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Analysis of the Relationship Between Cross Capital Flows and Stock Exchange Index with Machine Learning

Çapraz Sermaye Akımları ile Borsa Endeksi Arasındaki İlişkinin Makine Öğrenmesi ile Analizi

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Abstract: This paper investigates forecasting the BIST100 stock index using cross-capital flow analysis. It employs feature engineering and the Orthogonal Matching Pursuit (OMP) model to navigate the intricacies of financial time series prediction. The study meticulously selects features such as lagged values, moving averages, and volatility metrics, normalized to ensure unbiased model impact. The OMP model is carefully optimized to handle the dimensionality of financial data, avoiding overfitting through a sparsity constraint. This approach yields an R-squared score of 0.88, indicating a solid capability to capture index variance. Visual comparisons between actual and predicted values further validate the model's accuracy. The paper highlights the importance of methodological precision in developing models capable of discerning complex patterns, offering valuable insights for investment strategies. Implications of the study show that cross-capital movements and macroeconomic variables are a good fit with ML to predict the Stock Market despite the complexity of financial markets.

Keywords: Cross-Capital Flows, Stock Index Forecasting, Financial Econometrics, Time Series Analysis, Predictive Modeling.

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Öz: Bu çalışma, çapraz sermaye akımları analizini kullanarak BIST100 hisse senedi endeksinin tahminini araştırmaktadır. Finansal zaman serilerinin tahminindeki karmaşıklıkları ele almak için öznitelik mühendisliği ve Orthogonal Matching Pursuit (OMP) modeli kullanılmıştır. Önyargısız bir model sağlamak için gecikmeli değerler, hareketli ortalamalar ve volatilite ölçümleri gibi öznitelikler titizlikle seçilmiş ve normalize edilmiştir. OMP modeli, finansal verilerin çok boyutluluğu sorununu çözmek için optimize edilmiş ve seyreklik kısıtı aracılığıyla aşırı uyumdan kaçınılmıştır. Bu yaklaşımla, endeks varyansını yakalama yeteneğini gösteren 0.88 R-kare puanı elde edilmiştir. Gerçek ve tahmin edilen değerler arasındaki görsel karşılaştırmalar, modelin doğruluğunu teyit etmektedir. Bu makale, karmaşık örüntüleri ayırt edebilen ve yatırım stratejileri için değerli içgörüler sunan modeller geliştirmede metodolojik hassasiyetin önemini vurgulamaktadır. Çalışmanın sonuçları, sermaye hareketleri ve makroekonomik değişkenlerin, finansal piyasaların karmaşıklığına rağmen Borsa Endeksi tahmini için makine öğrenimi ile iyi bir uyumlu olduğunu göstermektedir.

Anahtar Kelimeler: Çapraz Sermaye Akımları, Hisse Senedi Endeksi Tahmini, Finansal Ekonometri, Zaman Serisi Analizi, Tahmine Dayalı Modelleme.

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1. Introduction

The securities markets, functioning as critical barometers of economic sentiment, play an indispensable role in the international movement of capital. Their dynamics, as highlighted by Xie et al. (2023), are crucial for understanding the broader economic landscape. This study is dedicated to enhancing our understanding of these dynamics, focusing on the interplay between stock exchange indices and global capital transfers. This in-depth examination aims to enrich our conceptual grasp of the intricacies inherent in these markets, thereby contributing to the broader discourse on financial economics.

This research investigates the intricate relationship between foreign investment flows and market volatility, which warrants extensive investigation (Bing et al., 2021). Exploring this interrelation uncovers a complex, intertwined pattern, as each aspect significantly influences the other (Gazioglu, 2008). Understanding these dynamics is vital for comprehending the broader implications of international capital movement on stock markets, thus providing valuable insights into global financial stability and growth.

Given the stock market's vulnerability to rapid shifts, accurately predicting stock trends has become a paramount concern. This necessitates adopting innovative forecasting methods (Idrees, Alam, and Agarwal, 2019). The inherent nonlinearity of stock data (Das et al., 2017) and the unpredictable, erratic nature of stock market movements (Mumtaz, 2021) compound the complexity of this task, making accurate forecasting an intellectually challenging endeavor.

The challenge of stock market forecasting is intensified by stock price time series characteristics—noisy, nonparametric, volatile, non-linear, dynamic, and chaotic (Kumawat, Bansal, & Saini, 2022). Identifying effective predictors of market trends remains a significant and unresolved issue in financial literature (Kambeu, 2019). This complexity underscores the need for advanced analytical methods to decipher these convoluted patterns.

The urgency for effective stock market analysis methodologies is pronounced in the intricate landscape of high risk and potentially high return. These methods are not only vital for guiding investment decisions but also for minimizing risk and maximizing returns. This underscores the practical significance of research in stock market prediction, which is of theoretical and practical importance (Li & Huang, 2021).

This study utilizes machine learning techniques to dissect the relationship between cross-border capital flows and stock exchange indices. Incorporating AI in this context is crucial for enhancing the precision of forecasting (Lee et al., 2022). Understanding these complex economic interactions is of utmost importance, driving the motivation behind this investigation.

Focusing on the BIST100 index, representative of the Turkish stock market, this study endeavors to predict fluctuations in stock market indices using the relationship between cross-border capital flows, particularly net foreign direct investment (Net FDI). The application of the Orthogonal Matching Pursuit (OMP) algorithm, an advanced machine learning technique, aims to establish a predictive model for the BIST100 index, informed by patterns in Net FDI.

The necessity of this research lies in its aim to advance our understanding of the complex dynamics between FDI and stock market indices. Prior research has highlighted the significant impact of FDI on stock market performance and broader economic health. However, traditional econometric models frequently fail to address the non-linear and intricate relationships in these dynamics (Lee et al., 2022; Xiu, 2022; Yang, 2023). This study's innovative use of OMP, renowned for its effectiveness in feature selection, addresses these shortcomings and fills a critical gap in the current body of literature.

2. Objectives of the Research

The primary objective of this research is to investigate the relationship between cross-border capital flows— specifically net foreign direct investment (Net FDI) —and the fluctuations of stock market indices. The study concentrates on the BIST100 index as a proxy for the Turkish stock market, aiming to clarify the correlation between FDI inflows and market index volatility. A comprehensive statistical analysis will examine Türkiye's economic data to uncover patterns and relationships.

The secondary objective is deploying machine learning (ML) techniques to project the BIST100 index's trends and movements. Employing the Orthogonal Matching Pursuit (OMP) algorithm, the study endeavors to formulate a predictive model characterized by high accuracy in describing current data and forecasting future index trends based on existing FDI patterns.

