Article

Not peer-reviewed version

Explaining the Dynamics of Key Macroeconomic Indicators through Deep Learning State-Space Models

Tamir Ariunsukh * and Tsolmon Sodnomdavaa

Posted Date: 22 January 2026

doi: 10.20944/preprints202601.1732.v1

Keywords: deep learning; forecasting model; macroeconomic forecasting; state-space model; economic dynamics; Mongolia

Article

Explaining the Dynamics of Key Macroeconomic Indicators Through Deep Learning State-Space Models

Tamir Ariunsukh [1,*] and Tsolmon Sodnomdavaa [2]

[1] Assistant Professor Tamir Ariunsukh, Huree University of Information and Communication Technology, Mongolia

[2] Department of Finance and Economics, Mandakh University, Ulaanbaatar, Mongolia

* Correspondence: tamir.a@huree.edu.mn

Abstract

To ensure economic stability, accurately forecasting the effects of domestic and external factors has become increasingly critical. This study aims to develop a novel model to predict Mongolia's macroeconomic dynamics by integrating theoretical economic relationships with deep learning methods. Quarterly macroeconomic data from 2015 to 2024 are employed, focusing on key indicators such as inflation, unemployment, GDP growth, and the policy interest rate. The interdependence among these variables is dynamically estimated using Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) neural networks. For comparison, traditional ARIMA and VAR models are also applied to assess the predictive performance of deep learning approaches. The results reveal that deep learning models achieve higher accuracy in short- and medium-term forecasts (MAPE ranging from 3.7% to 5.2%) and exhibit greater sensitivity to business cycle fluctuations and policy shifts. Moreover, by incorporating a theory-guided deep learning framework, the model's interpretability is enhanced, enabling a more realistic representation of the dynamic trade-off between inflation and unemployment. The primary contribution of this research is the development of a theoretically consistent deep learning state-space forecasting model that bridges economic theory and artificial intelligence. The proposed framework provides practical insights for macroeconomic policy analysis, fiscal planning, and monetary decision-making in Mongolia.

Keywords: deep learning; forecasting model; macroeconomic forecasting; state-space model; economic dynamics; Mongolia

---

1. Introduction

In modern economic policymaking and strategic decision-making, the accuracy of macro-level forecasting, theoretical *coherence*, and effective management of uncertainty have become increasingly important. Understanding the effects of business cycle fluctuations, external trade shocks, and monetary policy adjustments is essential for maintaining macroeconomic stability. In Mongolia, short- and medium-term economic dynamics over the past two decades have been strongly influenced by commodity price volatility, exchange rate movements, investment inflows, and fiscal expenditure cycles. Consequently, improving macroeconomic forecasts requires theoretically motivated modeling of dynamic interdependencies among key indicators rather than purely data-driven extrapolation.

Traditional macroeconomic models such as ARIMA, VAR, and DSGE are grounded in economic theory but face well-known limitations in capturing nonlinear dynamics and time-varying responses to internal and external shocks. At the same time, the increasing complexity and uncertainty of macroeconomic environments have challenged the empirical performance of these conventional approaches. Recent advances in deep learning have therefore been explored as complementary tools

 doi:10.20944/preprints202601.1732.v1

for modeling nonlinear patterns and long-term dependencies in economic time series (Lim & Zohren, 2021; Rangapuram et al., 2018). However, such methods often lack explicit theoretical structure and tend to function as black-box systems, limiting their interpretability and direct applicability for policy analysis, particularly in small-sample macroeconomic settings standard in emerging economies.

Recent studies have increasingly aimed to incorporate core economic relationships, such as the Phillips curve, Okun's law, and the Taylor rule, into deep learning models. This line of research has introduced approaches such as theory-guided deep learning (Raissi et al., 2019; Karniadakis et al., 2021) and structural regularization (Mao & Zheng, 2020), which create new opportunities to blend data-driven methods with theoretical consistency rather than purely predictive optimization. These techniques improve model interpretability and alignment with economic theory by embedding equilibrium relationships into the loss function as soft penalty terms, thereby guiding learning by economic principles while allowing flexibility under limited-data conditions.

In Mongolia, macroeconomic indicators such as inflation, unemployment, GDP growth, and exchange rate movements are closely linked and strongly influenced by external and policy-related factors, including exports, investment inflows, and changes in policy interest rates. To capture these dynamics in a small-sample macroeconomic setting, this study adopts a hybrid, exploratory modeling strategy that combines state-space modeling with sequence-based deep learning architectures, such as LSTM, GRU, and Transformer. Rather than treating these models as full-scale predictive systems, the hybrid framework is used to identify latent economic states and describe theoretically motivated dynamic relationships among key indicators, consistent with established macroeconomic reasoning (Rangapuram et al., 2018; Maliar et al., 2021).

Accordingly, the primary goal of this study is to propose a consistent and exploratory deep learning based state space framework that examines the dynamics of Mongolia's macroeconomy by combining fundamental theoretical relationships with data-driven learning methods. Using quarterly macroeconomic data from 2015 to 2024 under a limited data setting, the study dynamically estimates the relationships among inflation, unemployment, GDP growth, and the policy interest rate. The empirical performance of the proposed framework is evaluated through a comparative analysis with traditional ARIMA and VAR models, yielding exploratory evidence of favorable short- and medium-term forecasting performance in this specific empirical context, rather than definitive predictive dominance.

The methodological contributions of this research are threefold. First, it integrates core macroeconomic relationships into a deep learning framework through soft penalty-based loss constraints, thereby maintaining theoretical consistency under data constraints. Second, it employs a hybrid state-space and deep-learning approach to identify latent economic states and cyclical dynamics, providing an interpretable account of macroeconomic fluctuations rather than causal confirmation. Third, it presents a proof-of-concept forecasting framework that can support macroeconomic policy discussions, fiscal planning, and monetary analysis in Mongolia, without claiming to provide full-scale policy simulation or universal generalization.

