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POST-1980 EXCHANGE RATE MOVEMENTS IN TÜRKİYE: EMPIRICAL INSIGHTS FROM THE DOLLAR

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Abstract

This paper examines the uncertainty dynamics of the USD/TRY exchange rate over the period from January 1980 to September 2025, a span marked by profound structural transformations in the Turkish economy, recurrent financial crises, regime shifts in exchange rate policy, and deepening integration with global financial markets. Given the central role of the exchange rate in shaping inflationary pressures, external debt sustainability, trade competitiveness, and overall financial stability in Türkiye, an accurate characterization of USD/TRY conditional heteroscedasticity models is of critical importance. The empirical analysis proceeds in two stages. First, the dollar variable is modeled using AR(I)MA specifications. The estimation results indicate that current exchange rate values are influenced by both past exchange rate realizations and random shocks originating in previous periods. In the second stage, the dollar variable is modeled with symmetric (ARCH, ARCH-M, GARCH, and GARCH-M) and asymmetric (EGARCH, TARCH, and PARCH) conditional heteroscedasticity models. Model performance is evaluated using standard information criteria and residual diagnostics. The results provide strong evidence of persistent and asymmetric volatility in the USD/TRY exchange rate. Among the competing specifications, the TARCH model emerges as the preferred framework, highlighting the significance of power effects and asymmetric shock responses in explaining exchange rate uncertainty over the long run. Therefore, it can be stated that the measures that reduce uncertainty, reinforce monetary policy credibility, and mitigate excessive exchange rate pass-through effects are essential for containing volatility and supporting long-term economic stability.

Keywords: *Exchange Rate Uncertainty, Turkish Lira, Conditional Heteroscedasticity Models, TARCH model, Türkiye(Turkey).*

1980 SONRASI TÜRKİYE'DEKİ DÖVİZ KURU HAREKETLERİ: DOLAR TEMELLİ AMPİRİK BULGULAR

Öz

Bu çalışma, Ocak 1980 ile Eylül 2025 arasındaki dönemde, Türkiye ekonomisindeki derin yapısal dönüşümler, tekrarlayan finansal krizler, döviz kuru politikasındaki rejim değişiklikleri ve küresel finans piyasalarıyla derinleşen entegrasyonun damgasını vurduğu bir zaman diliminde, USD/TRY döviz kurunun belirsizlik dinamiklerini incelemektedir. Döviz kurunun enflasyon baskılarını, dış borç sürdürülebilirliğini, ticaret rekabet gücünü ve Türkiye'deki genel finansal istikrarı şekillendirmedeki merkezi rolü göz önüne alındığında, USD/TRY koşullu değişen varyans modellerinin doğru bir şekilde karakterize edilmesi kritik önem taşımaktadır. Ampirik analiz iki aşamada ilerlemektedir. İlk olarak, dolar değişkeni AR(I)MA spesifikasyonları kullanılarak modellenmiştir. Tahmin sonuçları, mevcut döviz kuru değerlerinin hem geçmiş döviz kuru gerçekleşmelerinden hem de önceki dönemlerden kaynaklanan rassal şoklardan etkilendiğini göstermektedir. İkinci aşamada, dolar değişkeni simetrik (ARCH, ARCH-M, GARCH ve GARCH-M) ve asimetrik (EGARCH, TARCH ve PARCH) koşullu değişen varyans modelleriyle modellenmiştir. Model performansı, standart bilgi kriterleri ve teşhis testleri kullanılarak değerlendirilmiştir. Sonuçlar, USD/TRY döviz kurunda kalıcı ve asimetrik oynaklığın güçlü kanıtlarını sunmaktadır. Rakip modeller arasında, TARCH modeli tercih edilen çerçeve olarak ortaya çıkmakta ve uzun vadede döviz kuru belirsizliğini açıklamada güç etkilerinin ve asimetrik şok tepkilerinin önemini vurgulamaktadır. Bu nedenle, belirsizliği azaltan, para politikasının güvenilirliğini güçlendiren ve aşırı döviz kuru geçiş etkilerini hafifleten önlemlerin, oynaklığı kontrol altına almak ve uzun vadeli ekonomik istikrarı desteklemek için gerekli olduğu söylenebilir.