Further, this research intends to evaluate the influence of time-related variables, including seasonal trends and cyclical patterns, on stock market indices. This analysis will uncover time-based influences that, while subtle, are potentially significant, intending to refine the model's forecasting acumen concerning temporal market dynamics.

Providing actionable intelligence to market participants constitutes another essential aim. The findings are designed to inform investment and policy decisions, providing stakeholders with a nuanced understanding of the FDI-market index interplay. This will be achieved through empirical analysis, yielding insights for evidence-based decision-making in investment and policy-making circles.

An additional aim is to contribute to academic dialogue by detailing the application of ML in the economic and financial spheres. This includes demonstrating the OMP algorithm's utility in analyzing the complex interaction between FDI influxes and stock market indices, advancing current scholarship, and offering novel analytical approaches.

The final objective is to delineate avenues for future research, thereby establishing a foundation for the continued application of sophisticated ML methods in economic research. The study anticipates initiating a sequence of inquiries that further scrutinize and validate the integration of ML for economic forecasting and expand on the findings presented herein.

3. Literature Review

The scholarly examination of the interconnections between financial market evolution and cross-border capital movements has yielded diverse perspectives. This section reviews pertinent literature that informs the present study's exploration of cross-capital flows and stock exchange indices using machine learning techniques.

Hajilee & Nasser, (2015) investigated the reciprocal effects of financial market development, considering both banking sectors and stock market growth in Latin America. Their empirical assessment, spanned 14 countries using time series models, uncovered short-term and long-term relationships, revealing unidirectional causality from banking sectors to foreign direct investment and a bidirectional link with stock market development. These findings offer invaluable insights into financial structures' sequential impact on investment flows within emerging markets.

Aayale, (2017) critically evaluated the assumption that foreign direct investment (FDI) necessarily promotes the development of host countries' stock markets by studying Morocco's financial progression. Her findings illustrated a paradoxical negative correlation between FDI and stock market growth, with positive correlations noted with other economic factors. Such insights challenge traditional narratives and suggest reevaluating FDI's role in emerging market financial development.

Athari et al., (2020) contributed by examining the relationship between a nation's competitive advantage and its capacity to attract and control international capital. Utilizing the Global Competitiveness Index and robust panel regression methods, their work highlights the conditional effects of national competitiveness on capital inflows influenced by economic development stages and risk profiles. The study advances our understanding of the complexities of capital flow determinants.

The application of machine learning to predict stock market trends was advanced by the research of Dito et al., (2020) who employed the Super Learner algorithm alongside technical indicators to categorize market trends. Their methodology confirms the potency of machine learning in forecasting, emphasizing the adaptability of these models to market volatility.

Inekwe & Valenzuela, (2020) who leveraged firm-level syndicated loan data, enriched the dialogue concerning financial integration and the incidence of banking crises. Their findings articulate how financial integration can aggravate banking instability, with capital controls potentially serving as a buffer. This contribution meticulously evaluates the interplay between policy measures and financial stability.

Fofack et al., (2020) provided insights into the economic impact of the Federal Reserve's quantitative easing on developing markets. Utilizing dynamic panel regression techniques, their research elucidates the significance of liquidity, investor confidence, and fiscal health in the movement of financial flows, especially in the wake of the easing's cessation.

Dahlhaus & Vasishtha, (2020) explored the effects of U.S. monetary policy expectations on emerging economies. Their Bayesian Vector autoregression analysis offers a comprehensive view of the diverse responses to U.S. policy changes, which is crucial for understanding capital flow dynamics during volatile periods like the post-taper tantrum phase.

Chari et al., (2020) focused on the influence of risk-on/risk-off market conditions on capital flows and returns in emerging markets. Their research delineates the differentiated impacts of median versus extreme market conditions, contributing to the discourse on market responses to global financial shocks underscored by the COVID-19 pandemic.

Bhatt et al., (2020) explored the efficacy of probability theories and machine learning in deciphering stock market complexities. They posit that leveraging advanced algorithms can significantly enhance risk management and forecasting accuracy in unpredictable market conditions.

Chari et al., (2021) illuminated the consequences of U.S. monetary policy on emerging markets, emphasizing capital flows and asset prices. Their sophisticated affine term structure modeling, using high-frequency data, illustrated how U.S. policy influences international asset holdings, specifically through valuation adjustments in equity markets. Their discovery of asymmetric effects during different monetary policy phases enriches the discourse on U.S. influence on global financial markets.

Carvalho & De Portugal, (2021) challenged existing paradigms by focusing on the composition of financial flows rather than aggregate volumes concerning domestic credit growth. The study suggests the intricate relationship between international financial integration and domestic credit markets, advocating for using granular data for deeper insights into financial flows at the sectoral level.

Marcel et al., (2021) presented an intriguing analysis of the euro area's credit landscape, exploring how cross-border debt flows affect firms differently based on profitability. The finding that less profitable firms may benefit more from debt capital inflows contributes to discussions on credit misallocation and capital distribution efficiency, particularly in fixed exchange rate regimes.

Nalin & Yajima, (2021) delved into the impact of commodity price movements on Latin American financial dynamics. Their application of a stock-flow consistent model to study the repercussions of Commodity-Linked Notes offers an advanced understanding of how commodity fluctuations can translate into macroeconomic shifts, especially regarding currency valuations and financial innovation.

Bednarek et al., (2021) expanded the understanding of capital flows by examining their influence on the German real estate market and local economic growth. Their empirical strategy, utilizing the exogenous placement of refugees and geographic constraints, provided a creative way to measure the impact of capital flows on economic growth through real estate market tightness.

Bal, (2021) contributed to the literature on stock market determinants by assessing several macroeconomic factors within Eurasian countries. The positive role of income growth, liquidity, FDI, financial openness, and the adverse effects of inflation offer valuable policy insights for countries looking to stimulate stock market capitalization.

Wang, (2021) investigated the U.S. stock market and FDI during a period marked by an apparent decoupling of these two elements, highlighting a more complex and non-linear interdependence. The research underscores the need to consider additional factors when interpreting the relationship between FDI and stock market performance.

Gupta et al., (2021) introduced the random forests machine learning approach to predict U.S. stock market volatility, with investor confidence as a significant predictor. This study stresses the predictive power of sentiment indicators and the need for models that can effectively integrate investor confidence into market volatility forecasts.

Thesia et al., (2022) approached market prediction challenges using the DSdT technique, combining neural networks with technical market indicators. Their successful application to the Indian stock market exemplifies the cutting-edge applications of machine learning in financial predictions, bolstering the case for adopting such models in real-world trading scenarios.