2. Literature Review

In recent years, economic modeling has become increasingly data-driven, with a growing emphasis on integrating traditional theoretical frameworks with machine learning methods rather than replacing them. Within this evolving research landscape, a wide range of models and frameworks has emerged, each characterized by distinct theoretical foundations, strengths, limitations, and varying degrees of compatibility with data-constrained macroeconomic settings. The following section reviews key approaches that are particularly relevant for theory-consistent and interpretable economic forecasting, thereby motivating the methodological positioning of this study.

Monotonic Machine Learning, which gained prominence in the early 2020s, represents a class of models that incorporate economically motivated monotonicity constraints into machine learning algorithms through regularization. This approach enforces theory-compliant behavior while offering partial interpretability within predictive systems. Its main advantage lies in improving forecast stability under theoretical restrictions. However, Monotonic ML relies on restrictive functional assumptions, offers limited flexibility for policy-oriented simulation, and is less suitable for capturing complex multivariate macroeconomic dynamics. Despite these limitations, Monotonic ML remains a relevant reference point for aligning economic theory with supervised learning environments (Lin et al., 2025, SSRN).

The Dynamic Stochastic General Equilibrium model, originating from the seminal work of Kydland and Prescott in the 1980s, is a dynamic optimization framework grounded in neoclassical economic theory. DSGE models provide a strong theoretical foundation and are widely used for policy simulation and the structural interpretation of macroeconomic fluctuations. Nevertheless, they face persistent challenges, including limited flexibility in handling nonlinear dynamics, weak accommodation of data-driven uncertainty, and substantial computational complexity, particularly in empirical applications.

The Stock Flow Consistent model, developed in the 1990s within the Post Keynesian tradition, ensures accounting consistency between economic stocks and flows and effectively captures macrofinancial linkages. This framework is beneficial for analyzing interactions between fiscal and monetary policy. However, SFC models are highly parameter-intensive, mathematically complex, and show limited integration with modern machine learning techniques, which constrains their applicability in nonlinear and data-driven forecasting environments (Godley and Lavoie, 2007, Palgrave).

The Global Vector Autoregressive model, introduced by Pesaran and colleagues in the early 2000s, is designed to analyze global economic linkages and cross country spillover effects. The framework provides flexibility for scenario based analysis of international transmission mechanisms and policy shocks. However, its explanatory capacity is constrained by relatively weak theoretical discipline, and estimation and interpretation become increasingly challenging as model dimensionality expands, particularly in data constrained empirical settings.

Agent Based Modeling, originating in the 1990s within the behavioral economics tradition, conceptualizes the economy as a complex adaptive system composed of heterogeneous interacting agents. This approach is well suited for capturing emergent dynamics arising from micro level interactions and adaptive behavioral rules. Nevertheless, ABM frameworks typically exhibit limited reliability for aggregate macroeconomic forecasting, weak mechanisms for uncertainty quantification, and high computational intensity, which restrict their practical use in policy oriented macroeconomic analysis (Tesfatsion and Judd, 2006, Springer).

Structural Regularization, emerging in the 2020s, incorporates causal and theoretical reasoning directly into the regularization structure of machine learning models. This approach enhances theory consistency and improves generalization beyond the estimation sample. However, Structural Regularization faces difficulties in jointly integrating multiple macroeconomic constraints and offers limited support for systematic policy simulation, particularly in complex multivariate environments (Mao and Zheng, 2020, arXiv).

Sequence-based deep learning models, including DeepAR, LSTM, and Transformer architectures, have been widely applied since 2015 for probabilistic time series forecasting. These models are effective in capturing nonlinear relationships and long-range temporal dependencies. Despite their predictive flexibility, they generally lack explicit theoretical structure, which limits interpretability and reduces their suitability for policy relevant macroeconomic analysis (Lim and Zohren, 2021; Rangapuram et al., 2018).

Recent empirical studies in Mongolia provide growing evidence that machine learning methods significantly outperform traditional econometric models in both macroeconomic forecasting and financial risk assessment. Tegshjargal et al. 2025 show that ensemble learning approaches particularly XGBoost achieve substantially higher accuracy in inflation forecasting than SARIMA and GARCH models highlighting the importance of nonlinear learning in environments exposed to frequent structural shocks. At the micro financial level Sodnomdavaa et al. 2025 demonstrate that machine learning based credit scoring models markedly improve default prediction accuracy in non bank

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 22 January 2026 doi:10.20944/preprints202601.1732.v1

financial institutions while also enhancing model transparency through explainable AI techniques. Taken together these findings indicate that machine learning methods are especially suitable for emerging economies characterized by complex data structures institutional heterogeneity and high macroeconomic volatility thereby providing strong empirical motivation for the use of ML based frameworks in both macroeconomic and financial policy analysis.

Helformer, introduced in 2025, represents a class of structurally informed Transformer architectures that integrate exponential smoothing components into attention mechanisms. By embedding structural priors, the model captures trend and seasonal patterns in high frequency data while remaining adaptable to complex temporal dynamics. However, Helformer remains limited in handling multiple theoretical constraints simultaneously and provides restricted support for macroeconomic policy simulation. Existing applications have focused primarily on financial and cryptocurrency markets, limiting its relevance for broader macroeconomic forecasting contexts.

The Hemisphere Neural Network, introduced in 2024, is a semi structured deep learning framework designed to estimate the output gap within the Phillips curve setting. By integrating nonlinear functional representations, the model improves interpretability and theory consistency in inflation forecasting. Nevertheless, HNN remains narrowly focused on a single theoretical relationship, with limited capacity to incorporate multiple macroeconomic constraints or support comprehensive policy simulation.

The Phase Adaptive Attention Long Short Term Memory model, introduced in 2025, incorporates attention mechanisms that adjust dynamically across business cycle phases. This design enhances the detection of nonlinear temporal asymmetries and has demonstrated promising performance in GDP forecasting tasks. However, its integration of macroeconomic theory remains limited, and the framework becomes less scalable and robust in multivariate macroeconomic environments.

