International Journal of Economics and Financial Issues

ISSN: 2146-4138

available at http: www.econjournals.com

International Journal of Economics and Financial Issues, 2025, 15(4), 317-326.

Decoding Turkish Lira Volatility Using Natural Language Processing, News and Twitter Sentiment, and Explainable AI

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Received: 27 January 2025 **Accepted:** 08 May 2025 **DOI:** https://doi.org/10.32479/ijefi.19724

ABSTRACT

This study examines the Turkish Lira/US Dollar exchange rate volatility from January 2015 through February 2024-a period when the Lira depreciated dramatically against the USD. This currency collapse triggered serious economic problems: High inflation, soaring import prices, reduced purchasing power, persistent price increases, lower real wages, higher external debt costs, limited monetary policy options, and volatile financial markets. While previous research has used Twitter sentiment for financial forecasting, our study contributes to the literature by analyzing both international news sources (The Economist, The New York Times, and The Guardian) and local Turkish sources (Yenisafak newspaper and social media Turkish Twitter content). Using explainable AI techniques, we investigate how news sentiment from different sources affects exchange rate volatility. The results indicate that international media sentiments impact the volatility of the Turkish lira/US dollar exchange rate. The overall sentiment derived from news sources effectively captures fluctuations in volatility. However, local media appears to have a comparatively weaker influence than international news.

Keywords: NLP, Explainable Ai, Machine Learning, Exchange Rate, Volatility, News Sentiment
JEL Classifications: G04, E37, E31

1. INTRODUCTION

Since time immemorial, humanity has been captivated by the unknowable future. From ancient oracles consulting entrails to modern data scientist wielding complex algorithms, our species has persistently sought to pierce the veil of tomorrow. This intellectual yearning permeates numerous disciplines from meteorologists predicting weather patterns (Price et al., 2025; Tripathy et al., 2021), to epidemiologists forecasting disease spread and pandemic dynamics (Chowell and Skums, 2024; Roosa et al., 2020), to astronomers anticipating celestial movements (Ni et al., 2024; Shirafkan et al., 2025), to transportation experts planning traffic and population flow (Chen et al., 2023; Hu and Xiong, 2023),-all employing time series forecasting to extract order from apparent chaos[1]. Economics and finance stand firmly within this tradition, utilizing mathematical models and algorithms to anticipate market movements, inflation rates, economic growth, stock prices, and currency valuations. Among these variables, exchange rates present perhaps the most formidable challenge to predictive methodologies, combining technical complexity with real-world implications.

The foreign exchange market has ascended to unprecedented prominence as the world's dominant financial marketplace, now facilitating an extraordinary daily transaction volume of \$7.51 trillion[2]. This enormous expansion, however, has been accompanied by a proportional amplification of foreign exchange risk exposure (Windsor and Cao, 2022). Moreover, the significance of exchange rates is that this rates function as essential economic indicators, influencing everything from international trade flows to investment decisions. A country's exchange rate serves as both barometer and determinant of its economic health, affecting

1 Time Series - an overview | ScienceDirect Topics

2 Forex Daily Trading Volume Statistics in 2025

import prices, export competitiveness, and capital flows. The foreign exchange market where currencies are traded in staggering volumes exceeding trillions of dollars daily responds sensitively to myriad macroeconomic variables: interest rate differentials, inflation expectations, fiscal stances, monetary policy decisions, and broader economic growth trajectories (He et al., 2021).

In the aftermath of the Bretton Woods system's dissolution in early 1970s, central banking authorities across the globe have predominantly embraced more flexible and adaptive exchange rate policies. This fundamental shift in monetary governance has substantially contributed to the inherently volatile character of contemporary currency markets. These unpredictable monetary fluctuations pose multifaceted threats extending well beyond the immediate profit concerns of multinational corporations. Indeed, such volatility represents a potentially destabilizing force that may undermine the structural integrity and operational resilience of international financial systems, raising vital questions about sustainable economic governance in an increasingly interconnected global economy.

Therefore, exchange rate forecasting represents one of the most crucial and challenging frontiers in contemporary financial economics (Kumari et al., 2022; Qureshi et al., 2023). The modern global economy, with its intricate web of international transactions, hinges upon the relative valuations of national currencies. These valuations, however, exhibit considerable volatility, driven by a constellation of factors that defy simplistic analytical frameworks. The quest to forecast these fluctuations thus embodies the economist's perpetual struggle against uncertainty.

The evolution of exchange rate forecasting methodologies mirrors broader technological transformations within global financial institutions. As these entities have embraced increasingly sophisticated computational capabilities, forecasting techniques have undergone parallel advancements. Particularly, machine learning algorithms, have emerged as preeminent tools for time series prediction. These algorithmic approaches have gained scholarly recognition for their capacity to identify subtle patterns within what appears to be chaotic data patterns that traditional econometric models and statistical techniques might overlook.