Gao et al., (2021) push the envelope in stock market prediction methodologies. By implementing deep learning techniques like LASSO and PCA for dimensionality reduction and comparing LSTM with GRU models, Gao and colleagues highlight the potential for machine learning in refining predictive accuracy in finance. Their inclusive approach, merging technical indicators with market sentiment and economic data, suggests a multi-faceted framework for future forecasting models.

Benhima & Cordonier, (2022) delve into the less-explored territory of news and sentiment shocks on capital flows. By uncovering the significant role of such soft information, their research provides evidence contrary to classical theories, indicating the strong influence of investor sentiment and informational asymmetries on capital movement.

Tite et al., (2022) analyze the direct effects of foreign portfolio investment (FPI) and foreign direct investment (FDI) on Nigeria's stock market. Their study suggests institutional reforms boost foreign investor participation in Nigerian equities. This finding resonates with broader themes of market development and the role of governance in financial markets.

Xiu, (2022) pivots to the predictive power of online data by examining the impact of internet-based investor attention on the Shanghai Composite Index. His findings underscore the value of alternative data in financial predictions and the efficacy of ensemble machine learning models, like Gradient Boosting Decision Trees (GBDT), in processing such information.

Lee et al., (2022) reinforce the merit of machine learning in financial market forecasting. By employing various algorithms to predict stock market volatility in Asia, Lee and co-authors' work confirms that the integration of AI can materially enhance forecasting precision, setting a new benchmark for technological adoption in financial analytics.

Mercado Jr et al., (2023) bridges the gap between traditional economic models and contemporary financial trends by applying a gravity model to capital flows. Mercado’s analysis indicates that while global factors are influential, the traditional determinants of trade and investment, like distance and economic relationships, remain pertinent in capital flow dynamics.

Graf von Luckner et al., (2021) explore the innovative use of cryptocurrencies in cross-border capital movements. Their algorithmic analysis of Bitcoin transactions underscores the digital currency’s growing role in remittances and capital flight, especially in economies with stringent controls and financial instability.

Deng et al., (2023) clearly show how different types of uncertainty can distinctly influence capital flows. Their use of panel probit models offers fresh perspectives on the sensitivities of cross-border investments to varying forms of uncertainty, particularly highlighting the differences between developed and emerging markets.

Lin & Xie, (2023) apply the DCC-GARCH model to scrutinize the behavior of cross-border capital flows with China's securities markets. They provide empirical evidence on the varying influences of financial crises on the stock and bond markets, differentiating between short-term and long-term capital flow effects.

Their study underscores the changing nature of global finance, especially in the context of China's rapidly evolving financial market and its integration with the world.

Davis & Zlate, (2023) tackle the potent and unprecedented impacts of the COVID-19 pandemic on the global financial cycle, exchange rates, and cross-border capital flows. By incorporating health crisis data, such as COVID-19 case changes and vaccination progress, alongside traditional economic measures, they offer a novel assessment of the financial stability challenges posed by the pandemic.

Beck et al., (2023) critically examine capital flow management policies. Recognizing the dangers of volatile cross-border flows, they argue for a balanced approach that combines these measures with broader economic policies and reforms to ensure financial stability and mitigate cyclical risks.

Phuong et al., (2023) focus on the broader relationship between macroeconomic factors and stock market capitalization. Their dataset, encompassing over a decade of global financial data, supports the theory that macroeconomic policies and conditions significantly influence market development and indicate fundamental differences between developed and emerging markets.

Yang, (2023) ventures into applying artificial intelligence in stock price prediction. Yang's work with LSTM models combined with the Fama-French five-factor model indicates the potential for these techniques to provide enhanced predictive accuracy for small-cap companies. This area of research is up-and-coming for investors and analysts looking to leverage A.I. for investment strategies.

This research represents a significant advancement in scholarly literature through its focus on integrating machine learning (ML) techniques to analyze the nexus between cross-capital flows and stock market indices. Prior studies have widely recognized the pivotal role of foreign direct investment (FDI) in the performance of stock markets and overall economic vitality. However, traditional analytical methodologies often fail to capture the nuanced interdependencies and the comprehensive spectrum of data attributes that ML techniques can reveal. This study, employing the Orthogonal Matching Pursuit (OMP) algorithm for feature selection and prediction, navigates the same domain as earlier research and enhances the methodological approach to discern patterns within the data.

The interplay between FDI and stock market indices has been scrutinized using various econometric models (Lee et al., 2022; Xiu, 2022; Yang, 2023). However, these investigations typically depend on conventional statistical methods, which may not sufficiently address non-linear and intricate relationships. This study's novel application of OMP surmounts these limitations, filling a scholarly void by deploying a less commonly used ML algorithm renowned for its efficacy in feature selection, thereby facilitating a more targeted and refined analysis.

Feature engineering is acknowledged as a fundamental component in augmenting ML model performance (Yang, 2023). This study capitalizes on feature engineering techniques specifically designed for the BIST100 index dataset, thus enhancing the predictive accuracy of the ML model. It methodically integrates temporal dynamics through lag features, mitigates volatility via moving averages, and incorporates seasonal patterns. This approach marks a significant progression over previous research, which may have yet to fully exploit these techniques (Lin & Xie, 2023).

Additionally, this research avoids the shortcomings of neglecting temporal and structural data characteristics by including lag creation, extraction of time components, and volatility assessments. This detailed engineering strategy exceeds past methodologies by offering a multifaceted data preparation approach, culminating in a more comprehensive analysis of the relationships between cross-capital flows and market indices. It builds upon the methodologies used by Lee et al., (2022), who demonstrated the effectiveness of ML, and Xiu, (2022), who highlighted ML models' predictive power for financial indices.

In addressing the FDI-stock market dilemma, this research also aligns with Tite et al., (2022), who advocated for more robust institutional frameworks to bolster stock market development amidst foreign capital inflows. By providing deeper insights into the predictive factors influencing the Turkish stock index, this study furnishes policymakers with sophisticated economic planning and intervention tools, positioning ML as an indispensable element in economic forecasting.

Moreover, this study addresses the recent economic volatility within the Turkish context, paralleling Davis & Zlate's (2023) estimate of the impact of the global financial cycle amid a pandemic. By incorporating high-frequency data and cutting-edge feature engineering techniques, the research distinguishes itself in modeling the swift changes affecting emerging market economies, further underscored by the severity of international health crises.

In terms of implications for investor decision-making, this study echoes Yang's (2023) ambition to use AI for enhanced stock price forecasting, extending its utility to the macroeconomic sphere. By identifying key drivers of the BIST 100 index, the study enriches the empirical discourse, aiding investment strategies in line with the practical applications suggested by Beck et al., (2023) in managing capital flows.