Anahtar Kelimeler: *Döviz Kuru Belirsizliği, Türk Lirası, Koşullu Değişen Varyans Modelleri, TARCH modeli, Türkiye.*

1. INTRODUCTION

The behavior of exchange rates and the determinants of their fluctuations represent a central concern in the study of macroeconomics, reflecting the intricate interplay between domestic economic structures and the global financial environment. Exchange rate dynamics are of particular significance for emerging economies such as Türkiye, where currency volatility has extensive consequences for inflation, trade balances, capital flows, and investment decisions. In these contexts, the exchange rate exhibits a dual character: while excessive volatility can obstruct macroeconomic stability and impede sustainable growth, a well-managed currency can act as a powerful catalyst for economic development. Understanding the evolution of the Turkish exchange rate therefore requires an integrated analysis of theoretical, historical, and policy-driven dimensions. The theoretical framework of exchange rate determination provides insight into the mechanisms through which currency fluctuations affect economic outcomes. Exchange rate movements fundamentally alter the relative prices of domestically produced versus foreign-produced goods and services, thereby affecting competitiveness, trade balances, and domestic price levels. Changes in these relative prices trigger a cascade of effects on production, inflation, and interest rates, with implications for both short-term macroeconomic stability and long-term growth (Manalo et al., 2015). Currency depreciation, in particular, denotes a reduction in the domestic value of a currency relative to foreign currencies and is often associated with heightened inflationary pressures, trade disruptions, and challenges to financial stability (Ullah & Nobanee, 2025). As such, investigating the drivers and consequences of exchange rate volatility is not only an academic endeavor but also a practical necessity for policy formulation and economic management.

The evolution of the international monetary system provides crucial context for understanding contemporary exchange rate behavior. The collapse of the Bretton Woods system in 1973, which marked the abandonment of fixed exchange rates in favor of market-determined regimes, fundamentally transformed global finance, hence, this shift introduced a permanent element of volatility, as exchange rates became increasingly sensitive to both domestic policy decisions and international financial flows for emergent economies (Kilicarslan, 2018). The structure of the International Monetary System, concentrated around one or two dominant currencies, further exacerbates these vulnerabilities. While centralization in a few currencies can reduce transaction costs and enhance liquidity, it creates structural misalignments with the multipolar distribution of global economic power, generating systemic risks for countries whose economic cycles and policy needs diverge from those of major currency issuers (Zhou, 2009). Türkiye's repeated exposure to external shocks illustrates the tangible effects of these systemic vulnerabilities, emphasizing the interdependence between global monetary structures and national economic stability.

Within the national context, the historical trajectory of the Turkish economy provides key insights into the determinants of exchange rate fluctuations. Analytically, the periodization into pre-1980 and post-1980 eras is particularly informative. The pre-1980 period, characterized by import-substitution industrialization policies, limited integration with global markets, and stringent exchange rate controls, contrasts sharply with the post-1980 era of liberalization, trade openness, and financial deregulation (Turan, 2005). The post-1980 reforms marked a decisive break from protectionist policies, with comprehensive measures to liberalize goods and capital markets, incentivize exports, and align industrial development with global competitiveness (Yeldan, 2001). Exchange rate flexibility became a strategic instrument, allowing currency movements to influence industrial orientation while maintaining policy tools for broader economic stabilization. This liberalization was not limited to trade but extended to financial markets, reflecting a holistic approach to integration with the global economy. The deregulation of capital flows, culminating in the removal of Law No. 32 in 1989, facilitated the movement of international finance and exposed the Turkish economy to both new opportunities and risks associated with global capital dynamics (Sever, 2012). The structural transformation reshaped the real and financial sectors, creating an economy more open, competitive, and susceptible to volatility. The post-1980 era thus embodies a paradox of economic liberalization: while it opened avenues for growth and modernization, it also increased the economy's vulnerability to internal imbalances and external shocks.

