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The Role of Liquidity and Global Uncertainty in Exchange Rate Fluctuations in Iran: A Machine Learning Approach

Parviz Rostamzadeh*[a], Masumeh Mohammadi[a], Zeinab Yadegar[a]

a. Department of Economics, Shiraz University, Shiraz, Iran

Highlights

- **Evaluates liquidity and uncertainty indicators using ensemble machine learning and SHAP.**
- **Identifies liquidity as the dominant predictor, accounting for nearly 89% importance.**
- **Finds global, geopolitical, energy, and oil uncertainties relatively less important.**
- **Applies tree-based models to capture nonlinear patterns and variable interactions.**
- **Highlights liquidity control and policy coordination for exchange rate stability.**

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Abstract

Although numerous studies have examined the determinants of exchange rate fluctuations, comparatively limited attention has been paid to evaluating their relative predictive importance. In particular, liquidity has seldom been assessed alongside multiple uncertainty indicators within a unified empirical framework. This study addresses this gap by comparing the predictive importance of liquidity with several dimensions of uncertainty, including global uncertainty, global economic policy uncertainty, geopolitical risk, energy uncertainty, and oil price uncertainty. To this end, tree-based ensemble machine learning models are combined with the SHAP framework to identify and interpret the key predictors of exchange rate fluctuations in Iran over 2012–2023. The empirical findings reveal a pronounced concentration of predictive importance in liquidity, which accounts for an average importance share of approximately 89%. By comparison, energy uncertainty (EUI), geopolitical risk (GPR), world uncertainty (WUI), and oil price uncertainty (OPU) each account for an average share of around 1%. This substantial difference suggests that liquidity contains considerably more predictive information about exchange rate fluctuations than the uncertainty measures considered. The results highlight the importance of domestic monetary conditions in explaining exchange rate movements in Iran, while indicating that the selected uncertainty indicators make only a limited contribution to the models' out-of-sample predictive performance. These findings concern predictive importance rather than causal effects.

1. Introduction

Following World War II, the U.S. dollar emerged as the dominant currency for international transactions, reflecting the growing economic and trade dominance of the United States (Gluschenko, 2024). Within this global monetary

* parvizrostamzadeh@shirazu.ac.ir
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system, fluctuations in exchange rates between the U.S. dollar and national currencies can pose significant economic challenges. For example, in recent years, the appreciation of the U.S. dollar against the Turkish lira has increased the cost of energy and essential goods imported into Turkey (Thorbecke and Sengonul, 2023). Similarly, in Argentina, recurrent financial crises have been associated with increases in dollar-denominated debt following the appreciation of the U.S. dollar against the Argentine peso (Castillo-Ponce and Lai, 2020).

Within the international monetary framework centered on the U.S. dollar, a stronger dollar can raise the domestic-currency price of goods purchased from abroad. This creates additional cost pressures for domestic firms whose production processes depend on overseas inputs, equipment, or services, potentially feeding through into higher prices in the domestic market. At the same time, an appreciation of the dollar increases the local-currency burden of foreign-denominated liabilities held by both governments and corporations, which can heighten fiscal stress and increase the risk of corporate insolvency (Ha et al., 2020).

Accordingly, responding promptly to exchange rate instability has become increasingly important. Monetary and fiscal policymakers have therefore devoted considerable attention to economic and political uncertainty, as well as liquidity, as key factors influencing exchange rate movements. Although global economic policy uncertainty, geopolitical risks, energy prices, and liquidity growth all affect exchange rates, the magnitude of their effects may vary.

Higher levels of uncertainty and liquidity can contribute to the depreciation of national currencies against safe-haven currencies such as the U.S. dollar. Inconsistent or unclear economic policies, political and geopolitical shocks, and fluctuations in energy prices can all contribute to heightened uncertainty. As uncertainty increases, investment risks in financial markets intensify, weakening confidence in domestic currencies and increasing demand for the U.S. dollar. At the same time, rising transaction costs and declining foreign-exchange earnings may further exacerbate currency depreciation. In addition, government budget deficits and the expansion of bank credit can increase liquidity in the economy, thereby placing additional pressure on exchange rates.

Although both uncertainty and liquidity influence exchange rate movements, their relative importance has not yet been systematically examined. Previous studies have investigated the effects of uncertainty on exchange rates (e.g., Yilmazkuday, 2025; Aftab et al., 2024; Glebocki and Saha, 2024; Değirmen et al., 2023; Kyriazis and Economou, 2022; Suah, 2022; Chang et al., 2022; Bush and Noria, 2021; Olanipekun et al., 2019), generally reporting a negative relationship between uncertainty and the value of domestic currencies. Other studies have examined the role of liquidity in exchange rate determination (e.g., Islam and Faisal, 2024; Bidabad, 2019), generally reporting a positive relationship between liquidity and exchange rates. However, these studies have primarily relied on statistical techniques and linear regression models. Given that uncertainty and liquidity may interact in complex and dynamic ways, linear

approaches may fail to capture nonlinear relationships and interactions among explanatory variables, thereby limiting their explanatory and predictive capabilities.

To address this research gap, the present study employs machine learning models in conjunction with the SHAP (SHapley Additive exPlanations) approach to capture nonlinear relationships and interactions among features while accounting for the dynamic nature of exchange rate determinants. In addition, the study focuses on Iran and evaluates the relative importance of uncertainty and liquidity in explaining fluctuations in the free-market exchange rate.

Examining and comparing the roles of uncertainty and liquidity as determinants of exchange rate movements provides valuable insights for policymakers and researchers into the dynamic mechanisms underlying exchange rate fluctuations. Furthermore, both factors play critical roles in shaping economic expectations and investor behavior. By jointly analyzing their effects, this study contributes to the development of more effective strategies for managing exchange rate volatility, enhancing monetary policy effectiveness, and promoting financial stability.

The remainder of the paper is organized as follows. Section 2 reviews the literature. Section 3 presents the research model, data, and econometric methodology. Section 4 reports the findings and empirical results. Section 5 provides the conclusion, discussion, and policy implications.

2. Literature review

2.1 .Theoretical literature

2.1.1. The Impact of Economic and Political Uncertainty on the Exchange Rate

Uncertainty can influence the exchange rate through several channels. First, rising uncertainty regarding economic policies or financial markets increases investment risk. This, in turn, may encourage capital outflows, reduce demand for the domestic currency, and increase demand for safe-haven assets, such as the U.S. dollar and the euro. Consequently, safe-haven currencies, particularly the U.S. dollar, tend to appreciate relative to other currencies. Second, by increasing transaction costs, uncertainty can reduce the volume of international trade, with potentially positive, negative, or mixed effects on the exchange rate. If exports decline more than imports, particularly in countries that rely heavily on oil or commodity exports, foreign exchange earnings may decrease, creating a shortage of foreign currency and putting upward pressure on the exchange rate. Conversely, if imports decline more than exports, the reduced domestic demand for foreign currency may weaken or even offset the upward pressure on the exchange rate (Glebocki and Saha, 2024).

Third, heightened uncertainty reduces the credibility of official information, including central bank forecasts. As a result, economic agents increasingly rely on subjective and potentially biased expectations when making decisions. Such reliance can amplify exchange rate volatility through heterogeneous expectations,

overreactions to incomplete information, herd and bandwagon effects, and increased speculative activity (Suah, 2022).

Fourth, greater economic policy uncertainty (EPU) makes it more difficult to anticipate the future path of interest rates. As a result, investors may become more uncertain about their borrowing decisions or adjust their preferences between borrowing in domestic and foreign currencies. These changes in borrowing preferences affect the supply and demand for currencies, thereby influencing the exchange rate (Chang et al., 2022).

2.1.2. The Impact of Monetary Variables on the Exchange Rate

Given the persistent budget deficits in the government's fiscal structure and the provision of non-productive bank loans, liquidity expansion has become a major policy challenge for controlling inflation and exchange rate movements. Several factors, including government budget deficits, bank credit creation, increases in the monetary base, expansionary monetary policies, and inflation expectations, contribute to liquidity growth and may exert upward pressure on the exchange rate. When the central bank expands liquidity through money creation or credit provision, purchasing power and aggregate demand for goods and services increase. If the supply of goods and services does not increase proportionately, excess demand emerges, leading to an increase in the general price level, or inflation (Siddiqi et al., 2025). Rising inflation erodes the purchasing power of the national currency, prompting individuals to shift their investments toward assets perceived as safe stores of value, such as foreign currencies (particularly the U.S. dollar), gold, and real estate. As demand for these assets increases, their prices rise relative to the national currency, contributing to an increase in the exchange rate (Bidabad, 2019).

2.2. Empirical literature

Numerous studies have investigated the relationships among liquidity, uncertainty, and the exchange rate. These studies can be broadly classified into two categories. The first focuses on liquidity as a key predictive feature associated with exchange rate movements, whereas the second examines the role of uncertainty in shaping exchange rate dynamics.

In the first category, Islam and Faisal (2024) examined the effects of liquidity and other macroeconomic determinants on the exchange rate in Uruguay over the period 2001–2021 using a linear regression model with Newey–West standard errors. Their findings indicate that liquidity, inflation, and the US lending rate (USLR) are negatively associated with the exchange rate.

A study by Doojav et al. (2023) examined how changes in international liquidity conditions influenced Mongolia's real exchange rate during 2000–2020. Using a structural vector autoregressive (SVAR) framework, the authors found that greater availability of global liquidity could strengthen demand for goods and raise the prices of exported commodities, thereby increasing the country's foreign-exchange receipts. The resulting improvement in foreign-currency

inflows increased the demand for the Mongolian tugrik and ultimately contributed to an appreciation of the domestic currency against the US dollar.

Bianchi et al. (2021) examined the effect of liquidity on fluctuations in the US dollar exchange rate against G10 currencies using panel data covering the period 2001–2021. Their findings indicate that an increase in global banking system liquidity, even in the absence of changes in interest rates or monetary policy, is a significant driver of US dollar appreciation.

Bidabad (2019) investigated the short- and long-run causal relationships among the exchange rate, the general price level (CPI), and liquidity (M2) in Iran to evaluate policies aimed at controlling the parallel foreign exchange market. Using the Granger causality test and time-series data covering the period from 1996 to 2001, the study found that an increase in liquidity weakens the national currency against the US dollar in the long run, whereas no significant relationship was found in the short run. Furthermore, an increase in the general price level raises the exchange rate in both the short and long run. The results also indicate that an increase in the supply of foreign currency in the open market reduces liquidity in the long run, thereby contributing to a decline in the exchange rate.

In the second category, Yilmazkuday (2025) examined the effects of geopolitical risk on the exchange rates of 35 countries over the period 2000–2024 using a structural vector autoregression (SVAR) model. The findings indicate that geopolitical shocks reduce the nominal effective exchange rate (NEER) in China, the United States, Israel, and the Philippines, while increasing the NEER in the remaining countries.

Aftab et al. (2024) investigated the short- and long-run effects of uncertainty on exchange rate volatility using a panel autoregressive distributed lag (ARDL) model for 26 developed and emerging economies over the period 2005–2020. Their findings indicate that uncertainty in global financial markets increases exchange rate volatility, while uncertainty surrounding US monetary policy also contributes to greater exchange rate fluctuations.

Glebocki and Saha (2024) examined the effects of economic policy uncertainty, US monetary policy uncertainty, US stock market volatility, the financial stress index, and the geopolitical risk index on the exchange rates of 29 advanced and emerging economies using a Global Vector Autoregression (GVAR) model over the period 1996–2022. Their findings indicate that these sources of uncertainty increase exchange rate volatility. While they weaken the value of domestic currencies in emerging economies, they strengthen domestic currencies in advanced economies.

Değirmen et al. (2023) examined the relationship between oil price uncertainty and key macroeconomic variables, including output, the exchange rate, and the interest rate, in the context of major global economic and political events during the first decade of the twenty-first century, such as the Arab Spring and the 2007–2008 global financial crisis. Using a block-exogeneity structural vector autoregression (SVAR) model for 12 developing countries—comprising six oil-exporting and six oil-importing economies—the authors found that the

effects of oil price uncertainty varied between the two groups but led to a decline in the exchange rate in all countries considered.