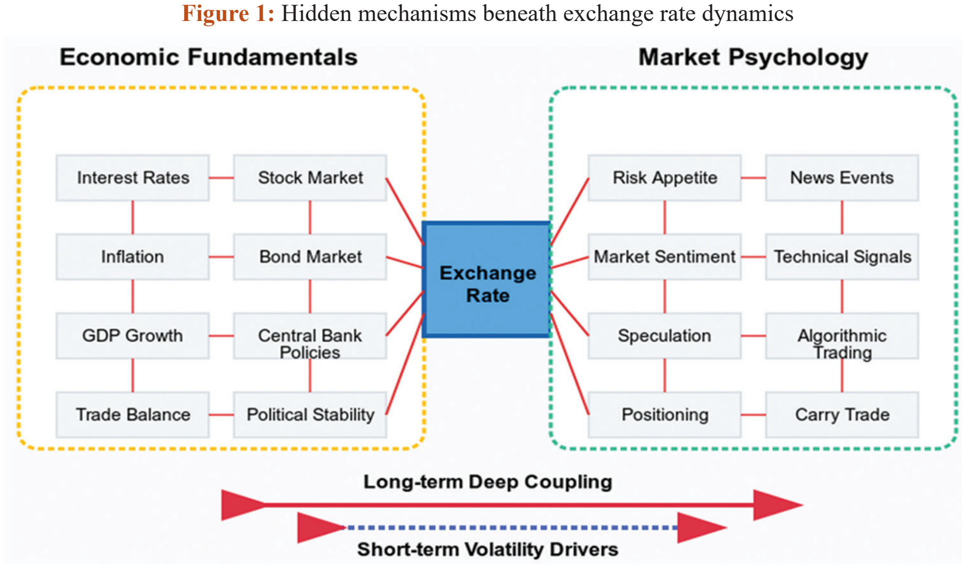
What renders exchange rate forecasting challenging is the fundamental obscurity of the data-generating process itself. Unlike physical phenomena governed by immutable natural laws, currency valuations result from the aggregated decisions of countless market participants as in in Figure 1, each responding to distinct incentives and information sets (Windsor and Cao, 2022). This complexity can be attributed to three primary factors (Cao et al., 2020). First, exchange rates emerge from an intricate system of coupled relationships between diverse market indicators, including stock performance and macroeconomic policies, each with distinctive transmission mechanisms that interact across multiple national markets. Second, market participants' decisions extend beyond numerical indicators to include sentiment responses to new information (Kočenda and Moravcová, 2018). The resultant price movements exhibit properties that statisticians characterize as "non-stationary" and "non-linear" mathematical terminology that essentially acknowledges the formidable complexity of these systems.

Two theoretical frameworks illuminate the role of sentiment in market dynamics. The Efficient Market Hypothesis (EMH) posits that markets rapidly incorporate new information (Fama, 1970; Jiao et al., 2020), a principle subsequently applied to currency markets (Shmilovici et al., 2009). Simultaneously, behavioral finance theory recognizes irrational elements in market behavior, including herding and risk aversion, which significantly influence price movements (Barberis and Thaler, 2005; Frank and Sanati, 2018). Third, profound bidirectional coupling exists between market indicators and investor sentiment, as illustrated in Figure 1.

The Figure 1 is constructed by the authors following (Windsor and Cao, 2022).

Given these multidimensional complexities, forecasting approaches limited to single information modalities whether quantitative indicators or sentiment analysis inevitably fall

Figure 1: Hidden mechanisms beneath exchange rate dynamics



short. Effective forecasting methodologies must capture both the internal dynamics within each information type and the complex interrelationships between these distinct modalities. The resulting analytical challenge has spurred methodological innovation. Researchers have progressed from rudimentary time series models to sophisticated neural networks capable of discerning previously undetectable relationships within financial data. Each algorithmic advancement represents an incremental step toward unraveling the mystery that is the future trajectory of currency valuations.

The existing literature establishes both methodological diversity and persistent challenges in exchange rate forecasting. The Turkish Lira case presents a particularly compelling research context, given its significant volatility and profound macroeconomic implications. This study attempts to forecast the Turkish Lira/US Dollar exchange rate from January 2015 through February 2024. During this period, the Lira depreciated against the dollar, resulting in severe macroeconomic consequences. The currency devaluation contributed to heightened inflation rates, significant increases in import prices, and substantial erosion of purchasing power. The pass-through effect from exchange rate depreciation to domestic prices created persistent inflationary pressures, while simultaneously reducing real wages and household wealth. Additionally, the currency crisis exacerbated external debt servicing costs for both public and private sectors, constrained monetary policy options, and increased financial market volatility.

While several studies have utilized Twitter sentiment for financial market predictions, to our knowledge no research has combined local and international news sources for exchange rate forecasting. Therefore, our study aims to fill this gap in the literature two ways: First, by analyzing international news outlets (The Economist, The New York Times, and The Guardian) as well as local news (proxied with Yenisafak and local tweets) sentiment on Turkish Lira/Us dollar exchange rate volatility. Secondly, the study employs explainable AI techniques alongside the conventional "black box" machine learning approaches to enhance interpretability, and transparency.

In the remaining part of this manuscript, section 2 reviews the concise literature on exchange volatility. Section 3 outlines data and methodology employed in the study. Section 4 presents empirical findings along with discussions, while section 5 concludes the manuscript with key findings and policy implications.

2. LITERATURE REVIEW

The exploration of exchange rate dynamics has garnered significant scholarly attention, yielding a diverse array of methodological approaches. Numerous researchers have applied various forecasting techniques to capture the inherent volatility and complexity of currency valuations. This literature review synthesizes relevant studies, examining both general time series forecasting approaches and specific applications to the Turkish Lira/US Dollar exchange rate, thereby establishing the theoretical and methodological foundation for our current investigation.

Time series forecasting faces challenges due to temporal dependencies and nonlinearity. Some studies utilize neural networks, such as Radial Basis Function Networks with weighted moving averages, to improve predictions for volatile financial data (Hota et al., 2017). Others highlight the limitations of linear models for economic data, advocating for hybrid deep learning and fuzzy logic approaches to better capture nonlinear patterns (Tealab et al., 2017).

