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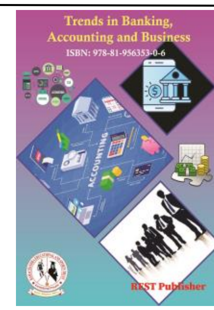

Machine-Learning Tree Models for Forecasting Foreign Direct Investment: Empirical Insights from International Data

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Abstract: *Foreign direct investment (FDI) is a key driver of economic growth, competitiveness, and integration into the global economy. Accurate forecasting of FDI is essential for policymakers who want to design informed investment strategies, anticipate macroeconomic trends, and improve regulatory frameworks. This study uses decision tree regression (DTR) to model and predict annual FDI inflows using selected macroeconomic indicators such as GDP growth, inflation, trade openness, and exchange rate stability. The DTR model was trained and tested using historical data, and its performance was assessed through graphical analysis and statistical measures. The results from the training set show a near-perfect alignment between the predicted and actual values, indicating strong model performance in learning the underlying patterns within the dataset. Testing the data reveals a wide spread from the best-fit prediction line, overestimating the limitations of tree-based models in capturing dynamic real-world financial behavior. Despite this, the model successfully identifies key determinants of FDI and provides useful directional forecasts. This study contributes to the international finance literature by demonstrating the applicability, transparency, and interpretability of machine learning techniques such as DTR for investment analysis. While traditional econometric models are valuable, DTR adds analytical flexibility, effectively handles nonlinear relationships, and provides the basis for improved forecasting performance when combined with ensemble methods. The findings underscore the importance of integrating machine learning tools into financial forecasting frameworks to support decision-making in both emerging and advanced economies.*

Key words: *Boring Direct Investment, Thesis Tree Note, International Finance, Economic Forecasting, Machine Learning, Macroeconomic Indicators.*

1. INTRODUCTION

International finance has emerged as one of the most dynamic and complex domains in the global economic system. It encompasses the cross-border movement of capital, the operation of exchange rate mechanisms, financial markets, and the policies that govern international economic interactions between countries [1]. As globalization has accelerated, financial interactions between countries have deepened, creating opportunities for growth while at the same time increasing vulnerability to external shocks. Increasing trade, investment, and monetary integration have fundamentally changed how economies respond to global events, making the discipline of international finance crucial to understanding contemporary economic developments [2]. A central component of international finance is the movement of capital, which allows countries to access global savings for investment and development. Developing economies, in particular, rely on international capital inflows, such as portfolio investments, foreign direct investment, and project finance, to finance infrastructure, industrial expansion, and long-term growth. Studies have shown that financial openness can help developing countries integrate more closely into global markets; the benefits often depend on domestic fiscal stability, institutional quality, and regulatory frameworks. The history of international financial crises underscores these vulnerabilities [3]. Episodes such as the debt crisis of the 1980s, the 1994–95 Mexican crisis, the 1997 Asian financial crisis, and the 2008 global financial crisis exposed patterns of excessive borrowing, currency mismatches, weak regulatory oversight, and fragile financial systems. Although occurring in different eras, these crises share common features: rapid credit expansion, growing external imbalances, inadequate fiscal supervision, and contagion effects across regions [4]. Scholars argue that global imbalances persistent surpluses in some countries and deficits in others play a significant role in shaping financial fragility [5]. Massive savings surpluses in emerging economies are combined with high liquidity, low global interest rates, and increased risk-taking in advanced economies, contributing to systemic vulnerabilities.

