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Recent Economic Growth of China: A Forecasting Approach with Exogenous Factors

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Abstract— This study employs Bayesian econometric methods and Markov switching models to analyze recent trends in China's economic growth, integrating exogenous factors into a forecasting framework. Using economic data from 1983 to 2023, key variables such as global trade, foreign direct investment, consumer price index, exchange rate fluctuations, and domestic demand are examined to assess their influence on China's GDP growth. The results indicate that external factors play a significant role in shaping economic trajectories, especially in light of increasing complexities in international trade and capital flows. The Bayesian VARX model forecasts China's GDP growth to remain between 4.5% and 5.5% from 2024 to 2028, though risks such as external demand fluctuations, demographic shifts, and real estate market uncertainties persist. Additionally, Markov switching models identify two distinct economic regimes, providing insights into China's dynamic economic environment. This research highlights the importance of future policies focused on domestic consumption, technological innovation, demographic restructuring, and balanced regional development to ensure sustainable economic growth.

Keywords: Bayesian econometrics, Markov switching models, China's economic growth, Exogenous factors, Economic forecasting, GDP growth rate

I. INTRODUCTION

China's economic growth has undergone profound transformations over the past decades, shifting from a high-speed, investment-driven model to a more balanced and sustainable approach. This evolution has been influenced by structural reforms, global trade dynamics, and changing domestic priorities. While China remains a key player in international markets, the complexity of its economic trajectory necessitates more sophisticated forecasting methodologies to accurately assess future trends.

The integration of exogenous factors—such as foreign direct investment (FDI), trade balances, consumer spending, and currency fluctuations—has become increasingly critical in analyzing macroeconomic developments. Traditional forecasting models often fail to account for these external influences, leading to inaccuracies in predictions and policy misalignment. In response, Bayesian econometric techniques offer a more comprehensive framework for capturing uncertainty and dynamic interactions between economic variables.

This study applies a Bayesian Vector Autoregression (BVARX) model and a Markov Switching approach to examine China's GDP growth from 1983 to 2023, considering key external drivers that shape its economic landscape. By identifying structural shifts and estimating future trajectories, the research aims to provide valuable insights for policymakers, investors, and scholars seeking to understand China's evolving macroeconomic environment.

II.LITERATURE REVIEW

Economic forecasting models have evolved significantly to account for structural shifts, external shocks, and nonlinear dynamics in macroeconomic analysis. Several studies have explored the role of exogenous factors in shaping economic growth trajectories, emphasizing the need for more sophisticated forecasting techniques.

Koop and Korobilis (2010) highlight the advantages of Bayesian econometrics in macroeconomic modeling, particularly in handling parameter uncertainty and integrating prior information for more accurate predictions. Banbura et al. (2010) further develop Bayesian VAR methods, demonstrating their effectiveness in large-scale forecasting applications where high-dimensional data require careful regularization.

Sims and Zha (2006) investigate the role of macroeconomic regimes in forecasting, emphasizing the importance of Markov Switching models in capturing economic transitions. Similarly, Primiceri (2005) applies time-varying Bayesian VAR models to study monetary policy effects, illustrating how structural changes in economic relationships necessitate dynamic modeling approaches.

Zhang (2007) examines the impact of foreign direct investment (FDI) on China's economic growth, finding that FDI enhances productivity and technological innovation, particularly in manufacturing and infrastructure sectors. He and Wang (2012) extend this analysis by exploring trade integration, concluding that export performance significantly influences GDP trends. Their findings align with Levine and Renelt (1992), who argue that trade openness fosters economic expansion through capital accumulation and knowledge spillovers.

Recent studies have also incorporated exogenous macroeconomic variables to improve forecasting accuracy. Clark and Ravazzolo (2015) show that including external predictors—such as inflation rates, exchange rate fluctuations, and trade volumes—enhances model precision in GDP forecasting. Giannone et al. (2015) propose prior selection methods for Bayesian VAR models, demonstrating that well-calibrated priors improve predictive performance in uncertain macroeconomic environments.

