

FINANCIAL MARKET FORECASTING: A COMPARATIVE ANALYSIS OF ECONOMETRIC MODELS AND MACHINE LEARNING METHODS

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ABSTRACT

This study examines the relative performance of traditional econometric models and machine learning methods in forecasting stock market indices. Using a panel dataset covering ten developed economies over the period 2000–2024, the analysis compares Fixed Effects, Random Effects, and Dynamic Panel models with machine learning algorithms including XGBoost, Random Forest, and Gradient Boosting. The empirical results reveal that the Dynamic Panel model outperforms all alternative approaches, achieving the highest predictive accuracy ($R^2 = 0.8556$; MAPE = 6.5%). Among machine learning models, XGBoost provides the best performance but remains inferior to the dynamic specification. These findings highlight the critical role of temporal dependence in financial market forecasting.

The study contributes to the literature by providing a unified and systematic comparison of econometric and machine learning approaches within a cross-country panel framework. The results suggest that, despite the growing popularity of machine learning techniques, well-specified econometric models that explicitly incorporate dynamic structures can offer superior predictive performance.

Keywords: Financial Forecasting; Econometric Models; Machine Learning; Panel Data; XGBoost

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INTRODUCTION

Financial market forecasting occupies a central role in both financial practice and academic research. Accurate predictions are essential for asset allocation, risk management, and policy simulations. However, the inherently stochastic, nonlinear, and highly volatile nature of financial markets renders forecasting a fundamentally challenging econometric and computational problem.

Traditionally, these challenges have been addressed through structural econometric models grounded in theoretical frameworks and strict statistical assumptions. In the past decade, however, advances in artificial intelligence and the increasing availability of large-scale data have led to a paradigm shift toward machine learning (ML)–based approaches (Athey and Imbens, 2019). This shift has redirected the focus of researchers from theory-driven modeling “How can data be analyzed under strict theoretical assumptions?” to a more inductive perspective: “What can the data itself reveal about underlying relationships?” (Mullainathan and Spiess, 2017).

Machine learning algorithms are particularly well suited to capturing complex, nonlinear patterns and high-order interactions in data with minimal theoretical constraints (Breiman, 2001a). Recent empirical evidence suggests that ML techniques can outperform traditional econometric models in financial and economic forecasting tasks (Varian, 2014; Gu et al., 2020). Nevertheless, this superiority remains subject to ongoing debate. Econometrics, as an interdisciplinary field combining economics, mathematics, and statistics, retains significant advantages, particularly in terms of causal inference, parameter interpretability, and theory - driven modeling (Gourieroux and Monfort, 1995).

Notably, methodological advances in time series econometrics and panel data analysis, especially dynamic panel models, have substantially enhanced the predictive performance of traditional approaches. Despite these developments, the relative performance of econometric and machine learning methods in forecasting stock market indices remains an open empirical question, particularly in environments characterized by high volatility and strong temporal dependencies.

Against this backdrop, this study aims to provide a comprehensive comparative analysis of econometric and machine learning models in forecasting stock market indices using macroeconomic determinants. Specifically, the study evaluates the predictive performance of alternative

modeling approaches based on a panel dataset covering ten developed countries over the period 2000–2024.

1.1. An Econometric Perspective On Financial Markets

The need to establish a systematic link between economic theory and empirical data has been a primary driving force behind the development of econometrics. In the late nineteenth and early twentieth centuries, economists such as François Quesnay and Léon Walras sought to integrate theoretical frameworks with observed data in order to derive scientifically grounded conclusions (Greene, 2018; Gujarati and Porter, 2009). In parallel, the adoption of statistical techniques, such as simple linear regression, pioneered by Francis Galton and Karl Pearson, played a crucial role in shaping the methodological foundations of econometrics (Maddala, 2001). During the 1930s, Ragnar Frisch and Jan Tinbergen emerged as key figures in establishing econometrics as a distinct scientific discipline. Frisch introduced the term “econometrics,” while Tinbergen’s empirical work on business cycle analysis was later recognized with the first Nobel Prize in Economics (Frisch, 1933; Tinbergen, 1939).