In addition to neural network approaches, Ensemble methods, including model averaging, bagging, and boosting, have also enhanced forecasting robustness (Barrow et al., 2010). Similarly, neural networks have been widely applied for temporal data analysis, with studies detailing architectures, training methods, and their trade-offs (Vijh et al., 2020). Hybrid systems combining linear and nonlinear techniques often outperform single models, as demonstrated by data-driven approaches that integrate linear time series modeling with nonlinear error correction (de O Santos Júnior et al., 2019). Comparative studies between traditional and deep learning methods, such as ARIMA and LSTM with attention mechanisms, show that while deep learning slightly outperforms classical methods, both remain relevant (Zhou et al., 2020). Evolutionary optimization techniques, like hybrid differential evolution and artificial bee colony algorithms, have further improved ARIMA's accuracy in multi-step forecasting (Kumari et al., 2022).

For the TRY/USD rate, machine learning methods including Multilayer Perceptron, Support Vector Machines, and Random Forest have been employed for prediction and investment modeling (Dirik, 2021). During high-volatility periods, simple exponential smoothing has surprisingly outperformed complex models in short-horizon forecasts, despite the exchange rate's long-memory trends (Sarkandiz and Ghayekhloo, 2024). Hybrid approaches, such as combining univariate models with NARDL and neural networks, reveal the currency's dependence on recent observations and asymmetric responses to macroeconomic factors (Sabri et al., 2022). Additionally, sentiment analysis integrated with time series modeling, using deep learning for social media text processing, has improved prediction robustness (Yasar and Kilimci, 2020).

3. DATA AND METHODS

3.1. Data

Our research employs a multifaceted approach to predict Turkish Lira/US Dollar exchange rates, combining international and local news sources with social media data. We selected three major international publication media outlets-The Economist, The New York Times, and The Guardian-due to their global influence and comprehensive financial coverage. To incorporate domestic perspectives, we included Yeni Safak newspaper which serve as proxies for local media sentiment and Turkish Twitter posts serves as local social media. To maintain relevance, we focused exclusively on economic, finance, and business sections across all sources.

The dataset spans January 1, 2015,-March 9, 2025, aligning with our financial market data that includes daily TRY/USD exchange rates, trading volumes, and price movements. All financial data was obtained from Yahoo Finance[3].

3 Yahoo Finance - Stock Market Live, Quotes, Business & Finance News

3.2. Data Acquisition

We streamlined the extraction process using available APIs from The New York Times, The Guardian, and Yeni Safak. For The Economist, we utilized university database subscriptions and manual collection methods. Twitter's academic API facilitated the extraction of relevant social media posts. We supplemented API access with Python libraries including Requests and BeautifulSoup, along with regular expressions for data refinement. The extraction captured publication dates, article titles, summaries, full text, and source URLs.

All collected data was consolidated into a single CSV file for subsequent preprocessing. Figure 2 illustrates our data extraction workflow.

3.3. Methodology

3.3.1. Data preprocessing

Raw text data required extensive cleaning to remove noise and irrelevant information. Using Pandas, SpaCy, and Neattext libraries, we implemented a systematic preprocessing pipeline that included:

1. Removal of URLs, HTML tags, excessive spaces, special characters, numbers, email addresses, hashtags, and improper quotations
2. Lemmatization to reduce words to base forms
3. Case conversion to lowercase
4. Punctuation and white space removal
5. Text normalization and spelling correction.

After comparative analysis, we retained stop words as their inclusion improved model performance.

Figure 3 depicts the preprocessing workflow.

The cleaned data was then processed using the FinBERT transformer model for feature extraction, followed by topic modeling to identify key themes in financial news. We conducted sentiment analysis to measure market attitudes and named entity recognition to identify relevant economic actors and indicators. Additional features included volatility indicators, event markers, market trend signals, n-grams (unigrams, bigrams, and trigrams), and parts of speech classification with sentiment levels-all tailored specifically for exchange rate prediction.