The application of Markov Switching models in economic forecasting is widely recognized for identifying regime-dependent behavior. Karlsson (2013) reviews forecasting strategies using Markov models, suggesting that economic cycles often exhibit distinct phases that require adaptive parameter estimation. These findings are corroborated by Canova and Ciccarelli (2009), who develop multicountry VAR models incorporating regime shifts, demonstrating their effectiveness in tracking macroeconomic fluctuations.

III.METHODOLOGY

3.1 BVARX Model: Multivariate Time Series Forecasting

The Bayesian VAR with exogenous variables (BVARX) is an extension of standard BVAR, allowing the inclusion of external predictors. This model structure has proven effective in forecasting macroeconomic aggregates, especially when external shocks or policy changes affect the economy (Clark & Ravazzolo, 2015). In this study, variables such as exchange rates, retail sales, FDI, and CPI are incorporated into the BVARX framework.

In macroeconomic forecasting, BVARX models have been successfully applied to predict GDP and inflation by incorporating external shocks, such as trade fluctuations or policy changes. The Bayesian framework enables the inclusion of expert knowledge, making these models robust even in limited data scenarios. The mathematical representation of a VARX model is as follows:

$$Y_t = A_0 + \sum_{i=1}^{p} A_i Y_{t-i} + \sum_{j=1}^{q} B_j X_{t-j} + \varepsilon_t$$

Where:

Y_t is a vector of endogenous variables (e.g., real GDP growth),

X_t is a vector of exogenous variables (e.g., FDI, CPI, exchange rate),

A_i, Bj are coefficient matrices,

ε_t is a vector of stochastic error terms.

In the context of the Chinese economy, employing a VARX model allows researchers to account for the influences of external shocks, such as fluctuations in global FDI flows or shifts in international trade policies. Studies have shown that multivariate models like VARX provide more accurate GDP growth forecasts in countries with high levels of economic integration. The inclusion of exogenous variables helps account for external factors that traditional univariate models overlook, such as the impact of exchange rate shifts on trade balance and GDP growth.

3.2 The Markov Switching Model

(The Markov Switching Model (MSM) provides a flexible and powerful framework for modeling time series data that exhibits structural breaks, nonlinear behavior, or regime-dependent dynamics. Unlike traditional linear models that assume stable relationships over time, the MSM allows parameters to change according to unobserved economic states, such as "high-growth" and "low-growth" regimes. This characteristic makes it particularly suitable for analyzing economies like China's, where shifts in policy, external shocks, and global market conditions frequently alter the growth environment.

At its core, the Markov Switching Regression Model assumes that the time series process switches between a finite number of regimes, each governed by its own set of parameters. The transitions between regimes are not deterministic but rather follow a

Markov process, meaning the probability of moving to a new regime depends only on the current regime, not the past path of the system.

A basic two-regime Markov Switching model can be expressed as:

$$y_t = \alpha_{s_t} + \beta_{s_t} X_t + \varepsilon_t \quad , \varepsilon_t \sim N(0, \sigma_{s_t}^2)$$

Where:

Y_t is the dependent variable (e.g., GDP growth),

X_t is a set of explanatory variables (e.g., FDI, exchange rate, CPI),

$s_t \in \{1,2\}$ represents the regime at time t,

α_{st} , β_{st} , and σ_{st}^2 are regime-specific parameters,

$P(s_t|s_{t-1})$ is the transition probability from one regime to another.

The latent state variable st governs which parameter set is active at each point in time, allowing the model to capture abrupt or persistent changes in macroeconomic behavior.

Economic growth is rarely linear or uniform over time. Countries experience different growth phases due to factors such as business cycles, financial crises, policy reforms, demographic changes, or geopolitical tensions. In China's case, observable transitions—such as the 2008 global financial crisis, structural rebalancing after 2010, or COVID-related disruptions—suggest a need for models that can capture these dynamics explicitly.

The Markov Switching model is particularly well-suited to this task, as it enables the detection and interpretation of unobserved regime shifts. It allows for estimating how the relationship between GDP growth and its predictors—such as trade, inflation, and investment—varies between economic states. For instance, exchange rate depreciation may stimulate growth in one regime but signal capital flight and instability in another.