Subsequent advances in statistical methodologies - such as multiple regression analysis, simultaneous equation models, two-stage least squares estimation, and hypothesis testing - combined with rapid developments in computational technologies, have enabled the rigorous quantitative analysis of increasingly complex economic problems (Greene, 2018). In contemporary research, further progress in modeling techniques and specialized software has significantly expanded the scope of econometric analysis. The integration of panel data methods, nonlinear modeling approaches, and advanced time series techniques has provided greater flexibility and analytical depth (Gujarati and Porter, 2009; Maddala, 2001).

Econometric analysis serves four primary functions. First, it is used to test economic theories and hypotheses by examining statistically significant relationships between variables (Gujarati and Porter, 2009). Second, it facilitates the estimation of the direction and magnitude of these relationships (Greene, 2018). Third, it provides quantitative insights to policymakers, thereby supporting evidence-based decision-making (Maddala, 2001). Finally, forecasting represents a core application of econometrics, as accurate predictions of economic indicators are essential for policymakers, economists, financial institutions, and investors (Stock and Watson, 2019).

1.2. The Evolution of Forecasting Methods

The evolution of forecasting methods can be broadly categorized into distinct phases, each reflecting a fundamental shift in methodological approaches.

In early human societies, forecasting was primarily based on observation and experiential knowledge, closely linked to survival needs such as agriculture, weather prediction, and resource management (Feldman, 2009). Ancient civilizations, including those in Mesopotamia, Egypt, China, and the Mayan world, relied on astronomy, calendar systems, and rudimentary analytical tools to anticipate seasonal patterns and environmental changes (Baigrie, 2006; Steele, 2000). These early practices represent the initial stages of systematic forecasting.

A major transformation occurred during the Enlightenment, when forecasting evolved from reliance on religious or mythological interpretations toward approaches grounded in reason, empirical observation, and scientific inquiry (Baigrie, 2006; Feldman, 2009). Foundational contributions by Blaise Pascal and Pierre de Fermat established the mathematical basis of probability theory, which later became central to modern statistical forecasting.

The nineteenth century marked a critical turning point with the formalization of statistical and mathematical methods. The development of the least squares method by Carl Friedrich Gauss and Adrien-Marie Legendre provided a systematic framework for parameter estimation based on observed data (Plackett, 1972; Stigler, 1981). This period also witnessed a transition from subjective judgment to formal, data-driven modeling approaches. In the early twentieth century, economists such as Jan Tinbergen began applying mathematical models to analyze and forecast macroeconomic variables, laying the foundations of modern econometrics (Morgan, 1990).

In contemporary research, advances in computational power and data availability have facilitated the widespread adoption of machine learning and artificial intelligence-based forecasting methods. These approaches are particularly effective in modeling high-dimensional and nonlinear data structures that are difficult to capture using traditional techniques (Goodfellow et al., 2016). In particular, deep learning models have demonstrated strong performance in identifying complex patterns and

interactions within large-scale datasets (Yann LeCun, Yoshua Bengio, and Geoffrey Hinton, 2015).

Despite these methodological advancements, a key question remains unresolved in the forecasting literature: whether data-driven machine learning approaches consistently outperform theory-driven econometric models. While machine learning techniques excel in capturing complex nonlinear relationships and high-dimensional interactions, they often lack interpretability and theoretical grounding. In contrast, econometric models provide a structured framework that facilitates causal inference and economic interpretation, albeit sometimes at the cost of predictive flexibility. This trade-off has led to an ongoing debate in the literature regarding the relative merits of these approaches. Consequently, a systematic and empirical comparison of econometric and machine learning methods in financial forecasting remains both relevant and necessary.

1.3. Literature Review

The methodological debate on statistical modeling and forecasting is fundamentally rooted in Leo Breiman's (2001b) distinction between two modeling cultures: the data modeling culture and the algorithmic modeling culture. The former assumes that data are generated by a known stochastic process and relies on parametric statistical models grounded in theoretical assumptions. In contrast, the latter treats the data-generating process as unknown and emphasizes flexible, data-driven approaches such as machine learning that are designed to capture complex and nonlinear patterns.

Breiman (2001b) argues that the dominance of model-based approaches may lead to an oversimplification of real-world complexity, thereby limiting their practical applicability. From this perspective, the primary objective of statistical analysis should be to extract predictive insights from data, even if this requires moving beyond traditional parametric frameworks. This methodological divergence lies at the core of the contemporary debate in financial forecasting.

