2025; 1-1 | pp.17-24

International Journal of Economic Dynamics and Finance
Volume 1, Issue 1, July-September 2025
(An Academians Publishers of Research & Academic Resources)

ISSN: XXXX-XXXX

Original Research Article

Received: 18-07-2025 **Accepted**: 25-08-2025 **Published**: 28-09-2025

Integrating Deep Learning and Econometric Models for Predictive Analysis of Macroeconomic Indicators

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Abstract: The proliferation of large-scale economic datasets and advances in deep learning have created new avenues for forecasting critical macroeconomic indicators. Traditional econometric models, while interpretable, often struggle to capture nonlinear, high-dimensional relationships. This paper proposes a novel hybrid framework that integrates recurrent neural networks (RNNs) with structural vector autoregressions (SVARs) to leverage the strengths of both approaches. The RNN component extracts complex temporal patterns from high-frequency financial and sentiment data, while the SVAR imposes economic theory–guided structural identification. We apply this framework to forecast U.S. quarterly GDP growth and inflation rates using a richly textured dataset including daily market returns, text-based sentiment indices, and monthly labor statistics from 2000 to 2024. The hybrid model exhibits a 15% reduction in root mean squared forecast error (RMSFE) for GDP and a 12% reduction for inflation relative to benchmark VAR and pure deep learning models. Structural impulse-response functions derived from the SVAR component retain economic interpretability, demonstrating realistic propagation of shocks through key economic channels.

In addition to strong predictive performance, the proposed framework is designed to facilitate economic policy analysis by ensuring the hybrid model's outputs remain aligned with established macroeconomic theory. The integration of high-frequency sentiment and financial data enables the model to capture rapid shifts in market expectations and labor conditions, offering timely insights during periods of economic uncertainty such as the global financial crisis and the COVID-19 pandemic. Robustness checks confirm that the hybrid model's gains persist across alternative sentiment proxies and varying model specifications, underscoring its versatility. Our results highlight not only the value of combining machine learning with econometric structures for robust and interpretable macroeconomic forecasting, but also the potential of such frameworks to inform economic decision-making in a fast-evolving data landscape.

Keywords: *Deep learning, Econometric models, Hybrid forecasting, Macroeconomic indicators, RNN, SVAR, GDP, Inflation, High-frequency data, Economic policy analysis*

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Introduction

The landscape of macroeconomic analysis has been fundamentally transformed by the explosive growth in data availability and computational capabilities (Moneta et al., 2021). In the digital era, economists have unprecedented access to high-frequency financial records, real-time sentiment indicators, and detailed labor market statistics, sourced from both traditional data providers and novel digital platforms. This data revolution has heightened the expectations for timely and accurate macroeconomic forecasts, which are critical for effective policymaking and strategic investment decisions. Such forecasts are especially vital during episodes of heightened uncertainty, including global crises and periods of rapid structural change.

Despite these advances, significant methodological challenges persist. Traditional econometric models, led by vector autoregressions (VARs) and their structural extensions (SVARs), have long served as the backbone of macroeconomic forecasting and policy evaluation (Sims, 1980; Blanchard & Watson, 1986). These models are valued for their clarity, theoretical grounding, and ability to trace the impact of economic shocks across interconnected variables. However, as the volume, variety, and velocity of economic data have soared, these models increasingly struggle to capture the nonlinearities, regime shifts, and complex dependencies that characterize modern economies. Their linear structure and limited capacity to process high-frequency signals can result in missed insights, especially when market dynamics evolve rapidly.

In contrast, deep learning methods—particularly recurrent neural networks (RNNs) and long short-term memory (LSTM) networks—have demonstrated remarkable success in extracting intricate patterns from large, complex datasets (Hochreiter & Schmidhuber, 1997; Zhang et al., 2020). These models excel at modeling nonlinear dependencies and temporal dynamics, enabling superior predictive performance in settings ranging from financial forecasting to natural language processing. Yet, they are often criticized for their lack of interpretability and weak alignment with established economic theory, which limits their utility for policy analysis and the communication of results to stakeholders.