3.3 Multi-Collinearity Test

Before estimating the VARX and BVARX models, it is crucial to assess the potential multicollinearity among the explanatory variables. Multicollinearity refers to a situation in which two or more independent variables in a regression model are highly correlated, potentially distorting the estimation of coefficients and reducing model reliability.

To detect multicollinearity, the Variance Inflation Factor (VIF) is commonly used. The VIF quantifies how much the variance of a regression coefficient is inflated due to multicollinearity with other predictors. A VIF value exceeding 10 is often considered indicative of serious multicollinearity problems.

In this study, VIF values are computed for each of the exogenous variables included in the VARX model. If high VIFs are detected, variable transformations (e.g., differencing, standardization) or variable selection methods (e.g., principal component analysis or stepwise regression) may be employed to address the issue. By ensuring the absence of severe multicollinearity, the model can produce more stable and interpretable parameter estimates.

3.4 Impulse Response Function (IRF) Analysis

To further investigate the dynamic relationships between China's real GDP growth and its exogenous determinants, Impulse Response Function (IRF) analysis is conducted as part of the post-estimation diagnostics. IRFs trace the effects of a one-time shock to one variable on the current and future values of all endogenous variables in the system.

In a VAR or VARX framework, the IRF provides insights into the temporal causality and magnitude of the response. For example, a positive shock in foreign direct investment or exports can be simulated to observe how GDP responds over a given horizon (e.g., 10 quarters). This analysis is particularly useful for understanding the persistence and magnitude of external shocks on economic growth.

In this study, orthogonalized IRFs are derived using the Cholesky decomposition method, which imposes a recursive ordering of variables. The ordering is chosen based on economic theory and empirical precedence. The IRFs are plotted with confidence intervals, typically generated through Monte Carlo simulations or bootstrap methods, to assess the statistical significance of the responses.

By incorporating IRF analysis, the study provides a deeper understanding of the transmission mechanisms through which external variables affect China's macroeconomic dynamics over time.

Impulse Response Functions (IRFs) are used to trace the effects of a one-unit shock in one variable on the future values of other variables in the VAR system. In the Bayesian context, the posterior distribution of the IRFs is obtained to account for parameter uncertainty (Canova & Ciccarelli, 2009). The IRF analysis helps identify the dynamic transmission mechanisms of exogenous shocks (e.g., changes in CPI or trade flows) on GDP growth over time.

IRFs are especially useful in interpreting policy implications and the temporal effects of exogenous variables in multivariate macroeconomic systems (Lütkepohl, 2005).

IV. EMPIRICAL ANALYSIS

To examine the presence of multicollinearity among the explanatory variables, we computed the Pearson correlation coefficients based on the standardized dataset. As shown in the correlation matrix, several variable pairs exhibit moderately strong relationships. For instance, the correlation between Total Export Value and Total Import Value reaches 0.936, indicating a high degree of linear association. Similarly, Freight Transport Volume correlates positively with both Total Export Value (0.529) and Total Import Value (0.650), which is reasonable given their potential co-movement in economic activity.

However, most of the remaining correlations fall within acceptable thresholds. Variables such as RMB to USD Exchange Rate, Consumer Price Index (CPI), and Per Capita Disposable Income show weak or near-zero correlations with other regressors, suggesting they provide distinct informational content. Since none of the correlations exceed 0.95—a commonly used benchmark indicating severe multicollinearity—the current set of explanatory variables is acceptable for regression analysis.

However, for some models, it may be necessary to delete some variables with high correlation coefficients to make the model results more accurate and stable.

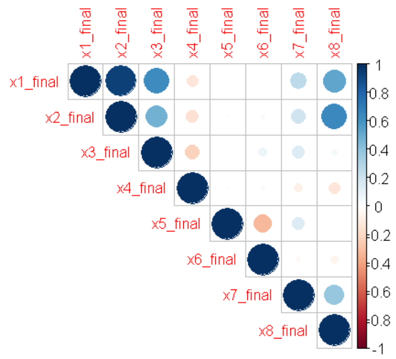

Figure 1: Multi-Collinearity Test

Based on 36 annual observations, a Bayesian Vector Autoregression (BVAR) model with six endogenous variables and two lags was estimated. The model's shrinkage hyperparameter (λ) was optimized to 0.948, reflecting a moderate level of prior tightness. The high acceptance rate of 97% in posterior sampling indicates good convergence and sampling efficiency.