Figure 2: Data extraction workflow

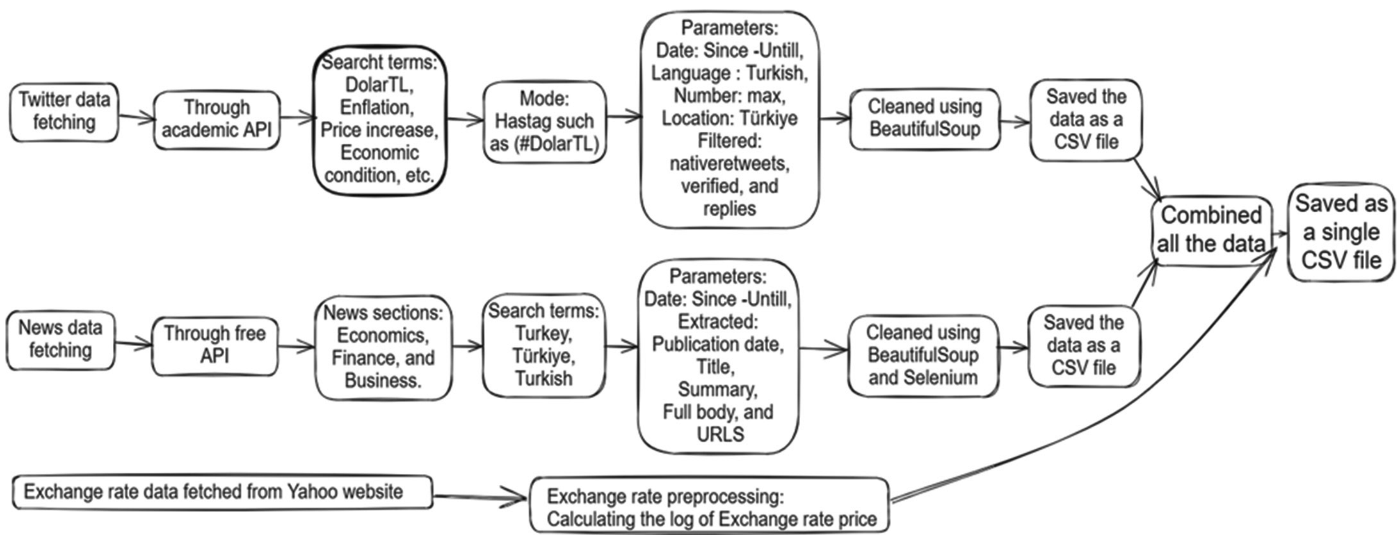
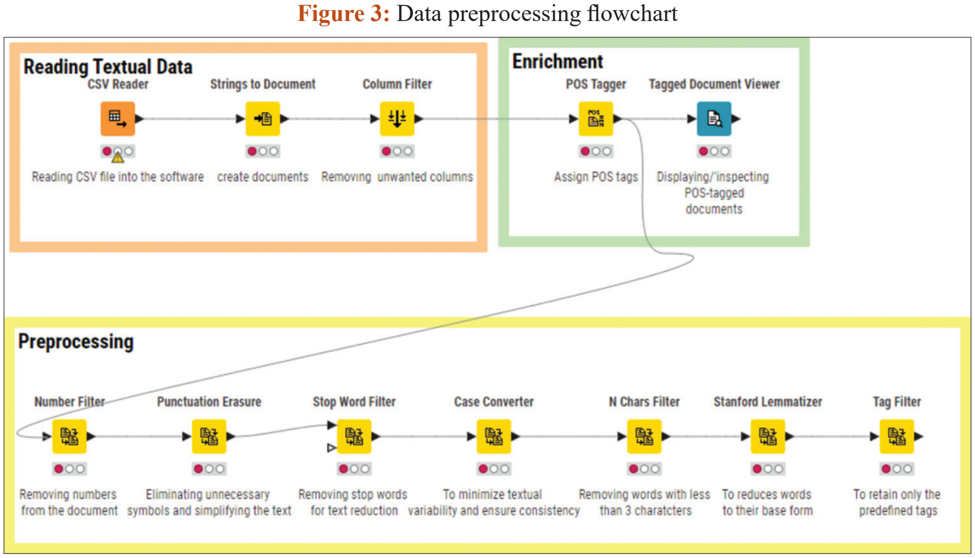


Figure 3: Data preprocessing flowchart



3.3.2. Basic Bert model

The attention mechanism is defined as:

$$Attention(Q,K,V) = soft\max\left(\frac{QK^{\top}}{\sqrt{d_k}}\right)V \tag{1}$$

The output of the attention layer is then transformed as follows:

$V_l = linear(W_l\ Concat\ (Attention_1,\ Attention_2,\ Attention_3, \ldots.\ Attention_h) + b_l)$

Here, Q, K, and V represent different transformations of the input vector X_a. The softmax function is applied to generate the attention output V_l.

Next, residual connections are introduced $V_a = X_a + V_l$

This output is then normalized and passed through a feed-forward neural network, leading to the final transformer output V_t: Which is computed as follows:

$$V_t = h\ (W_f V_a + b_f) + V_a \tag{2}$$

Since BERT is composed of multiple bidirectional transformer layers, this process is repeated iteratively for any given input X_a, ultimately producing the BERT output representation V_b.

3.3.3. Machine learning models

In this study, we use GARCH (1,2) as a baseline and various machine learning techniques including Decision Tree, Random Forest, Gradient Boosting, AdaBoost, XGBoost, and Neural Networks to predict Turkish Lira/US Dollar exchange rates. These forecasting techniques, each offering distinctive advantages for capturing the exchange rate dynamics.

Decision Tree Regression (Breiman et al., 1984; Quinlan, 1986) serves as the foundational building block for many ensemble methods. It partitions the feature space into regions and assigns constant values to each, offering interpretability but often suffering from high variance and over estimation. To overcome this inherent weakness, Random Forest Regression (Breiman, 2001) emerged as an ensemble methodology founded on the bagging paradigm, aggregating predictions from multiple decision trees to enhance forecasting precision while mitigating overfitting through dual mechanisms of bootstrap aggregation and feature randomization. Also, building upon the decision tree framework through a different approach, Gradient Boosting Regression (Friedman, 2001) employs sequential model construction to rectify predecessor errors through differentiable loss function optimization. Though powerful, it necessitates further parameter calibration to prevent variance amplification. Hence, further advancing the boosting paradigm, XGBoost Regression (Chen and Guestrin, 2016) operates within the gradient boosting framework yet distinguishes itself through advanced optimization techniques, regularization capabilities, and parallel processing architecture. Similarly addressing the limitations of single decision trees, AdaBoost Regression (Freund and Schapire, 1997) implements adaptive instance weighting to prioritize problematic observations. On the contrary, Neural Network Regression models complex non-linear relationships through layered neuronal architectures (Rumelhart et al., 1986).

3.3.4. The role of explainability (XAI) in machine learning

Conventional machine learning techniques, while powerful in capturing patterns and delivering predictive accuracy, often suffer from a lack of transparency and interpretability (Hassija et al., 2024). These models typically operate as "black boxes," producing outputs that obscure the underlying mechanisms driving their predictions. This opacity undermines trust and limits the practical utility of such models in critical decision-making contexts. To address these limitations, the field of Explainable Artificial Intelligence (XAI) has emerged, aiming to enhance the interpretability of machine learning models. Among the various XAI techniques, SHapley Additive exPlanations (SHAP) has gained prominence as a robust framework for model interpretability (Lundberg and Lee, 2017).