Another important dimension of international finance is exchanging rate dynamics and global adjustment mechanisms [8]. Exchange rates affect not only trade balances but also the valuation of external assets and liabilities. Research has shown that currency fluctuations can generate substantial wealth transfers between countries, altering their net foreign asset positions [9]. These valuation effects form an important part of the international financial adjustment process, complementing traditional trade-based mechanisms. As global portfolios have become larger and more diversified, valuation changes due to exchange rate movements and asset price fluctuations have become central to international macroeconomic stability [10]. The landscape of international finance is shaped by the regulatory and institutional frameworks that govern cross-border financial activities. In the absence of global financial regulation, countries have relied on cooperation through transnational regulatory networks, bilateral agreements, and regional arrangements [12]. The concept of mutual recognition, whereby countries adopt each other's regulatory standards, has emerged as an important strategy for reducing barriers to global financial integration [13]. The European Union exemplifies a multilateral approach built on strong national institutions, while bilateral agreements between the United States, Australia, and other jurisdictions illustrate alternative avenues for regulatory harmonization [14]. International project finance has become an indispensable tool for facilitating large-scale infrastructure development around the world. By allocating risks among multiple stakeholders and relying on future project revenues rather than sponsors' balance sheets, project finance enables the implementation of complex, high-risk initiatives in a variety of contexts [15]. As infrastructure needs expand globally, project finance increasingly intersects with international trade, risk management, and global financial markets, making it a key area of study within international finance [16]. Resolving international financial crises and the dynamics of financial integration remain central concerns for the global economy, particularly for developing and emerging economies (DEEs). Despite a modest 4% increase in global foreign direct investment (FDI) to $1.5 trillion, the apparent recovery has been marred by deep structural challenges, including a 22% decline in FDI to advanced economies and persistent vulnerabilities in emerging markets [17].

2. METHODOLOGY

The relationship between the USD/INR exchange rate and India's measures of financial integration reveals important dynamics in international capital flows and macroeconomic stability. Foreign direct investment (FDI) inflows, measured in millions of US dollars, serve as a primary indicator of India's attractiveness to foreign investors and the extent of its practical financial integration. When the rupee depreciates against the dollar, FDI inflows may initially increase as Indian assets become cheaper for foreign investors, but continued depreciation may indicate underlying economic vulnerabilities that deter investment. Inflation rates directly affect exchange rate stability and investment decisions. High inflation generally leads to depreciation of the rupee, as purchasing power declines and the real income of foreign investors declines. Conversely, contained inflation increases macroeconomic credibility and supports stable capital inflows. The interest rate differential between India and developed economies affects both exchange rates and portfolio flows – higher domestic rates attract foreign capital seeking income, but may also reflect monetary tightening to combat inflation or currency weakness. The International Financial Subordination Index (IFSI), which captures India's position within the global monetary hierarchy, reflects constraints on policy autonomy and vulnerability to external shocks. A high IFSI indicates high subordination, which is often manifested through currency volatility, limited ability to borrow in domestic currency, and reliance on foreign capital flows. Together, these variables illustrate how developing economies like India navigate the tensions between financial transparency, macroeconomic stability, and the structural constraints imposed by their external position in the international financial system.

Decision Tree Regression: Decision tree construction methods use iterative refinement strategies to transform training data into hierarchical predictive models. The basic mechanism involves partitioning datasets by attribute-based criteria, which systematically divide observations into increasingly homogeneous groups. This recursive partitioning process continues until the terminal nodes contain predominantly uniform class members, with intermediate decision points forming the internal structure of the tree and the final partitions forming its leaf structure. Classification of new events continues by traversing the tree from root to leaf, with predictions derived from the major class labels within the terminal node reached. Since the foundational work of the 1970s, pioneering researchers including Quinlan have advanced decision tree methods through contributions to machine learning and statistical analysis. The strength of the technique lies in identifying discriminatory features that maximize information gain while minimizing entropy within the resulting clusters. To address over fitting challenges – where models capture training data noise rather than underlying patterns – regularization techniques such as tree pruning are commonly used, although some misclassification remains inevitable. Decision trees serve dual purposes as classification and regression tools, distinguished by their output properties. This study presents an Internet-of-Things-based aquaculture monitoring system using decision tree regression (DTR) algorithms for server-side analysis of sensor streams to predict aquatic environmental conditions. When anomalous parameters, such as elevated water temperature, are detected, the framework automatically makes predictions and initiates appropriate actions. Real-time information dissemination occurs through push notification mechanisms, which eliminates the delays associated with manual monitoring protocols. As symbolic learning architectures, decision trees encode training methods within interpretable node-branch structures, providing outputs as graphical representations or explicit rule sets. Their versatility extends to handling mixed data types – both numerical measurements and categorical attributes. This method includes classification variants that output class probability distributions on the leaves, and regression variants that produce continuous value prediction.