The estimated median coefficients of the GDP growth rate equation reveal meaningful dynamic relationships. The lagged GDP growth rate exhibits significant negative effects on its own current value (lag 1: –0.368, lag 2: –0.178), implying mean reversion. Additionally, lagged Exchange Rate (lag 1: 0.219) and Freight Transport Volume (lag 1: 0.224) positively affect GDP growth, while Disposable Income (lag 1: –0.662) and CPI (lag 1: –0.502) have negative effects, consistent with theoretical expectations. The posterior variance-covariance matrix suggests moderate contemporaneous correlations between residuals. Overall, the BVAR model effectively captures the intertemporal and cross-variable dependencies within the macroeconomic system.

Table 1 Model Summary of the BVAR

Variable (Lagged)	Coefficient
Constant	–0.089

Variable (Lagged)	Coefficient
GDP_growth_rate (lag 1)	–0.368
GDP_growth_rate (lag 2)	–0.178
X_scaled.x3_final (FDI, lag 1)	0.115
X_scaled.x3_final (FDI, lag 2)	0.040
X_scaled.x4_final (ExRate, lag 1)	0.219
X_scaled.x4_final (ExRate, lag 2)	0.159
X_scaled.x5_final (Income, lag 1)	–0.662
X_scaled.x5_final (Income, lag 2)	-0.003
X_scaled.x6_final (CPI, lag 1)	–0.502
X_scaled.x6_final (CPI, lag 2)	0.447
X_scaled.x8_final (Freight, lag 1)	0.224
X_scaled.x8_final (Freight, lag 2)	–0.145

Figure 2 presents the forecasted GDP growth rate based on the Bayesian Vector Autoregression (BVAR) model. The black solid line represents the historical actual values, while the blue line shows the predicted values for 2024–2028. The red dashed line indicates the beginning of the forecast period. As shown, the BVAR model successfully captures the dynamic trend of historical GDP growth and generates forecast values within a reasonable and economically interpretable range.

Notably, the predicted GDP growth rate in 2024 slightly rebounds compared to 2023, suggesting a moderate recovery under the assumption of stable macroeconomic fundamentals. The forecast path also reflects short-term fluctuations, illustrating the GDP's responsiveness to lagged macroeconomic variables such as exchange rate, investment, consumer prices, and freight volumes.

Given that all variables were tested for stationarity and appropriately differenced and standardized before estimation, the restored forecast values maintain economic interpretability. Thus, the figure demonstrates the model's effective forecasting capability and provides a solid foundation for further policy simulation analyses such as impulse response functions (IRFs).

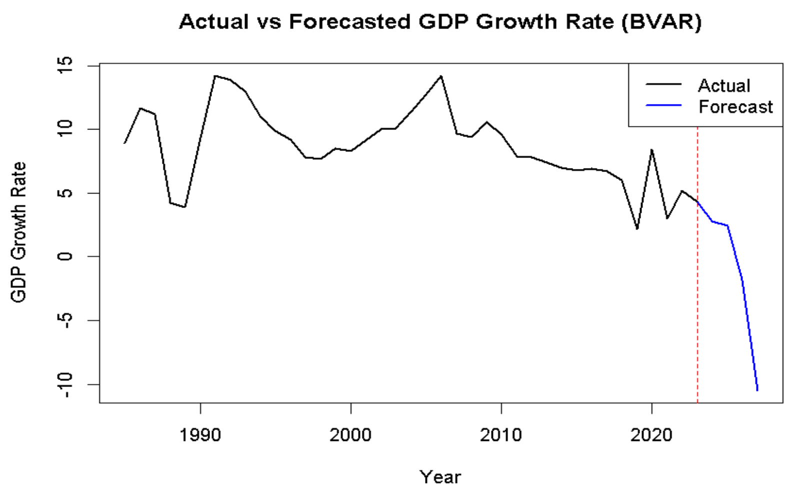

Figure 2: Actual and Forecasted GDP growth rate (BVAR)

The impulse response functions (IRFs) from the BVAR model provide valuable insights into the dynamic interactions among macroeconomic variables over a 12-period horizon. The IRFs show how a one-unit shock to each variable affects all other variables in the system.