Kyriazis and Economou (2022) employed a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model to investigate the effects of geopolitical uncertainty on the Turkish currency's exchange-rate performance relative to major global currencies during 2003–2021. Their results reveal that heightened geopolitical uncertainty is associated with a depreciation of the Turkish currency when its value is expressed in US dollars, Swedish kronor, and Swiss francs.

Suah (2022) investigated the impact of uncertainty on exchange rates using a Panel Vector Autoregression (Panel VAR) model for 16 advanced and emerging economies over the period 2013–2020. The results indicate that increased uncertainty leads to exchange rate depreciation in emerging economies, whereas it is associated with exchange rate appreciation in advanced economies.

Chang et al. (2022) examined the effects of Economic Policy Uncertainty (EPU) and Global Economic Policy Uncertainty (GEPU) on exchange rates in G7 countries over the period 1998–2021. The study employed the nonlinear autoregressive distributed lag (NARDL) and multiple asymmetric threshold nonlinear autoregressive distributed lag (MATMARDL) models. The findings reveal asymmetric short- and long-run effects of uncertainty on exchange rates, which vary across different levels of the variables. Moreover, periods of greater uncertainty are generally followed by unfavorable exchange rate responses, whereas a decline in uncertainty does not generate a statistically meaningful effect.

Bush and Noria (2021) examined the effect of uncertainty on Mexican peso–US dollar exchange rate volatility using the System Generalized Method of Moments (GMM-SYS) over the period 1999–2018. Their findings indicate that heightened uncertainty increases exchange rate volatility, with international sources of uncertainty exerting stronger effects than domestic sources.

Olanipekun et al. (2019) examined the impact of Economic Policy Uncertainty (EPU) on Exchange Market Pressure (EMP), while accounting for changes in foreign exchange reserves. Using the Common Correlated Effects Mean Group (CCEMG) and Augmented Mean Group (AMG) estimators for a sample of 20 countries over the period 2003–2017, the study found a long-run relationship between economic policy uncertainty and exchange market pressure, indicating that heightened economic uncertainty intensifies pressure in foreign exchange markets.

Beckmann and Czudaj (2017) examined the effects of uncertainty surrounding US economic, monetary, and fiscal policies on four major exchange rates—the euro (Europe), Japanese yen (Japan), Canadian dollar (Canada), and British pound (UK)—against the US dollar over the period 1986–2014 using a Vector Autoregression (VAR) model. Their findings indicate that policy uncertainty affects exchange rate movements by increasing forecast errors for the

euro, British pound, and Canadian dollar, while reducing forecast errors for the Japanese yen.

The present study contributes to the existing literature by assessing the relative predictive importance of liquidity and multiple dimensions of uncertainty in explaining exchange rate movements. Although previous studies have identified liquidity and uncertainty as important determinants of exchange rates, limited attention has been paid to comparing their contributions to exchange rate fluctuations. To address this gap, the study examines the predictive importance of liquidity and several uncertainty indicators, including Energy Uncertainty (EUI), Geopolitical Risk (GPR), the World Uncertainty Index (WUI), and Oil Price Uncertainty (OPU). Identifying the most influential factors is important because they represent key sources of volatility in foreign exchange markets and have direct implications for monetary, trade, and investment policies. A clearer understanding of their relative influence can enhance economic assessments and support the formulation of more effective policy measures to promote financial stability and sustainable economic growth.

3. Data and Methodology

3.1. Data

The empirical dataset is constructed at a monthly frequency over 2012–2023 and combines Iran-specific macroeconomic indicators with measures of uncertainty in the global economy. Since Iran operates under more than one exchange rate arrangement, the free-market rate is selected as the outcome variable. This choice is motivated by its relatively limited exposure to direct official intervention, making it more representative of market-based exchange rate movements. The daily series reported by Tgju.org was transformed into monthly figures using Python, allowing the exchange rate series to be aligned temporally with the other variables in the dataset.

To identify the key predictive features associated with exchange rate fluctuations, this study incorporates both monetary variables and uncertainty indicators. The inflation rate was selected as a monetary variable based on the study by Monadjemi and Lodewijks (2021) and the Purchasing Power Parity (PPP) theory. Unlike the general price level, the inflation rate, measured as the percentage change in Iran's general price level, more effectively captures changes in price dynamics. In addition, the total money supply in Iran's economy, measured in billion rials, was included as a key monetary determinant of the exchange rate, consistent with the studies by Islam and Faisal (2024) and Doojav et al. (2023).

Furthermore, consistent with Chang et al. (2022) and Olanipekun et al. (2019), uncertainty measures reflecting both domestic and global conditions are included to assess their relevance to exchange rate dynamics.

The monthly series for M2 and inflation were sourced from the Central Bank of Iran (CBI). Data for the uncertainty measures—namely the World Uncertainty Index (WUI), Global Economic Policy Uncertainty Index (GEPU), Geopolitical

Risk Index (GPR), Energy Uncertainty Index (EUI), and Oil Price Uncertainty Index (OPU)—were retrieved through the Policy Uncertainty database (www.policyuncertainty.com). Information on Brent crude oil prices was downloaded from Investing.com. The exchange rate series represents Iran's free-market rate and was compiled from daily observations reported by Tgju.org; these observations were subsequently converted to a monthly frequency using Python.

Table 1. Data description

Variables	Symbol	period	Data source	Obs	Min	Max
Exchange Rate	ER	Daily	https://www.tgju.org	132	0.50049	16866.55
World Uncertainty Index	WUI	Monthly	https://www.policyuncertainty.com	132	0	1.189
Global Economic Policy Uncertainty	GEPU	Monthly	https://www.policyuncertainty.com	132	91.764	418.615
Geopolitical Risk	GPR	Monthly	https://www.policyuncertainty.com	132	58.42	318.95
Energy Uncertainty Indexes	EUI	Monthly	https://www.policyuncertainty.com	132	0.676	3.045
Broad Money	M2	Monthly	https://cbi.ir	132	3587966	63400000
Inflation Rate	INF	Monthly	https://cbi.ir	132	-0.346	10.591
Oil Price Uncertainty Index	OPU	Monthly	https://www.policyuncertainty.com	132	18.698	364.255
Brent oil	Oil	Monthly	https://www.investing.com/	132	26.35	119.47

Source: *Authors' compilation*

3.2. Methodology

One of the main challenges in analyzing economic and financial data is the presence of nonlinear relationships, as economic variables often interact in complex and interdependent ways. Several classical econometric models, such as nonlinear and polynomial regression models, can capture nonlinear patterns by imposing a predetermined functional form, including exponential, logarithmic, or polynomial relationships. When the underlying functional form is correctly specified, these models can enhance explanatory power and reduce estimation errors.

More advanced econometric approaches, such as the Nonlinear Autoregressive Integrated Moving Average (Nonlinear ARIMA) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models, have also been developed to capture nonlinear patterns in time-series data. Nonlinear ARIMA models capture nonlinear dynamics through nonlinear functions of lagged

variables, whereas GARCH models account for nonlinear behavior by explicitly modeling the conditional variance.

Similarly, autoregressive models with nonlinear dynamics, such as the Markov-Switching Autoregressive (MS-AR) and Threshold Autoregressive (TAR) models, capture nonlinear relationships by allowing for changes across different regimes. In the MS-AR model, transitions between regimes occur probabilistically according to a Markov chain, whereas in the TAR model, regime changes are triggered when a threshold variable crosses a specified threshold value.

Despite their usefulness, these conventional modeling techniques require the researcher to determine the mathematical structure of the relationship before estimating the model, for instance, by assuming an exponential, logarithmic, or polynomial specification. This means that some prior understanding of the data-generating mechanism is needed to select an appropriate representation of the underlying relationships. In empirical applications, however, the actual form of these relationships is rarely known with certainty, which can make such pre-specified structures overly restrictive. These approaches can also encounter multicollinearity problems when numerous predictors are incorporated, especially when the variables exhibit intricate patterns of interaction. Machine learning techniques provide a more flexible alternative by allowing the structure of the associations within the data to emerge during the learning process rather than being predetermined by the researcher. They are therefore capable of identifying nonlinear dependencies, intricate patterns, and high-dimensional structures from the observed data. In addition, such methods can simultaneously process numerous predictors and capture complicated interactions among them without imposing a predetermined mathematical equation on the model.

In general, machine learning algorithms can be classified into four main categories: supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning, along with hybrid methods that combine classical econometric techniques with machine learning algorithms. Supervised learning is appropriate when both input features and target outputs are available. Since the explanatory variables and target variable are clearly defined in this study, a supervised learning approach is the most appropriate.

In supervised learning, a dataset is typically divided into training and testing subsets. The training data are used to develop the predictive model, whereas the testing data are used to evaluate its out-of-sample predictive performance. Predictions generated by supervised learning algorithms are generally subject to three main sources of error:

Bias error: When a model relies on overly simplistic assumptions, it tends to underfit the data, thereby limiting its ability to capture complex underlying patterns.

Variance error: Highly complex models are often sensitive to small variations in the training data, making them more susceptible to overfitting.

Excessive adaptation to random fluctuations and noise can reduce the model's ability to generalize to unseen observations.

Noise error: Random, erroneous, or unobservable components of the data do not contain systematic patterns that can be learned by the model. Consequently, even highly sophisticated models cannot eliminate this source of error or consistently generate accurate predictions.

To reduce bias and variance, Breiman (1996) introduced ensemble methods, which combine multiple learning algorithms to construct a more robust and accurate predictive model. By integrating the complementary strengths of individual learners, ensemble methods can improve model robustness and predictive accuracy.

This study employs two widely used ensemble learning techniques, namely Bagging and Boosting. Bagging primarily aims to reduce variance, whereas Boosting is designed to reduce bias. In the Bagging framework, multiple bootstrap samples are generated through random sampling with replacement, and the same base learning algorithm is trained independently on each sample. The final prediction is obtained by averaging the individual predictions in regression tasks or by majority voting in classification tasks. In contrast, boosting constructs a sequence of models in which each successive model focuses more heavily on observations that were incorrectly or inadequately predicted by the preceding models. This sequential learning process progressively reduces prediction errors and improves the overall predictive performance of the ensemble. The final prediction is obtained through a weighted combination of the individual models (Freund and Schapire, 1997).

Given the time-series structure of the monthly observations, the dataset was partitioned into two sequential subsets, with the earlier observations assigned to model development and the later observations reserved for out-of-sample assessment. The initial 80% of the sample was used for training, whereas the remaining 20% was held out exclusively for testing. Min–Max normalization was estimated using only the training subset, after which the same scaling parameters were applied to the observations in the test subset. This approach prevented any information from the evaluation period from entering the training stage and thus eliminated the possibility of data leakage. During the model-building stage, five-fold cross-validation was conducted solely on the training observations. In each iteration, four subsets were employed to estimate the model, while the fifth subset served as the validation sample. Model specifications were ultimately determined according to their cross-validation results, and the test observations were not accessed until the final out-of-sample assessment.

In the present study, the Decision Tree (DT) and Random Forest (RF) algorithms were employed as Bagging-based methods, whereas Extremely Randomized Trees (Extra Trees), Gradient Boosting (GB), Extreme Gradient Boosting (XGB), and Histogram-based Gradient Boosting (HGB) were employed as Boosting-based methods.

To enhance model performance, hyperparameter tuning was conducted for the Random Forest and Gradient Boosting models using Grid Search with five-fold cross-validation, following Géron (2022). Importantly, both Grid Search and cross-validation were performed exclusively on the training set, with the test set completely excluded from the hyperparameter optimization process. Various combinations of hyperparameters were evaluated based on their cross-validated performance, and the configuration yielding the lowest cross-validated RMSE was selected as the optimal specification. The selected models were then refitted using the entire training set and evaluated once on the previously unseen test set.