3. ANALYSIS AND DISSECTION

TABLE 1. International Finance Descriptive Statistics

	Exchange Rate (USD/INR)	FDI Inflows (USD Mn)	Inflation (%)	Interest Rate (%)	IFSI
count	20.00000	20.00000	20.00000	20.00000	20.00000
mean	82.93500	5425.00000	5.46000	6.27000	76.55000
std	1.02817	684.70124	0.56699	0.43054	5.76263
min	81.20000	4600.00000	4.60000	5.60000	68.00000
25%	82.05000	4875.00000	4.97500	5.97500	71.75000
50%	83.00000	5075.00000	5.40000	6.25000	76.00000
75%	83.85000	6050.00000	5.92500	6.62500	80.50000
max	84.50000	6500.00000	6.40000	7.00000	86.00000

The dataset shows moderate variation in international financial indicators. Exchange rates are tight, averaging INR 82.93, while FDI inflows vary widely, averaging USD 5,425 million. Inflation and interest rates are relatively stable, at 5.46% and 6.27%, respectively. The International Financial Stability Index (IFSI) averages 76.55, indicating generally stable financial conditions. The minimum and maximum values indicate that high FDI inflows, moderate inflation, and stable interest rates are associated with strong sustainability scores.

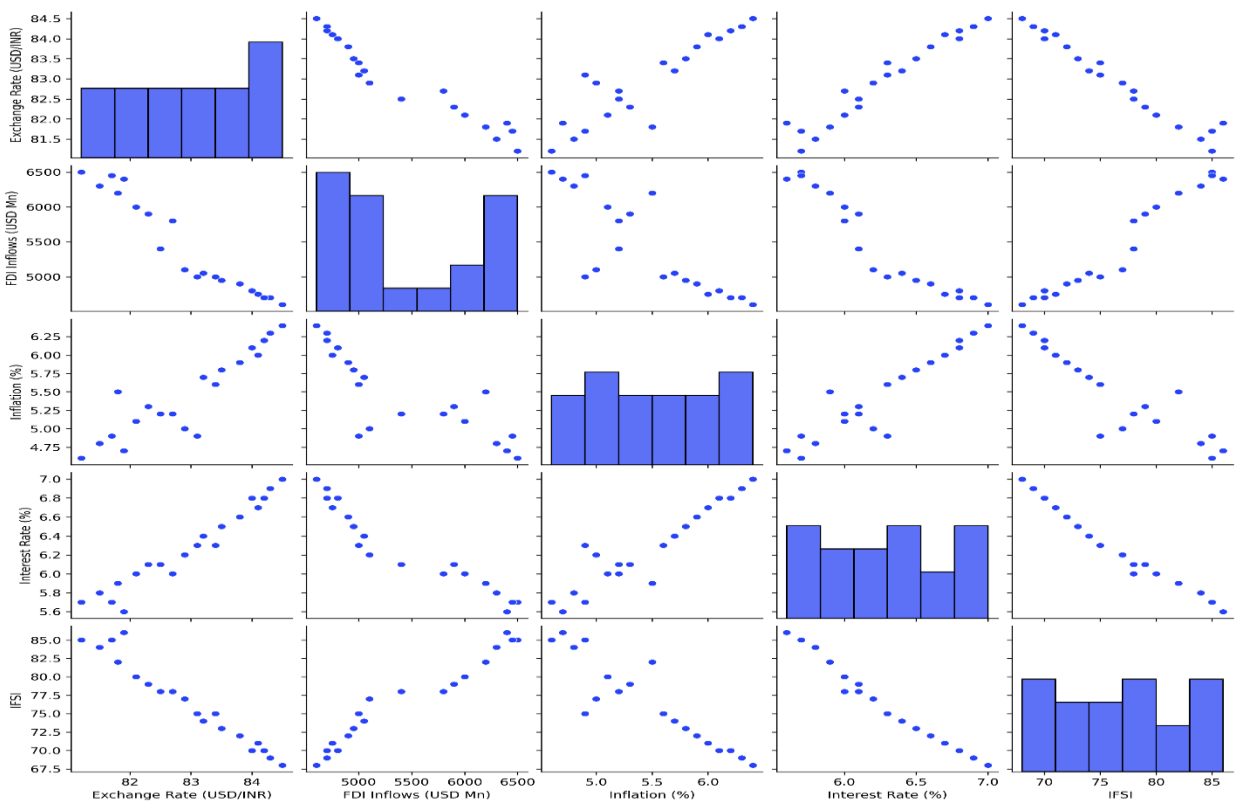

FIGURE 1. International Finance Effect of Process Parameters

The scatterplot matrix highlights clear relationships between financial variables. Foreign direct investment inflows show a strong negative relationship with the exchange rate and interest rate, indicating that higher foreign direct investment is associated with a stronger currency and lower borrowing costs. Inflation and interest rates show a positive relationship, reflecting typical monetary dynamics. The International Financial Stability Index (IFSI) decreases as exchange rates and interest rates rise, indicating that currency depreciation and higher interest rates reduce financial stability. Conversely, higher foreign direct investment and moderate inflation are associated with stronger stability.