CNN based models have been applied to extract nonlinear trends from complex economic data by leveraging convolutional feature representations. These models exhibit strong pattern recognition capabilities and effectively capture localized temporal structures. Nonetheless, CNN based frameworks show weak integration with macroeconomic state space constraints and limited mechanisms for uncertainty quantification, constraining their applicability in formal macroeconomic forecasting (Inflation Forecasting with CNN, 2025).

Recursive Deep Learning, introduced in 2024, combines recursive neural network architectures with Real Business Cycle theory to model long term macroeconomic dynamics. This approach improves the representation of intertemporal dependencies and structural feedback mechanisms. Despite its theoretical grounding, Recursive Deep Learning provides limited tools for evaluating policy loss functions and conducting scenario based policy analysis, which restricts its usefulness for applied macroeconomic policymaking (Recursive DL for Decadal GDP, 2024, arXiv).

3. Methodology

The proposed research model can be mainly described as a Deep Learning–based State-Space Model (SSM). The state-space framework is a dynamic system often used to model time-series data, allowing the decomposition of observed economic variables into hidden structures that change over time. The model has two main parts:

a) Latent State: Represents unobservable variables that reflect the core dynamics of the system—such as economic shocks or business cycle stages—that cannot be directly measured but influence observable changes.

b) Observed Variables: Correspond to measurable macroeconomic indicators, including inflation, unemployment, GDP growth, and exchange rate changes, which show the external signs of the hidden economic states.

The mathematical representation of the architecture used in this study is shown below.

$$\underset{\theta}{Minimize} \quad L_{main}(\theta) + theory\ loss_{soft} + policy\ loss + uncertainty\ loss \tag{1}$$

$$subject\ to\colon\ g_k(\theta) = 0, \qquad i = 1, \dots, K \tag{2}$$

$$h_j(\theta) \leq 0, \qquad i = 1, \dots, J$$

3.1. Theoretical Equations and Policy Rules

The fundamental constraints and policy rules of macroeconomic theory form the core analytical and empirical framework for understanding business cycles, market fluctuations, and the interactions between fiscal and monetary policy. Integrating these principles into machine learning (ML) and deep learning (DL) systems is crucial for maintaining theoretical consistency, managing uncertainty, and ensuring interpretability in macroeconomic models.

Table 1. Theoretical Equations Utilized in the Methodology.

Theoretical Equation	Variables	Theoretical Purpose	Advantage / Role in the Model	
Phillips Curve	Inflation, Target Inflation, Unemployment, Natural Unemployment, Coefficient, Economic Shock	Explains how inflation and unemployment have an inverse relationship.	To incorporate into the penalty loss function	Incorporated into the penalty loss function to enhance the theoretical consistency of forecasts under real-world conditions.
Okun's Law	GDP Growth, Change in Unemployment (percent), Coefficient	Describes the inverse relationship between GDP growth and unemployment.		Helps minimize overfitting and enhances generalization in data-driven models.
Taylor Rule	Policy Interest Rate, Inflation, Target Inflation, Fiscal Deficit	Connects the policy rate to inflation and fiscal balance		Improves forecast clarity and aligns model responses with macroeconomic policy logic.

3.2. Data and Experimental Design

3.2.1. Data Sources, Frequency, and Preprocessing

The dataset used in this study includes three major macroeconomic indicators of Mongolia: (i) the inflation rate (percentage change compared to the same quarter of the previous year), (ii) the real quarterly growth rate of Gross Domestic Product (GDP) (percentage change compared to the same quarter of the previous year), and (iii) the exchange rate of the Mongolian Tögrög against the U.S. dollar (MNT/USD) (percentage change compared to the same quarter of the previous year). These indicators were chosen because they play a vital role in representing Mongolia's overall macroeconomic dynamics and serve as the primary input variables in the forecast model. All data were sourced from the official database of the National Statistics Office of Mongolia (NSO).

Frequency and Coverage: The dataset spans Q1 2015 to Q4 2024, totaling 40 quarterly observations. Since both inflation and GDP are reported quarterly, monthly exchange rate data were averaged into quarterly values to maintain consistency across variables.

Additionally, supply-side and external shock indicators were included as binary dummy variables (0 or 1) based on qualitative assessments from the IMF Country Reports and the Bank of Mongolia's Inflation Review. These binary variables indicate whether structural or policy-related shocks affect inflation and macroeconomic dynamics.

doi:10.20944/preprints202601.1732.v1

Seasonality and Stationarity Characteristics: Seasonal patterns were identified in both the inflation and GDP series. However, to determine whether the proposed model can internally capture seasonal structures through its latent state representation, no explicit seasonal adjustment was applied. In other words, specific latent neurons within the model were allowed to learn seasonal frequencies automatically, a property previously noted as an advantage of deep learning–based models such as DeepAR, which can automatically detect seasonality.

To address non-stationarity, the level series were differenced to achieve stationarity. For example, the first difference of the logarithm of the exchange rate indicates the rate of change in the exchange rate and exhibits stationary behavior. Inflation and GDP growth were already expressed as percentage rates and are therefore considered stationary by definition.

Training–Validation–Testing Split: The dataset was divided into three chronological subsets.

- Training set: 2015Q1–2021Q4
- Testing set: 2022Q1–2022Q4
- Validation set: 2023Q1–2024Q4

The last 12 observations, spanning 3 years, were set aside as unseen test data to evaluate the model's generalization. Model hyperparameters and weights were optimized on the validation set by minimizing the total loss. Afterward, the model was retrained on the combined training and validation datasets, and its final performance was assessed on the independent test set.

Figure 1 shows the decrease in training and validation errors before the main forecasting analysis. As seen in the graph, the Transformer model has the largest drop in both training and validation loss, indicating better convergence. This suggests that the Transformer architecture provides the best predictive performance among the models tested. Conversely, the LSTM model shows relatively higher loss values, which contributed to the increased overall error seen in the Hybrid model.