SHAP is rooted in cooperative game theory, drawing on the concept of Shapley values (Shapley, 2016) to fairly allocate contributions among participants in a cooperative game. In machine learning, SHAP leverages this theoretical foundation to quantify the contribution of each feature to a model's predictions. Through the assignment of Shapley values to individual features, SHAP provides a unified and interpretable framework for explaining the output of any machine learning model (Lundberg et al., 2020). This approach enhances transparency, and fosters trust in model predictions, enabling users to understand the key drivers behind specific outcomes.

The SHAP framework has demonstrated significant effectiveness in applications requiring high interpretability. Using SHAP analysis, researchers can identify and interpret the features within news content that most significantly influence model predictions. This capability is critical for ensuring that machine learning models are not only accurate but also accountable and understandable to end-users. The computation of Shapley values can be expressed as show in equations 1-2 (Lundberg and Lee, 2017).

$$\phi_m(v) = \sum_{S \subseteq N\{m\}} \frac{|S|!\left(|N|-|S|-1\right)}{|N|!}\left(v\left(S \cup \{m\}\right) - v(S)\right) \tag{3}$$

Where, $\phi_m\ (v)$, represents the Shapley value for a feature , quantifying its contribution by considering all possible subsets of features. The $\phi_m\ (v)$ is computed as a weighted average of the marginal contributions of feature across every possible subset of the feature set . The marginal contribution is given by $(v(S \cup \{m\})- v(S))$, where $v(S)$ is the value function evaluating the prediction for subset S. The weights are determined by the factorials of the subset sizes, ensuring a fair distribution of contributions. Thus, the Shapley value is essentially a weighted average of the marginal contributions of feature across all possible subsets of features.

$$g(x') = \phi_0 + \sum_{m=1}^{M} \phi_m z'_m \tag{4}$$

Where, $g(x')$, describes the model's prediction for an instance x' as the sum of a baseline prediction ϕ_0 and the weighted contributions of each feature, represented by their Shapley values ϕ_m and binary indicators z'_m.

3.3.5. Model evaluation

We allocated 80% of the dataset for training the machine learning regression models (Decision Tree Regression, Random Forest, Gradient Boosting, AdaBoost, XGBoost, and Neural Networks) while employing Grid Search Optimization methodology to determine optimal hyperparameters for each algorithm. We selected the grid search hyperparameter tuning approach for two key reasons: its exhaustive examination of every potential hyperparameter combination, which guarantees optimal solution identification; and its methodological clarity, which facilitates straightforward implementation (Ogunsanya et al., 2023). Following the training phase, we validated all regression models using the reserved 20% of data, assessing their predictive capability through multiple statistical metrics: coefficient of determination (R^2), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Feature importance. These metrics are computed as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2} \tag{5}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2 \tag{6}$$

$$RMSE = \sqrt{\Sigma_{i=1}^{n}\left(\frac{y_i - \hat{y}_i}{n}\right)^2} \tag{7}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \tag{8}$$

Whereby, y_i represents the actual value and $\hat{y}_i$ denotes the predicted value of the observation and N stands for the total number of observations.

R^2 measures how well the model explains the variation in the data, while MSE calculates the average squared difference between predicted and actual values. RMSE is the square root of MSE and presents errors in the same units as the original data, whereas MAE measures the average absolute difference between predicted and actual values. On the other hand, feature importance analysis identified which news sources most influenced exchange rate predictions, extracting coefficient magnitudes from linear models and native importance scores from tree-based models.

4. RESULTS AND DISCUSSION

The GARCH (1, 2) results in Table 1 indicate that international news sources, such as The Economist, The Guardian, and The New York Times, have a significant impact on the volatility of the Turkish Lira/US Dollar exchange rate. The Economist shows a positive effect, while The Guardian and The New York Times have negative impacts. On the other hand, local media sources, such as Yenisafak, and social media content, such as Tweets, exhibit weaker or insignificant effects on the exchange rate volatility. AS shown in Figures 4-6 the news sentiment captures the exchange rate volatility quiet well. This aligns with previous studies suggesting that text mining and AI models provide a promising approach for predicting trends in the foreign exchange market (Naderi Semiromi et al., 2020; Xueling et al., 2023).

The evaluation metrics presented in Table 2 provide a comparison of various machine learning models in predicting exchange rates. Among the models evaluated, Gradient Boosting, Random Forest, and XGBoost emerge as the top performers, indicating that these models explain a significant proportion of the variance in exchange rates. Both models exhibit the lowest Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) values, further indicating their predictive accuracy. In contrast, AdaBoost performs comparatively poorly, capturing less of the variance in exchange rate volatility, and showing the highest MSE and RMSE values, indicating substantial prediction errors. Decision Tree show intermediate performance, providing reasonable predictive accuracy with moderate MSE and RMSE values. The Neural Network model also shows lower performance, suggesting that while it captures some variance in exchange rates, it is less effective than the ensemble methods like Gradient Boosting and Random Forest. Overall, Gradient Boosting, Random Forest, and XGBoost are the most effective models for predicting exchange rates based on the provided metrics. Their high explanatory power and low error metrics make them superior choices for this task. While Decision Tree and offer decent performance, AdaBoost and Neural Network are less suitable for this specific predictive challenge. Neural networks are data-hungry algorithms that require substantial amounts of data to achieve optimal performance. Consequently, ensemble methods often outperform neural networks in scenarios with limited data. However, no single technique holds a monopoly on predictive accuracy-model efficacy depends on the specific use case and constraints.