To compare the predictive performance of the machine-learning models, three evaluation metrics were employed: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). For all three metrics, lower values indicate greater predictive accuracy in forecasting the free-market exchange rate.

To address the instability associated with standalone decision trees, the Random Forest (RF) method combines the results of numerous independently developed trees. During model construction, each tree is generated from a resampled version of the training observations, while the splitting process is restricted to a randomly selected group of available features. The predictions produced by these individual trees are subsequently combined to obtain the final output, which enhances the model's ability to generalize and limits the influence of variance on predictive performance (Breiman et al., 1996; Breiman, 2001).

The Extremely Randomized Trees (Extra Trees) algorithm extends this ensemble framework by introducing additional randomness through the random selection of split thresholds, in addition to random feature selection. Unlike Random Forest, Extra Trees typically uses the entire training dataset to construct each tree while introducing greater randomness into the node-splitting process. This strategy can further reduce variance and improve computational efficiency in various applications (Geurts et al., 2006).

Gradient Boosting is a sequential ensemble method that iteratively constructs decision trees, with each successive tree fitted to the residual errors of the preceding learners. By minimizing a differentiable loss function through gradient-based optimization in function space, this method progressively improves predictive accuracy and reduces systematic prediction errors (Friedman, 2001). Extreme Gradient Boosting (XGBoost) extends the conventional Gradient Boosting framework by incorporating second-order gradient optimization, L1 and L2 regularization, sparsity-aware learning, parallel processing, and efficient tree pruning. These enhancements make XGBoost particularly well suited to structured economic and financial datasets (Chen and Guestrin, 2016). Similarly, Histogram-based Gradient Boosting (HGB) improves computational efficiency by discretizing continuous variables into histogram bins before constructing the trees. This procedure reduces memory requirements and accelerates the optimization of split points while maintaining strong predictive performance on medium- and large-scale datasets (Ke et al., 2017).

Overall, these ensemble learning algorithms offer complementary advantages by effectively balancing the bias–variance trade-off and capturing complex nonlinear patterns in economic relationships. Despite their high predictive accuracy, these methods often function as black-box models. Although their inputs and outputs are clearly defined, the underlying relationships between the input features and model predictions remain opaque, thereby limiting model interpretability.

To address this limitation, the SHapley Additive exPlanations (SHAP) approach was adopted to provide greater insight into the model's decision-making process. SHAP offers a systematic means of interpreting complex machine-learning algorithms by determining how strongly each input variable influences a given model output. Accordingly, the prediction generated by the model can be represented as the sum of the individual effects attributed to the input features, expressed as follows:

$$f(x) \approx g(x) = \emptyset_0 + \sum_{i=1}^{M} \emptyset_i\,(x_i) \qquad (1)$$

In the above expression, represents the prediction generated by the original ensemble model, denotes the additive explanation model, and is the base value, which is typically defined as the mean prediction over the entire dataset. represents the contribution of feature i to the prediction for a given sample, while denotes the total number of features in the sample (Lundberg and Lee, 2017).

Within the additive explanation framework, Shapley values are derived from cooperative game theory. This approach satisfies three fundamental properties: fairness, local accuracy, and consistency.

Fairness: The contribution of each feature is quantified based on its marginal contribution to the model's prediction. If a feature has no contribution to the prediction, its corresponding Shapley value is zero.

Local Accuracy: The sum of the baseline value and the contributions of all features exactly equals the model's prediction for a given observation.

Consistency: If the contribution of a feature to the model's prediction increases or remains unchanged when the model is modified, its corresponding Shapley value should not decrease.

Accordingly, the extended additive explanation model based on Shapley values can be expressed as follows:

$$\emptyset_i(f,x) = \sum_{S \subseteq N/\{i\}} \frac{|S|!\,(M-|S|-1)!}{M!}\left[f_{S\cup\{i\}}\left(x_{S\cup\{i\}}\right) - f_S(x_S)\right] \qquad (2)$$

$$f(x) \approx g(x) = \emptyset_0 + \sum_{i=1}^{M} \emptyset_i(f,x) \qquad (3)$$

In the equations above, denotes the total number of features, represents the set of all features, and is a subset of features that does not include feature i. The

term denotes the model prediction based only on the features in, whereas represents the prediction after adding feature i. The coefficient represents the Shapley weighting assigned to each possible feature ordering. The term denotes the baseline prediction, defined as the model's average output when no specific features are considered, while denotes the Shapley value of feature i (Lundberg and Lee, 2017).

In this study, SHAP was used exclusively as an interpretability tool to assess the relative predictive importance of features within the trained models. Accordingly, SHAP values represent the contributions of individual features to model predictions and should not be interpreted as evidence of causal relationships among the variables.

4. Empirical Results and discussion

4.1. Empirical results

Prior to constructing the forecasting framework, the statistical association between each explanatory variable and the exchange rate was investigated. Pearson's correlation coefficient was employed to identify the direction and strength of linear associations, with the corresponding results illustrated in Figure 1. The findings indicate that the free-market exchange rate is strongly and positively associated with broad money, the Global Economic Policy Uncertainty (GEPU) index, and inflation. This pattern suggests that variations in liquidity, economic policy uncertainty, and price inflation contain potentially informative signals for predicting movements in the free-market exchange rate. By comparison, the associations between the exchange rate and the other explanatory variables are relatively limited, with correlation coefficients remaining below 20%.

Based on the theoretical framework and the correlation matrix presented in Figure 1, economic and political uncertainty, as well as monetary variables—particularly the money supply—may influence the free-market exchange rate. However, the relative importance of these input features may vary. Therefore, ensemble learning models were employed for prediction in conjunction with the SHAP approach, which enables the contribution of each input feature to the model predictions to be quantified and interpreted.

To identify the most accurate forecasting method, the performance of the ensemble-based machine learning models was evaluated and compared using three prediction error metrics: Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE), as reported in Table 2. To preserve the temporal structure of the monthly observations, the dataset was divided chronologically, with the first 80% of the observations used for model training and the remaining 20% retained as an out-of-sample test set. The Min–Max transformation was calibrated using only the observations allocated to the training stage, and the resulting scaling parameters were then used to transform the held-out observations, thereby avoiding any transfer of information from the test period into the model development process. Model

development and hyperparameter optimization were conducted through five-fold resampling confined to the training portion of the data. The observations reserved for testing remained completely separate from these procedures and were considered only after model selection to provide an unbiased evaluation of out-of-sample predictive performance.

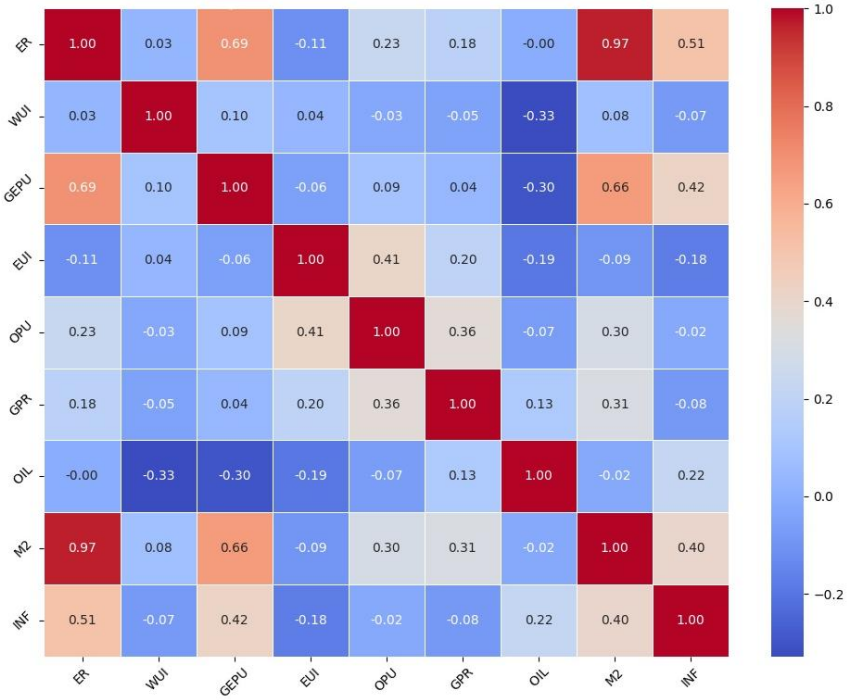

Figure 1. ***Correlation among the model's input features***
Source: *Research findings*

As presented in Table 2, the Random Forest (RF) model achieved MAPE, MAE, and RMSE values of 7.94%, 0.012, and 0.026, respectively, on the test dataset. The Gradient Boosting (GB) model yielded corresponding values of 9.23%, 0.012, and 0.024, respectively, indicating strong predictive performance for both models. Overall, RF and GB demonstrated the highest forecasting accuracy among the evaluated models, as reflected by their relatively low prediction errors.

Furthermore, the target variable (ER) ranged from 16,866.55 to 500,493.1 IRR, with a mean of 117,524 and a standard deviation of 114,757.2. Given the magnitude and variability of the target variable, the relatively small prediction errors indicate that the models achieve a high level of forecasting accuracy.

Table 2. Performance of tree-based machine learning models (ensemble methods) based on error metrics.

Error metrics	Models					
	DT[6]	RF[5]	HGB[4]	XGB[3]	GB[2]	Extra Trees[1]
MAPE (%)	9.99	7.94	22.23	9.98	9.23	13.71
MAE	0.015	0.012	0.022	0.016	0.012	0.007
RMSE	0.030	0.026	0.035	0.032	0.024	0.011

Source: *Research findings*

To enhance the interpretability of the forecasting models, the SHAP framework was utilized to quantify the extent to which the predictor variables influenced the estimated free-market exchange rate. The percentage share attributed to each feature in generating the model outputs is illustrated in Figure 1.

Figure 2 demonstrates that liquidity is the dominant predictor across the forecasting techniques considered, accounting for a markedly larger share of the models' predictive output than any other explanatory variable. In contrast, the predictive relevance of the other variables remains relatively limited. These variables comprise measures of global economic-policy uncertainty (GEPU), geopolitical risk (GPR), energy-market uncertainty (EUI), uncertainty surrounding crude-oil prices (OPU), global uncertainty (WUI), the Brent crude benchmark (OIL), and inflation (INF), with each individually representing less than 10% of the total predictive contribution across the models.

Furthermore, Figure 3 presents the average importance of the input features across the six models examined in this study. The results indicate that broad

money (M2) is the most influential predictive feature for the free-market exchange rate, with an average relative importance of 89%. Inflation (INF), the Global Economic Policy Uncertainty (GEPU) index, and the Brent oil price (OIL) are the next most important features, each accounting for approximately 2% of the overall feature importance. This finding highlights a substantial difference in predictive importance between broad money and the other input features. The remaining variables, including the Energy Uncertainty Index (EUI), Geopolitical Risk (GPR), World Uncertainty Index (WUI), and Oil Price Uncertainty Index (OPU), each contribute approximately 1% to the overall feature importance.