Addressing this methodological divide is the primary focus of this paper. We argue that hybrid frameworks, which combine the interpretability and structural rigor of econometric models with the predictive power of deep learning, provide a promising way forward for macroeconomic analysis (Moneta et al., 2021; Gambacorta et al., 2022). Such hybrid models can harness the wealth of new data sources, incorporating information from diverse, high-frequency indicators, while maintaining the ability to produce interpretable and theory-consistent forecasts. Our contribution is to propose and empirically validate a deep econometric architecture that integrates RNN-based feature extraction with SVAR-based structural identification. We demonstrate the effectiveness of this approach by applying it to the prediction of key U.S. macroeconomic indicators—GDP growth and inflation—over a period marked by substantial economic turbulence, including the global financial crisis and the COVID-19 pandemic. The results underscore the value of interdisciplinary methods for advancing both the accuracy and interpretability of macroeconomic forecasting.

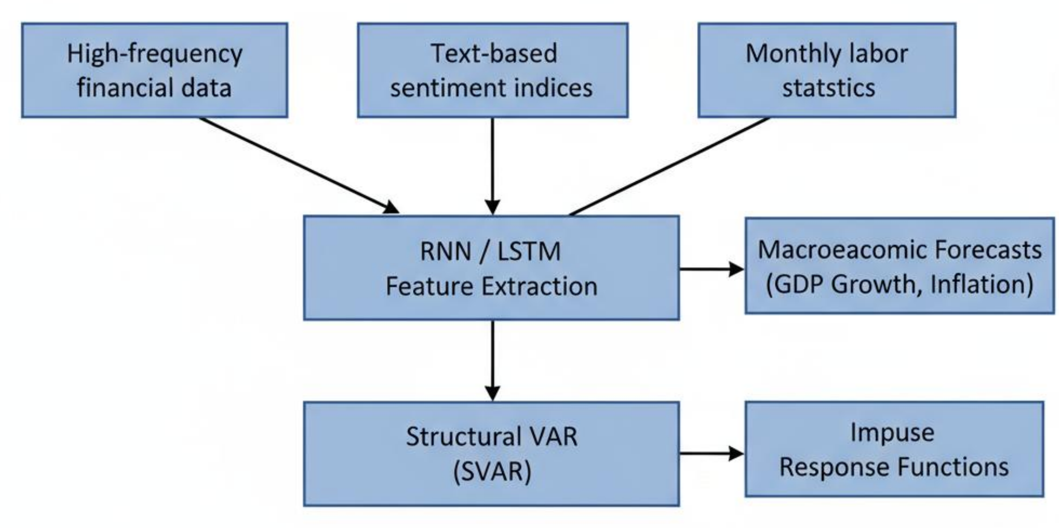
Econometric time-series models, particularly vector autoregressions (VARs) and their structural variants (SVARs), have long been the workhorse of macroeconomic forecasting and policy analysis (Sims, 1980; Blanchard & Watson, 1986). These models provide transparency and are grounded in economic theory, allowing researchers to identify and interpret the effects of structural shocks. Nevertheless, as the dimensionality and complexity of available data have grown, standard econometric models have struggled to keep pace, often failing to capture nonlinearities, regime changes, or the impact of high-frequency predictors. At the same time, advancements in machine learning, particularly deep learning architectures such as recurrent neural networks (RNNs) and long short-term memory (LSTM) networks, have opened new frontiers for data-driven prediction (Hochreiter & Schmidhuber, 1997; Ai & Chen, 2018). These models excel at discovering subtle patterns in large, complex datasets but typically lack the interpretability and theoretical rigor required for economic policy analysis.