The SHAP value visualizations in Figures 7-9 highlight the varying influence of different news sources on the model's exchange rate predictions. Among them, The Economist emerges as the most influential, consistently exhibiting high SHAP values. This suggests that sentiment from this source plays a key role in

Table 1: Coefficients of exogenous variables in the mean equation GARCH (1,2) (best model)

Variables	Coefficients	P-value	Impact on exchange rate returns	Statistical outcome
The Economist	0.086365	0.0000	Positive impact on returns	Significant
The New-York times	−0.020956	0.0000	Negative impact on returns	Significant
The Guardian	−0.016174	0.0000	Negative impact on returns	Significant
Yenisafak	−0.002532	0.0569	Negative impact	Significant
Tweets	0.000802	0.1251	Positive impact	Not significant

Figure 4: Overall news sentiment

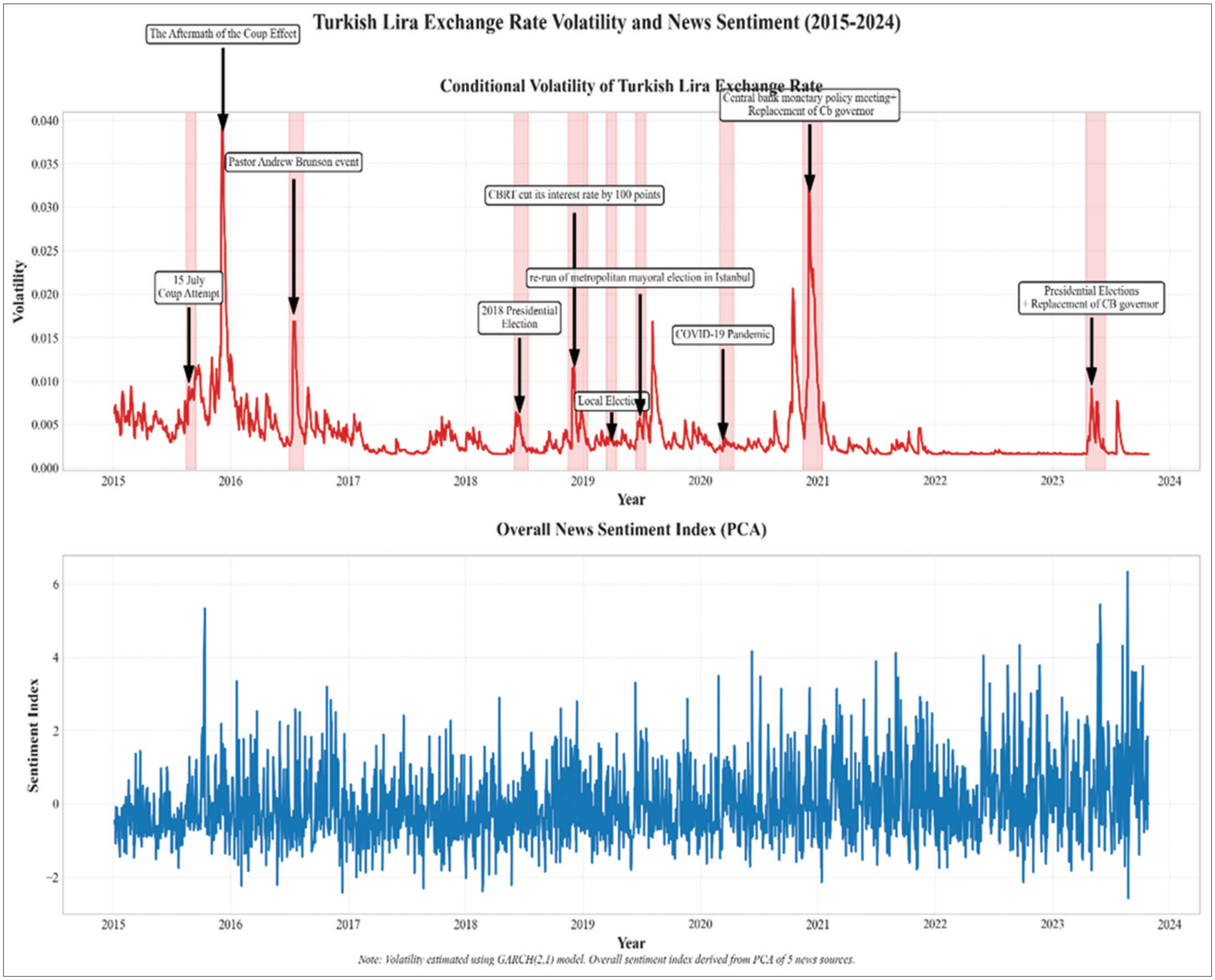


Figure 5: Periods with both high overall sentiment and high volatility

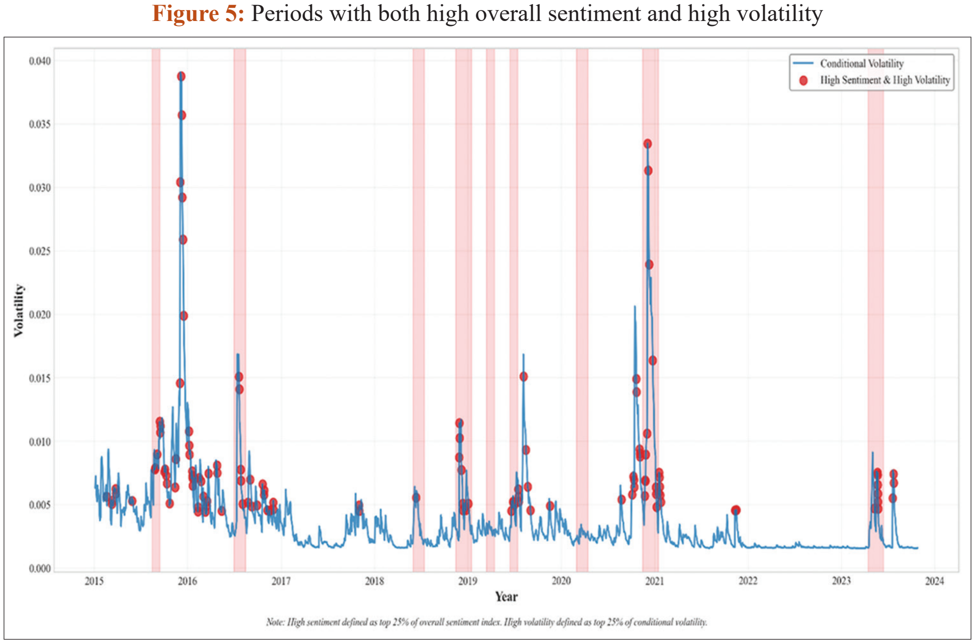