1 Extremely Randomized Trees
2 Gradient Boosting
3 Extremely Gradient Boosting
4 Hist Gradient Boosting
5 Random Forest
6 Decision Tree

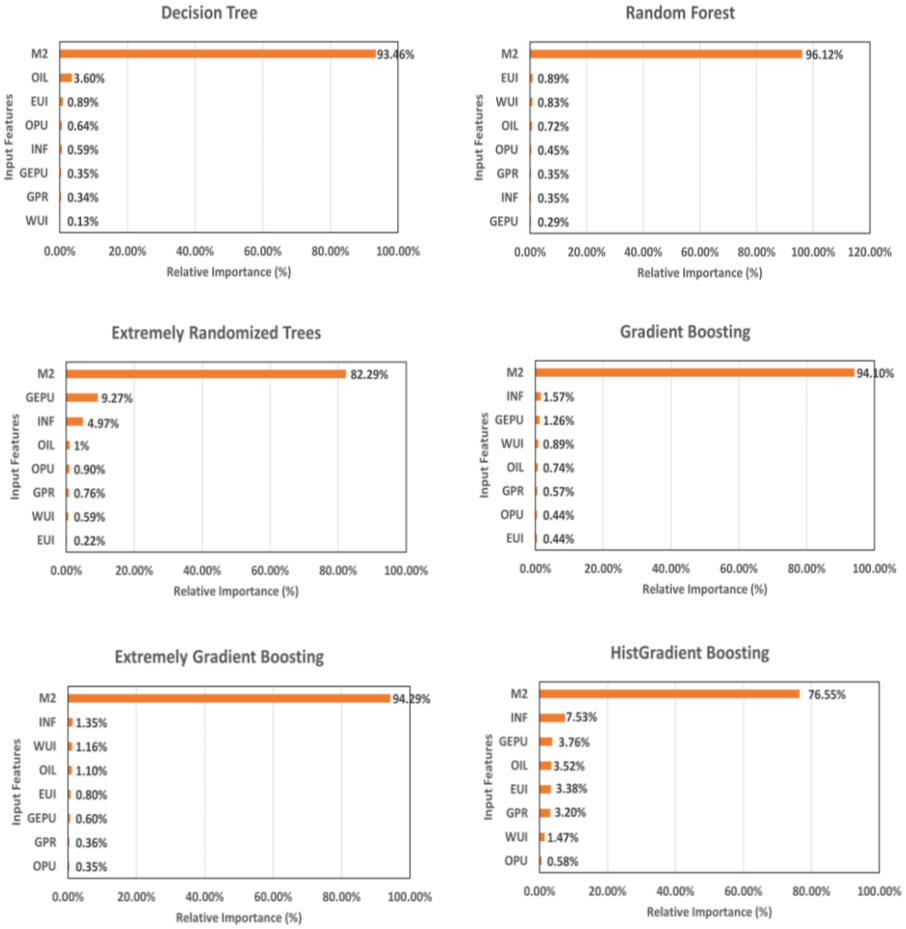

Figure 2. Relative importance of the input features for the free-market exchange rate across the evaluated machine learning models

Source: *Research findings*

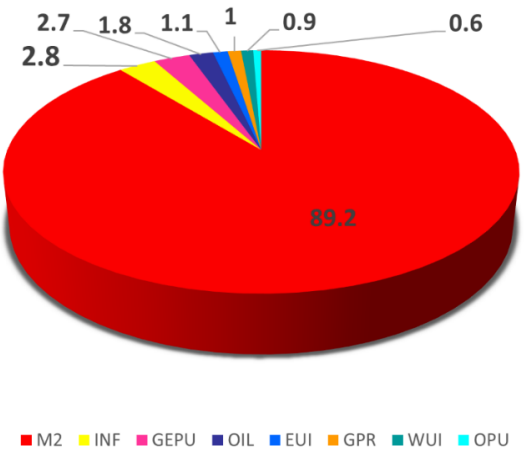

Figure 3. Average relative importance of input features for the free-market exchange rate across all examined models
Source: *Research findings*

The SHAP findings demonstrate that liquidity has a markedly stronger predictive contribution to exchange-rate fluctuations than the global uncertainty measures considered in the analysis. One possible explanation lies in the underlying features of Iran's economic structure. In particular, prolonged growth in the money supply, persistent fiscal imbalances, and the financing of government budget shortfalls through monetary expansion have maintained significant inflationary pressures. In such an environment, changes in domestic liquidity conditions may influence expectations regarding the future value of the domestic currency more rapidly and intensely, thereby exerting a stronger influence on the free-market exchange rate than shocks originating from international uncertainty. This result also accords with established monetary perspectives on exchange-rate behavior and is supported by earlier evidence emphasizing the role of monetary expansion in driving exchange-rate variability in Iran (Tajdini et al., 2023).

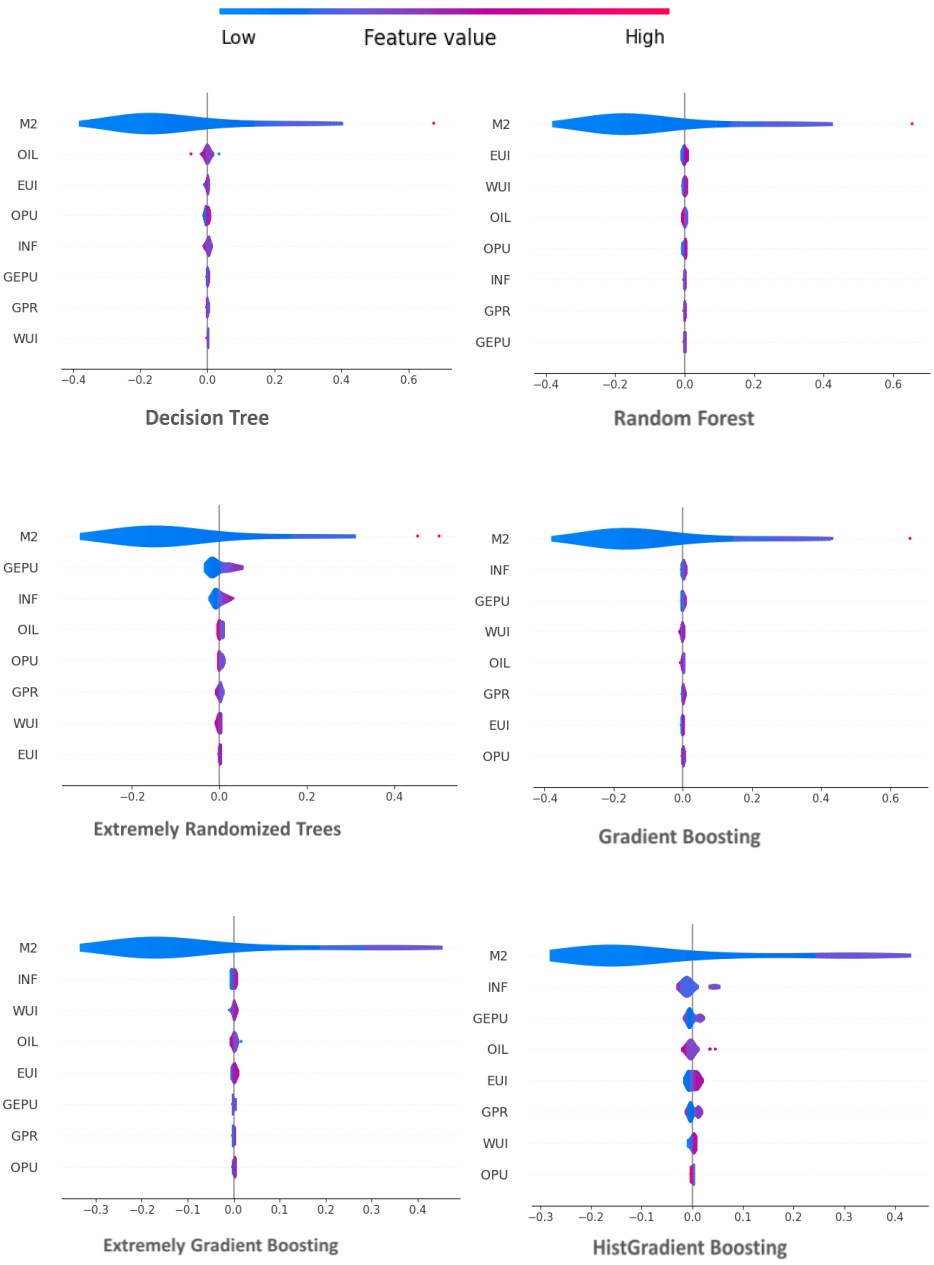

Figure 4. The direction of effect and relative importance of each input feature on the free market exchange rate in each of the models under study.

Source: *Research findings*

The relatively lower predictive importance of global uncertainty measures, such as the Global Economic Policy Uncertainty (GEPU) and Geopolitical Risk (GPR) indices, should not be interpreted as evidence that external uncertainty is irrelevant to exchange-rate dynamics. Rather, it may reflect the Iranian economy's relatively limited exposure to international financial channels. Prolonged sanctions, restricted access to global financial markets, and extensive government intervention in the foreign exchange market have weakened the direct transmission of global shocks to domestic exchange-rate movements. Consequently, although global uncertainty may influence the exchange rate indirectly through channels such as trade flows, oil revenues, and market expectations, domestic monetary factors remain the primary determinants of exchange-rate dynamics within Iran's distinctive economic environment (Glebocki and Saha, 2024).

These findings should be interpreted within the context of Iran's institutional and economic structure and should not be generalized to other emerging economies with different levels of financial integration. In more financially open economies, global uncertainty indicators have been found to exert stronger effects on exchange-rate volatility. In Iran, however, exchange-rate regulations, international sanctions, and structural constraints limit the transmission of external shocks, thereby increasing the relative importance of domestic monetary variables in explaining exchange-rate movements (Celasun, 2003).

To examine whether the main findings remained stable under alternative model specifications, two sensitivity exercises were performed. In the first exercise, the original level measures of liquidity (M2) and the exchange rate (ER) were transformed into their respective logarithmic growth measures, denoted by ΔlM2 and ΔlER. The complete modeling procedure was then repeated using these transformed variables. The comparative results indicated that Extra Trees delivered the most accurate forecasts under this alternative specification. The subsequent SHAP analysis also produced a different pattern of variable relevance compared with the baseline results. While the level of liquidity had been the dominant predictor in the original models, inflation, the World Uncertainty Index (WUI), and oil prices received greater predictive weight when exchange-rate returns were used as the dependent measure. At the same time, the contribution associated with liquidity growth became considerably smaller. Overall, the sensitivity results indicate that the determinants associated with movements in the exchange rate over short horizons may not necessarily coincide with those associated with variations in its underlying level.

In the second robustness assessment, CPI was introduced into the model as a substitute for the conventional inflation indicator. The findings indicate that Extra Trees remained the best-performing predictive method. Moreover, using CPI in place of the original inflation variable produced no meaningful changes in the contribution patterns of the predictors or in their ordering within the models. Hence, the main empirical conclusions remain stable when inflation is represented through a different price-based indicator. Comprehensive outputs from the two

robustness exercises, together with their associated tables and graphical evidence, are reported in Appendix A.

To capture the temporal dynamics underlying the relationships between macroeconomic variables and the exchange rate, lagged structures were incorporated into the machine learning models. Specifically, three- and six-month lags were applied to liquidity (M2) and inflation (INF), whereas a three-month lag was introduced for oil prices (OIL). To further reduce potential contemporaneous effects, the current values of liquidity and inflation were excluded from the analysis, and only their lagged values were employed as input features. In addition, given the time-series nature of the dataset, the data were partitioned chronologically, and normalization was performed solely on the training set to avoid data leakage. A comprehensive description of the data preprocessing procedures and the implemented modifications is provided in Appendix C.

4.2. Discussion

In this section, we first compare the findings of the present study with those reported in previous research and then interpret the results in light of the existing literature. The primary objective of this analysis is to identify the key determinants of the free-market exchange rate in the Iranian economy and to highlight the factors that warrant greater attention in policymaking and future research.

The high predictive importance of liquidity can be understood in the context of several structural characteristics of the Iranian economy. Persistent government budget deficits, together with the allocation of bank credit to relatively unproductive activities, may contribute to sustained monetary expansion and an increase in aggregate purchasing power. When monetary expansion is not accompanied by a commensurate increase in the supply of goods and services, it can generate inflationary pressures. Under such conditions, exchange-rate expectations and demand for foreign currency may become increasingly sensitive to domestic monetary conditions. These mechanisms provide an economic rationale for the strong predictive relationship between liquidity and the free-market exchange rate identified by the machine-learning models (Siddiqi et al., 2025; Bidabad, 2019).

Second, heightened economic and political uncertainty associated with sanctions may coincide with greater financial-market risk and increased precautionary demand for liquid assets. Such conditions may also affect monetary aggregates and strengthen demand for safe-haven assets, particularly the U.S. dollar. These channels provide a plausible economic interpretation of the relationship between liquidity and exchange-rate movements identified by the predictive models (Bianchi et al., 2021). These findings are also consistent with those reported by Bidabad (2019).