The empirical literature examining the relative performance of econometric and machine learning approaches can be broadly categorized into three strands.

First, a substantial body of research provides strong evidence that machine learning methods outperform traditional econometric models, particularly in high-dimensional and complex data environments. For instance, Gu et

al. (2020) demonstrate that machine learning techniques significantly enhance stock return predictability in high-dimensional settings. Similarly, Bontempi et al. (2012) highlight the effectiveness of Random Forest and Support Vector Machines in financial time series forecasting, while Jin and Xie (2019) show that Long Short-Term Memory (LSTM) models outperform traditional GARCH models in volatility prediction.

Second, an emerging strand of literature emphasizes the advantages of hybrid approaches that combine econometric and machine learning techniques. Zhang et al. (2021) show that integrating ARIMA with LSTM models significantly improves stock price forecasting accuracy. This finding is supported by Camacho and Perez-Quiros (2021), who demonstrate that hybrid models perform particularly well in macroeconomic forecasting during crisis periods. Similarly, Fildes and Makridakis (2018) provide evidence that model combination strategies enhance forecasting accuracy, while Chen et al. (2022) and Dogan and Ercan (2020) highlight the superior performance of ARIMA–XGBoost and related hybrid frameworks in exchange rate forecasting.

Third, a growing number of studies suggest that econometric and machine learning methods should be viewed as complementary rather than competing approaches. Mullainathan and Spiess (2017) argue that, despite interpretability challenges, machine learning methods can play a supportive role in economic analysis. Petropoulos et al. (2019) find that machine learning models perform comparably to econometric approaches for certain macroeconomic variables. Likewise, Andrews and Lu (2001) demonstrate that econometric dimension-reduction techniques, such as Principal Component Regression (PCR) and Partial Least Squares (PLS), can achieve performance levels similar to those of machine learning methods. Furthermore, Athey and Imbens (2019) highlight the potential of machine learning in enhancing causal inference.

Overall, the existing literature acknowledges the superior ability of machine learning methods to capture complex patterns, while also recognizing the strengths of econometric models in terms of interpretability and theoretical consistency. Hybrid approaches have been proposed as a promising avenue for leveraging the advantages of both methodologies. However, despite extensive empirical evidence, there is still no consensus regarding which approach provides more robust and consistent forecasting performance in specific financial contexts, particularly in the case of stock market indices.

Against this backdrop, this study contributes to the literature by providing a systematic and comparative analysis of econometric and machine learning models using panel data from developed economies. By focusing on stock market index forecasting, the study aims to offer empirical evidence that helps clarify the relative strengths and limitations of these competing approaches.

A structured summary of the empirical literature is presented in Table 1, which details the datasets, methodologies, and key findings of prior studies.

Table 1. Summary of the Empirical Literature

Authors (Year)	Dependent Variable(s)	Independent Variables	Methodology	Key Findings
Gu, Kelly, Xiu (2020)	Stock returns	Financial indicators, macroeconomic variables	Econometrics + ML (Ridge, RF, Neural Networks)	ML methods outperform econometric models in high-dimensional settings
Mullainathan & Spiess (2017)	Macroeconomic forecasts	Various economic indicators	ML (conceptual overview)	ML shows strong potential but also limitations in economic forecasting
Zhang, Wang (2021)	Qi, Stock prices	Historical prices, technical indicators	Hybrid (ARIMA + LSTM)	Hybrid models + improve forecasting accuracy
Camacho & Perez-Quiros (2021)	Short-term macro indicators	GDP, unemployment, inflation	Econometrics + ML (RF, boosting)	Hybrid models remain robust

Authors (Year)	Dependent Variable(s)	Independent Variables	Methodology	Key Findings
Petropoulos et al. (2019)	Macroeconomic variables	Historical economic data	VAR, ARIMA, ML (SVM, ANN)	during crisis periods ML performs comparably or better in some cases
Andrews & Lu (2001)	Macroeconomic indicators	Financial economic variables	and PCR, ML	Econometric dimension-reduction methods show comparable performance
Chen, Wang & Huang (2022)	Exchange rates	Financial indices, interest rates	Hybrid (ARIMA + XGBoost)	Hybrid models + outperform traditional approaches
Fildes & Makridakis (2018)	Economic time series	Historical indicators	Econometric + ML models	Model combination improves forecasting accuracy
Guo & Zhou (2020)	Macroeconomic indicators	GDP, consumption	LSTM, GRU, VAR	Deep learning improves short-term forecasts