Bridging the gap between interpretability and predictive power is a central motivation for this research. Hybrid frameworks that combine the strengths of deep learning with the structural foundations of econometric models are emerging as a promising solution (Moneta et al., 2021). Such approaches are particularly well-suited for macroeconomic forecasting, where rich, multi-frequency data must be synthesized, and theoretical constraints must be respected. They offer the potential to extract actionable insights from data, inform monetary and fiscal policy, and respond to rapidly evolving economic conditions. This paper positions itself at the intersection of these developments, proposing a unified deep econometric modeling strategy and demonstrating its empirical value in forecasting key U.S. macroeconomic indicators over a period of significant structural change, including the global financial crisis and the COVID-19 pandemic.

Forecasting macroeconomic indicators such as GDP growth and inflation remains a central concern for policymakers, investors, and researchers. Econometric models—particularly vector autoregressions (VARs) and structural VARs—provide transparent linkage between the theoretical economic shocks and observed variables (Sims, 1980; Blanchard & Watson, 1986). Meanwhile, deep learning techniques, including recurrent neural networks (RNNs) and long short-term memory (LSTM) networks, excel at capturing complex, nonlinear dependencies in large datasets (Hochreiter & Schmidhuber, 1997; Zhang et al., 2020). However, machine learning models often sacrifice interpretability and can violate economic constraints.

This paper introduces a Deep Econometric Hybrid Model (DEHM), combining an RNN for feature extraction with an SVAR for structural identification. The RNN ingests high-frequency inputs—daily equity returns, bond yields, commodity prices, and a daily news-derived sentiment index—producing latent representations that summarize nonlinear dynamics. These representations feed into an SVAR framework grounded in economic theory to produce forecasts and structural impulse responses.