Moreover, the forecasting models indicate that uncertainty-related variables account for less than 10% of the contribution to exchange-rate movements. Specifically, global economic policy uncertainty (GEPU), geopolitical risk (GPR), the energy uncertainty index (EUI), oil price uncertainty (OPU), and

world uncertainty (WUI) do not appear to be among the primary determinants of the free-market exchange rate in Iran. Rather, these variables seem to be more closely associated with short-term fluctuations around the long-run exchange-rate level, whereas the overall predictive performance of the models is primarily driven by other underlying factors.

First, because international sanctions have severely restricted Iran's access to global financial systems, the primary transmission channels of external shocks—including financial, trade, expectations, and commodity and currency channels—have been substantially weakened. Consequently, global economic shocks may be only partially transmitted to Iran's domestic economic and financial conditions, which may help explain the relatively limited predictive importance of global uncertainty indicators in the models (Baker et al., 2016; Yilmazkuday, 2025).

Second, Iran's economy appears to have reached a degree of sanctions saturation that has reduced the sensitivity of the free-market exchange rate to geopolitical shocks. At the same time, the economic and security interests of major countries, particularly their dependence on the region's energy resources, have constrained the escalation of geopolitical conflicts. Consequently, most geopolitical tensions involving Iran have remained largely confined to diplomatic disputes, resulting in only temporary and unstable effects on the exchange rate. Furthermore, the recurrent occurrence of geopolitical tensions in the Middle East may have contributed to psychological adaptation among market participants, thereby increasing the resilience of the foreign exchange market to geopolitical risks (Yilmazkuday, 2025; Bahrieh et al., 2025).

Third, sanctions have been associated with a decline in foreign-exchange revenues from Iran's oil exports, while part of the remaining export proceeds is settled through barter arrangements. Under these conditions, the relatively limited predictive importance of global oil-price uncertainty may reflect the weak sensitivity of foreign-currency availability in Iran's free market to fluctuations in international oil prices (Değirmen et al., 2023).

Fourth, since monetary expansion constitutes an important source of inflationary pressure in Iran, variations in inflation are generally reflected after changes in the money supply have already occurred. Given that money supply growth emerged as the dominant predictive factor in the baseline specifications, monetary developments appear to have a stronger and more immediate association with exchange-rate movements than inflation itself. Inflation may instead represent a delayed transmission of monetary conditions into the foreign-exchange market, which can explain its comparatively smaller predictive contribution in the estimated models (Bidabad, 2019). The observed pattern is broadly in line with the evidence presented by Bahrieh et al. (2025), Glebocki and Saha (2024), and Bidabad (2019), but differ from those reported by Ashena et al. (2020).

5. Conclusion, Policy implications

5.1. Conclusion

The present study examines the relative significance of economic and political uncertainty, together with monetary factors, in accounting for movements in Iran's open-market exchange rate during 2012–2023. Despite the extensive literature on the factors associated with exchange rate dynamics, the comparative role of these determinants has received comparatively less empirical consideration, especially when the Iranian open-market exchange rate is examined. This study therefore evaluates how strongly monetary conditions and uncertainty-related factors are reflected in variations in the Iranian exchange rate. For this purpose, machine learning techniques introduced by Breiman (1996) are applied to determine which variables provide the greatest predictive value for exchange rate movements.

Based on the interpretation of the predictive models using the SHAP approach, money supply emerged as the most influential predictive feature of the open-market exchange rate. In contrast, the inflation rate (INF), Global Economic Policy Uncertainty (GEPU), Brent oil price (OIL), Energy Uncertainty Index (EUI), Geopolitical Risk (GPR), World Uncertainty Index (WUI), and Oil Price Uncertainty Index (OPU) exhibited considerably smaller contributions to exchange rate fluctuations. Overall, the average impact of money supply on the open-market exchange rate across all evaluated models was 31.85 times greater than that of the inflation rate and 11.15 times greater than the combined effects of the economic and political uncertainty measures considered in this study.

The methodological framework adopted in this study offers several advantages. First, tree-based ensemble learning methods, including Random Forest (RF) and Gradient Boosting (GB), effectively capture complex nonlinear relationships and interactions among predictor variables. Second, rather than relying solely on the coefficient of determination (R^2), as is common in many econometric studies, model performance was evaluated using three complementary error metrics: Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Squared Error (RMSE). These metrics provide a more comprehensive assessment of predictive accuracy and model performance. Third, the SHAP (Shapley Additive Explanations) framework was employed to enhance the interpretability of the predictive models. Although machine learning algorithms generally exhibit strong predictive performance, they do not inherently explain the contribution of individual input features to model predictions. The SHAP framework, which is based on Shapley values from cooperative game theory, quantifies the contribution of each feature by considering all possible combinations of input variables, thereby providing a transparent and theoretically grounded interpretation of model predictions.

5.2. Policy Implications, Limitations, and Suggestions for Future Research

Given the limited predictive importance of economic and political uncertainties for the free-market exchange rate and the strong predictive

importance of liquidity identified in this study, policies aimed at improving liquidity management may contribute to greater exchange-rate stability. However, these implications should be interpreted as policy considerations based on predictive associations rather than as evidence of a causal effect of liquidity on the exchange rate. Therefore, the formulation and implementation of appropriate monetary and fiscal policies are essential for promoting exchange-rate stability.

An assessment of Iran's exchange-rate policies following the Islamic Revolution reveals a series of distinct policy phases and their associated consequences. During 1978–1992, the Central Bank operated a differentiated currency-allocation system, directing foreign currency toward priority areas such as basic commodities, intermediate inputs, and development-related activities. This approach was largely intended to manage scarce foreign-exchange resources in response to the economic pressures created by the war and international sanctions. However, the coexistence of several exchange rates, coupled with persistent shortages of foreign currency, generated a substantial divergence between the administered and market-determined rates. As a result, parallel currency trading expanded and the stability of the national currency deteriorated.

A major policy shift occurred during 1993–2002, when the authorities attempted to replace the multiple-rate arrangement with a unified exchange-rate framework. Despite this reform, weak synchronization between fiscal and monetary policies, along with increasing pressure from domestic demand, created new sources of instability and placed additional pressure on the value of the national currency. From 2002 to 2010, the substantial increase in oil revenues provided the Central Bank with greater access to foreign currency and allowed it to pursue a managed-floating regime. The increased availability of foreign exchange helped moderate fluctuations in the exchange rate and improved short-term stability. Nevertheless, the escalation of international sanctions after 2009 progressively constrained the effectiveness of this policy framework and once again intensified pressure on the currency.

During 2011–2021, policymakers increasingly relied on administrative controls over currency transactions and direct Central Bank intervention to contain fluctuations in the exchange rate. Although these measures were able to limit volatility for certain periods, the gradual deterioration of foreign-exchange reserves, together with continued discrepancies between monetary and fiscal policy, exerted persistent downward pressure on the domestic currency. In addition, the preferential currency mechanism used for imports during 2018–2021 created a pronounced difference between the officially administered rate and the rate prevailing in unrestricted transactions. The subsequent discontinuation of preferential currency allocation in 2021, accompanied by the introduction of a negotiated foreign-exchange trading arrangement, helped reduce opportunities for rent extraction and corrupt practices and provided stronger incentives for exporters to return their foreign-currency earnings to the country. These changes contributed to a reduction in the differential between exchange rates; nevertheless, underlying distortions and instability in currency pricing continued to persist.

The evaluation of Iran's exchange rate policies indicates that, despite the implementation of various measures aimed at stabilizing the exchange rate, persistent inconsistencies among exchange rate, monetary, and fiscal policies have limited their effectiveness over the long term. Accordingly, the findings of this study underscore the need for a comprehensive policy framework centered on effective liquidity management as a prerequisite for stabilizing the free-market exchange rate.

Liquidity control has been a recurring objective of Iran's national development plans. During the Fourth Development Plan (2005–2009), policymakers sought to control liquidity growth by enhancing the independence of the Central Bank, increasing reserve requirements and interest rates, directing financial resources toward productive sectors, reducing the government's reliance on bank financing, and expanding tax revenues. However, these objectives were only partially achieved, as rising oil revenues strengthened fiscal dominance, reserve requirements were temporarily reduced, and direct cash subsidy payments contributed to a rapid expansion of liquidity.

Similarly, the Fifth Development Plan (2011–2015) sought to reduce annual liquidity growth to below 20% through bond issuance and restrictions on government borrowing from the Central Bank. In practice, however, these measures were largely ineffective, with annual liquidity growth remaining at approximately 25%–30%.

During the Sixth Development Plan (2017–2021), open market operations were introduced with the aim of limiting liquidity growth to approximately 17%. However, substantial government budget deficits and the high level of commercial banks' indebtedness to the Central Bank significantly constrained the effectiveness of these measures. Consequently, liquidity growth reached 38.3% and 40.1% in 2020 and 2021, respectively.

During the Sixth Development Plan (2017–2021), open market operations were introduced with the aim of limiting liquidity growth to approximately 17%. However, substantial government budget deficits and the high level of commercial banks' indebtedness to the Central Bank significantly constrained the effectiveness of these measures. Consequently, liquidity growth reached 38.3% and 40.1% in 2020 and 2021, respectively.

Under the Seventh Development Plan (2023–2027), policies aimed at containing bank balance-sheet expansion and requiring the issuance of special deposit certificates at an interest rate of 30% contributed to moderating liquidity growth. Consequently, liquidity growth declined from 37.4% in 2022 to 31.3% in 2023 and 28.1% in 2024.

Overall, the evolution of Iran's monetary and fiscal policies indicates the absence of a comprehensive, coordinated, and effective long-term policy framework. Based on the findings of this study, several policy recommendations are proposed to improve liquidity management and enhance exchange rate stability.

The findings indicate that liquidity growth is the most important predictive feature associated with exchange-rate fluctuations in Iran. This expansion in liquidity may be attributable to government borrowing from the Central Bank to finance current expenditures, including inflation-related adjustments to public-sector wages and cash subsidy payments. In this context, given Iran's extensive supply of developable land, allocating government-owned land to low-income households without adequate housing through 99-year leasehold arrangements, subject to restrictions on resale before the expiration of the lease and requirements to complete construction within a specified period, could reduce the need for liquidity-creating fiscal transfers while improving household welfare. In addition, such a policy could stimulate activity in the housing sector, thereby promoting investment and employment.

Moreover, Iran's energy subsidy system, which disproportionately benefits higher-income households, contributes to fiscal deficits, liquidity expansion, and exchange rate depreciation. One potential policy response is to allocate a transferable per capita gasoline quota to each citizen through a secure, transparent, and officially regulated platform. Such a policy could help reduce liquidity growth, moderate inflationary expectations, and promote exchange rate stability.

Finally, to limit liquidity creation through banking activities, banks should focus on their core functions of providing financial services and extending credit to productive sectors, while direct investment in capital assets, such as real estate and equities, should be prohibited. Furthermore, greater transparency, stricter supervision of banks' non-performing and non-productive assets, and tighter regulations governing real estate transactions and speculative investments could help contain liquidity growth and reduce exchange rate volatility.

This research is subject to several constraints. While the modeling framework captures major monetary factors and measures of international uncertainty, a number of other variables that may influence movements in Iran's exchange rate could not be considered. These include the severity of economic sanctions, the country's foreign-currency reserve position, changes in interest rates, revenues generated from oil exports, external trade conditions, and the use of foreign-exchange restrictions. The exclusion of these factors was mainly related to the defined scope of the analysis and the difficulty of obtaining dependable and comparable observations at a sufficiently high frequency. Subsequent studies may overcome this limitation by expanding the set of explanatory variables, which would allow for a broader representation of exchange-rate dynamics and may also enhance the accuracy of the resulting forecasts.

Since this study employs machine-learning models and the SHAP approach, the findings should be interpreted as reflecting the relative predictive importance of the variables in exchange rate forecasting rather than as evidence of causal relationships. Establishing causal effects requires econometric approaches based on appropriate identification strategies, such as instrumental variables, natural experiments, or other causal inference methods.