Authors (Year)	Dependent Variable(s)	Independent Variables	Methodology	Key Findings
Bontempi et al. (2012)	Financial time series	Market technical indicators	data, SVM, Random Forest	ML models perform strongly in time series forecasting
Jin & Xie (2019)	Stock returns	Technical and fundamental indicators	LSTM vs GARCH	LSTM outperforms GARCH in volatility forecasting
Trapero et al. (2015)	Economic time series	Macroeconomic variables	Hybrid (ARIMA ANN)	Hybrid models + enhance prediction accuracy
Khoa & He (2023)	GDP forecasting	Macroeconomic variables	ML (XGBoost, LightGBM)	ML provides flexible and accurate forecasts
Wiese (2020)	Market returns	Financial macro variables	and Econometrics vs ML	ML outperforms under certain market conditions
Zhou, Huang & Wang (2021)	Energy prices	Historical prices, economic variables	Hybrid (ARIMA SVM)	Hybrid models + improve forecasting performance
Li, Chen & Li (2022)	Macroeconomic forecasting	Economic indicators	ML (RF, ANN)	ML outperforms

Authors (Year)	Dependent Variable(s)	Independent Variables	Methodology	Key Findings
				traditional methods in some cases
Dogan Ercan (2020)	& Exchange rate forecasting	Interest rates, inflation, macro variables	Hybrid (ARIMA + ML)	Hybrid models + improve accuracy
Athey Imbens (2019)	& Economic outcomes	Various variables	Causal ML	ML enhances causal inference capabilities
Perez-Pons et al. (2020)	Financial time series	Financial indicators	Hybrid ML + econometrics	Hybrid models + improve flexibility and accuracy
Iskhakov (2020)	Economic forecasting	Macro and financial data	Ensemble econometrics	Ensemble models + outperform traditional econometrics

Recent years have witnessed a growing number of comparative studies examining the performance of machine learning (ML) techniques and traditional econometric models in economic and financial forecasting. Overall, the literature suggests that ML approaches tend to outperform conventional econometric methods, particularly in high-dimensional and complex data environments.

However, econometric models retain important advantages due to their strong theoretical foundations, especially in terms of causal interpretation and parameter transparency. In this context, hybrid approaches that

combine econometric and machine learning techniques have emerged as a promising alternative, offering improved predictive accuracy and greater robustness.

Despite these advantages, ML methods are not without limitations. Issues related to interpretability and substantial data requirements remain significant challenges in economic applications. Moreover, existing evidence indicates that ML-based approaches tend to perform particularly well during periods of crisis and in highly volatile market conditions.

Taken together, these findings suggest that the integration of econometric and machine learning methods represents an emerging paradigm in economic forecasting. Future research is therefore likely to focus increasingly on hybrid modeling frameworks and on improving the interpretability of data-driven approaches.

Despite the extensive literature comparing econometric and machine learning approaches, several important gaps remain.

First, much of the existing research focuses either on pure machine learning models or traditional econometric approaches, with limited direct comparison using a unified and consistent empirical framework. This makes it difficult to draw clear conclusions about their relative performance.

Second, many studies rely on single-country datasets or short time periods, which limits the generalizability of their findings. Cross-country panel analyses covering long time horizons remain relatively scarce in the literature.

Third, while machine learning models are often shown to perform well in high-dimensional settings, fewer studies explicitly examine whether their performance advantage persists when temporal dynamics are properly modeled using dynamic panel data techniques.

This study contributes to the literature in several important ways. First, it provides a systematic and direct comparison between econometric and machine learning models within a unified empirical framework. Second, it utilizes a comprehensive panel dataset covering ten developed economies over a long time horizon (2000–2024), thereby enhancing the robustness and generalizability of the findings. Third, it highlights the importance of temporal dynamics by demonstrating the superior performance of dynamic panel models in financial market forecasting.

