the time series;

4) Search for the state closest to the current state in matrix $\begin{pmatrix} d_1^x & \cdots & d_n^x \\ d_1^y & \cdots & d_n^y \end{pmatrix}$ (calculated using Euclidean distance), sort the calculation results in ascending order, select the first k states, assign a label j to each state, set the pattern matrix to $P_d' = \begin{pmatrix} d_{j-l}^x & \cdots & d_j^x \\ d_{j-l}^y & \cdots & d_j^y \end{pmatrix}$, set the difference matrix of P_d' to $Q_{d'} = \begin{pmatrix} q_{j-l}^x & \cdots & q_{j-1}^x \\ q_{j-l}^y & \cdots & q_{j-1}^y \end{pmatrix}$, and record the next differences of the h th matching difference vector as $\hat{Q}_j^h$ and $\tilde{Q}_j^h$.

5) Calculate the final difference estimates $\hat{x}_{n+1}$ and $\hat{y}_{n+1}$ based on all nearest neighbors;

$$\begin{aligned} \hat{x}_{n+1} &= x_n + \hat{Q}_m \\ \hat{Q}_m &= \sum_{h=1}^{k} \frac{\hat{Q}_j^h}{k} \\ \hat{y}_{n+1} &= y_n + \tilde{Q}_m \\ \tilde{Q}_m &= \sum_{h=1}^{k} \frac{\tilde{Q}_j^h}{k} \end{aligned} \tag{6}$$

6) Calculate the root mean square error (RMSE) between the actual values and the predicted values based on the selected k and l values.

$$\begin{aligned} RMSE_x &= \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left[x(i)-\hat{x}(i)\right]^2} \\ RMSE_y &= \sqrt{\frac{1}{N}\sum_{j=1}^{N}\left[y(j)-\hat{y}(j)\right]^2} \end{aligned} \tag{7}$$

7) Set the pattern scale to $l+1, l+2, \cdots, l_{\max}$ and repeat steps 3-6;

8) Set the number of nearest neighbors to $k+1, k+2, \cdots, k_{\max}$ and repeat steps 2-7;

9) Select the optimal values of k and l using the principle of minimum root mean square error.

As k and l are gradually increased from the beginning, the prediction accuracy also improves gradually. However, when they reach a certain value, the prediction accuracy decreases as they continue to increase. This is because the more nearest neighbors there are, the lower the similarity to the current state, leading to inaccurate predictions.

The process of the EEMD-MKNN method is as follows: First, the EEMD algorithm decomposes the given time series $F(t)$ into a finite number of eigenmode functions and a sequence of residual waves r_n:

$$F(t) = \sum_{i=1}^{n} F_i + r_n \tag{8}$$

Then, use KNN to calculate the predicted values $P_i\left(i = 1, 2, \ldots, n+1\right)$ for $F_i\left(i = 1, 2, \ldots, n\right)$ and r_n respectively. The final predicted value P is obtained using the following formula:

$$P = \sum_{i=1}^{n+1} P_i \tag{9}$$

III. Practical research on financial market liquidity based on time series

III. A. Empirical Research on the Asymmetric Impact of Economic Policies on Long-term Volatility in Financial Markets

III. A. 1) Indicator Selection and Data Analysis

As the most important component of China's financial markets, abnormal fluctuations in stock market prices will directly lead to increased financial pressure in China and cause instability across the entire financial market. Therefore, this paper selects the stock market as a representative of the overall financial market situation to be studied, using yield to measure financial market returns. Additionally, since the stock market is intended to represent the overall financial market situation, the CSI 300 Index, which combines the Shanghai Composite Index and the

Shenzhen Component Index, is chosen to represent the stock market. This index not only provides investors with price trends for related industries but also facilitates investors, industry practitioners, and government departments in making corresponding capital allocations and economic policy decisions based on the index.

Figure 2 shows the closing prices and yield time series of the stock market from 2008 to 2024. From the closing price series, it can be seen that the Chinese stock market experienced significant fluctuations during economic crises such as the 2008-2010, 2015-2017, and 2020-2022 periods, indicating that crises such as the novel coronavirus pandemic have had a significant impact on China's financial markets. From the time dynamics of the yield series, the Chinese stock market exhibited relatively significant volatility clustering characteristics during crises similar to those mentioned above, indicating that China's financial markets can respond to such crisis events under the regulation of economic policies, and that this volatility clustering characteristic has significant persistence.