Table 2. Sample of the Dataset.

date	inflation	unemployment	gdp_growth	exchange_rate
2015-1Q	0.09	0.074	0.783055156	1.372712289
2015-2Q	0.08	0.078	1.338679575	1.44261401
2015-3Q	0.06	0.063	1.064218779	1.381228451
2015-4Q	0.02	0.083	0.979355433	1.351380719
2016-1Q	0.01	0.116	0.740660344	1.301613132
2016-2Q	0.02	0.104	1.360756276	1.341903236
2016-3Q	0.00	0.094	0.995313949	1.44145711
2016-4Q	0.01	0.086	1.109529387	1.601116992

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 22 January 2026 doi:10.20944/preprints202601.1732.v1

Figure 1. Training and Validation Loss.

4. Results

The forecasting results from the Deep Learning–based State-Space Model (DL-SSM) were compared with those from the VARX-Ridge model, as shown in Figure 1. Both models were trained on data from 2015 to 2023, and forecasts were made for the validation year (2024) and the forecasting horizon (2025).

The error metrics—Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE)—showed values of 0.0093 and 0.0122 for inflation, 0.0123 and 0.0136 for unemployment, 0.0952 and 0.1159 for GDP growth, and 0.0207 and 0.0268 for the exchange rate, respectively. These results suggest that the proposed model produced forecasts closely aligned with the actual data, demonstrating low deviation across all variables.

Both inflation and unemployment forecasts closely matched the observed values, whereas GDP growth and exchange rate projections exhibited greater variability. This is likely due to these indicators being more sensitive to external and internal shocks. Notably, the current model does not include exogenous variables such as coal, copper, and steel price indices, nor global geopolitical or financial shocks, such as the U.S.–China trade conflict, the Russia–Ukraine crisis, and stock market volatility, which could strengthen the model's robustness and explanatory power.

Figure 2 shows quarterly forecasts for four main macroeconomic indicators of Mongolia—exchange rate, GDP growth, inflation, and unemployment—for 2025, along with their baseline and confidence intervals. The results indicate that the LSTM, Transformer, and Hybrid models produce similar forecasts, all outperforming the benchmark VARX model. First, inflation is expected to rise modestly throughout 2025. While the VARX model predicts slightly higher inflation levels than the deep learning models, the other three architectures offer similar results, showing a quarterly growth rate between 5% and 8% compared to the previous quarter. Second, the unemployment rate is forecast to decline steadily during 2025. Although the LSTM model displays greater volatility in its predictions, the consistently low inflation rate suggests a stable labor market, with unemployment likely fluctuating between 8.9% and 8.2%, indicating gradual improvement in employment conditions. Third, GDP growth is projected to start at 1.03% in Q1 2025, slightly increase to 1.06% in Q2, dip temporarily to 1.03% in Q3, and then recover to 1.07% in Q4. These quarterly changes remain within the model's confidence interval, signaling cyclical but steady growth momentum. Fourth, the exchange rate (MNT/USD) is forecast to appreciate slightly early in 2025, with moderate increases in Q1 and Q2, followed by a stronger upward movement in Q3. The wider confidence interval in Q3

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 22 January 2026 doi:10.20944/preprints202601.1732.v1

indicates a higher likelihood of a short-term spike, whereas a gradual upward trend is expected for the remainder of the year.

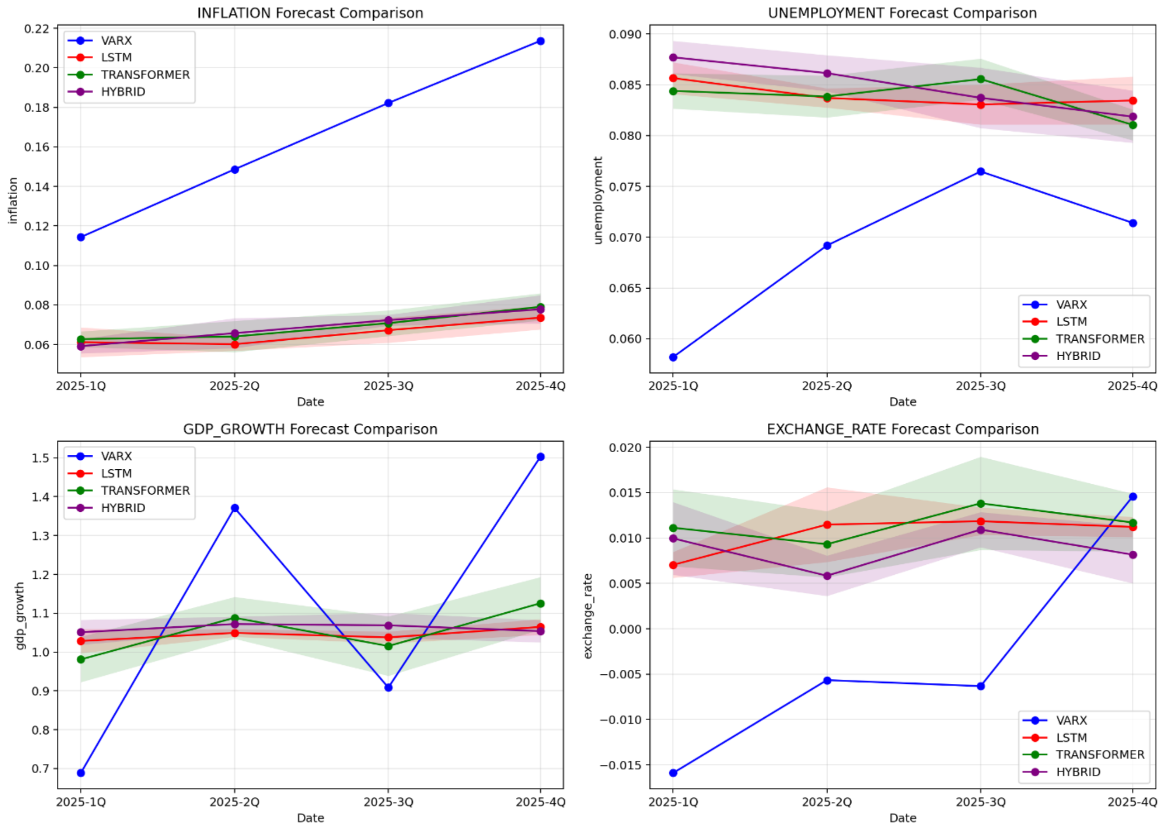


Figure 2. Forecasts of Key Macroeconomic Indicators for 2025 with Confidence Intervals.