Future research could further evaluate the robustness of the findings by comparing the predictive performance of machine learning models with that of conventional econometric approaches, such as ARIMA and VAR models. Moreover, assessing predictive accuracy across different economic regimes and sub-periods, particularly those characterized by major sanctions episodes or significant economic shocks, could provide additional evidence regarding the stability and generalizability of the findings.

Author Contributions:

For example: Conceptualization, all authors; methodology, P.R., M.M. and Z.Y.; validation, P.R., M.M. and Z.Y.; formal analysis, all authors; resources, P.R., M.M. and Z.Y.; writing—original draft preparation, P.R., M.M. and Z.Y.; writing—review and editing, all authors; supervision, P.R., M.M. and Z.Y. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest:

The authors declare no conflict of interest.

Data Availability Statement:

The data used in this study were obtained from the Central Bank of Iran (https://cbi.ir), the World Uncertainty Index and Economic Policy Uncertainty databases (https://www.policyuncertainty.com), TGJU (https://www.tgju.org), and Investing.com (https://www.investing.com/).

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Appendix A

Robustness Check

To examine whether the empirical results remain stable when alternative specifications of the variables are adopted, an additional sensitivity analysis is conducted. In this exercise, liquidity is represented by its logarithmic growth rate (ΔlM2) rather than its level, and the exchange-rate variable is expressed as its logarithmic return (ΔlER) instead of its level. Following these substitutions, the complete empirical framework is re-estimated from the beginning, encompassing model training as well as the assessment of predictive contributions through SHAP-based analysis.

From a theoretical perspective, and in line with the correlation patterns illustrated in Figure (a.1), ΔlER displays different degrees of linear association with monetary factors and the selected measures of economic and political uncertainty. Among the explanatory variables, inflation records the highest correlation with the exchange-rate return, with a coefficient of 0.30. The WUI follows with a substantially weaker coefficient of 0.15, whereas the remaining variables exhibit correlations that are either weak or approximately zero. These patterns provide only an initial indication of linear comovement and, therefore, should not be interpreted as establishing any causal connection between the variables. Table a.2 reports the predictive contribution assigned to each explanatory variable under the six alternative model specifications considered in this analysis.

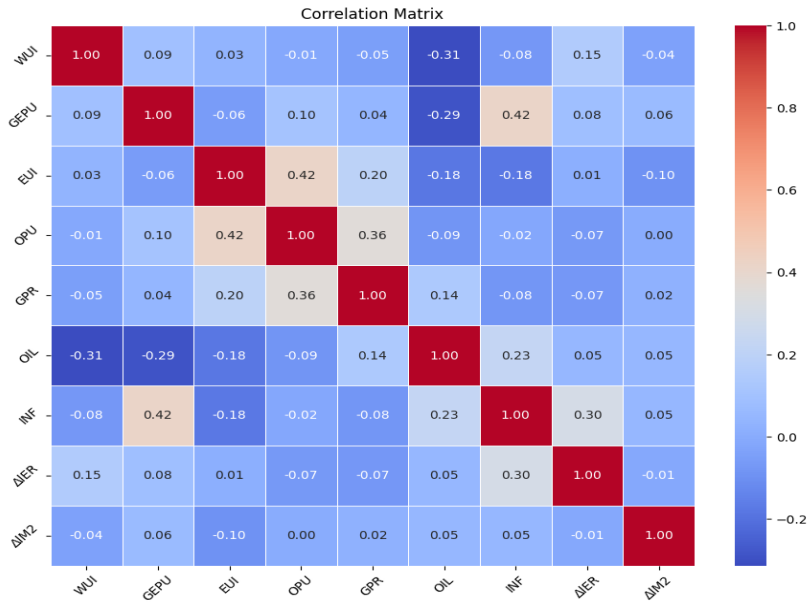

Figure. a.1. Correlation among the model's input features
Source: *Research findings*

To determine which forecasting technique provided the most reliable results, the predictive performance of the ensemble learning algorithms was assessed based on three standard error measures—MAE, MAPE, and RMSE—with the corresponding results presented in Table (a.3). Among the models considered, the Extremely Randomized Trees (Extra Trees) algorithm yielded the most accurate forecasts, as reflected by its comparatively smaller prediction errors across the evaluation criteria. Since the robustness assessment maintained the monthly temporal structure of the original specification, the dataset was partitioned according to the chronological order of the observations. The earliest 80% of the sample constituted the training period, whereas the remaining 20% was kept aside as an independent out-of-sample period for assessing forecasting performance. The parameters required for Min–Max scaling were calculated using the training data only and then used unchanged to transform the test observations. Model tuning and internal validation were conducted solely on the training portion through a five-fold cross-validation procedure. Consequently, none of the test-period observations contributed to model fitting, validation, or the determination of model settings; they were used only once, at the final stage, to measure the models' out-of-sample forecasting accuracy.

Table a.1. Performance of tree-based machine learning models (ensemble methods) based on error metrics.

Error metrics	Models					
	DT[6]	RF[5]	HGB[4]	XGB[3]	GB[2]	Extra Trees[1]
MAPE (%)	32.229	26.278	26.178	27.397	27.006	**25.675**
MAE	0.120	0.098	0.0948	0.099	0.097	**0.0942**
RMSE	0.175	0.129	**0.116**	0.135	0.124	0.121

Source: *Research findings*

The results presented in Table (a.1) indicate that the Extremely Randomized Trees (Extra Trees) model achieved MAPE, MAE, and RMSE values of 25.675%, 0.0942, and 0.121, respectively, on the test set. These findings demonstrate the model's satisfactory predictive performance, as evidenced by its lower prediction errors compared with those of the other evaluated methods.

To examine how the models performed in forecasting, SHAP analysis was applied to assess the influence of the explanatory variables on the logarithmic exchange-rate return (ΔlER). The results provide an indication of the extent to

[1] Extremely Randomized Trees
[2] Gradient Boosting
[3] Extremely Gradient Boosting
[4] Hist Gradient Boosting
[5] Random Forest
[6] Decision Tree

which each predictor contributes to the model's output. Figure a.2 presents the variable-importance profile obtained from the Extra Trees model.

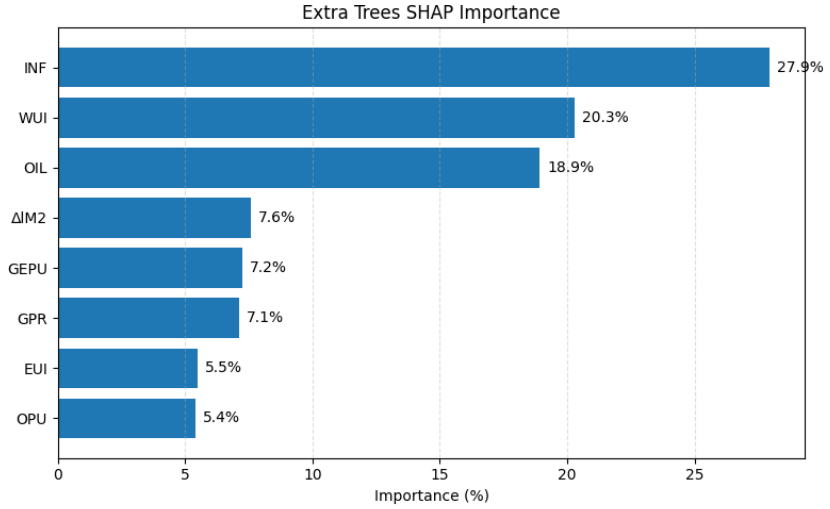

Figure a.2. Relative importance of input features in predicting ΔlER using the Extra Trees model

Source: *Research findings*

Table a.2. Relative importance of input features for free-market exchange rate prediction

Models	**input features**							
	ΔlM2	**WUI**	**OPU**	**OIL**	**INF**	**GPR**	**GEPU**	**EUI**
DT	6.51	20.88	2.64	19.57	25.49	2.32	10.36	12.19
RF	11.97	15.66	4.33	18.37	30.27	5.92	6.22	7.23
HGB	6.9	7.25	8.43	8.58	14.05	16.38	17.92	20.44
XGB	12.89	20.64	4.21	11.7	28.35	6.74	6.61	8.82
GB	11.77	21.452	4.721	17.16	21.65	4.47	9.90	8.86
Extra Trees	7.57	20.3	5.41	18.93	27.93	7.11	7.24	5.48

Source: *Research findings*

As illustrated in Figure a.2, inflation exhibits the highest relative importance among the input features in predicting exchange rate returns. The other input variables, including the World Uncertainty Index (WUI), Brent crude oil price (OIL), logarithmic liquidity growth rate (ΔlM2), Global Economic Policy Uncertainty (GEPU), Geopolitical Risk Index (GPR), Energy Uncertainty Index (EUI), and Oil Price Uncertainty Index (OPU), exhibit comparatively lower levels of importance in the model's predictions.

The results indicate that changing the definitions of the dependent and monetary variables alters the relative contributions of the explanatory factors.

Unlike the baseline model, in which the liquidity level was identified as the most influential predictive feature for the exchange rate, the return-based specification places greater emphasis on variables such as inflation, global uncertainty (WUI), and oil prices, while the contribution of liquidity growth becomes comparatively weaker.

These findings suggest that the predictive features associated with the exchange rate level are not necessarily the same as those associated with its short-term fluctuations. Specifically, liquidity accumulation appears to have greater predictive importance for the long-term exchange rate level and trend, whereas short-term exchange rate movements are more strongly associated with macroeconomic conditions and external indicators, such as inflation, global uncertainty, and oil price fluctuations. Therefore, the robustness analysis confirms that the relative importance of the explanatory variables is partly sensitive to the definitions of the dependent and independent variables. Accordingly, the interpretation of the results should take this distinction into account.

Furthermore, as an additional sensitivity test, the Consumer Price Index (CPI) was employed as an alternative measure of inflation, and all analyses were subsequently repeated using this alternative measure.

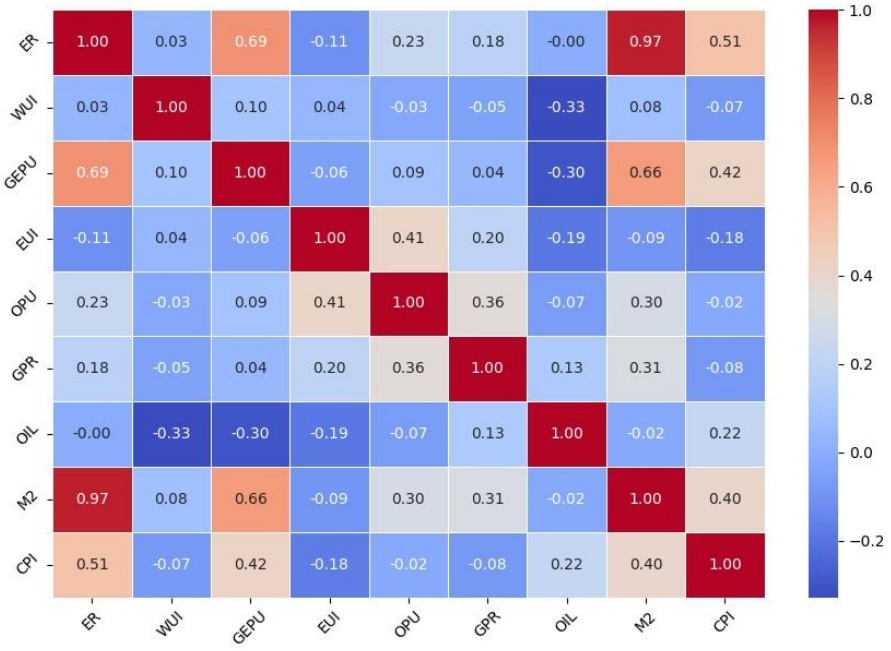

Figure a.3. Correlation among the model's input features

Source: *Research findings*

Drawing on the theoretical framework and the correlation matrix shown in Figure a.3, fluctuations in the free-market exchange rate can be associated with a range of economic, political, and monetary conditions. To examine these relationships from a predictive perspective, ensemble-based machine learning techniques were integrated with the SHAP methodology to forecast exchange rate changes and determine the contribution of each explanatory factor to model predictions. The results for all six machine learning algorithms are presented in Table a.3, which provides a model-specific assessment of how strongly each predictor contributes to the forecasting outcomes.