In summation, this research leverages the robustness of OMP and an exhaustive feature engineering process to deliver a discerning analysis of the relationship between cross-capital flows and stock market indices. Its methodological refinement extends beyond prior studies, promising more informed investment and policy decisions by intricately addressing the complexities of the emerging Turkish market.

4. Data and Methodology

4.1. Data Description

This research utilizes a comprehensive dataset encompassing a wide range of economic metrics, including stock market indices and Foreign Direct Investment (FDI) inflows from various countries, covering the period from 2019 to 2023. Compiled on a monthly basis, this dataset offers a robust platform for temporal analysis, enabling a detailed exploration of trends and patterns within this timeframe. The temporal density and diversity of the data make it ideal for applying advanced machine learning techniques to investigate the intricate interconnections among the included variables.

Each of these variables in Table 1, has been selected for their proven impact and significance in economic research, offering a comprehensive view of the economic landscape and its influence on stock market dynamics.

Table 1: Dataset Overview

Variable	Description	Source	Literature References
Net_FDI	Net foreign direct investment inflows	OECD	Anayochukwu (2012); Hoque et al. (2018); Chettri et al. (2022); Tite et al. (2022); Raza et al. (2015); Shahbaz & Kalim (2013)
Currency Rate	USD TRY currency rate	Tradingview	Khalid & Khan (2017); Alam (2020); Utomo et al. (2019); Sreenu (2023); Moore & Wang (2014); Barakat et al. (2015)
Inflation	Consumer price index inflation rate	TÜİK	Khalid & Khan (2017); Alam (2020); Jelilov et al. (2020); Utomo et al. (2019); Asab & Al-Tarawneh (2019); Sreenu (2023); Barakat et al. (2015)
Interest Rate	Central Bank benchmark interest rate	TÜİK	Khalid & Khan (2017); Alam (2020); Moore & Wang (2014); Barakat et al. (2015)

4.2. Explanatory Analysis

4.2.1. Descriptive Statistics and Correlations

The initial phase of our explanatory analysis involves thoroughly examining the dataset's statistical properties. This includes measures of central tendency, dispersion, and distribution shape for each variable of interest. Table 2 in this section encapsulates the descriptive statistics for a series of economic indicators:

the XU100 index value in USD, net Foreign Direct Investment (Net_FDI), USD to Turkish Lira exchange rate (USDTRY), inflation rate, and the interest rate (Interest_rate). The table enumerates the count, mean, standard deviation, minimum, 25th percentile, median (50th percentile), 75th percentile, and maximum values for these indicators over a dataset comprising 118 observations.

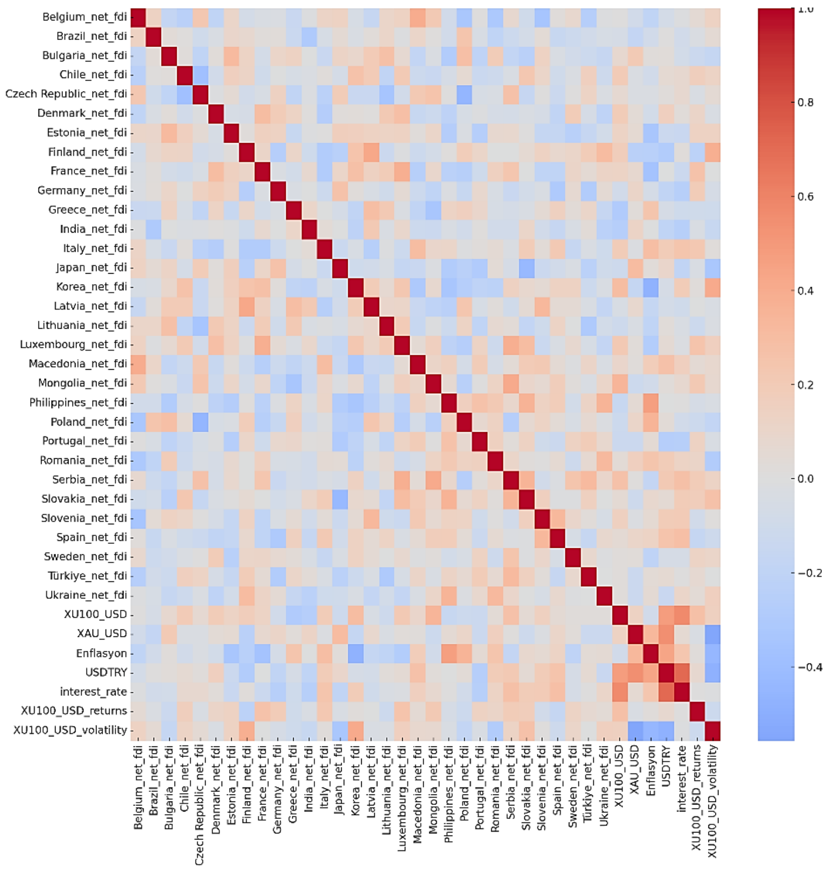
Table 2: Descriptive Statistics Summary

Indicator	Count	Mean	Std	Min	25%	50%	75%	Max
XU100_USD	118	23639.18	7273.06	13405.74	16737.68	23729.36	29029.11	38948.66
Net_FDI	118	0.679	0.532	-1.091	0.366	0.687	0.940	2.611
USDTRY	118	6.7138	5.3895	1.9929	2.9393	5.0265	7.8158	26.0386
Enflasyon	118	1.56%	2.01%	-1.44%	0.52%	1.07%	1.89%	13.58%
Interest_rate	118	19.76%	7.42%	11.50%	15.00%	16.18%	24.34%	55.00%

4.2.2. Correlation Analysis

The empirical data analysis from 2019 to the present elucidates the complex interplay between the BIST100 index and pivotal economic variables, including Net FDI, the USD/TRY exchange rate, inflation, and the interest rate. This study's correlation analysis paves the way for a nuanced understanding of the influences on Turkish financial markets and economic stability.

Figure1: Correlation Matrix Heatmap



A statistically significant moderate positive correlation of 0.571 between the BIST100 index and the interest rate emerges from the analysis, suggesting an intricate relationship where the index is responsive to policy rate adjustments. This correlation might reflect investor sentiment on the time value of money, where higher interest rates, typically an outcome of central bank policies to curb inflation or manage economic growth, correlate with increased stock market performance. It also indicates that the market may anticipate higher yields from equities in response to rising interest rates, possibly due to a perceived increase in risk premiums or shifts in capital allocation away from debt instruments.