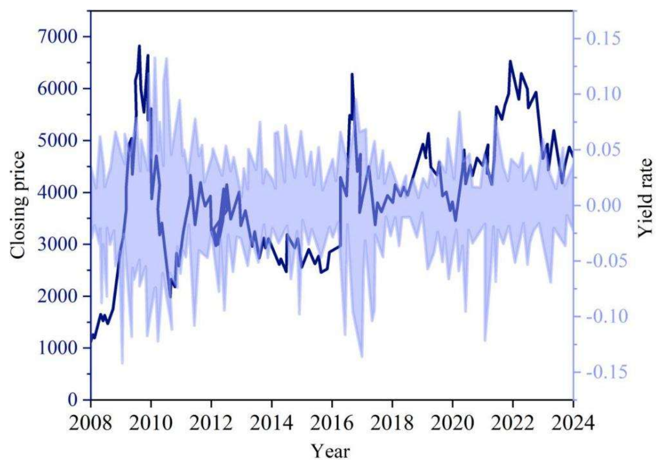


Figure 2: The closing price and return rate time series of the stock market

III. A. 2) Analysis of Long-Term Fluctuations in Financial Markets Under the Influence of Economic Policy

Figure 3 illustrates the impact of economic policies on the long-term volatility of the stock market. The figure shows the total variance of the stock market represented by the CSI 300 Index and its long-term volatility. The light purple line represents the actual daily variance, while the dark purple line represents the long-term volatility of the stock market under the influence of economic policies. It can be observed that there is a connection between the long-term volatility of the stock market driven by economic policies and the total volatility. In the stock market, the trend of changes in long-term volatility aligns well with the trend of the corresponding daily conditional variance. For example, during the economic crisis from 2008 to 2010, the stock market was significantly influenced by economic policies, with daily volatility and long-term volatility reaching approximately 20% and 10%, respectively. During this period, market volatility was primarily determined by macroeconomic policies, and the implementation of relevant economic policies led to long-term volatility in the stock market measured in years. This also demonstrates that financial markets, represented by the stock market, are regulated by economic policies.

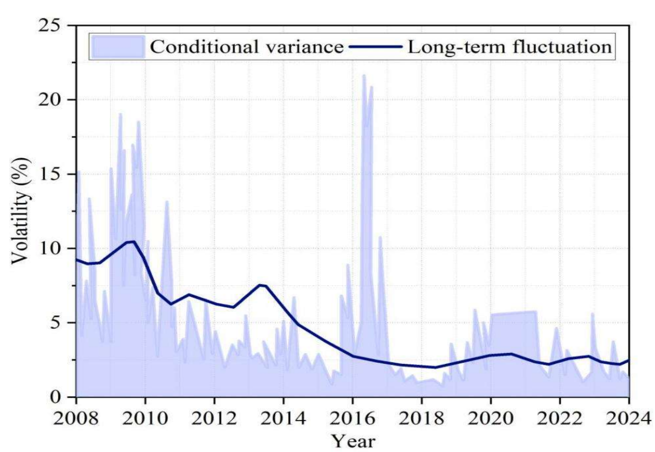


Figure 3: Financial market fluctuates for a long time under the economic policy

III. B. Construction of a financial market liquidity model based on TCN-BNN

From the data analysis in Section 3.1, it can be observed that the stock market, represented by the CSI 300 Index, exhibits peak values followed by rapid declines in certain years, while in other years, the fluctuations are relatively minor. This indicates a clear non-stationary time series, necessitating the construction of a time series model for subsequent forecasting. First, the time series of the CSI 300 Index is subjected to first-order differencing to obtain a stationary data set. Figure 4 shows the time series Xt of the CSI 300 Index and the first-order differenced series ∇Xt after processing. The index fluctuations in the original time series range from 2,500 to 5,000, with a wide fluctuation range. After first-order differencing, the index fluctuations in the time series are confined to the range of -150 to 150, with most fluctuations concentrated between 0 and 150, resulting in a more stable time series that facilitates subsequent model construction.