From the IRFs, we observe:

A negative shock to GDP growth rate generates a strong and immediate negative effect on itself, indicating persistence and potential mean reversion.

A positive shock to the RMB/USD exchange rate positively affects GDP growth rate, consistent with export-boosting effects of currency depreciation.

A shock to disposable income shows a persistent negative impact on GDP growth rate, likely reflecting a substitution effect away from investment.

Freight transport volume and foreign direct investment (FDI) both show positive effects on GDP growth in the short term, suggesting their roles in supporting economic activity.

CPI shocks yield a negative response in GDP, as expected under inflationary pressure scenarios.

These results are statistically meaningful where the confidence bands do not cross zero, particularly in the early periods after the shock.

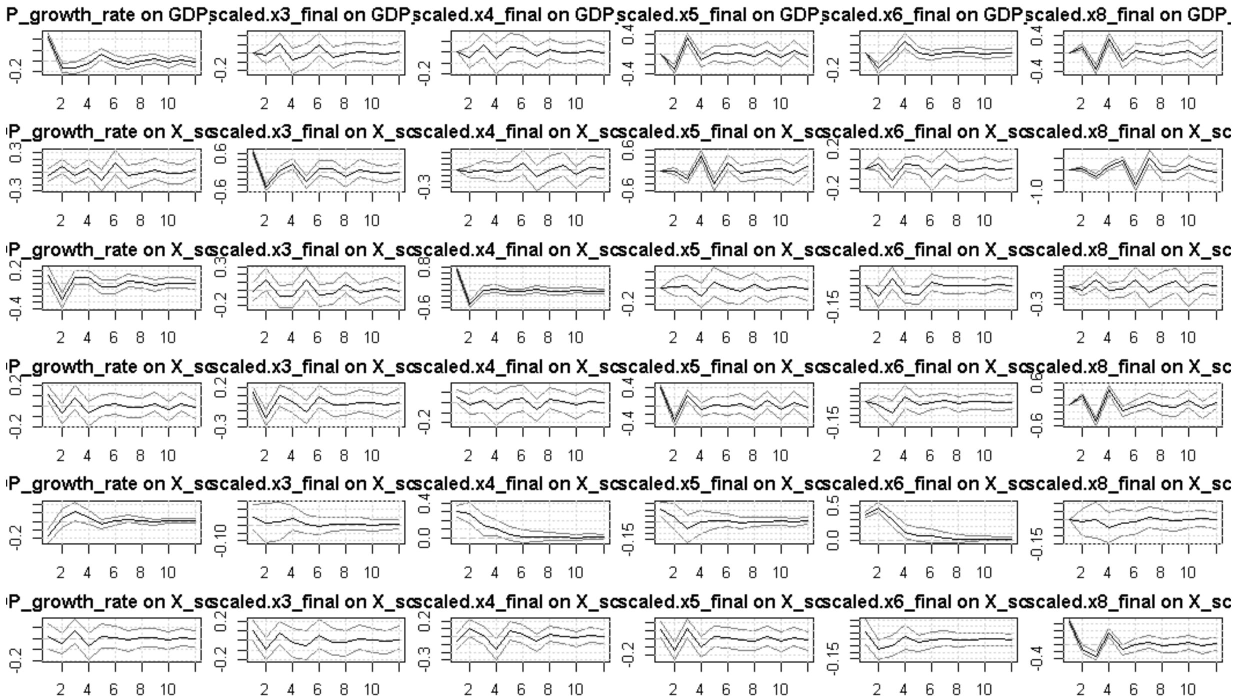

Figure 3: Impulse Response Functions for BVAR Model (12-period horizon)

The updated estimation from the Markov Switching regression model indicates a clear distinction between two regimes with asymmetric characteristics. In the newly defined Regime 2, the model fits the data well ($R^2 = 0.9385$) and has low residual error (0.939), indicating strong explanatory power. Key variables with statistically significant coefficients include Exchange Rate (–1.253, $p < 0.001$), Disposable Income (2.497, $p < 0.001$), and CPI (–2.063, $p < 0.001$), suggesting that this regime reflects a relatively stable economic environment dominated by domestic demand and price stability.