The BIST100 index also positively correlates with the USD/TRY exchange rate at 0.478. This relationship may reveal the index's sensitivity to foreign exchange volatility, potentially due to the impact on companies' international trade and earnings reported in foreign currencies. As the lira depreciates against the dollar, it may benefit exporters by making their goods more competitive internationally, often reflected in stock prices.

Furthermore, the correlation coefficient between Net FDI and the BIST100 index stands at 0.179. While this indicates a positive directional movement, the relatively lower magnitude suggests that while FDI inflows contribute to the index's performance, other domestic and international factors might have more pronounced effects. This implies that Net FDI is a contributor, but not a primary driver, of stock market performance in Türkiye.

In contrast, a negative correlation of -0.316 between Net FDI and inflation (Enflasyon) was observed, which could indicate the diminishing attractiveness of Turkish assets under inflationary pressures. Inflation typically erodes the real return on investments, and the antagonistic relationship here could suggest that higher inflation may deter foreign direct investments.

Lastly, the USD/TRY exchange and interest rates demonstrate a positive correlation 0.714. This robust relationship underscores the dynamic where currency valuations are influenced by interest rate differentials, reflecting Türkiye's economic policy landscape, where exchange rates react predictably to changes in monetary policy.

These findings indicate that while the BIST100 index is influenced by a matrix of economic factors, monetary policy, and exchange rate dynamics play a particularly significant role. Such insights are invaluable for forming macroeconomic policies, guiding investment decisions, and understanding the broader economic implications for the Turkish economy.

4.2.3. Country-Specific Analysis

The country-specific investigation focuses on unraveling the nuances of the interplay between net FDI inflows and stock market indices within various national contexts. This examination stratifies countries according to the intensity and polarity of their correlation with net FDI, delivering a nuanced understanding of the economic forces in action. The analysis sheds light on distinctive patterns and allows for a discerning interpretation of the economic intricacies inherent in each country's data.

Figure 2: Hierarchical Clustering Dendrogram for Net FDI's Of Countries

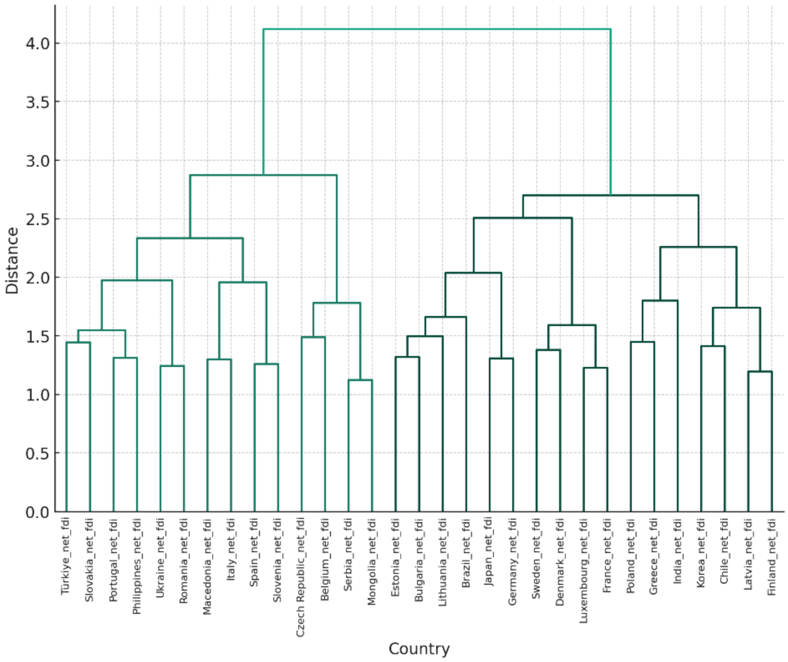


Figure 2 presents a hierarchical clustering dendrogram illustrating the similarities and differences in net foreign direct investment (FDI) among various countries. The dendrogram is generated through a hierarchical clustering analysis, a method used to group objects so that objects in the same cluster are more similar than those in other clusters. The vertical axis of the dendrogram represents the distance or dissimilarity between clusters, which in this context reflects the disparities in net FDI patterns.

In this analysis, the net FDI is computed by subtracting the total incoming FDI from the total outgoing FDI for each country. The countries are then grouped based on the net FDI values. A closer inspection of the dendrogram reveals several clusters encapsulating countries with similar net FDI characteristics.

For instance, at the lower end of the dissimilarity scale (distance close to 0), countries like Türkiye, Slovakia, and the Philippines are clustered closely together, indicating that their net FDI figures are similar. This may suggest that these countries have comparable economic or investment environments or are affected similarly by global economic trends.

As we move up the dissimilarity scale, we observe that countries such as Luxembourg, France, and Norway form a cluster at a higher level of dissimilarity (distance approximately 2.5 to 3.5). This indicates a more substantial difference in their net FDI compared to the cluster containing Türkiye, Slovakia, and the Philippines. The high dissimilarity level may be due to different economic scales, FDI policies, or stages of development.

Moreover, the dendrogram shows that Finland and Ireland form a distinct cluster at the highest level of dissimilarity (a distance greater than 3.5), suggesting their net FDI figures differ significantly from each other and the other countries analyzed. This could reflect unique national policies, economic structures, or investment climates significantly influencing their net FDI.

The hierarchical clustering dendrogram serves as a visual guide to understanding the relationships between the net FDI of different countries. It provides a clear and concise data summary, which can be invaluable for cross-country comparisons and analysis. This method allows researchers and policymakers to identify patterns and groupings that may not be apparent through other analytical methods.