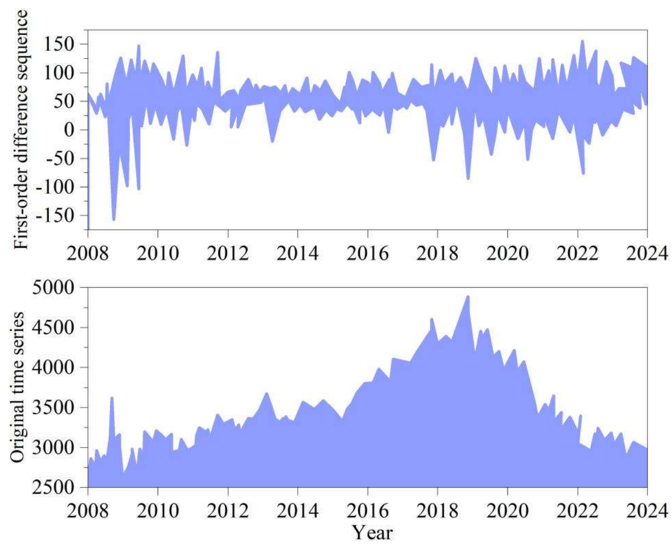


Figure 4: The time series and first-order difference series of the CSI 300 Index

Use the processed data to establish a financial time series model. Figure 5 shows the autocorrelation of the financial time series model. Figure 6 shows the partial autocorrelation of the financial time series model. From the autocorrelation and partial autocorrelation plots of the model, it can be seen that the constructed financial time series model uses a one-year interval as the unit. Considering the timeliness of economic policies, selecting a one-year time unit is reasonable. The autocorrelation between the CSI 300 Index and economic policies across different years ranges from [-0.31, 0.17], while the partial autocorrelation ranges from [-0.23, 0.18]. This indicates significant variability, which aligns with the temporal dynamics of financial markets. The model can be used for subsequent algorithmic predictions and provide reference for investors.

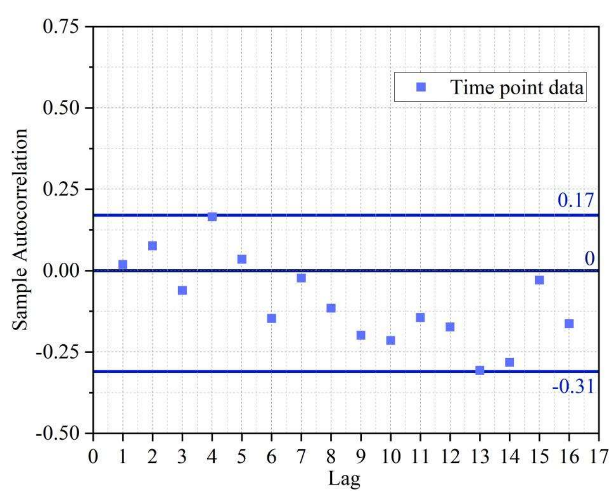


Figure 5: The autocorrelation situation of financial time series models

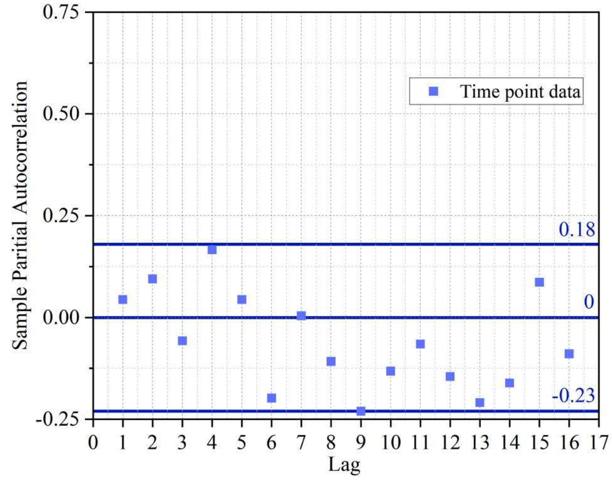
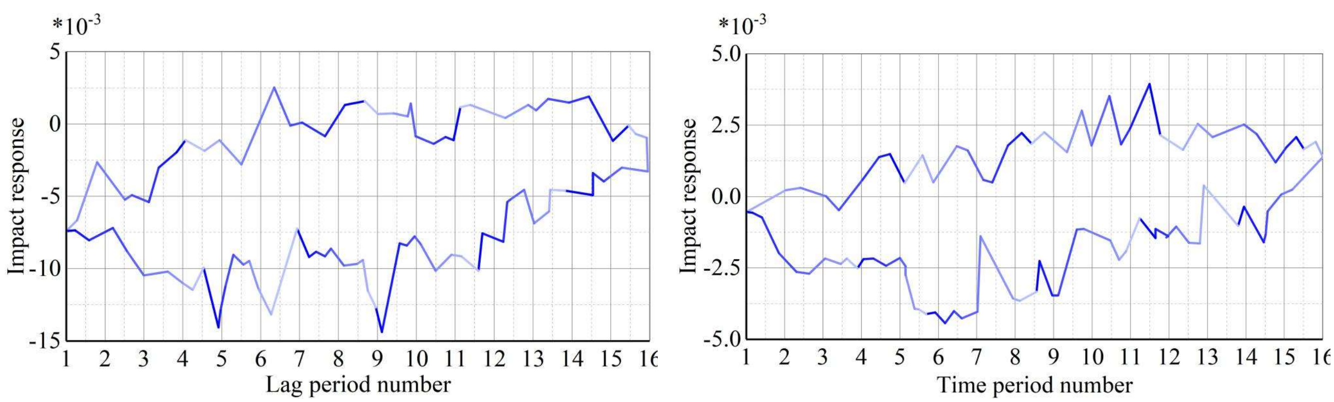