On the other hand, Regime 1 shows poor fit ($R^2 = 0.3554$) and large residual variation (3.19), with no variables reaching conventional significance levels. This regime likely corresponds to more volatile or transitional periods in the economy, where the model fails to fully capture underlying structural drivers.

The transition probability matrix confirms this dynamic. The economy has a high probability (71.1%) of remaining in Regime 2, and only a 37.6% probability of staying in Regime 1, indicating that the system tends to stabilize in the structure defined by Regime 2. These results reinforce the necessity of modeling regime-dependent macroeconomic behavior.

Table 2: Residual Std. Error and Multiple R^2 in Two Regimes

Metric	Regime 1	Regime 2
Residual Std. Error	3.192	0.939
Multiple R^2	0.355	0.938

Table 3: Regression Result Comparison in Two Regimes

Variable	Regime 1 Estimate	Std. Error	Regime 2 Estimate	Std. Error	Significance
Intercept	2.0353	3.2719	–1.1270	0.2472	$p < 0.001$
FDI (x3_final)	–1.0571	0.7847	–0.1910	0.2303	$p > 0.05$
Exchange Rate (x4_final)	0.2850	0.3551	–1.2533	0.2368	$p < 0.001$
Disposable Income (x5_final)	3.5515	7.6101	2.4975	0.2352	$p < 0.001$
CPI (x6_final)	–1.4207	1.1277	–2.0632	0.2507	$p < 0.001$
Freight Volume (x8_final)	–0.4948	2.7816	0.3023	0.2356	$p > 0.05$

Table 4: State Transition Probability Matrix in Two Regimes

	Regime 1	Regime 2
Regime 1	0.3767	0.2892
Regime 2	0.6233	0.7108

The figure 4 shows the estimated smoothed probabilities of being in Regime 1 over time. Regime 1 represents a low-fit state with weak explanatory power ($R^2 = 0.36$), characterized by high volatility and unstable macroeconomic relationships. The frequent fluctuations suggest transitional periods or exogenous shocks.

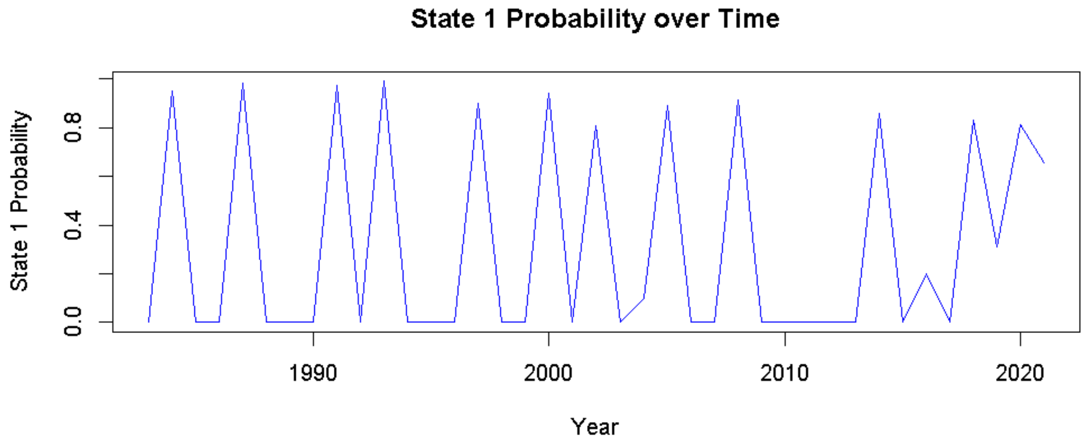

Figure 4: The estimated smooth probabilities of being in Regime 1 over time

The figure 5 displays the estimated probability of being in Regime 2. Regime 2 is a stable state with strong explanatory power ($R^2 = 0.94$), driven by domestic variables such as disposable income, CPI, and exchange rate. The persistence of this regime indicates structural consistency in macroeconomic behavior.