The historical record of economic crises in Türkiye illustrates the consequences of this delicate balance. The 1994 crisis, for instance, emerged amid declining GNP growth below 2%, persistently high inflation exceeding 60%, and growing public sector deficits (Kazgan, 2006). Policy responses centered on devaluation and fiscal stabilization measures, underscoring the challenges of maintaining monetary and financial stability in a liberalizing environment. The 2001 crisis, among the most severe in modern Turkish history, arose from a combination of domestic economic mismanagement and political instability, necessitating an IMF-supported stabilization program and leading to a paradigm shift in exchange rate policy toward a floating regime (Yalçıner, 2024). The shift aimed to buffer the currency against shocks but simultaneously increased exposure to market sentiment and global financial volatility, illustrating the trade-offs inherent in open-economy policy frameworks. External shocks have further shaped Türkiye's exchange rate trajectory. The 2008 global financial crisis, originating in the United States and spreading worldwide, exemplifies how global disturbances can affect emerging economies, reducing capital inflows, constraining growth, and exacerbating volatility (Verick & Islam, 2010). The interplay between domestic vulnerabilities and international shocks highlights the interconnectedness of national and global financial systems, emphasizing that the management of exchange rate volatility requires consideration of both domestic policy design and external conditions.

Another significant development in this trajectory was the currency shock experienced in 2018. This shock had far-reaching consequences for the Turkish economy, reflecting the structural vulnerabilities associated with dependence on external capital inflows and access to low-cost credit sources. When global financial conditions tightened in 2018, Türkiye emerged as one of the emerging markets most affected, experiencing severe pressure on its currency and financial system (Akçay & Güngen, 2019). Keyder (2022) further emphasizes that this period marked the continuation of a domestic crisis, characterizing it as a global-scale phenomenon. The combination of reduced investment confidence, a deteriorating trust environment, and heightened exposure to external financing constraints culminated in a "foreign exchange and debt crisis." The onset of the COVID-19 pandemic in 2020 exacerbated these vulnerabilities, amplifying the economic strain and underscoring the persistence of the economic downturn that began in 2018. Collectively, these developments highlight the interconnection between domestic structural weaknesses, global financial conditions, and the susceptibility of the Turkish economy to compounded external shocks. Volatility in the exchange rate is not merely a monetary phenomenon; it functions as a structural determinant of economic welfare and industrial performance. Fluctuations in the Turkish Lira influence competitiveness, export orientation, investment decisions, and industrial output, reflecting the centrality of currency management in broader macroeconomic strategy (Yeldan, 2001). Moreover, the synchronization observed between exchange rate changes and national income growth suggests that currency stability is a critical factor in sustaining long-term development trajectories, particularly in an open, export-oriented economic environment.

Given this complex interplay of historical, domestic, and international factors, a comprehensive analysis of exchange rate volatility in Türkiye requires a long-term perspective. This study examines the interval from 1980:01 to 2025:09, encompassing all major economic crises, periods of liberalization, integration into global financial systems, and external shocks. By analyzing this extensive period, the study seeks to isolate persistent trends in exchange rate behavior from transient fluctuations, offering both historical insight and policy-relevant conclusions. The structure of the study reflects this integrated approach. In accordance with these aims, we use ARCH/GARCH family models that dynamically address exchange rate volatility following AR(I)MA specifications. These models can model volatility using conditional variance, taking into account both the magnitude and direction of exchange rate shocks; in particular, TARCH, EGARCH, and PARCH models can capture asymmetric effects in volatility.