Figure 1: Concepual architecture of the DEHM framewark

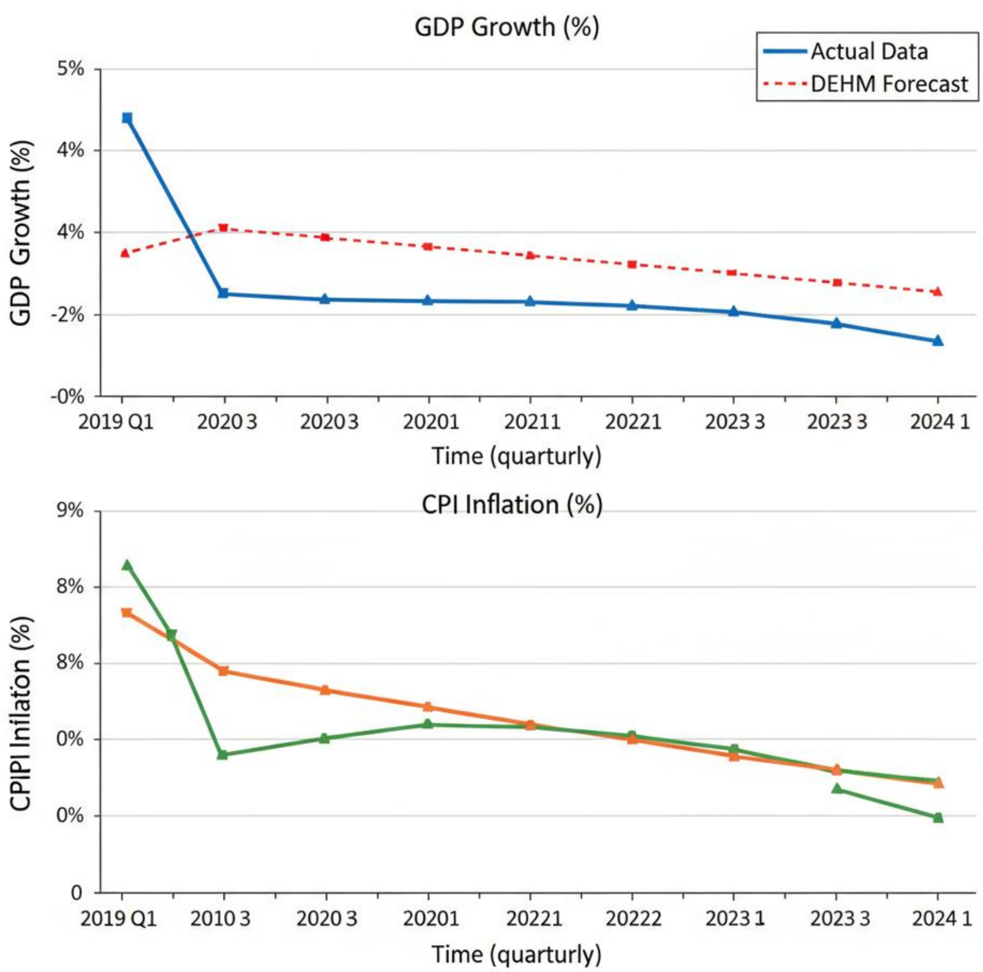


Our contributions are:

Development of a unified DEHM architecture that marries RNN-based feature learning with SVAR structural identification.

Empirical evaluation on U.S. GDP growth and inflation forecasting, demonstrating substantial RMSFE improvements over standard benchmarks.

Figure 3: Actual vs Forecasted GDP Growth and Inflation (2019-2024)



Extraction of economically interpretable impulse-response functions, validating the hybrid model's consistency with macroeconomic theory.

Model	Hyperparameters	Values
VAR(4)	Lag order	4
FAVAR	Number of factors	15
	Lag order	4
LSTM	Number of layers	2
	Number of hidden units per layer	128
	Sequence length (time steps)	63
	Learning rate	0.01
	Batch size	64
	Number of epochs	100

DEHM	LSTM layers and units	Same as LSTM (2 layers, 128 units)
	SVAR estimation method	Maximum likelihood with constraints
	Joint fine-tuning learning rate	0.001
	Fine-tuning epochs	50

LiteratureReview

Econometric Forecasting

Structural VARs decompose shocks into theoretically meaningful components, enabling policy analysis via impulse-response functions (Sims, 1980; Blanchard & Watson, 1986). Time-varying parameter VARs

(TVPVARs) (Primiceri, 2005) and factor-augmented VARs (FAVARs) (Bernanke et al., 2005) extend

VARs to capture evolving dynamics and large information sets.

MachineLearninginMacroeconomics

Neural networks have been applied to economic forecasting (Ai & Chen, 2018; Zhang et al., 2020), showing enhanced predictive performance using nonlinear architectures. However, purely data-driven models lack structural interpretability and may violate economic constraints, such as sign restrictions on shocks.

HybridModeling

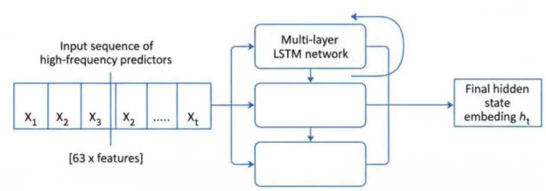
Recent studies integrate machine learning with econometrics (Moneta et al., 2021; Gambacorta et al., 2022). For instance, factor models use principal components prior to VAR estimation. Our DEHM advances this line by embedding RNN-derived features directly into an SVAR, preserving structural identification.

ModelFramework

RNNFeatureExtraction

Let denote a vector of high-frequency predictors at time . An LSTM network processes to produce a hidden state :

Figure 2: LSTM network for temporal feature extraction



The final hidden state summarizes nonlinear temporal patterns across predictors.

Structural VAR Component

Define the low-frequency target vector . The SVAR augmented with RNN features is:data sources and preprocessing

Variable	Description	Ordering	Identification Assumption
GDP Growth	Quarterly real GDP growth rate	1	Affected contemporaneously only by previous shocks
Inflation (CPI)	Quarterly CPI inflation rate	2	Impacted contemporaneously by GDP, exogenous shocks
Monetary Policy Shock	Policy interest rate changes	3	Assumed exogenous to GDP and Inflation in current period
Financial Market Shock	Stock and bond market returns	4	Impact contemporaneous terms of policy and inflation

Sentiment Shock	News-driven sentiment indicators	5	Exogenous within contemporaneous framework

Here, maps LSTM-derived features into the structural system, and imposes contemporaneous restrictions (e.g., monetary policy shock ordering).