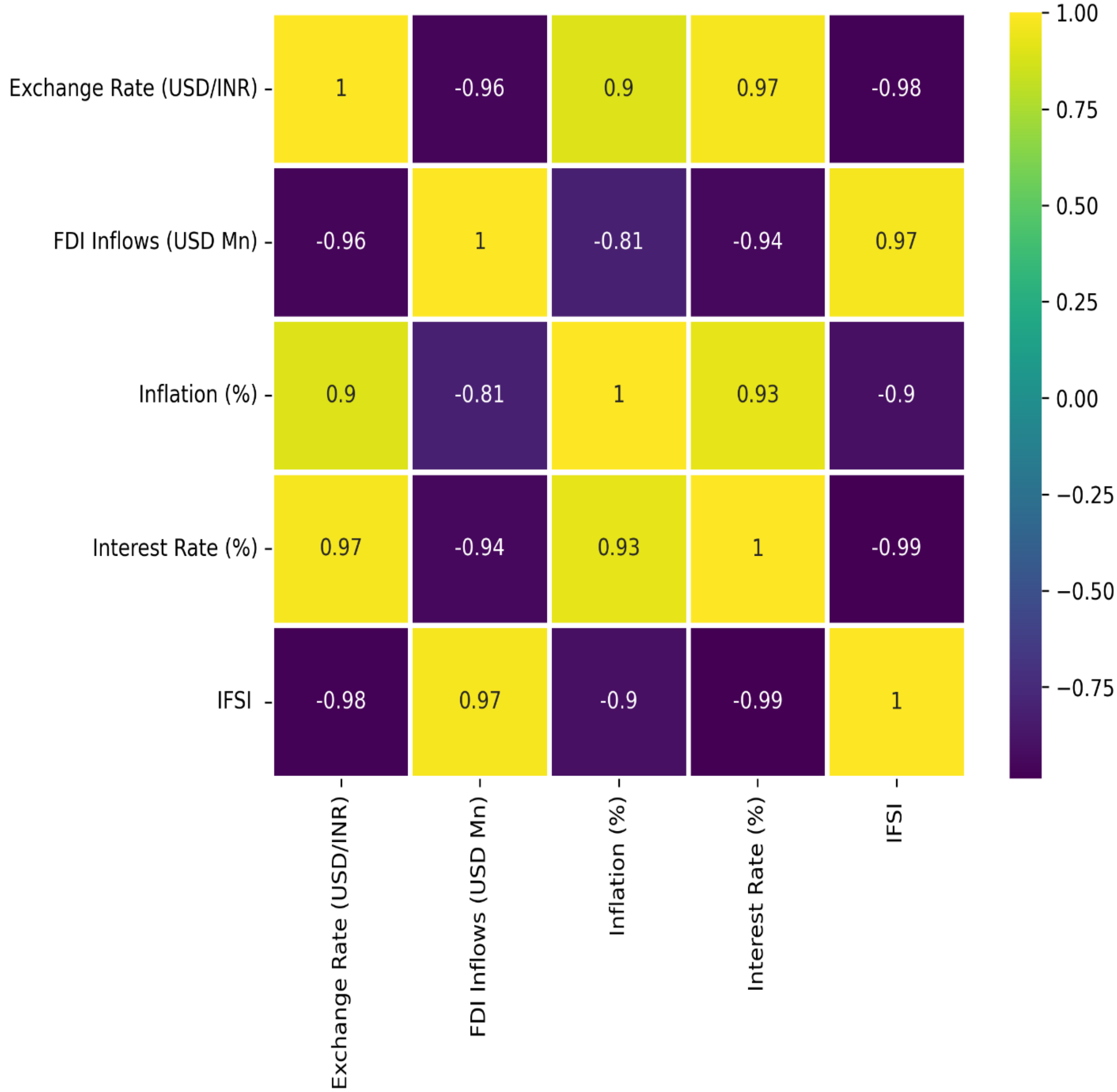

FIGURE 2. International Finance Correlation Heat Ma

The correlation heat map reveals strong and consistent relationships between all variables. Exchange rate, inflation and interest rate are highly positively correlated, indicating that they move together. FDI inflows show strong negative correlations with these factors, such that higher FDI is associated with lower exchange rates, lower inflation and lower interest rates. The International Financial Stability Index (IFSI) is strongly negatively correlated with exchange rate, inflation and interest rate, but positively correlated with FDI inflows. This suggests that financial stability improves with higher FDI and deteriorates with rising inflation, interest rates or currency depreciation

TABLE 2. Decision Tree Regression Models FDI Inflows Train and Test performance metrics

Decision Tree Regression	Train	Test
R2	1.0000	0.8314
EVS	1.0000	0.8637
MSE	0.0000	29375.0000
RMSE	0.0000	171.3914
MAE	0.0000	137.5000
Max Error	0.0000	400.0000
MSLE	0.0000	0.0010
Med AE	0.0000	100.0000