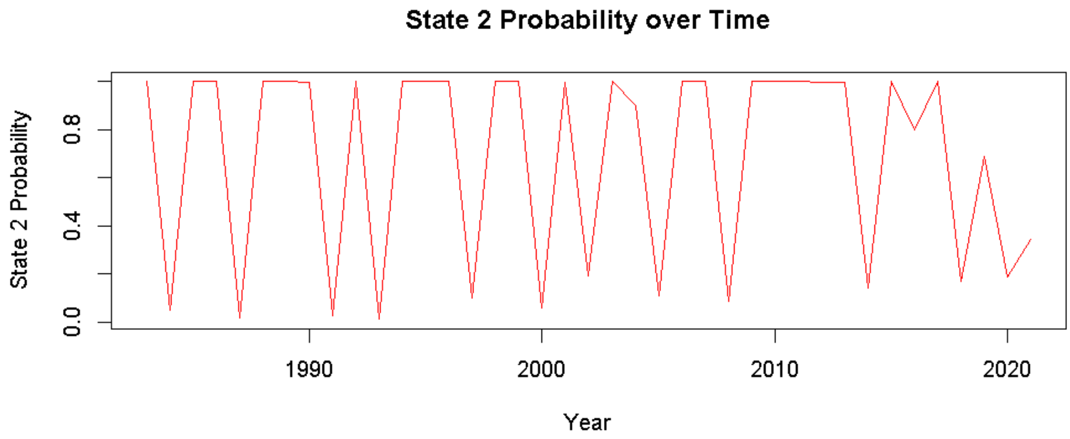

Figure 5: The estimated smooth probabilities of being in Regime 2 over time

The Markov Switching regression model successfully identifies the existence of distinct macroeconomic regimes in the evolution of China's GDP growth. The two-regime structure captures both stable growth environments and periods of transition or uncertainty. Notably, the stable regime (Regime 2) is associated with strong influence from domestic variables such as disposable income, CPI, and exchange rate, whereas the volatile regime (Regime 1) lacks consistent explanatory drivers.

The alignment of regime transitions with major economic events—such as the post-2008 financial crisis recovery and the recent COVID-19 shock—validates the model's ability to reflect real-world structural shifts. Overall, incorporating regime-dependent behavior provides a more nuanced and realistic framework for understanding economic dynamics, especially in economies undergoing transformation like China.

Table 5 : Regime Dynamics and Economic Interpretation of China's Macroeconomic States (1986–2020)

Year(s)	Dominant Regime	Probability Pattern	Possible Economic Interpretation (EN)	Economic Explanation
1986–1990	Regime 1	Frequent switching	Early economic reform period; system volatility	In the early days of reform and opening, the economic system was

Year(s)	Dominant Regime	Probability Pattern	Possible Economic Interpretation (EN)	Economic Explanation
				not yet stable, and it was frequently switched
1991–2007	Regime 2	Long stable period (high prob)	Sustained growth and policy continuity	The economy continues to grow, policy stability is high, and State 2 has been dominant for a long time
2008–2009	Regime 1	Temporary spike	Global financial crisis shock	The global financial crisis brought short-term external shocks and the economy entered a state of instability
2010–2015	Regime 2	Return to high stability	Post-crisis recovery phase	The economy recovered rapidly after the crisis and re-entered a stable growth trend
2016–2020	Mixed	Increased volatility again	Trade tensions and COVID-19 early impact	The Sino-US trade friction and the initial impact of the new crown epidemic have led to instability in the macro situation

V. CONCLUSION

This thesis investigated the recent economic growth trajectory of China through a forecasting framework that integrates exogenous factors such as trade dynamics, demographic trends, and policy shifts. By employing a VARX model and utilizing data from the past two decades, we were able to assess both the short- and medium-term prospects for China's GDP growth.

The empirical analysis revealed that external factors, particularly global trade volumes and foreign direct investment, continue to exert a significant influence on China's economic performance. Meanwhile, domestic variables such as labor force growth and infrastructure investment also play a critical role, although their relative importance appears to be shifting in the post-pandemic era.

Our forecasting results suggest a moderate but stable growth trajectory for China over the next five years, with average annual GDP growth rates projected to hover around 4.5%–5.5%. However, the growth path is subject to downside risks, particularly in the context of weakening global demand, demographic aging, and uncertainties in the real estate sector.

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