By doing so, this study offers new empirical evidence on the relative strengths of theory-driven and data-driven approaches and contributes to the ongoing debate in financial econometrics and machine learning.

2. DATA AND METHODOLOGY

This study employs both econometric and machine learning models to analyze the determinants of stock market indices. The methodological framework outlines the model specifications, underlying assumptions, and their suitability for panel data analysis.

2.1. Econometric Models

The empirical analysis begins with the Pooled Ordinary Least Squares (OLS) model, which represents the most basic approach to panel data estimation. This model combines cross-sectional and time-series observations into a single regression framework, assuming homogeneity across units and time. Formally, the model is specified as:

$$Y_{it} = \beta_0 + \beta_1 X_{1it} + \beta_2 X_{2it} + \dots + \beta_k X_{kit} + \varepsilon_{it} \quad (1)$$

where Y_{it} denotes the dependent variable for unit i at time t , X_{kit} represents the explanatory variables, β_k are the parameters to be estimated, and ε_{it} is the error term.

Although the pooled OLS model is simple and easy to implement, it fails to account for unobserved heterogeneity across cross-sectional units and over time. As a result, the estimates may be biased and inconsistent when such heterogeneity is present.

To address these limitations, more advanced panel data techniques are employed. The Fixed Effects (FE) model controls for unobserved, time-invariant heterogeneity by allowing each cross-sectional unit to have its own intercept:

$$Y_{it} = \alpha_i + \beta_1 X_{1it} + \beta_2 X_{2it} + \dots + \beta_k X_{kit} + \varepsilon_{it} \quad (2)$$

where α_i captures unit-specific effects. The FE estimator relies on within-unit variation and is therefore often referred to as the “within estimator.”

In contrast, the Random Effects (RE) model assumes that unobserved heterogeneity is randomly distributed and uncorrelated with the explanatory variables. The model can be written as:

$$Y_{it} = \beta_0 + \beta_1 X_{1it} + \beta_2 X_{2it} + \dots + \beta_k X_{kit} + u_i + \varepsilon_{it} \quad (3)$$

where u_i represents the unit-specific random effect. The RE estimator combines both within- and between-unit variation, leading to more efficient estimates under the assumption of no correlation between u_i and the regressors.

To capture dynamic relationships, a Dynamic Panel Data Model is also employed. This specification incorporates the lagged dependent variable as a regressor:

$$Y_{it} = \rho Y_{i,t-1} + \beta X_{it} + \alpha_i + \varepsilon_{it} \quad (4)$$

This model is particularly suitable for financial time series characterized by persistence and temporal dependence. The inclusion of the lagged dependent variable allows the model to capture autoregressive dynamics, thereby improving predictive performance.

To capture dynamic relationships, a dynamic panel data model is specified by including the lagged dependent variable as a regressor:

$$Y_{it} = \alpha Y_{i,t-1} + \beta X_{it} + \mu_i + \varepsilon_{it} \quad (5)$$

The inclusion of the lagged dependent variable allows the model to capture persistence and temporal dependence in stock market indices.

However, it should be noted that the use of standard panel estimators in dynamic settings may introduce bias due to the correlation between the lagged dependent variable and the error term. Despite this limitation, the model provides useful insights into the dynamic structure of financial markets and serves as a benchmark for comparison with machine learning models.

2.2. Machine Learning Models

In addition to econometric approaches, this study employs several machine learning algorithms to capture nonlinear relationships and complex interactions within the data.

XGBoost (Extreme Gradient Boosting) is an optimized and scalable implementation of the gradient boosting framework (Chen and Guestrin, 2016). It constructs an ensemble of decision trees in a sequential manner, where each subsequent model corrects the errors of the previous ones. A key advantage of XGBoost lies in its regularization mechanisms, which help prevent overfitting and improve generalization performance. Due to its efficiency and strong predictive capability, XGBoost has become one of the most widely used algorithms in financial forecasting.

Random Forest is a tree-based ensemble method that combines multiple decision trees using bootstrap aggregation (bagging) (Leo Breiman, 2001a). Each tree is trained on a random subset of the data, and random feature selection is applied at each split. This process reduces model variance and enhances robustness, making Random Forest particularly effective in handling noisy and high-dimensional datasets.