The decision tree regression model shows perfect performance on the training set, with R^2, EVS, and all error metrics indicating zero error. However, the experimental results show a significant over fitting. The experimental R^2 of 0.83 and EVS of 0.86 indicate moderate prediction accuracy, but high MSE, RMSE, and MAE indicate large deviations between predicted and actual values. The maximum error of 400 indicates poor generalization. Although the model memorizes the training data correctly, it has difficulty generalizing to new data. This indicates the need for pruning, parameter tuning, or switching to more robust models to improve experimental performance.

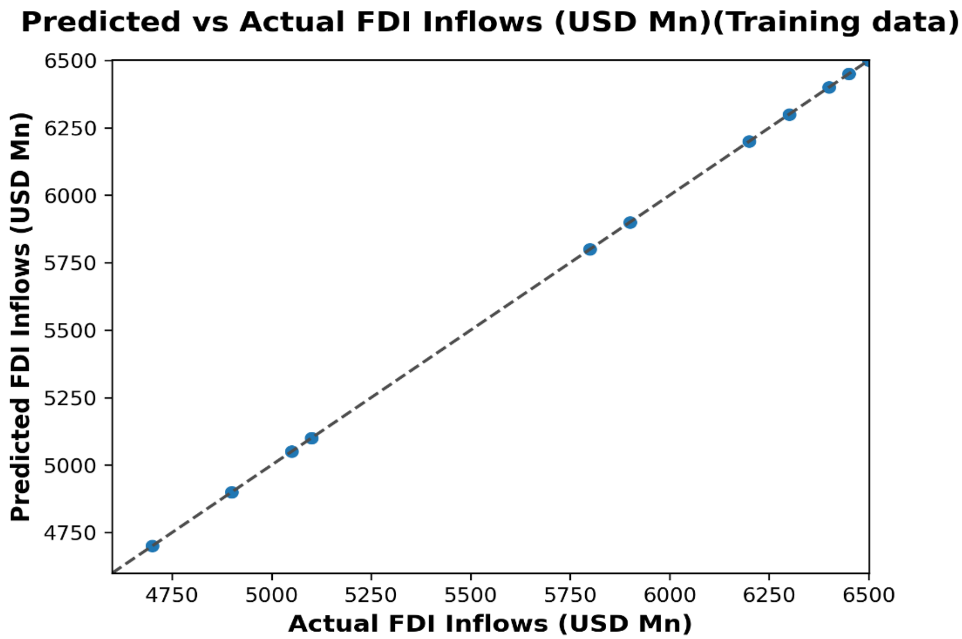

FIGURE 3. Decision Tree Regression FDI Inflows Training

The predicted and actual FDI inflows for the training dataset are compared using a decision tree regression model. The points lie almost exactly on the 45-degree reference line, indicating a good fit. This indicates that the model captures the underlying patterns of the training data very well, with minimal deviation between the predicted and actual values. The close clustering of the data points reflects strong model performance.