Figure 6: The partial autocorrelation situation of financial time series models

III. C. Predicting the Impact of Economic Policy Uncertainty on Financial Market Efficiency

III. C. 1) Three-dimensional impulse response of financial markets to economic policies in a bear market

After constructing a financial time series model, we use data on the impact of economic policies on financial markets during a bear market as an example to introduce the EEMD-MKNN algorithm to predict the volatility caused by economic policy uncertainty in the stock market during a bear market. Figure 7 shows the lag and time-varying nature of economic policy uncertainty on the stock market during a bear market. Analyzing the lag and time-varying nature, the uncertainty of economic policies causes the stock market in a bear market to exhibit significant volatility within the 5th to 10th lag periods and time-varying periods, with volatility ranges of -14.38×10^{-3} to 2.55×10^{-3} and -4.43×10^{-3} to 3.95×10^{-3}, respectively. The impact gradually weakens but continues to cause volatility. In a bear market, market sentiment is already low, and investors are highly sensitive to policy changes. Policy uncertainty further exacerbates market panic, quickly affecting corporate profit expectations and investment decisions, leading to sharp stock market fluctuations. Over time, the market gradually digests information about policy uncertainty, and volatility weakens. The predictions based on the financial time series model align with actual conditions.



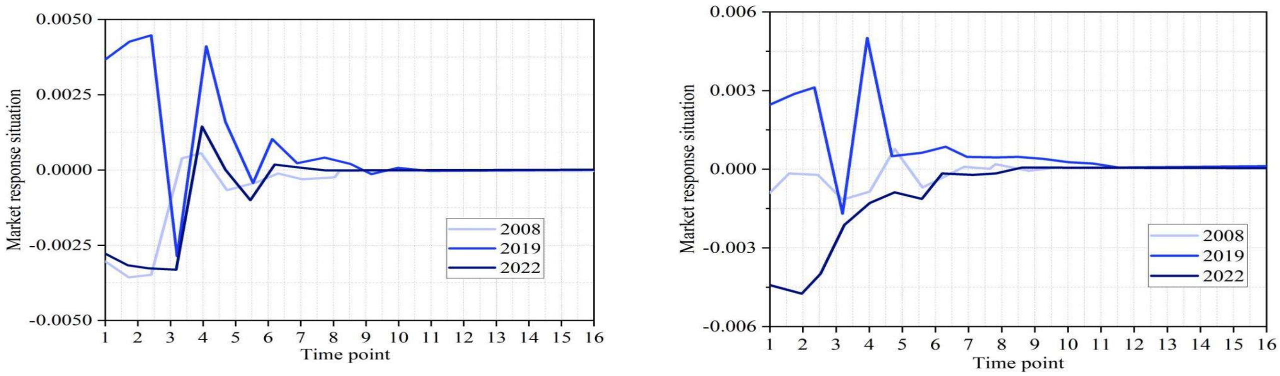
(a) Lag

(b) Time-varying

Figure 7: Impact of policy uncertainty on Stock market in a bear market

III. C. 2) Economic policy response to major events in bear markets: point-in-time pulse response in financial markets

The stock market is not always stable, and major events often have a profound impact on the market. Globally, the outbreak of major events such as economic crises, the COVID-19 pandemic, and the Russia-Ukraine war has made the impact of economic policy uncertainty on the market more complex and profound. Economic crises often lead to severe volatility in global stock markets, the COVID-19 pandemic disrupted the existing economic order, causing global supply chain disruptions and market panic, while the Russia-Ukraine war triggered geopolitical risks and uncertainty in the energy market. This section uses the EEMD-MKNN algorithm to further study the impact of economic policy uncertainty on the S stock market and Z stock market of the CSI 300 Index at three different time points (2008, 2019, and 2022). Figure 8 shows the time-point impulse response of economic policy on the two stock markets under bearish conditions during major events. Overall, the S stock market is less affected by economic policy uncertainty. In all three major events, the S stock market recovered to a stable state (0.000) before the 11th lag period, while the Z stock market generally required more than 11 lag periods to return to the same stable state. This may be attributed to the higher level of marketization in the S stock market, which provides investors such as enterprises with more diverse sources of economic policy information and facilitates the restoration of investment confidence. This research result aligns with actual conditions, further validating that the EEMD-MKNN algorithm can reasonably predict and analyze data related to the constructed financial time series model, providing reference for investors such as enterprises and enhancing financial market liquidity.