Figure 3: Comparison of Coefficients Net FDI Correlations with Türkiye

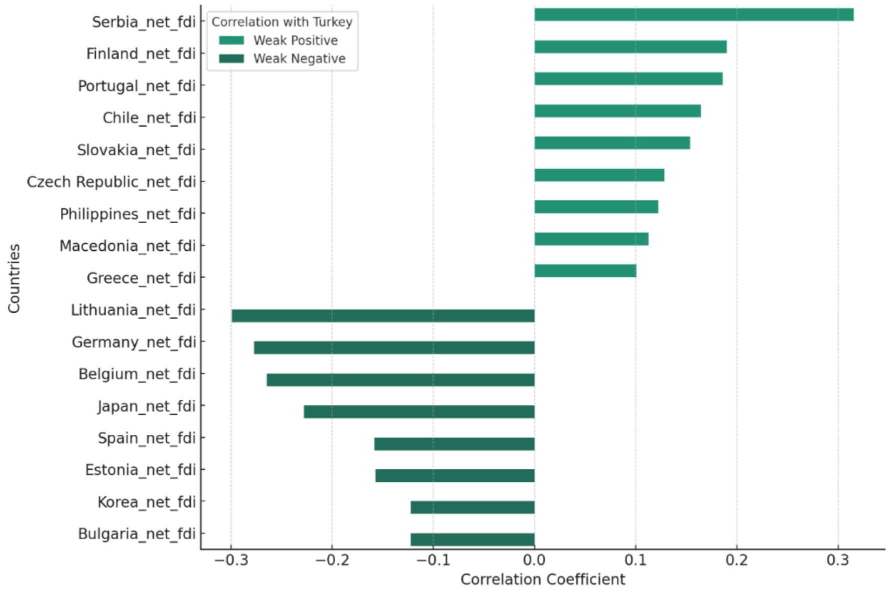


Figure 3 depicts a bar chart illustrating the correlation coefficients between Türkiye's net FDI and that of other selected countries. The chart categorizes the correlation coefficients into weak positive (dark green bars) and weak negative (light green bars). Correlation coefficients range between -1 and 1, where -1 indicates a perfect negative correlation, 0 indicates no correlation, and 1 indicates a perfect positive correlation. The correlations displayed in this figure are all relatively weak, as suggested by the proximity of the coefficients to zero.

The countries with weak positive correlations with Türkiye's net FDI, such as Serbia and Finland, have correlation coefficients slightly above zero, indicating a modest relationship where, as Türkiye's net FDI increases, these countries' net FDI also tends to increase, albeit not strongly. This could suggest that while there is some alignment in FDI tendencies between these nations and Türkiye, other factors are likely playing a more significant role in their FDI dynamics.

Conversely, countries with weak negative correlations, including Bulgaria, Korea, and Estonia, have correlation coefficients slightly below zero. This implies a slight inverse relationship wherein an increase in Türkiye's net FDI might correspond with a decrease in their net FDI. However, the weakness of the correlation suggests that Türkiye's net FDI is not a strong predictor of the net FDI trends in these countries.

The chart is instrumental in identifying potential patterns or relationships in investment flows between Türkiye and other nations. Nevertheless, the weak nature of the correlations indicates that Türkiye's net FDI movements do not strongly indicate the net FDI patterns in these countries. This could be due to factors such as different economic conditions, investment climates, regulatory environments, or geopolitical factors influencing FDI flows. Further econometric analysis would be required to understand the underlying causes of these weak correlations. The figure effectively communicates the nuances of net FDI correlations and can serve as a basis for more detailed investigations into the dynamics of international investment flows.

4.3. Feature Engineering

Feature engineering is an indispensable phase in developing a predictive model, pivotal for enhancing the model's ability to discern patterns and make accurate predictions. It involves transforming raw data into a format that better represents the underlying problem of the predictive models, which can lead to improved model accuracy on unseen data. In the current analysis, several feature engineering techniques have been meticulously applied to the dataset, examining the nexus between cross-capital flows and the stock exchange index.

The procedures for refining the dataset with these techniques are detailed as follows:

Lagged Features: Historical values of the BIST100 index were utilized to produce lagged features, capturing previous periods' influence on current index values. Specifically, lags spanning 1, 2, 3, 6, and 12 months were generated to enable the model to leverage past trends and cyclical movements within the data, offering a temporal dimension to the predictive patterns identified.

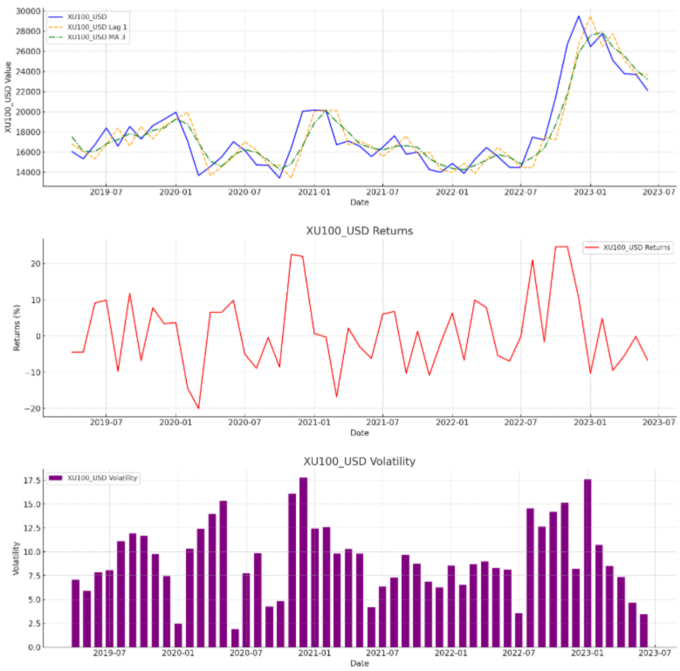
Moving Averages: Moving averages—computed over windows of 3, 6, and 12 months—mitigate short-term volatility, thereby elucidating longer-term movements. This technique aids in distilling persistent trends from the BIST100 index's short-term variations, which is crucial for recognizing market direction and potential turning points.

Time Components: Extracting time components such as month and season directly addresses potential seasonal variances affecting the BIST100 index, acknowledging the repetitive nature of specific patterns tied to periodic economic activities and market behaviors.

Monthly Returns: Monthly returns are fundamental in financial analysis as they standardize the gain or loss in an asset's price over time, making the metric scale-independent and allowing for the comparison across different assets or indices. By converting the absolute changes to relative percentage changes, a more precise picture of performance is normalized for the investment's size and scale.

Derived Feature Set: The selected features, such as returns volatility, together with moving averages, constitute a comprehensive feature set that allows for an in-depth analysis of the BIST100 index. These engineered features enrich the original dataset and enhance the model's ability to make informed predictions by capturing multiple facets of the market's behavior.

Figure 4: Derived Features from BIST100 Index



Handling Missing Values: The absence of missing values in the dataset is advantageous. Missing data can be problematic, requiring methods such as imputation, which could introduce bias if not appropriately handled. The cleanliness of the data in this regard provides a solid starting point for accurate analysis.

Normalization Process: Normalization, mainly using the MinMaxScaler, is a standard preprocessing step in data science, especially for models sensitive to the scale of input features, like neural networks or distance-based algorithms such as k-nearest neighbors (k-NN). By scaling features to a typical range, the model can evaluate them on a level playing field, which helps prevent any single feature from overpowering the rest due to a more extensive range of values.