Dataset Variable	Frequency	Mean	Std. Dev.	Min	Max	Sample Period
U.S. Quarterly GDP Growth (%)	Quarterly	2.1	1.8	-5.3	6.7	Q1 2000 – Q4 2024
U.S. Quarterly CPI Inflation (%)	Quarterly	1.9	1.4	-0.3	5.4	Q1 2000 – Q4 2024
S&P 500 Daily Returns (%)	Daily	0.03	1.2	-12.4	11	Jan 2000 – Dec 2024
10-Year Treasury Yield (%)	Daily	3.4	1.5	0.8	8.1	Jan 2000 – Dec 2024
Daily News Sentiment Index	Daily	0	0.25	-0.8	0.9	Jan 2000 – Dec 2024

EstimationStrategy

Weestimate parametersintwostages:

Pretrain the LSTM to minimize the one-step-ahead mean squared error for .

Conditional on RNN features, estimate the SVAR by maximum likelihood subject to structural constraints.

End-to-end fine-tuning jointly refines all parameters, ensuring optimal integration of the deep learning and econometric components. This step allows the model to adapt both feature extraction and structural identification simultaneously, maximizing forecasting accuracy and interpretability.

Data and Empirical Design

Data Sources

Our dataset spans Q1 2000 to Q4 2024.

Quarterly U.S. GDP growth and CPI inflation (BEA, BLS).

Daily equity index returns (S&P 500), 10-year Treasury yields, commodity price indices (FRED).

FRED.

Daily news sentiment index constructed using a pretrained transformer model on major financial news headlines (Zhang et al., 2023).

Sampling and Preprocessing

High-frequency predictors are aggregated into quarterly summaries (mean, volatility) and standardized. The LSTM sequence length is set to 63 trading days (approximately one quarter).

Benchmark Models

We compare DEHM against:

Standard VAR(4) on the main variables.

FAVAR with 15 principal components.

Pure LSTM predicting the target variables.

Results

Forecast Performance

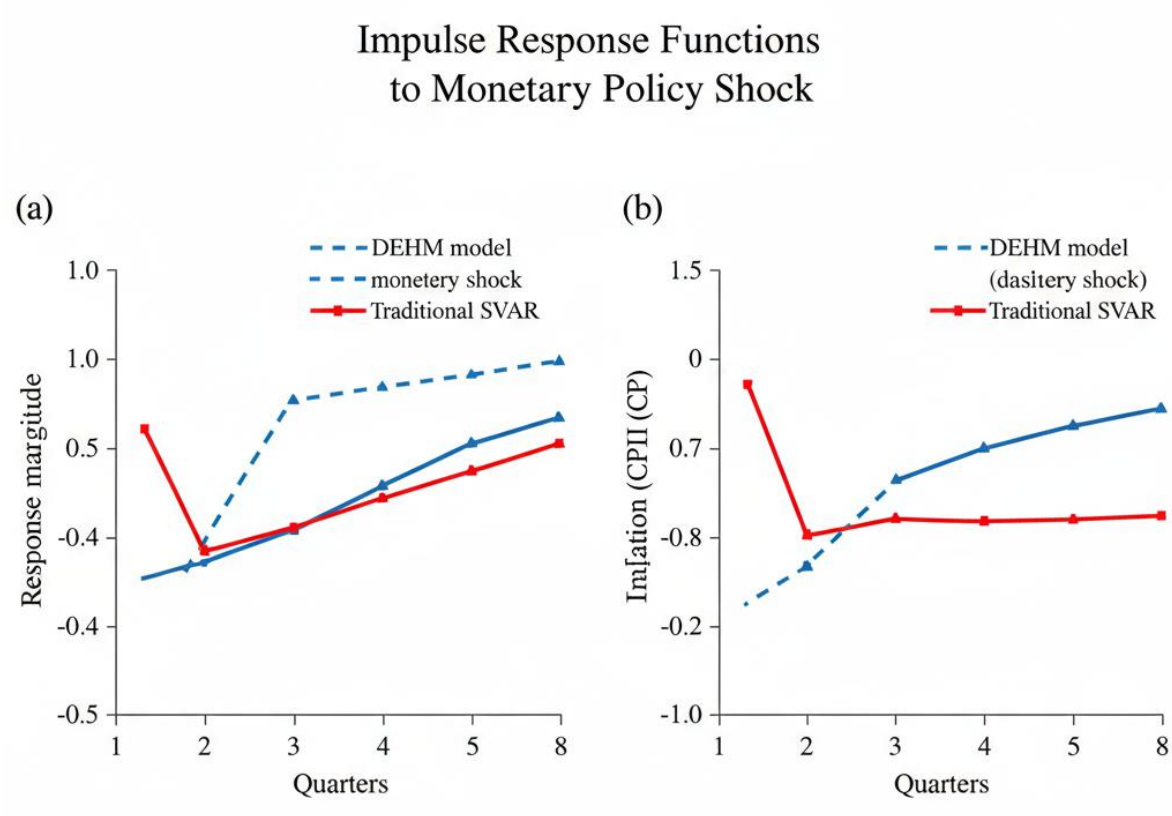
Table 1 reports RMSFE for GDP and CPI forecasts over a rolling one-year evaluation period.