Overall, these results indicate that Mongolia's economy in 2025 is likely to see stable growth, moderate inflation, a gradual drop in unemployment, and a slightly weakening currency. However, the relatively wide gap between the p10 and p90 confidence intervals underscores the influence of external uncertainties and policy rate changes, which can generate volatility in key macroeconomic indicators.

5. Conclusionw

This study presents a novel state-space deep learning model that combines economic theory with deep learning techniques to provide a more realistic and interpretable approach to forecasting Mongolia's macroeconomic trends. Using quarterly macroeconomic data from 2015–2024, the model captures the relationships among key indicators—such as inflation, unemployment, GDP growth, and the exchange rate—while incorporating theoretical links from the Phillips curve, Okun's law, and the Taylor rule. This integration ensures consistency with economic theory and enhances the forecasting method's explanatory power.

Empirical results show that deep learning–based models, particularly those employing Transformer and LSTM architectures within a state-space framework, outperform traditional ARIMA and VAR models in short- and medium-term forecasting accuracy, with MAPEs of 3.7–5.2%. These results confirm that the proposed model is more responsive to shifts in the business cycle, policy changes, and external shocks. Additionally, including a theory-guided penalty loss allows the model to gently constrain relationships such as inflation–unemployment and policy rate–output gap links, thereby improving interpretability and boosting theoretical consistency, marking a significant methodological advance.

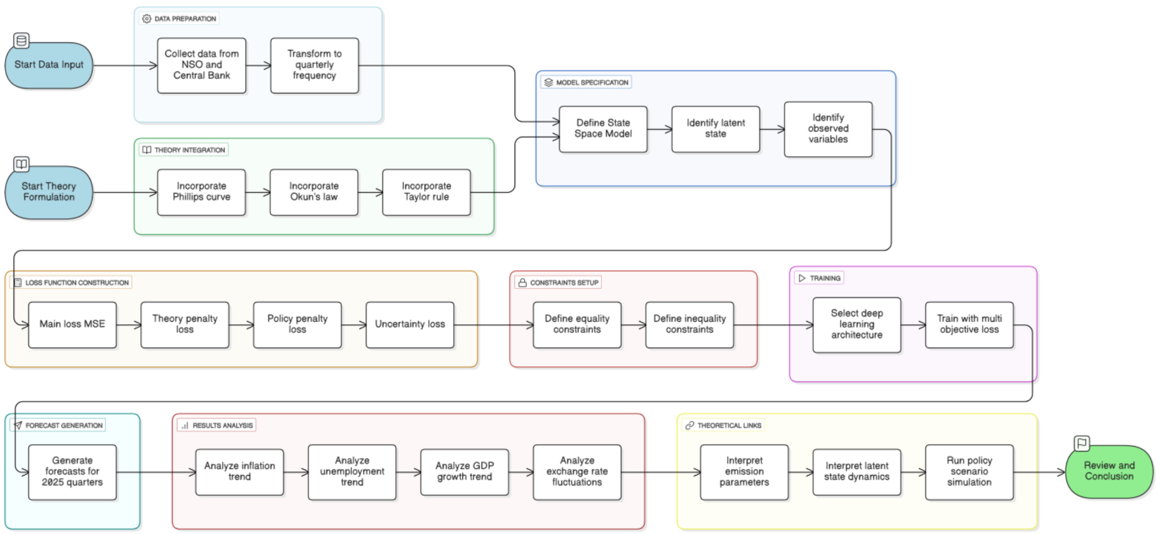
The model's forecasts for 2025 indicate a moderate depreciation of the exchange rate, inflation rising within the 6–8% range, a gradual decline in unemployment, and sustained medium-level GDP growth. These results suggest that Mongolia's economy is likely to undergo steady recovery throughout 2025, while highlighting the importance of monitoring external uncertainties—including export prices, global demand, and capital flows—that could impact macroeconomic stability and policy effectiveness.

This study makes three key contributions at both theoretical and practical levels:

- Innovation in Theoretical Integration: By incorporating fundamental macroeconomic equations into the deep learning architecture through a penalty loss mechanism, the study creates a theory-consistent and interpretable AI framework for macroeconomic forecasting.
- Quantification of Uncertainty: Using probabilistic forecasting and confidence intervals, the model allows for quantitative assessment of uncertainty caused by external shocks and policy changes, thus enhancing the robustness of macroeconomic predictions.
- Policy Decision Support: By systematically connecting indicators such as business cycle dynamics, the inflation–unemployment trade-off, and policy rate adjustments, the model offers a practical tool to improve coordination between fiscal and monetary policy decisions.