(a) S Stock Market (b) Z Stock Market

Figure 8: The point-in-time impulse response situation under major events

IV. Conclusion

This paper addresses market volatility caused by economic policy uncertainty by employing model construction and algorithmic prediction methods to analyze the impact of financial market liquidity. The autocorrelation between financial markets and economic policies reached a maximum of 0.17, and the partial autocorrelation reached a maximum of 0.18 across different years. In two scenarios—different market conditions and the impact of major events—economic policy uncertainty significantly amplifies volatility in financial markets. In bear market conditions, market volatility becomes evident during the 5th to 10th lag periods and time-varying periods. Under major event conditions, it takes approximately 11 lag periods for the market to return to a stable state. Since this study uses the stock market as a representative of financial markets, and other sub-financial markets may have unique characteristics, further research should be conducted on other types of financial markets to assess their relationship with economic policies, thereby enhancing the applicability of the conclusions drawn in this paper.

References

[1] Kim, K. M., Kim, G., & Tsolacos, S. (2019). How does liquidity in the financial market affect the real estate market yields?. Journal of Property Investment & Finance, 37(1), 2-19.

[2] Schwartz, R., Francioni, R., Nuti, G., & Weber, P. (2020). Market liquidity: An elusive variable. Journal of Portfolio Management.

[3] Liu, Q., Tse, Y., & Zheng, K. (2021). The impact of trading behavioral biases on market liquidity under different volatility levels: Evidence from the Chinese commodity futures market. Financial Review, 56(4), 671-692.

[4] Jeanne, O., & Sandri, D. (2023). Global financial cycle and liquidity management. Journal of International Economics, 146, 103736.

[5] Liu, X. (2024). Unraveling systemic risk transmission: An empirical exploration of network dynamics and market liquidity in the financial sector. Journal of the Knowledge Economy, 1-36.

[6] Logan, L. K. (2021, August). Liquidity shocks: Lessons learned from the global financial crisis and the pandemic. In Remarks at Financial Crisis Forum, Panel on Lessons for Emergency Lending, virtual, August (Vol. 11).

[7] Rhee, J., Feldberg, G., Metrick, A., & Smith, A. (2020). Market Liquidity Programs: GFC and Before. Journal of Financial Crises, 2(3).

[8] Tran, L. T. H., Hoang, T. T. P., & Tran, H. X. (2018). Stock liquidity and ownership structure during and after the 2008 Global Financial Crisis: Empirical evidence from an emerging market. Emerging Markets Review, 37, 114-133.

[9] Goodell, J. W., McGee, R. J., & McGroarty, F. (2020). Election uncertainty, economic policy uncertainty and financial market uncertainty: a prediction market analysis. Journal of Banking & Finance, 110, 105684.

[10] Keister, T. (2019). The interplay between liquidity regulation, monetary policy implementation and financial stability. Global Finance Journal, 39, 30-38.

[11] Inekwe, J. N., Jin, Y., & Valenzuela, M. R. (2018). Global financial network and liquidity risk. Australian Journal of Management, 43(4), 593-613.