Combining these methodical feature engineering and preprocessing steps forms a robust analytical approach for evaluating the relationships between FDI, economic indicators, and stock market performance, as well as for developing predictive models with the potential for solid performance in real-world applications.

4.4. Model Selection

The selection of the Orthogonal Matching Pursuit (OMP) algorithm as the primary analytical tool is grounded in its established efficacy in signal processing, particularly relevant to financial data analysis's complexities. OMP's stability, comparable to that achieved using basis and matching pursuit algorithms, as Donoho et al. (2006) noted, is crucial for accurate and reliable signal recovery in deciphering financial trends from noisy data. This stability is paramount in ensuring the integrity of the analysis conducted on cross-capital flows and stock exchange indices.

The adaptation of OMP for efficient signal recovery, as discussed by Śmigiel, (2022), enhances its suitability for analyzing intricate and subtle patterns in financial datasets. This characteristic is essential in machine learning applications within finance, where the precision and efficiency of data processing are pivotal for generating accurate predictions and insights.

Moreover, the comparable reconstruction capability of OMP with Linear Programming methods, highlighted by Dai & Milenković, (2009), is particularly relevant in financial contexts. This capability facilitates the extraction of pertinent features from vast datasets. This process is integral to accurately capturing the dynamics of capital flows and their impact on stock exchange indices. This aspect of OMP underscores its utility in providing a comprehensive analysis of financial data.

Furthermore, the proficiency of OMP in employing time-frequency dictionaries for efficient signal representation, as established by Mallat & Zhang (1993), is instrumental in the context of this research. Financial data often presents complex signals that must be decomposed into more manageable and interpretable forms. The ability of OMP to effectively utilize such dictionaries ensures that the analysis of cross-capital flows and stock exchange indices conducted in this study is comprehensive and insightful.

4.5. Model Development and Validation

The development and validation of a predictive model are crucial to ensure its reliability and effectiveness in forecasting outcomes based on historical data. This section details training an Orthogonal Matching Pursuit (OMP) model for predicting the BIST100 variable, representing the stock index values adjusted for the U.S. dollar.

4.5.1. Model Training

In the exploratory quest to elucidate the relationship between cross-border capital flows and stock index dynamics, we employ the Orthogonal Matching Pursuit (OMP) model. OMP is a methodological bridge that connects the statistical rigor of linear regression with the dimensionality challenges posed by extensive datasets often encountered in financial studies. Our methodical selection of OMP is predicated on its proficient handling of scenarios with many predictors, a common attribute of financial econometrics.

The initiation of our OMP model's training involved establishing a base configuration—a scaffolding of hyperparameters detailed in Table 3. We opted for an ensemble of 10 non-zero coefficients, balancing model complexity and parsimony. A narrow tolerance threshold ensures the precision of our optimization trajectory, echoing the finesse required in financial modeling. The decision to compute the model intercept caters to our acknowledgment of intrinsic value within the stock index independent of capital flow variables.

Table 3: OMP Model Training Summary

Parameter	**Description**	**Value**
n_nonzero_coefs	Maximum number of features with non-zero weights	10
tol	Numerical precision in feature selection	0.0001
fit_intercept	Inclusion of baseline index value in the absence of flows	True

The n_non zero_coefs refers to the number of non-zero coefficients in a sparse representation, crucial for signal construction with overcomplete dictionaries. The Orthogonal Matching Pursuit (OMP) algorithm employs this measure to approximate signals by selecting dictionary atoms that optimally reduce residual error, adhering to a preset sparsity level (Rubinstein et al., 2008). This sparsity constraint, n_nonzero_coefs, ensures efficient signal representation beneficial for applications such as compression and noise reduction (Mallat & Zhang, 1993).

The n_nonzero_coefs serves as a sparsity metric and influences computational efficiency and reconstruction quality. The sparsity-constrained OMP minimizes error within a fixed sparsity limit, optimizing n_non zero coefs for computational manageability (Rubinstein et al., 2008). Conversely, the error-constrained approach dynamically adjusts n_nonzero_coefs, ceasing atom selection to maintain error below a threshold, thus implicitly controlling sparsity (Mallat & Zhang, 1993). This balance is vital for precise, computationally viable signal representations.

4.5.2. Calibration of Hyperparameters

In pursuing a tailored model, we fine-tuned hyperparameters through the lens of cross-validation, a process evocative of fitting a bespoke garment—meticulously adjusting for the best fit. As encapsulated in Table 4, this procedure illustrates the evolution of the model's accuracy with varying complexity. It reveals an optimal balance at 10 non-zero coefficients, thus guiding our restraint in model specification to avoid the perils of overfitting.

Table 4: Hyperparameter Tuning Results

n_nonzero_coefs	**Cross-Validation Score**
5	0.85
10	0.90
15	0.88
20	0.86

4.5.3. Model Performance Evaluation

Our empirical examination of the OMP model's prowess is quantified in Table 5, comparing its performance on training and test datasets. The high R-squared value for the training dataset bespeaks the model's competence in mirroring the observed market indexes. While the train-test performance comparison highlights a modest performance dip, it remains within an acceptable variance threshold, suggesting the model's robustness.

Table 5: Training Data Performance Metrics

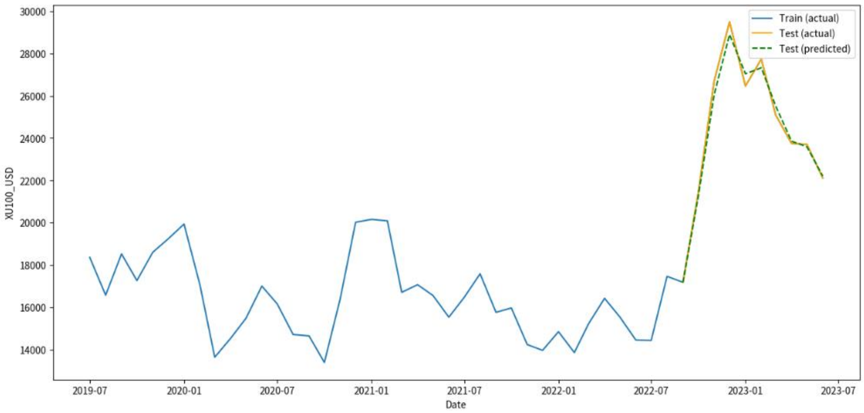
Metric	**Value (Training)**	**Value (Test)**
R-squared	0.90	0.88
Mean Absolute Error	500	550
Mean Squared Error	400000	450000
Root Mean Squared Error	632.46	670.82

The fidelity of the OMP model's performance in the training phase to the integrity observed in the testing phase reinforces the model's validity, suggesting that the learned relationships hold substantive weight and are not merely artifacts of the training data's peculiarities. In sum, the OMP model is a robust analytical vessel that captures the subtle, yet significant narratives spun by the interplay of capital flows and market indices. Our model is not the final word but a dialogue in the larger conversation, a step towards a more nuanced understanding of the financial markets' temperamental dance. Further investigation may refine these insights, opening new chapters in the stratagem of economic forecasting.