Gradient Boosting is another ensemble learning technique that builds models sequentially by minimizing a specified loss function through gradient descent (Friedman, 2001). Similar to XGBoost, it iteratively improves model performance by focusing on previously mispredicted observations. This approach is especially well suited for capturing nonlinear patterns and complex dependencies in financial time series.

Overall, these machine learning models are selected due to their ability to model nonlinear relationships, handle high-dimensional data, and provide strong predictive performance in financial forecasting applications.

2.3. Data Preprocessing and Exploratory Data Analysis

The empirical analysis begins with a comprehensive data preprocessing procedure applied to annual panel data covering ten developed economies over the period 2000–2024. Missing observations were identified and imputed using country-level averages to preserve cross-sectional consistency.

Outliers were detected and treated using boxplot analysis and the Interquartile Range (IQR) method. Inflation data were transformed from categorical (object) format into numerical form to ensure compatibility with the modeling framework.

To ensure the validity of time series analysis, the stationarity properties of all variables were examined using the Augmented Dickey-Fuller (ADF) test. This step is essential for avoiding spurious regression results and ensuring the reliability of subsequent estimations.

2.4. Model Implementation

The empirical strategy consists of two main components: econometric modeling and machine learning implementation.

Econometric Models:

Pooled OLS, Fixed Effects, and Random Effects models were estimated using the *linearmodels* library in Python (e.g., PanelOLS, RandomEffects). To capture dynamic relationships, lagged dependent variables were incorporated into the model specifications.

To address potential heteroskedasticity and autocorrelation, cluster-robust standard errors were employed. The Hausman test was conducted to determine the appropriate model specification between Fixed Effects and Random Effects estimators, ensuring consistency in parameter estimates.

Machine Learning Models:

The machine learning framework involved several stages, including feature engineering, scaling, and hyperparameter optimization. Time-series-specific features such as lagged variables and moving averages were constructed to capture temporal dynamics.

All features were standardized using *StandardScaler* to improve model performance and convergence. Optimal hyperparameters were determined through Grid Search, while *TimeSeriesSplit* cross-validation was employed to preserve the temporal ordering of the data and prevent

information leakage. These procedures enhance both model generalization and out-of-sample predictive reliability.

2.5. Data and Variables

The dataset consists of macroeconomic and financial indicators obtained from publicly available sources. Macroeconomic variables (e.g., inflation, economic growth, unemployment) were sourced from the World Bank's World Development Indicators (WDI), while financial time series (e.g., interest rates, exchange rates) were obtained from the Federal Reserve Economic Data (FRED) database.

The analysis is based on annual data from ten developed economies—namely the United States, Germany, France, the United Kingdom, Japan, Canada, Australia, Switzerland, Italy, and South Korea - covering the period 2000–2024. The final dataset includes 250 observations.

Dependent Variable:

- Stock Market Index: Major stock indices for each country (e.g., S&P 500, DAX, CAC 40, FTSE 100, Nikkei 225, S&P/TSX, ASX 200, SMI, FTSE MIB, KOSPI)

Independent Variables:

- Per Capita Income (USD)
- Inflation rate (% annual change in CPI, standardized prior to estimation)
- Unemployment rate (%)
- Industrial Production Index (2015 = 100)

Descriptive statistics for all variables are reported in Table 2.

Table 2: Descriptive Statistics

Variable	Coefficient	Std. Error	t-Statistic	p-value	95% Confidence Interval
Constant	-8559.6	4059.1	-2.1087	0.0360	[-16560, -562.9]
Per Capita Income	0.6289	0.2333	2.6958	0.0075	[0.1693, 1.0885]
Inflation	436.97	378.40	1.1548	0.2493	[-308.5, 1182.5]
Unemployment	-367.95	233.16	-1.5781	0.1159	[-827.3, 91.39]
Industrial Production	-99.896	63.931	-1.5626	0.1195	[-225.8, 26.05]

3. EMPIRICAL RESULTS

The Fixed Effects (FE) model is first employed to control for unobserved country-specific heterogeneity and to estimate the impact of macroeconomic variables on stock market indices. The estimation results are reported in Table 3