Table a.3 presents the forecasting results obtained from the evaluated machine learning algorithms, with model performance assessed through three error measures: MAE, MAPE, and RMSE. Among the models examined, the Extremely Randomized Trees (Extra Trees) algorithm demonstrates the strongest forecasting capability, producing the smallest error values under each of the reported performance measures.

Table a.3. Performance of tree-based machine learning models (ensemble methods) based on error metrics.

Error metrics	Models					
	DT	**RF**	**HGB**	**XGB**	**GB**	**Extra Trees**
MAPE (%)	9.990	**7.936**	22.232	9.979	9.231	13.712
MAE	0.0157	0.0126	0.022	0.016	0.0124	**0.007**
RMSE	0.0301	0.026	0.035	0.032	0.024	**0.011**

Source: Research findings

To facilitate the interpretation of the machine learning forecasts, SHAP analysis was applied. Figure a.4 presents the contribution of each predictor to the output generated by the Extremely Randomized Trees (Extra Trees) model.

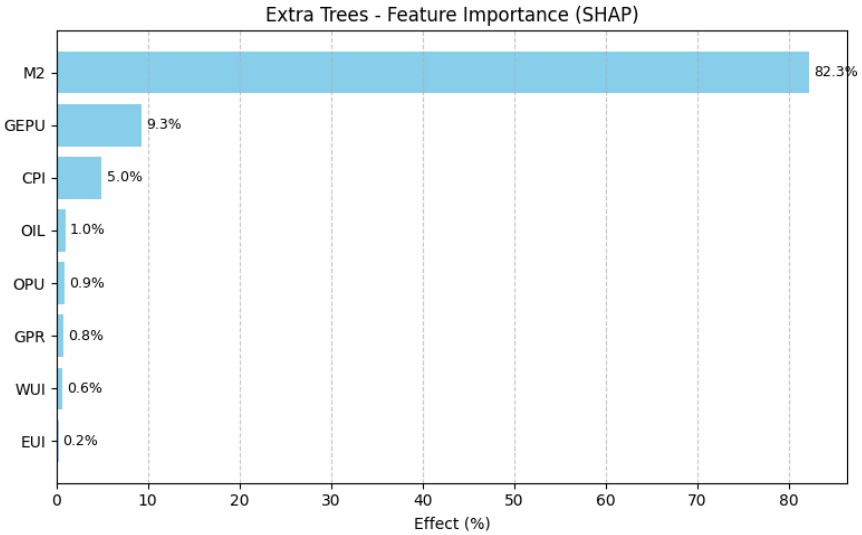

Figure a.4. Relative importance of input features for predicting the free-market exchange rate across the evaluated models: the Extra Trees model

Source: Research findings

Figure a.4 indicates that liquidity is the most influential feature in the Extra Trees model for predicting the free-market exchange rate. In contrast, each of the remaining input variables contributes less than 20% to the model's predictive performance. Furthermore, replacing the inflation rate with the Consumer Price Index (CPI) did not result in a meaningful change in the distribution of feature importance, and the ranking of the most influential variables remained largely unchanged. These findings confirm the robustness of the results to the use of an alternative measure of inflation.

Table a.3. Relative importance of input features for free-market exchange rate prediction

Models	input features							
	WUI	**OPU**	**OIL**	**M2**	**GPR**	**GEPU**	**EUI**	**CPI**
DT	0.13	0.638	3.605	93.464	0.341	0.345	0.886	0.589
RF	0.826	0.45	0.722	96.123	0.346	0.292	0.894	0.347
HGB	1.473	0.583	3.524	76.547	3.196	3.765	3.381	7.531
XGB	1.159	0.35	1.096	94.287	0.362	0.599	0.797	1.35
GB	0.885	0.437	0.739	94.103	0.565	1.26	0.44	1.569
Extra Trees	0.593	0.901	0.997	82.292	0.764	9.27	0.218	4.965

Source: Research findings

Appendix B

Robustness Test: Examining the Role of Domestic Uncertainty

Given that global uncertainty indices may not fully capture uncertainty dynamics in Iran's domestic economy because of country-specific factors, including external sanctions, financial constraints, and limited integration with global markets, a robustness test was conducted by constructing a Domestic Uncertainty Index (DU).

The domestic uncertainty measure was constructed based on the short-term volatility of two key macroeconomic variables in Iran: the free-market exchange rate (ER) and inflation (INF). Specifically, the 12-month rolling standard deviation of each variable was first calculated as follows:

$$ER_VOL_t = SD(ER_{t-11}, \dots, ER_t)$$
$$INF_VOL_t = SD(INF_{t-11}, \dots, INF_t)$$

To construct a composite index and mitigate potential multicollinearity between the two variables, they were combined into a single measure. The resulting index was incorporated into the machine learning models as the Domestic Uncertainty Index (DU).

To investigate the contribution of domestic uncertainty, three distinct model configurations were considered: (1) a specification based on global uncertainty, (2) a specification incorporating the Domestic Uncertainty (DU) Index, and (3) a comprehensive specification combining domestic and global uncertainty measures. For each configuration, Tables b.2, b.3, and b.4 present the contribution of the explanatory variables to the predictions generated by the six ensemble machine learning algorithms. In addition, the forecasting accuracy of the three specifications was assessed and compared according to the mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE).

All three specifications were evaluated using the same time-series forecasting protocol as that employed for the baseline model. The observations were divided chronologically into 80% training and 20% testing sets. Min–Max normalization was fitted exclusively to the training sample and subsequently applied to the test sample using the scaling parameters derived from the training data. Five-fold cross-validation was conducted exclusively within the training sample, while the test sample was kept completely separate from model development and hyperparameter tuning. Thus, the reported MAE, RMSE, and MAPE values represent genuine out-of-sample predictive performance and are directly comparable across the global, domestic, and combined uncertainty specifications.

Table b.1. Performance Evaluation of Tree-Based Ensemble Machine Learning Models Using Forecast Error Metrics

Specification	Model	MAE	RMSE	MAPE
Combined_Model	Extra Trees	**5518.623**	**8800.416**	**4.435133**
Combined_Model	Random Forest	6456.268	10047.52	5.175653
Combined_Model	Gradient Boosting	6429.215	10363.5	5.321435
Combined_Model	XGBoost	6842.053	12913.86	4.811199
Combined_Model	Decision Tree	9158.867	17844.13	7.210614
Combined_Model	Hist Gradient Boosting	13535.5	25351.75	12.35534
Domestic_Uncertainty	Random Forest	**5765.657**	**9260.638**	4.89316
Domestic_Uncertainty	Extra Trees	5797.782	9639.729	**4.322882**
Domestic_Uncertainty	Gradient Boosting	6456.958	10547.25	5.126283
Domestic_Uncertainty	XGBoost	6967.502	12106.89	4.991618
Domestic_Uncertainty	Decision Tree	8471.85	14530.21	6.331799
Domestic_Uncertainty	Hist Gradient Boosting	9119.42	17010.55	8.668178
Global_Uncertainty	Extra Trees	**4725.579**	**7921.341**	4.840851
Global_Uncertainty	Gradient Boosting	5450.649	9009.235	**4.744378**
Global_Uncertainty	Random Forest	6297.458	10182.09	5.376828
Global_Uncertainty	XGBoost	6778.354	13287.24	5.008515
Global_Uncertainty	Decision Tree	10542.22	19303.4	7.919589
Global_Uncertainty	Hist Gradient Boosting	16106.07	30066.27	14.8679

Source: *Research findings*

The results reported in Table b.1 indicate that, among the evaluated models, the Extra Trees algorithm achieved the best predictive performance. Under the global uncertainty specification, this model yielded the lowest prediction errors, with an RMSE of 7,921.34 and a MAPE of 4.84%. By comparison, the domestic uncertainty specification also demonstrated satisfactory predictive performance, with the Extra Trees model achieving an RMSE of 9,639.73 and a MAPE of 4.32%.

Table b.2. Relative importance of input features for free-market exchange rate prediction under global uncertainty specification

Models	input features							
	EUI	GEPU	GPR	INF	M2	OIL	OPU	WUI
DT	0.159	0.389	1.686	0.986	93.223	1.727	0.383	1.448
RF	1.069	0.523	0.182	0.632	95.652	0.873	0.462	0.607
HGB	2.034	9.699	4.735	4.748	75.199	2.317	0.171	1.097
XGB	1.042	1.552	0.323	1.272	94.201	0.515	0.34	0.754
GB	1.018	2.095	0.472	2.008	92.023	0.996	0.567	0.82
Extra Trees	0.654	7.662	0.973	5.065	83.852	1.156	0.349	0.288

Source: *Research findings*

Table b.3. Relative importance of input features for free-market exchange rate prediction under domestic uncertainty specification

Models	input features			
	OIL	**M2**	**INF**	**DU**
DT	4.314	93.298	2.179	0.21
RF	1.183	94.946	1.156	2.715
HGB	3.754	84.903	2.106	9.238
XGB	0.833	95.611	1.846	1.71
GB	1.623	94.66	1.647	2.07
Extra Trees	1.417	74.191	2.421	21.972

Source: *Research findings*

Table a.4. Relative importance of input features for free-market exchange rate prediction under combined specification

Models	input features								
	DU	**EUI**	**GEPU**	**GPR**	**INF**	**M2**	**OIL**	**OPU**	**WUI**
DT	2.88	0.18	1	0.81	1.07	91.53	1.18	0.98	0.32
RF	2.53	0.95	0.54	0.19	0.58	93.26	0.82	0.46	0.64
HGB	6.48	2.38	7.11	3.82	3.87	72	2.39	0.38	1.43
XGB	1.08	0.89	1.72	0.41	1.09	93.17	0.51	0.48	0.62
GB	1.14	1.05	1.05	0.43	1.10	92.86	0.79	0.72	0.82
Extra Trees	18.75	0.19	3.79	0.53	1.61	73.37	1.17	0.23	0.31

Source: *Research findings*

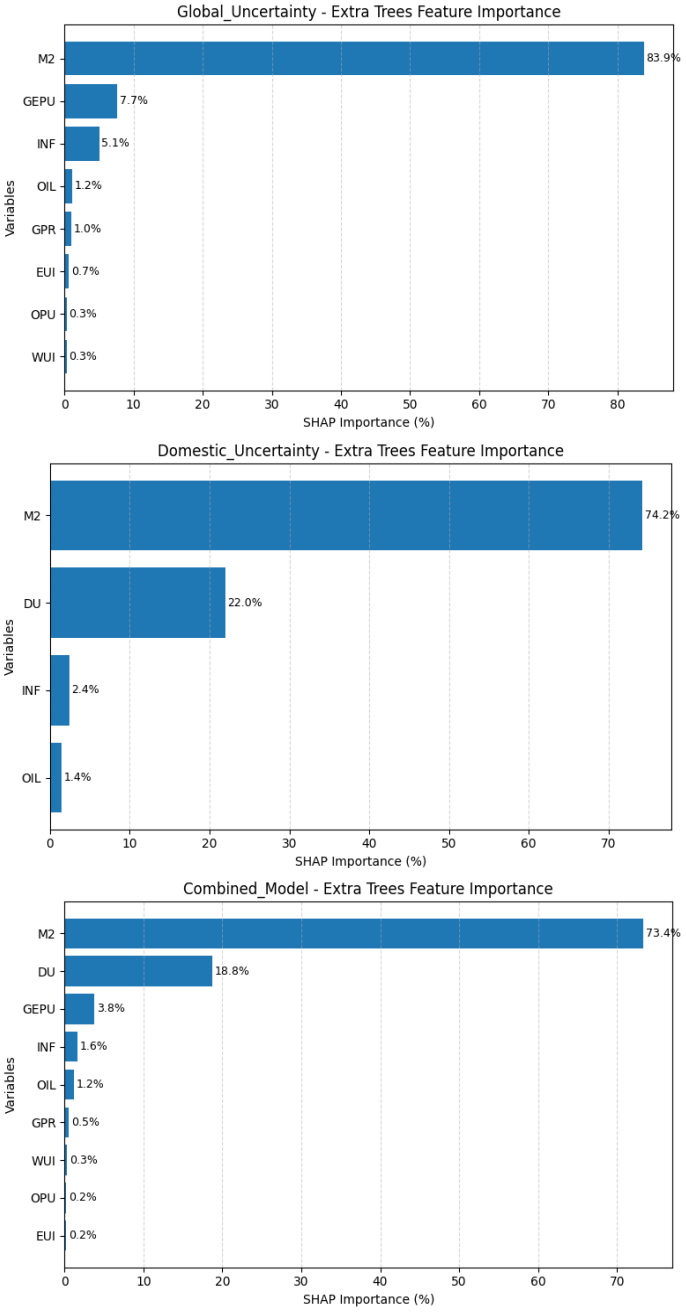

Figure b.1. Relative importance of input features in predicting ΔIER using the Extra Trees model

Source: *Research findings*

From a model interpretability perspective, the SHAP results indicate that the Domestic Uncertainty (DU) index makes a substantial contribution to explaining exchange rate fluctuations in models that include this variable. Specifically, in the Extra Trees model, DU accounts for approximately 21.97% of the SHAP-based feature importance in the domestic uncertainty specification and 18.76% in the combined specification. By contrast, global uncertainty indices make only a limited contribution across most models.