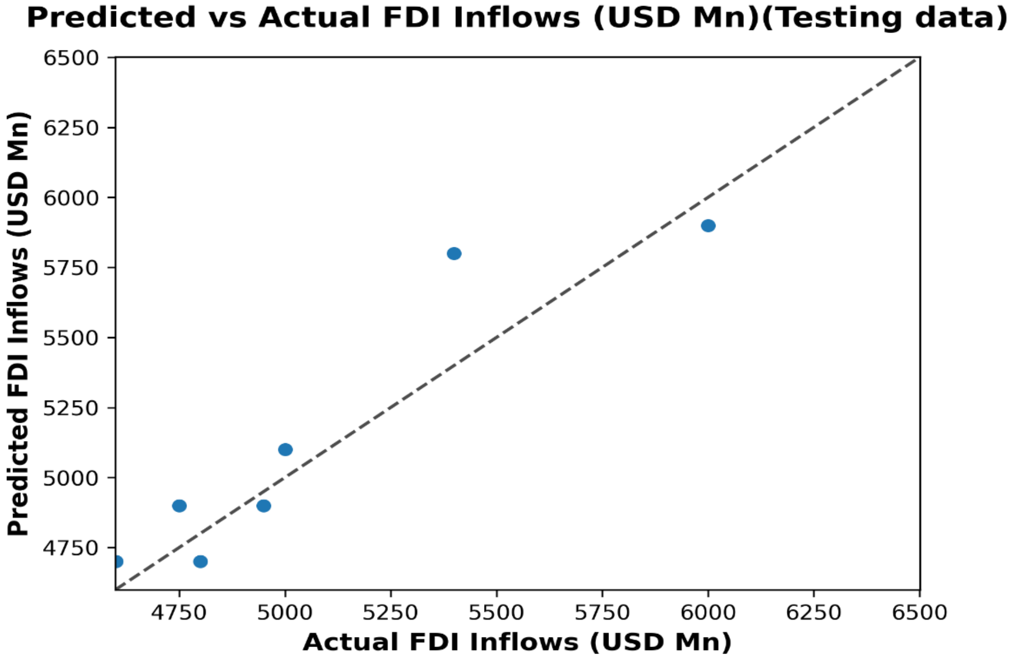

FIGURE 4. Decision Tree Regression FDI Inflows Testing

The performance of the model is illustrated on the test data, where the spread of points around the diagonal line increases significantly. Many predictions fall below or above the reference line, indicating reduced accuracy when applied to missing data. This scatter indicates that the model may be overfitting - performing strongly on the training data and less reliably on new observations. Wide variation highlights the need for further adjustment or model comparison.

4. CONCLUSION

This study demonstrates that decision tree regression offers promising potential for forecasting foreign direct investment (FDI) inflows in the international financial sector. By capturing nonlinear relationships among macroeconomic variables, DTR provides a flexible modeling framework that can be adapted to complex economic environments. The robust performance on training data indicates that the model effectively learns historical patterns, indicating its usefulness in identifying key determinants of FDI and supporting policy analysis. However, the reduced accuracy observed on the test data highlights the important problem of overfitting common in single decision tree models. This suggests the need for model optimization by adopting ensemble extensions such as random forests or gradient boosting. Despite these limitations, the use of DTR in this study provides valuable insights into forecasting methods in international finance. The model's transparency enables a clear explanation of the importance of the factor, and provides policymakers with a practical tool for understanding how variables such as GDP growth, inflation, and trade openness affect FDI inflows. In an increasingly data-driven global financial landscape, such explanatory power is essential for designing effective investment strategies and promoting macroeconomic stability. The findings also underscore the broader relevance of machine learning in economic forecasting. While traditional econometric approaches remain fundamental, integrating data-driven techniques improves forecast accuracy and complements classical models by capturing patterns that may otherwise go unnoticed.

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