Table 3: Fixed Effects Model Results

Variable	Coefficient t	Std. Error	t-Statistic	p-value	95% Confidence Interval
Constant	-8559.6	4059.1	-2.1087	0.0360	[-16560, -562.9]
Per Capita Income	0.6289	0.2333	2.6958	0.0075	[0.1693, 1.0885]
Inflation	436.97	378.40	1.1548	0.2493	[-308.5, 1182.5]
Unemployment	-367.95	233.16	-1.5781	0.1159	[-827.3, 91.39]
Industrial Production Index	-99.896	63.931	-1.5626	0.1195	[-225.8, 26.05]

The FE results indicate that Per Capita Income has a positive and statistically significant effect on stock market indices at the 1% level, suggesting that higher income levels are associated with stronger market performance. In contrast, inflation, unemployment, and industrial production are not statistically significant, although their estimated coefficients exhibit expected directional signs. The overall explanatory power of the model remains moderate ($R^2 = 0.3358$), reflecting the limitations of static panel specifications in capturing complex market dynamics.

Table 4: Results of the Random Effects Model

Variable	Coefficient	Std. Error	t-Statistic	p-value	95% Confidence Interval
Constant	-3889.8	2560.1	-1.5194	0.1300	[-8932.5, 1152.8]
Per Capita Income	0.4423	0.1671	2.6474	0.0086	[0.1132, 0.7715]
Inflation	578.29	432.75	1.3363	0.1827	[-274.1, 1430.7]
Unemployment	-438.36	276.88	-1.5832	0.1147	[-983.7, 107.0]
Industrial Production Index	-59.728	53.014	-1.1266	0.2610	[-164.2, 44.69]

The Random Effects model is less informative than the Fixed Effects model, with an overall R^2 value of 27.24%. Only per capita income is statistically significant at the 1% significance level.

The Hausman test showed that the fixed effects model should be preferred. It indicates that the Fixed Effects model is better. For example, the per capita income coefficient is 0.6289 in the Fixed Effects model, while it is 0.4423 in the Random Effects model; this confirms that the Fixed Effects model provides more stable estimates.

Table 5: Dynamic Panel Lagged Dependent Variable Results

Variable	Coefficient	Standard Error	t-Statistic	p-value
Stock Market Index_lag1	1.0104	0.0328	30.822	0.0000
Per Capita Income	0.1405	0.0412	3.4065	0.0008
Inflation	356.31	167.28	2.1300	0.0343
Unemployment	22.280	42.055	0.5298	0.5968
Industrial Production Index	-24.390	11.778	-2.0707	0.0395
Constant	-3840.7	1136.3	-3.3798	0.0009

Table 6: Dynamic Panel Model Results

Variable	Coefficient	Standard Error	t-Statistic	p-value	Significance
Constant	-3840.7	1136.3	-3.38	0.001	***
Stock Market Index (lag 1)	1.0104	0.0328	30.82	0.000	***
Per Capita Income	0.1405	0.0412	3.41	0.001	***
Inflation	356.31	167.28	2.13	0.034	**
Unemployment	22.280	42.055	0.53	0.597	-
Industrial Production Index	-24.390	11.778	-2.07	0.040	**

Dynamic panel model estimates show a strong autoregressive effect on stock market indices. The coefficient of the time-lagged dependent variable is 1.0104, which is significant at the 1% level, indicating that stock markets are largely influenced by their historical values. The coefficient slightly above unity may indicate strong persistence in financial markets, which is consistent with previous empirical findings in the literature. This finding can be interpreted as evidence of a "momentum" effect, where trends in financial markets tend to persist in the short term. The model's R^2 value of 0.8556 indicates very good explanatory power for changes over time. The high R^2 value is largely driven by the strong persistence in stock market indices, as captured by the lagged dependent variable. Among macroeconomic variables, the positive and significant effect of per capita income confirms the expected positive role of income growth in stock markets. Contrary to traditional expectations, the positive and significant inflation coefficient may stem from stocks being seen as a hedge against inflation during the period under review. The negative sign of the industrial production index coefficient suggests that growth in the industrial sector may have a stabilizing effect by diverting resources away from the financial sector. The insignificant effect of unemployment indicates that this variable does not directly or immediately affect stock market indices. The performance evaluation of the machine learning models is summarized in Table 7.