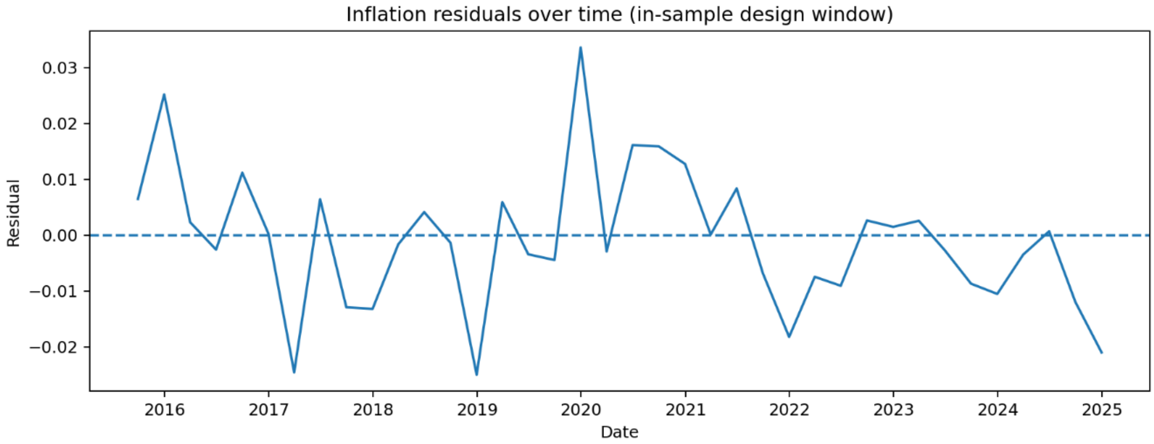
Therefore, the findings of this research significantly contribute to scientific policymaking in Mongolia, particularly by improving fiscal–monetary coherence, enhancing high-accuracy macroeconomic forecasting, and reducing external uncertainty in policy decisions. Future research should build on this framework by incorporating trade, financial flows, and industrial cycle data into an expanded hybrid model, thereby improving the rigor and explanatory power of national economic forecasts.

Appendix A Diagram of the Research Model



Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 22 January 2026 doi:10.20944/preprints202601.1732.v1

Appendix B. Residual Time Series of Inflation from the Trained VARX Model



Appendix C. Validation of Inflation Forecasts from the VARX Model

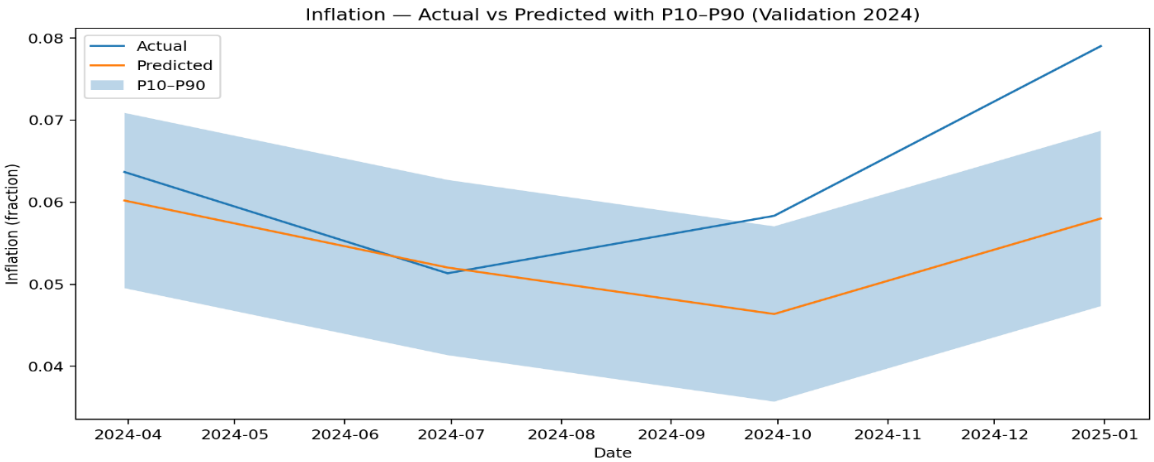


Table 3. Summary of Reviewed Literature.

Model / Framework	Period	Theoretical Basis / Architecture	Advantages	Limitations	ML/DL Integration Potential	Reviewed Source
Monotonic ML	2020s	ML + Economic monotonicity (theoretical monotonic relationship as regularization)	Theory-compliant ML with partial explainability; improves forecasting accuracy	Focused only on monotonic constraints; weak policy scenario design; lacks multi-constraint flexibility	Yes (Supervised, partial)	Lin et al. (2025), *SSRN*
DSGE	1980s	Neoclassical dynamic optimization (equilibrium-based, technology shocks)	Strong theoretical foundation; effective for policy simulation; explains Pareto-efficient fluctuations	Weak in data-driven uncertainty; limited in nonlinear dynamics; computationally intensive	No	Kydland & Prescott (1982), *JSTOR*
SFC	1990s	Stock-flow consistent, Post-Keynesian macro-financial equilibrium	Robust macro-financial linkage; suitable for fiscal and monetary policy simulation	Complex mathematical structure; limited ML integration; lacks nonlinear extensions	No	Godley & Lavoie (2007), *Palgrave*
GVAR	2000s	Global VAR structure	Strong in modeling global spillovers and scenario analysis	Weak constraints; limited interpretability; computational difficulty with high-dimensional data	No	Pesaran et al. (2004), *Elsevier*