[12] Drechsler, I., Savov, A., & Schnabl, P. (2018). Liquidity, risk premia, and the financial transmission of monetary policy. Annual Review of Financial Economics, 10(1), 309-328.
[13] Czapkiewicz, A., Jamer, P., & Landmesser, J. (2018). Effects of Macroeconomic Indicators on the Financial Markets Interrelations. Finance a Uver: Czech Journal of Economics & Finance, 68(3).
[14] Singh, G., Wilson, A., & Halari, A. (2019). The efficacy of macroeconomic policies in resolving financial market disequilibria: A cross‐country analysis. International Journal of Finance & Economics, 24(1), 647-667.
[15] Adeloye, F. C., Olawoyin, O., & Daniel, C. (2024). Economic policy uncertainty and financial markets in the united state. International Journal of Research and Innovation in Social Science, 8(6), 998-1016.
[16] Zhuang, Z., Zou, J., & Liu, D. (2023). Financial shocks, deleveraging and macroeconomic fluctuations in China. China Finance and Economic Review, 11(3), 23-45.
[17] Zheng, Z., He, J., Yang, Y., Zhang, M., Wu, D., Bian, Y., & Cao, J. (2023). Does financial leverage volatility induce systemic financial risk? Empirical insight based on the Chinese fintech sector. Managerial and Decision Economics, 44(2), 1142-1161.
[18] Qin, Y., Xu, Z., Wang, X., Škare, M., & Porada-Rochoń, M. (2021). Financial cycles in the economy and in economic research: A case study in China. Technological and Economic Development of Economy, 27(5), 1250-1279.
[19] Xu, Z., Tang, Y., & Cao, Y. (2018). Promoting China’s financial market reform and innovation with opening-up policies. China Economic Journal, 11(1), 71-80.
[20] Qiu, B., Tian, G. G., & Zeng, H. (2022). How does deleveraging affect funding market liquidity?. Management Science, 68(6), 4568-4601.
[21] Jiang, Z., & Tang, L. (2019, September). Impact of Deleveraging on the Liquidity Crisis of China's Stock Market. In 2019 3rd International Conference on Education, Management Science and Economics (ICEMSE 2019) (pp. 724-727). Atlantis Press.
[22] Liu, K. (2019). China's reserve requirements and their effects on economic output and assets markets during 2008-2018. International Journal of Monetary Economics and Finance, 12(3), 212-232.
[23] Shenghua, F. (2021). Analysis of the impact of China's deposit reserve policy on the liquidity of local legal person financial institutions. Academic Journal of Business & Management, 3(12), 14-20.
[24] Li, Z., & Zhong, J. (2020). Impact of economic policy uncertainty shocks on China's financial conditions. Finance Research Letters, 35, 101303.
[25] Dash, S. R., Maitra, D., Debata, B., & Mahakud, J. (2021). Economic policy uncertainty and stock market liquidity: Evidence from G7 countries. International Review of Finance, 21(2), 611-626.
[26] Broto, C., & Lamas, M. (2020). Is market liquidity less resilient after the financial crisis? Evidence for US Treasuries. Economic Modelling, 93, 217-229.
[27] Varamesh, M., Nasl Mosavi, S. H., & Abbasian Fredoni, M. M. (2023). Financial openness and market liquidity level in financial markets. International Journal of Finance & Managerial Accounting, 8(28), 31-42.
[28] Christensen, J. H., & Gillan, J. M. (2022). Does quantitative easing affect market liquidity?. Journal of Banking & Finance, 134, 106349.
[29] Ton, U. T. H., & Tatay, T. (2021). Monetary policy and stock market liquidity in emerging market economies: A literature review. Regional and Business Studies, 13(2), 55-68.
[30] Smales, L. A., & Lucey, B. M. (2019). The influence of investor sentiment on the monetary policy announcement liquidity response in precious metal markets. Journal of International Financial Markets, Institutions and Money, 60, 19-38.
[31] Hasanzadeh, I., Sheikh, M. J., Arabzadeh, M., & Farzinfar, A. A. (2023). The Role of Economic Policy Uncertainty in Relation to Financial Market Instability and Stock Liquidity in Tehran Stock Exchange Companies. Dynamic Management and Business Analysis, 2(3), 163-178.
[32] Sequeira, J. M. (2021). Monetary policy surprises, stock returns, and financial and liquidity constraints, in an exchange rate monetary policy system. The Quarterly Review of Economics and Finance, 81, 226-236.
[33] Onyendi, H. U. (2023). Foreign Exchange Market Liquidity and Currency Rate: A Causality Approach. Social Science Research, 9(1).
[34] Onyele, K. O., Ikwuagwu, E. B., & Onyekachi-Onyele, C. (2020). Macroeconomic policies and stock market liquidity: Evidence from Nigeria. Economy, Asian Online Journal Publishing Group, 7(1), 25-35.