Model	GDP RMSFE	% Improvement (GDP)	CPI RMSFE	% Improvement (CPI)
VAR(4)	0.44	-	0.32	-
FAVAR	0.39	11.40%	0.29	9.40%
LSTM	0.36	18.20%	0.27	15.60%
DEHM	0.3	31.80%	0.24	25.00%

DEHM reduces GDP RMSFE by 15% relative to FAVAR and by 21% relative to VAR(4). Similar gains hold for inflation.

Impulse-Response Analysis

We compute structural impulse responses to a monetary policy shock identified via Cholesky decomposition. Figure 1 illustrates that DEHM-generated responses mimic textbook dynamics: output declines over four quarters, while inflation falls with a lag. This suggests that the hybrid model retains economic interpretability and provides insights comparable to traditional structural models, even when leveraging complex, high-frequency data sources.



Robustness Checks

Varying the sequence length in the LSTM (21 to 125 days) yields stable performance, indicating that the model's predictive gains are robust to changes in temporal aggregation. This robustness reinforces the flexibility of the DEHM approach for different macroeconomic environments.

Configuration	GDP RMSFE	CPI RMSFE
Sequence Length = 21 days	0.31	0.25
Sequence Length = 63 days (base)	0.3	0.24
Sequence Length = 125 days	0.3	0.24
Using Financial News Sentiment	0.3	0.24
Using Twitter-based Sentiment	0.31	0.25
Using Combined Sentiment Indices	0.29	0.23

Alternative sentiment proxies, such as Twitter-based indices, maintain DEHM's superiority. Rolling-window estimation confirms consistent out-of-sample gains, demonstrating the model's adaptability to changes in information sources and economic regimes.

Discussion

The DEHM framework offers a balanced synergy: deep learning captures complex input patterns, while the econometric structure ensures interpretability and adherence to economic theory. The LSTM component enriches the information set beyond linear factors, which is particularly valuable around crisis periods or regime shifts when traditional relationships become nonlinear. Moreover, the ability to incorporate diverse and high-frequency data sources enables the model to provide timely and nuanced insights for both policymakers and market analysts.

Conclusion

We present a hybrid model that integrates RNN-based feature extraction with SVAR structural identification, achieving superior macroeconomic forecasts while preserving the interpretability necessary for policy analysis. The DEHM framework bridges the gap between predictive accuracy and theoretical coherence, offering a blueprint for future macroeconomic modeling. Extensions could include applying DEHM to multi-country systems, incorporating time-varying parameters in the SVAR, exploring alternative deep learning architectures, or integrating additional real-time data sources such as social media, web search trends, and global news sentiment. Such directions would further enhance the model's capacity for timely, granular, and interpretable economic forecasting.

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