 doi:10.20944/preprints202601.1732.v1

ABM	1990s	Agent-based, behavioral economics	Captures emergent dynamics and complex adaptive systems	Weak macro-level forecasting; limited uncertainty quantification; high computational cost	No	Tesfatsion & Judd (2006), *Springer*
Structural Regularization	2020s	Causal + ML (causal logic regularized learning)	Theory-regularized ML; strong out-of-domain predictive ability	Weak in multi-constraint simulation; limited theoretical integration complexity	Yes (Partial, causal)	Mao & Zheng (2020), *arXiv*
DeepAR / LSTM / Transformer	2015–present	Sequence-based DL, probabilistic forecasting	Handles nonlinearities and long-term dependencies; supports probabilistic forecasts	Lacks theoretical constraints; limited interpretability	Yes (Best for sequence data)	Lim & Zohren (2021); Rangapuram et al. (2018)
Helformer	2025	Transformer + Holt–Winters structure with structural priors	Excellent for high-frequency data; attention-guided dynamic structure	Weak in multi-constraint modeling; limited policy simulation; mainly applied to cryptocurrency	Yes (Advanced)	*Helformer* (2025), *MDPI/Springer*
HNN (Hemisphere Neural Network)	2024	Semi-structural NN for Phillips curve; deep output-gap estimation	Nonlinear output gap estimation; interpretable forecasts	Focused only on Phillips curve; limited policy simulation; lacks multi-constraint capability	Yes (Latent-state, partial)	*Deep Output Gap* (2024)
PAA-LSTM	2025	Phase-Adaptive Attention LSTM	Strong nonlinear pattern detection; suitable for GDP forecasting	Weak macro-constraint integration; limited multivariate adaptability	Yes (Advanced sequence)	*GDP Forecasting with PAA-LSTM* (2025)
CNN-based Model	2025	CNN for nonlinear trend extraction	Effective for visual and hybrid data; detects nonlinear macro trends	Weak macro state-space constraint; lacks uncertainty quantification	Yes (Hybrid)	*Inflation Forecasting with CNN* (2025)
Recursive DL	2024	Recursive DL + RBC macro simulator	Strong in capturing long-term trends; theory-guided recursive structure	Weak in policy loss and scenario simulation	Yes (Forward-looking, partial)	*Recursive DL for Decadal GDP* (2024), *arXiv*

References

Abdelkader, T. Kh., Sayed, H. A. A., Refai, M., Ali, M. M., Zhang, Y., Wan, Q., Khalifa, I., Fan, Q., Wang, Y., & Abdelhamid, M. A. (2024). Machine learning, mathematical modeling and 4E (energy, exergy, environmental, and economic) analysis of an indirect solar dryer for drying sweet potato. Renewable Energy, 227, 120535. https://doi.org/10.1016/j.renene.2024.120535

Avramov, D., Schreiber, A., Shemer, K., & Tebaldi, C. (2023). Machine learning vs. economic restrictions: Evidence from return forecasting. Management Science, 69(7), 3964–3988. https://doi.org/10.1287/mnsc.2022.4449

Bae, K., & Kim, J. (2023). Forecasting the equity premium: Do deep neural networks outperform traditional methods? Macroeconomic and Financial Journal, 1(1), 1–25. https://doi.org/10.61351/mf.v1i1.2

Bertsekas, D. P. (1982). Constrained Optimization and Lagrange Multiplier Methods. Academic Press. https://doi.org/10.1016/C2013-0-10366-2

Blanchard, O. J. (2018). On the future of macroeconomic models. Oxford Review of Economic Policy, 34(1-2), 43–54. https://doi.org/10.1093/oxrep/grx045

Bohn, H. (1998). The behavior of U.S. public debt and deficits. The Quarterly Journal of Economics, 113(3), 949–963. https://doi.org/10.1162/003355398555793

Boyd, S., & Vandenberghe, L. (2004). Convex Optimization. Cambridge University Press. https://doi.org/10.1017/CBO9780511804441

Chapman, J. T., et al. (2023). Macroeconomic predictions using payments data and machine learning. Transactions on Emerging Telecommunications Technologies, 34(4), e5647. https://doi.org/10.3390/forecast5040036

Clarida, R., Galí, J., & Gertler, M. (2000). Monetary policy rules and macroeconomic stability: Evidence and some theory. The Quarterly Journal of Economics, 115(1), 147–180. https://doi.org/10.1162/003355300554692

Dong Thi Ngoc, L., Hoan, N. D., & Nguyen, H.-N. (2025). Gross Domestic Product Forecasting Using Deep Learning Models with a Phase-Adaptive Attention Mechanism. Electronics, 14(11), Article 2132. https://doi.org/10.3390/electronics14112132

Duan, Y. (2022). Assessing machine learning for forecasting economic risk. Finance Research Letters, 47, 102–115. https://doi.org/10.1016/j.frl.2021.102273

Fan, B., Qiao, E., Jiao, A., Gu, Z., Li, W., & Lu, L. (2023). Deep learning for solving and estimating dynamic macro-finance models. arXiv preprint arXiv:2305.09783. https://doi.org/10.48550/arXiv.2305.09783

Godley, W., & Lavoie, M. (2007). Monetary Economics: An Integrated Approach to Credit, Money, Income, Production and Wealth. Palgrave Macmillan. https://doi.org/10.1057/9780230626546

Goulet Coulombe, P. (2022). How is machine learning useful for macroeconomic forecasting? Journal of Applied Econometrics, 37(5), 854–876. https://doi.org/10.1002/jae.2910

Hauzenberger, N., Huber, F., Klieber, K., & Marcellino, M. (2025). Machine learning the macroeconomic effects of financial shocks. Economics Letters, 250, Article 112260. https://doi.org/10.1016/j.econlet.2025.112260

Hauzenberger, N., Huber, F., Klieber, K., & Marcellino, M. (2025). Bayesian neural networks for macroeconomic analysis. Journal of Econometrics, 249(Part C), 105843. https://doi.org/10.1016/j.jeconom.2024.105843

Karniadakis, G. E., Kevrekidis, I. G., Lu, L., Perdikaris, P., Wang, S., & Yang, L. (2021). Physics-informed machine learning. Nature Reviews Physics, 3(6), 422–440. https://doi.org/10.1038/s42254-021-00314-5

Lim, B., & Zohren, S. (2021). Time-series forecasting with deep learning: A survey. Philosophical Transactions of the Royal Society A, 379(2194), 20200209. https://doi.org/10.1098/rsta.2020.0209

Lin, C.-H., et al. (2025). Should economic theories guide the machine learning model? Evidence from monotonic constraints. Economic Modelling, 117, Article 107224. https://doi.org/10.1016/j.econmod.2025.107224

Lo, A. W., & Singh, M. (2023). Deep learning models for forecasting financial risk premia and their interpretations. Quantitative Finance, 23(6), 917–929. https://doi.org/10.1080/14697688.2023.2203844