Figure 6: Individual news outlet's sentiments

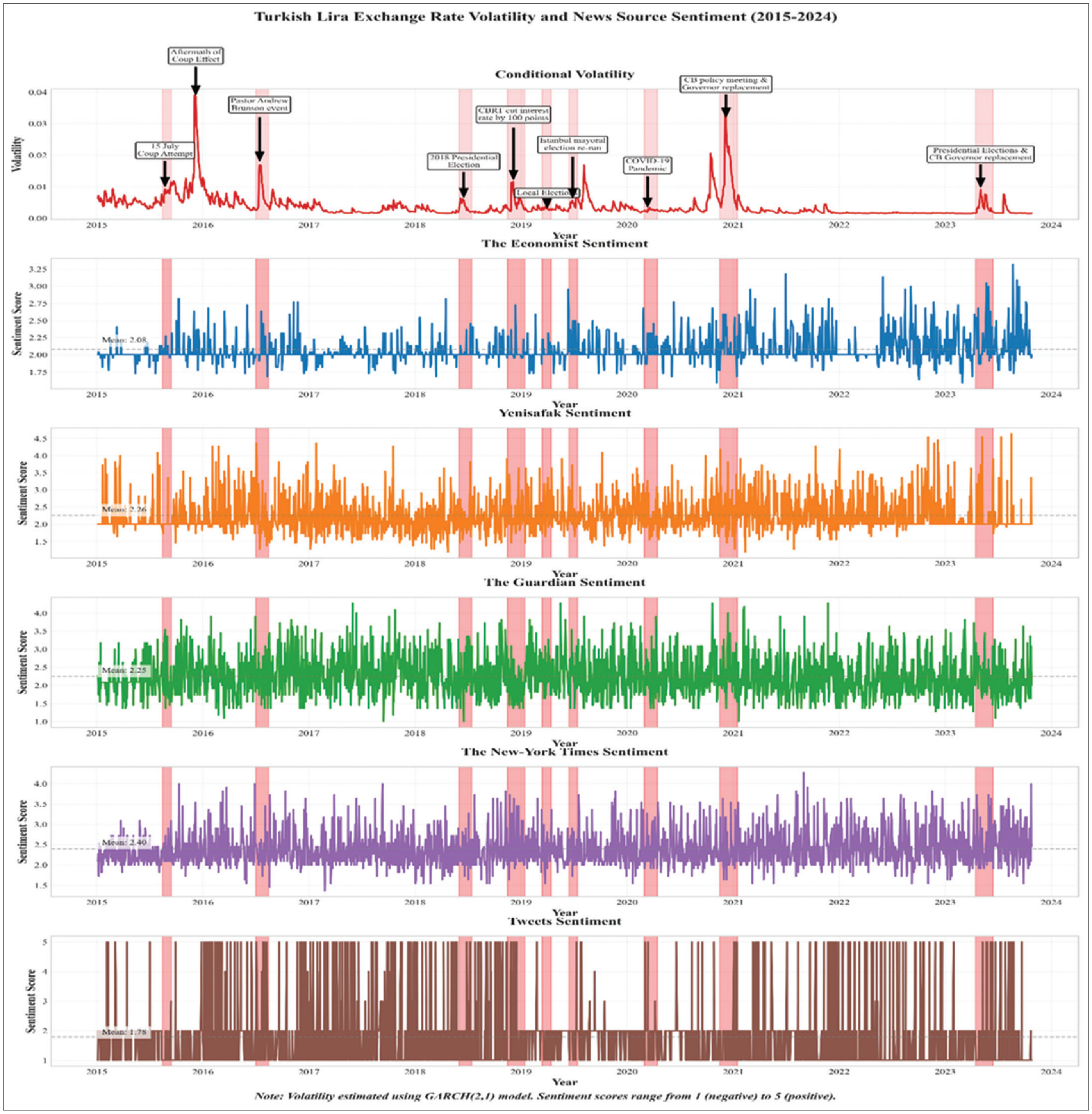


Table 2: Evaluation metrics of the machine learning models

Model	R²	MSE	MAE	RMSE
Gradient boosting	0.736	0.093	0.163	0.304
AdaBoost	0.228	0.270	0.465	0.520
Decision Tree	0.630	0.130	0.178	0.360
Random Forest	0.735	0.093	0.175	0.305
XGBoost	0.724	0.097	0.176	0.311
Neural Network	0.401	0.210	0.363	0.458

driving positive changes in the exchange rate. The publication's strong reputation for global economic analysis and its audience of policymakers, investors, and financial institutions likely amplifies its impact on market sentiment. Similarly, The New York Times also contributes positively to exchange rate movements, though to a lesser extent. Its influence, while still notable, appears to be more moderate compared to The Economist. The findings suggest that these two sources provide coverage that aligns with developments perceived as favorable for the Turkish lira, shaping expectations among market participants.