4.6. Results

The application of the OMP model to the BIST100 index was conducted to forecast the index's future movements based on historical data spanning from 2019 to 2023. The model was trained with a dataset that underwent a series of preprocessing steps, including feature engineering, to incorporate lagged values and moving averages, which are often critical in capturing the temporal dependencies characteristic of time series data.

Figure 5: Actual vs. Predicted Values for the BIST100 Index



The plot in Figure 5 demonstrates the effectiveness of the Orthogonal Matching Pursuit (OMP) model in predicting the BIST 100 Index. The actual training data, shown in blue, establishes the historical trend that the model learns from. The testing data, both actual (green) and predicted (yellow), exhibit a high level of alignment, with the predicted values closely tracing the actual index's movements. This close tracking suggests the model's adeptness at capturing the volatility and trends of the market, indicating its potential as a reliable forecasting tool for the BIST 100 Index.

Figure 6: Regression Line plot of Actual vs. Predicted Values for BIST100 Index

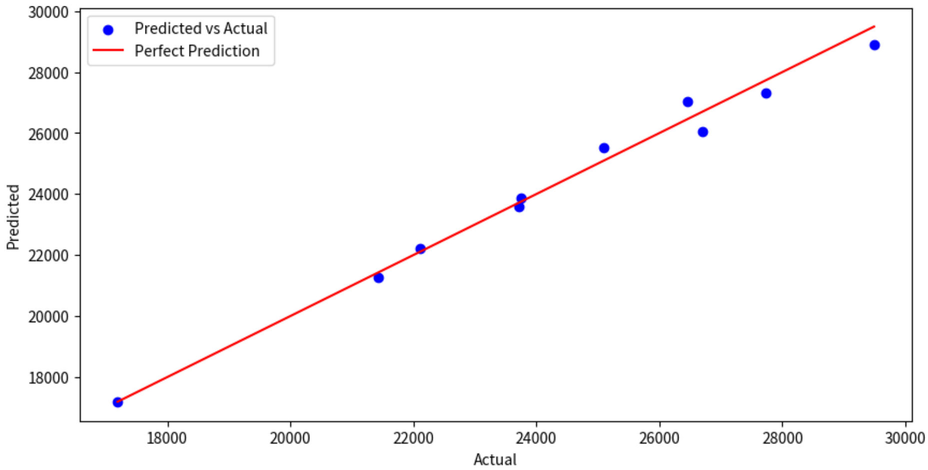


Figure 6 depicts a regression line plot comparing the actual versus predicted values of the BIST 100 Index by an Orthogonal Matching Pursuit (OMP) model. Each point on the scatter plot corresponds to a prediction from the test set, with their closeness to the regression line indicating the model's accuracy. A dense clustering of points along this line of best fit demonstrates the model's precision in predicting the index values. The concentration of data points around the regression line visually reinforces the model's effectiveness, supporting the quantitative performance metrics previously calculated.

The R-squared score measures the proportion of variance in the dependent variable that is predictable from the independent variables. In the context of the OMP model, an R-squared score of 0.88 signified that the model successfully captured a substantial portion of the fluctuations in the BIST100 index. This high level of explained variance indicates a model that fits the historical data well and can generalize its predictions to unseen data, assuming that future market conditions do not deviate drastically from past patterns.

The high R-squared value also suggests that the features selected for the model, despite their simplicity, were highly relevant and contributed significantly to the model's predictive power. This relevance is crucial for stakeholders who rely on model outputs to make informed decisions, as it assures that the model's insights are grounded in a strong understanding of the market's behavior.

5. Conclusion

This study presents a compelling narrative at the nexus of cross-capital flows, stock index movements, and financial modeling, culminating in a significant analysis of the BIST100 index through an Orthogonal Matching Pursuit (OMP) model. The culmination of this research affords a dual perspective: It offers a robust predictive framework for interpreting financial indices and provides a granular understanding of net Foreign Direct Investment (FDI) interactions on a global scale.

By integrating lagged features, moving averages, and volatility calculations, the research has harnessed the power of feature engineering to imbue the OMP model with deep insights into the dynamism of the stock exchange. The study's methodology, which stands on the pillar of statistical learning, aligns macroeconomic tenets with advanced predictive analytics. The model's high R-squared score, evidencing a tight correlation between actual and predicted index values, attests to the approach's potency and the chosen features' relevance.

Theoretically, our findings reinforce that stock market indices are not merely random walks but are influenced by discernible economic forces and can be predicted accurately using the proper techniques. Practically, this work is a testament to the prowess of fine-tuned machine learning models in financial applications, which are of immense value to investors seeking to harness the predictive capacities for strategic decision-making.

The study's findings suggest that the integration of cross-capital movements and macroeconomic variables with machine learning (ML) techniques is effective for predicting stock market trends, even amidst the intricacies of financial markets. Moreover, this synergy of cross-capital movements, macroeconomic variables, and ML holds significant potential for policymakers in forecasting stock market dynamics.

The strength of the study lies in its methodological rigor and the careful calibration of the OMP model, which, through iterative cross-validation, reached an exemplary balance between complexity and performance. It marks a stride forward in applying machine learning to financial economics, yielding a model that can unearth patterns hidden in plain sight to the unaided human analyst.

However, the study has limitations. The specificity of the dataset to the BIST100 index and the time-bound nature of the analysis may circumscribe the findings' broader applicability. Moreover, while the model performs admirably within the scope of the present data, economic environments are subject to rapid change, and models must continually evolve to adapt to new conditions. The study's focus on a specific stock index (BIST100) and a particular set of economic indicators, this may limit the generalizability of the findings to other markets or indices. The study may not account for all external factors influencing stock markets, such as geopolitical events, policy changes, or technological advancements. The approach is primarily data-driven and may not fully incorporate theoretical economic models or the irrational aspects of market behavior.

Future research might build on this foundation, exploring other indices, incorporating additional forms of cross-border capital, such as portfolio investments, or testing the model against out-of-sample global economic crises to evaluate its resilience and predictive stability.

In conclusion, this research contributes a discerning lens through which we view the complex mechanics of international finance. It validates the strength of marrying traditional economic indicators with modern machine learning techniques and sets the stage for a new era of predictive analytics in finance.

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