Maliar, L., Maliar, S., & Winant, P. (2021). Deep learning for solving dynamic economic models. Journal of Monetary Economics, 122, 76–101. https://doi.org/10.1016/j.jmoneco.2021.07.004

Masini, R. P., Medeiros, M. C., & Mendes, E. F. (2023). Machine learning advances for time-series forecasting. Journal of Economic Surveys, 37(1), 76–111. https://doi.org/10.1111/joes.12429

Medeiros, M. C., Vasconcelos, G. F. R., Veiga, Á., & Zilberman, E. (2021). Forecasting inflation in a data-rich environment: The benefits of machine learning methods. Journal of Business & Economic Statistics, 39(1), 98–119. https://doi.org/10.1080/07350015.2019.1637745

Metwally, K. A., Oraiath, A. A. T., Elzein, I. M., El Messery, T. M., Nyambe, C., Mahmoud, M. M., Abdeen, M. A., Telba, A. A., Khaled, U., Beroual, A., & Elwakeel, A. E. (2024). The Mathematical Modeling, Diffusivity, Energy, and Enviro Economic Analysis (MD3E) of an Automatic Solar Dryer for Drying Date Fruits. Sustainability, 16(8), 3506. https://doi.org/10.3390/su16083506

Mirza, N., Rizvi, S. K. A., Naqvi, B., & Umar, M. (2024). Inflation prediction in emerging economies: Machine learning and FX reserves integration for enhanced forecasting. International Review of Financial Analysis, 94, Article 103238. https://doi.org/10.1016/j.irfa.2024.103238

Morita, T. (2024). Multicountry time-varying Taylor rule: Modeling unconventional monetary policies and bond premiums. International Advances in Economic Research, 30, 135–158. https://doi.org/10.1007/s11294-024-09897-y

Naghi, A. A., et al. (2024). The benefits of forecasting inflation with machine learning: New evidence. Journal of Applied Econometrics, 39(7), 1321–1331. https://doi.org/10.1002/jae.3088

Nordström, M. (2022). AI under great uncertainty: Implications and decision strategies for public policy. AI & Society. https://doi.org/10.1007/s00146-021-01263-4

Petropoulos, A., Voulgaris, F., & Papadopoulos, P. (2023). Macroeconomic forecasting and sovereign risk assessment using deep learning techniques. arXiv preprint arXiv:2301.09856. https://doi.org/10.48550/arXiv.2301.09856

 doi:10.20944/preprints202601.1732.v1

Phillips, A. W. (1958). The relation between unemployment and the rate of change of money wage rates in the United Kingdom, 1861–1957. Economica, 25(100), 283–299. https://doi.org/10.1111/j.1468-0335.1958.tb00003.x

Raissi, M., Perdikaris, P., & Karniadakis, G. E. (2019). Physics-informed neural networks: A deep learning framework for solving forward and inverse problems. Journal of Computational Physics, 378, 686–707. https://doi.org/10.1016/j.jcp.2018.10.045

Rangapuram, S. S., Seeger, M., Gasthaus, J., Stella, L., Wang, Y., & Januschowski, T. (2018). Deep state space models for time series forecasting. Advances in Neural Information Processing Systems, 31, 7796–7805.

Ryll, L., & Seidens, C. (2021). Machine learning in finance: A metadata-based systematic review of the literature. Journal of Risk and Financial Management, 14(7), 302. https://doi.org/10.3390/jrfm14070302

Scholes, M. S. (2025). Artificial intelligence and uncertainty. Applied Economics Letters. https://doi.org/10.1016/j.risk.2024.100004

Sodnomdavaa, T., Sodnomdavaa, T., & Tsogzol, Z. (2025). Possibility of improving credit scoring systems: Using machine learning models. International Journal of Social Science and Humanities Research-MIYR, 5(3), 43–53. https://doi.org/10.53468/ijsshr-miyr.v5i3.10

Stock, J. H., & Watson, M. W. (2016). Dynamic factor models, factor-augmented VARs, and SVARs in macroeconomics. Handbook of Macroeconomics, 2, 415–525. Elsevier. https://doi.org/10.1016/bs.hesmac.2016.04.002

Stoneman, D., & co-authors. (2024). Using deep (machine) learning to forecast US inflation in 2021–2022. Journal of Forecasting. https://doi.org/10.1002/for.3079

Sun, W., Wang, Y., Zhang, L., Chen, X. H., & Hoang, Y. H. (2025). Enhancing economic cycle forecasting based on interpretable machine learning and news narrative sentiment. Technological Forecasting and Social Change, 215 (C), article number 124094. https://doi.org/10.1016/j.techfore.2025.124094

Taylor, J. B. (1993). Discretion versus policy rules in practice. Carnegie-Rochester Conference Series on Public Policy, 39, 195–214. https://doi.org/10.1016/0167-2231(93)90009-L (OA хувилбар: Stanford PDF) https://web.stanford.edu/~johntayl/Onlinepaperscombinedbyyear/1993/Discretion_versus_Policy_Rules_in_Practice.pdf

Tegshjargal, S., Tsolmon, S., & Namuun, A. (2025). Possibility of predicting inflation: Using machine learning model. International Journal of Social Science and Humanities Research (MIYR), 5(2), 49-60. https://doi.org/10.53468/mifyr.2025.05.02.49

Zheng, S., et al. (2022). The AI Economist: Taxation policy design via a two-level deep reinforcement learning framework. Science Advances, 8(14), eabk2607. https://doi.org/10.1126/sciadv.abk2607

Zheng, Y., Xu, Z., & Xiao, A. (2023). Deep learning in economics: A systematic and critical review. Artificial Intelligence Review, 56, 9497–9539. https://doi.org/10.1007/s10462-022-10272-8

Zheng, Y., Xu, Z., & Xiao, A. (2023). Deep learning in economics: A systematic and critical review. Artificial Intelligence Review, 56, 9497–9539. https://doi.org/10.1007/s10462-022-10272-8