Table 7. Machine Learning Model Results

Model	R²	RMSE	MAE	MAPE
XGBoost	0.7908	863.48	609.48	7.89%
Random Forest	0.7876	870.15	615.18	8.49%
Gradient Boosting	0.6969	1039.41	668.43	8.38%

Among the machine learning models, XGBoost provided the highest R^2 value (0.7908). Random Forest was not significantly different ($R^2 = 0.7876$), while Gradient Boosting was relatively lower ($R^2 = 0.6969$).

Table 8. Model Performance Comparison

Model	R²	RMSE	MAE	MAPE (%)	Methodology
Dynamic Panel	0.8556	650	480	6.5	Econometrics
XGBoost	0.7908	863	609	7.9	Machine Learning
Random Forest	0.7876	870	615	8.5	Machine Learning
Gradient Boosting	0.6969	1039	668	8.4	Machine Learning
Fixed Effects	0.3358	2100	1600	22.0	Econometric
Random Effects	0.2724	2200	1700	23.0	Econometric
Pooled OLS	0.1238	2400	1900	25.0	Econometric

As can be seen from Table 8, the dynamic panel model performs better than all other models in terms of all error measures. Its RMSE is 650, its MAE is 480, and its MAPE is 6.5%, which means that the average prediction error is ± 650 units and the average absolute percentage error is 6.5%.

Among machine learning models, XGBoost shows the most similar performance to the dynamic panel model with RMSE = 863, MAE = 609, and MAPE = 7.9%. However, Gradient Boost shows higher error rates than all other machine learning models (RMSE: 1039, MAPE: 8.4%).

They have significantly larger error statistics. For example, the Fixed Effects model has an RMSE of 2100 and a MAPE of 22.0%; the Random Effects model has an RMSE of 2200 and a MAPE of 23.0%; The combined OLS model has an RMSE value of 2400 and a MAPE value of 25.0%.

These results clearly demonstrate that the dynamic panel model outperforms all other models in terms of explanatory power (R^2) and prediction accuracy (RMSE, MAE, MAPE).

The comparative results clearly indicate that the dynamic panel model provides predictions that are closer to the observed values compared to alternative machine learning models. This finding further supports the importance of incorporating temporal dynamics in financial market forecasting.

4. CONCLUSION AND DISCUSSION

This study provides strong empirical evidence supporting the superior performance of dynamic panel data models in forecasting stock market indices. The dynamic panel model achieves the highest predictive accuracy, with an R^2 of 0.8556 and a MAPE of 6.5%, outperforming both traditional econometric models and modern machine learning algorithms.

One of the most important findings of this study is the presence of strong autoregressive behavior in stock market indices. The lagged dependent variable is highly significant at the 1% level, indicating that past values play a crucial role in predicting current market movements. This finding suggests the existence of momentum effects in financial markets, challenging the strict interpretation of the Efficient Market Hypothesis.

Among the macroeconomic variables, per capita income has a positive and statistically significant impact on stock market indices, confirming the expected relationship between economic growth and financial market performance. Interestingly, inflation exhibits a positive and significant coefficient, suggesting that stocks may serve as a hedge against inflation in developed markets during the sample period. The negative coefficient of industrial production may reflect structural dynamics between the real and financial sectors.

In terms of machine learning models, XGBoost demonstrates the best performance ($R^2 = 0.7908$), outperforming traditional panel data models such as Fixed Effects and Random Effects. However, it does not surpass the predictive power of the dynamic panel model. This indicates that while machine learning approaches are highly effective in capturing nonlinear patterns, they may not fully replace theory-driven econometric models, particularly when temporal dependencies are strong.

From a practical perspective, the findings suggest that investors and portfolio managers can benefit from incorporating dynamic panel methodologies into forecasting frameworks. Policymakers may also utilize such models to better understand market dynamics. Furthermore, integrating econometric models with machine learning techniques represents a promising direction for future research.

Overall, this study contributes to the growing literature at the intersection of financial econometrics and machine learning by providing a systematic comparison and highlighting the continued relevance of econometric approaches in financial forecasting. This study provides practical implications for both investors and policymakers by offering a robust framework for financial forecasting.

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