In contrast, The Guardian and Twitter exhibit a markedly different pattern, consistently displaying negative SHAP values. This suggests that sentiment from these sources exerts downward

Figure 7: Gradient boosting Beeswarm plot

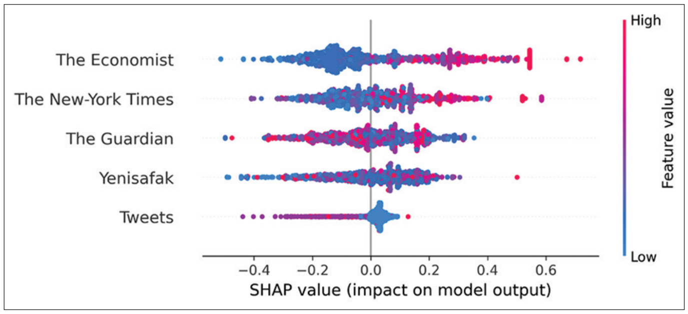


Figure 8: Random forest Beeswarm plot

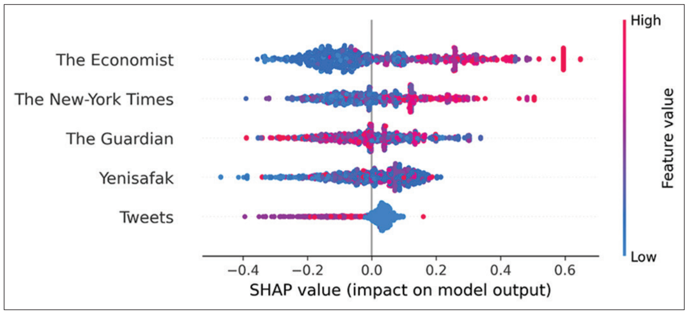
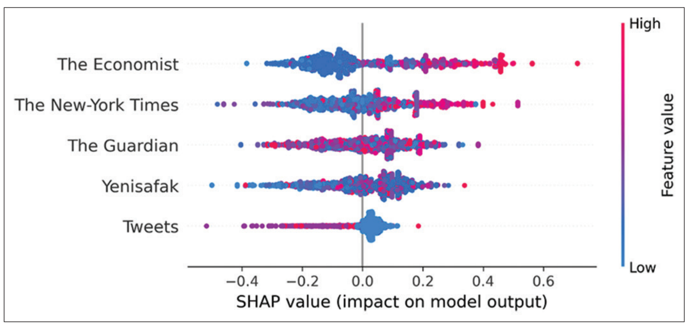


Figure 9: Xgboost Beeswarm plot



pressure on exchange rate predictions. The effect could stem from a more critical tone in reporting, particularly concerning economic and political risks. Given The Guardian's emphasis on social and political issues, its influence may reflect broader concerns about governance, policy uncertainty, or external geopolitical risks that could weigh on the Turkish economy. Similarly, Twitter-being a platform where diverse opinions, including speculative and reactionary content, are widely shared-may amplify negative sentiment, particularly during periods of economic volatility or political uncertainty.

Yeni Şafak, a domestic news outlet, has a minimal effect on the model's predictions, with SHAP values close to zero. Unlike international financial media, its sentiment does not appear to meaningfully shape expectations about the exchange rate. This suggests that global investors and currency traders place greater weight on international sources when assessing the Turkish lira, possibly due to differences in credibility, audience reach, and the perceived objectivity of reporting. While Yeni Şafak is influential within domestic discourse, its limited impact on exchange rate movements highlights the role of internationally recognized publications in shaping financial market expectations.

5. CONCLUSION

Predicting exchange rates is of paramount importance due to their significant role in shaping economic stability, trade, investment, and inflation. Exchange rates are influenced by a range of domestic and international factors, making their accurate prediction essential for policymakers, investors, and financial analysts. This study examined the Turkish Lira exchange rate's (in USD) volatility during a period of substantial depreciation, employing advanced methodologies to analyze the role of news sentiment in exchange rate movements.

The study implemented a range of methods, including natural language processing techniques, sentiment analysis, and machine learning models. News data was collected from international sources such as The Economist, The New York Times, and The Guardian, as well as domestic sources (Yeni Şafak) and social media (Twitter). The data was preprocessed using Python tools for feature extraction, and cleaning, FinBERT was utilized for sentiment extraction and machine learning models such as Gradient Boosting, Random Forest, and XGBoost were employed to forecast exchange rate movements. Additionally, explainable AI techniques (SHAP), were used to interpret the influence of individual features on model predictions using Shap and Shapash python libraries. The findings revealed that international news sources, especially The Economist and The New York Times, had the most significant impact on exchange rate predictions. In contrast, domestic sources like Yeni Şafak and Twitter had a comparatively weaker influence, reflecting the preference of global investors for internationally recognized media when assessing the Turkish Lira.

One of the key limitations of the study is the underrepresentation of local news sources, which stems from data unavailability of other domestic media outlets. While Yeni Şafak was included as a representative local source, its coverage, although highly active in policy-related areas, may not fully capture the economic and financial dimensions of the Turkish economy, even though the analysis focused exclusively on its economics and financial sections. This could limit the ability of the study to comprehensively assess the influence of domestic media on exchange rate movements.

Additionally, while Twitter was incorporated to reflect social media sentiment, its content is often speculative and reactionary, which may dilute its relevance in predicting exchange rates. These limitations suggest that future research could benefit from broader access to local media data and more refined methods for analyzing social media sentiment to enhance the robustness of the findings. The study also acknowledges the potential bias inherent in both international and domestic media, which may influence the tone and focus of their reporting, thereby affecting the sentiment analysis and its predictive power.

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