These findings suggest that, although global uncertainty may affect the Iranian economy through channels such as oil prices and international financial conditions, a substantial portion of the uncertainty relevant to the foreign exchange market stems from domestic factors and endogenous fluctuations in key macroeconomic variables, particularly the exchange rate and inflation. Therefore, incorporating a measure of domestic uncertainty alongside global uncertainty indices provides a more comprehensive representation of the mechanisms through which uncertainty is transmitted and enhances our understanding of exchange rate dynamics in Iran.

Appendix C

Robustness Check: Lag Structure and the Mediating Role of Inflation

C-1. Incorporating a Lag Structure

In the initial specification, all explanatory variables were included in the machine learning models contemporaneously. However, monetary theory suggests that the effects of monetary and macroeconomic variables on the exchange rate may occur with a time lag. Accordingly, the revised version of the study incorporates lagged values of the selected explanatory variables.

Specifically, three- and six-month lags were introduced for the money supply (M2) and inflation (INF), while a three-month lag was applied to oil prices (OIL). Following the construction of the lagged variables, observations with missing values arising from the lag structure were removed from the dataset prior to model estimation.

C-2. Reducing Simultaneity Bias

To mitigate potential simultaneity bias, the contemporaneous values of money supply (M2) and inflation (INF) were excluded from the set of explanatory variables, and only their lagged values were retained in the models. This specification allows the models to better capture the temporal relationships between the variables and is more consistent with the gradual transmission of monetary shocks to the exchange rate.

C-3. Time-Based Data Splitting

Because the dataset consists of monthly time-series observations, a random train–test split could allow information from future observations to enter the training process, resulting in data leakage. Therefore, the data were partitioned chronologically, with the first 80% of the observations used for model training and the remaining 20% reserved for out-of-sample evaluation.

C-4. Data Normalization

To prevent data leakage, Min–Max normalization was fitted exclusively to the training set. The scaling parameters derived from the training data were subsequently applied to the test set without modification, ensuring that no information from the test data was used during model training.

C-5. Results After Incorporating the Lag Structure

Following these methodological revisions, all machine learning models were retrained using the revised dataset. Feature importance was then reassessed using the SHAP framework to quantify the contribution of each explanatory variable under the revised model specification.

Table c.1. Performance of tree-based machine learning models (ensemble methods) based on error metrics.

Model	MAE	RMSE	MAPE
Decision Tree	52591.38	82739.55	14.41415
XGBoost	61513.41	90881.15	16.96463
Random Forest	69625.49	99005.23	19.4549
Extra Trees	86378.42	111006.1	25.17375
Gradient Boosting	87624.1	113120.1	25.48623
HistGradient Boosting	152216.6	168659.2	47.4592

Source: Research findings

The results indicate that, across most models, lagged liquidity variables—particularly M2_lag3 and M2_lag6—make the largest contributions to explaining exchange rate fluctuations. For example, in the Decision Tree model, these two variables jointly accounted for approximately 93.7% of the total feature importance. Their combined contribution increased to approximately 97.4% in the Random Forest model and 93.4% in the Gradient Boosting model. Furthermore, in the XGBoost model, M2_lag3 alone accounted for approximately 93.8% of the total feature importance.

In contrast, lagged inflation, oil prices, and indicators of economic and political uncertainty exhibited substantially lower contributions. These findings suggest that, during the study period, the effects of monetary shocks were transmitted to the foreign exchange market primarily with a time lag. Moreover, the incorporation of lagged variables enhances the economic interpretability of the machine learning models compared with specifications based solely on contemporaneous variables.

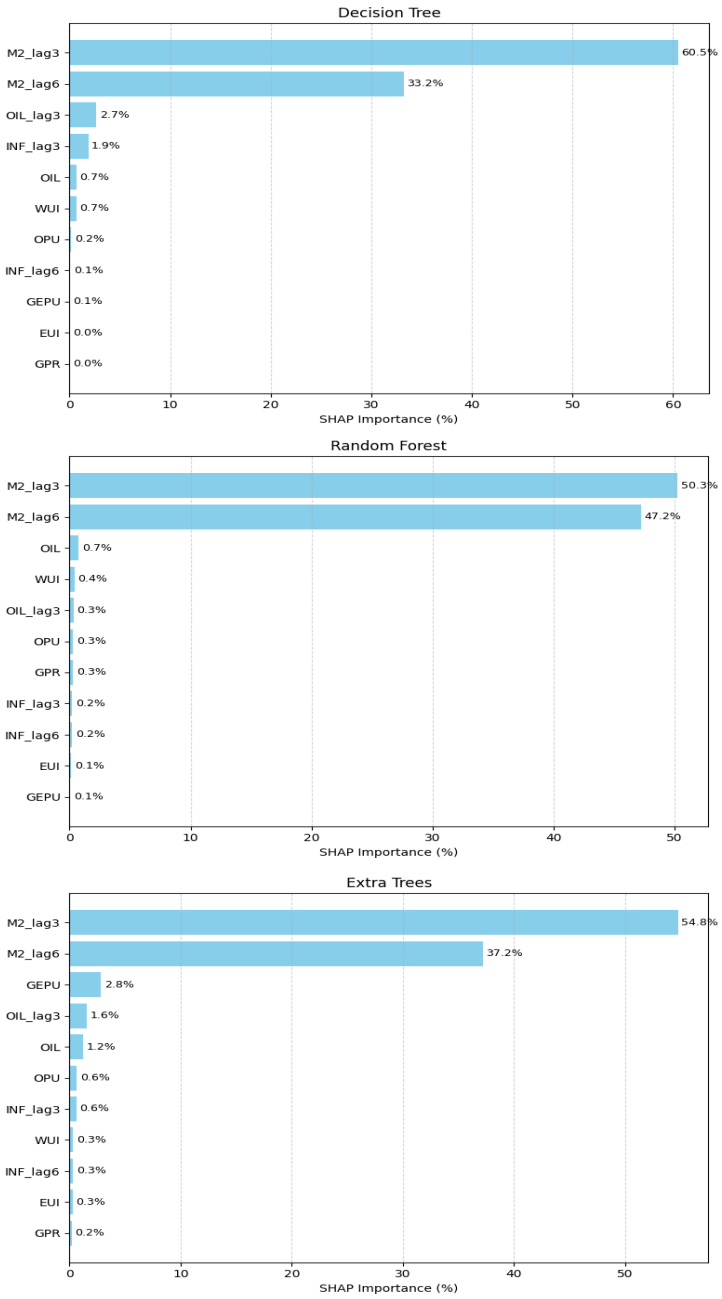

Figure c.1. Relative importance of the input features for the free-market exchange rate across the evaluated machine learning models

Source: *Research findings*

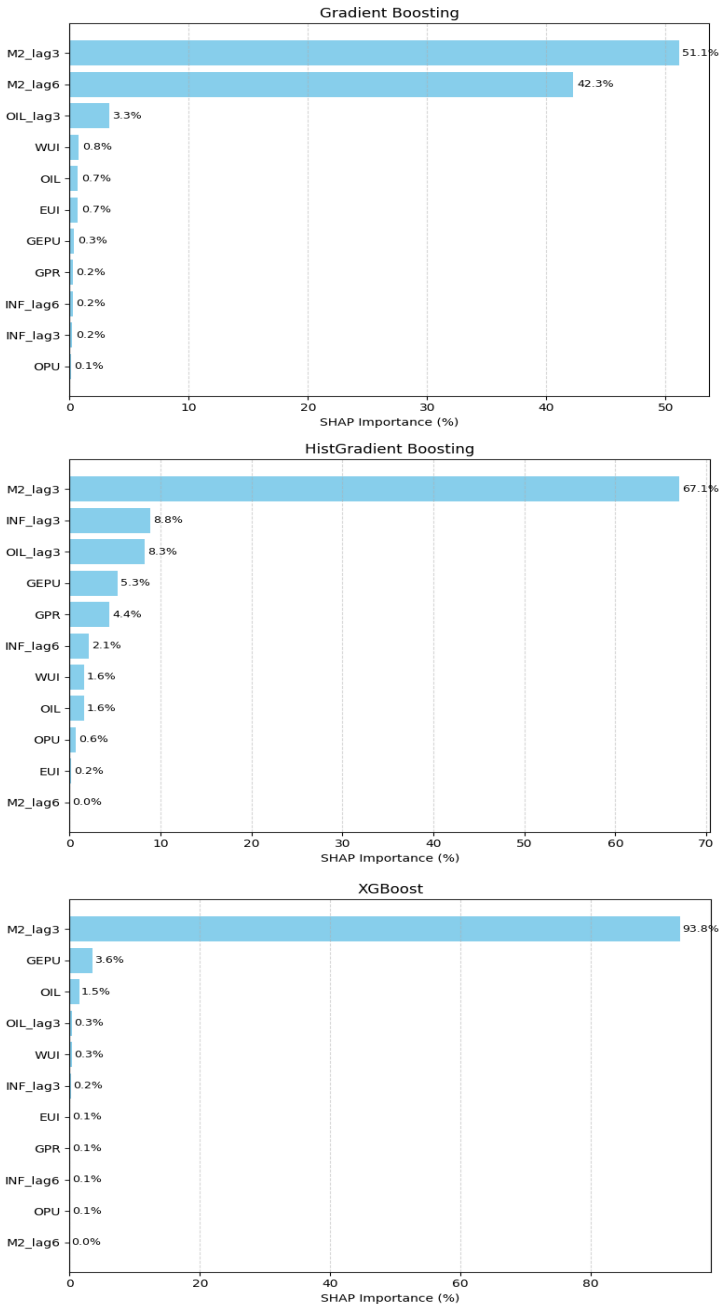

Figure .C.2. Relative importance of the input features for the free-market exchange rate across the evaluated machine learning models

Source: *Research findings*

C-6. Limitation

Despite incorporating a lag structure, it is important to emphasize that the models employed in this study are designed for exchange rate prediction and that the SHAP-based results capture the predictive contributions of the explanatory variables rather than causal relationships. Accordingly, the potential mediating role of inflation is not formally examined in the present study. A rigorous assessment of the direct and indirect effects of liquidity through the inflation channel would require specialized mediation analysis techniques or causal econometric frameworks. Such approaches could provide a valuable avenue for future research.