Following this introduction, the second section provides a review of the literature on exchange rate dynamics. The third section outlines the methodological framework employed, detailing the econometric approaches and analytical tools used to assess volatility. Subsequent sections present empirical findings, identifying trends and determinants of exchange rate fluctuations, while the final section synthesizes the results, offering interpretation and policy recommendations grounded in both historical and quantitative analysis. Through this comprehensive approach, the study contributes to a deeper understanding of the dynamics of the Turkish exchange rate, situating national experiences within the broader global financial system, and highlighting the intricate connections between currency movements, macroeconomic performance, and policy choices.

2. LITERATURE REVIEW

Exchange rate movements have garnered significant attention in academic research due to their far-reaching implications for economic activity, as well as their central role in the functioning of international trade. As a critical determinant of trade balances, investment flows, and overall macroeconomic stability, exchange rates are considered a key variable in understanding the dynamics of open economies. Consequently, a wide array of studies has been conducted to analyze the factors driving exchange rate fluctuations and to understand the extent and causes of exchange rate volatility across different countries. These efforts aim to enhance the understanding of exchange rate behavior and to inform policy decisions that address the economic challenges posed by exchange rate instability. One of the studies to understand the volatility of exchange rate is carried out by Karuthedath & Shanmugasundaram (2012), which stated that understanding the volatility of the Indian Rupee against the US Dollar over a long-term horizon is crucial for analyzing the behavior of exchange rates under structural changes. Using daily data from 1973 to 2012, it is applied both symmetric GARCH (1,1) and asymmetric models such as EGARCH and TGARCH, finding that volatility is highly persistent and the leverage effect is more pronounced in the post-LERMS period following India's liberalization in 1993. This finding suggests that market liberalization can increase exchange rate volatility and asymmetry.

Building upon the importance of capturing non-linear patterns in exchange rate volatility, the study by Lahmiri (2017) emphasizes the predictive power of artificial neural networks (ANN) when combined with technical indicators. The study applies ANN to forecast US/Canada and US/Euro exchange rate volatility and reports that this simple hybrid approach outperforms conventional GARCH and EGARCH models in terms of mean absolute error and Theil's inequality coefficient. This indicates that integrating machine learning methods can improve volatility prediction accuracy.

Similarly, a comprehensive study on seven major currencies conducted by Alexandridis et al. (2024) highlights the role of both financial and macroeconomic variables in forecasting future volatility. This research employs linear models, machine learning techniques, and forecast combination approaches, concluding that amalgamated forecasts produce superior predictive performance. Additionally, wavelet analysis allowed for the extraction of frequency-related information, emphasizing the importance of time-scale decomposition in capturing volatility dynamics.

Moreover, Qona'ah (2023) examines USD/GBP exchange rate volatility using ARIMA and GARCH-type models, finding that EGARCH (1,1) performs best in out-of-sample forecasting. The results show that the asymmetric EGARCH model better captures patterns of volatility, highlighting the importance of accounting for leverage effects in exchange rate modeling.

Furthermore, in the research conducted by Havi (2019) for GHC/USD, it is suggested that the series correlation in the yield series significantly affects volatility modeling. The study compares multiple models including GARCH, TARCH, EGARCH, PARCH, and APARCH, ultimately selecting ARMA (3,3)-TARCH (2,1)-GED as appropriate. The results emphasize that ignoring serial correlation could lead to biased and inefficient parameter estimates, and that previous information on volatility has significant effects on current-day volatility.

Research on Turkish currency pairs (USD/TRY and EUR/TRY) by Almisshal & Emir (2021) further confirms the superiority of combining symmetric and asymmetric GARCH models. While GARCH (1,1) and GJR-GARCH (1,1) are found most suitable for USD/TRY, PGARCH (1,1) complements EUR/TRY modeling. These findings also indicate that static forecasting using GJR-GARCH (1,1) produces the most accurate predictions.

In a study of the Naira-Yuan interbank market, Abdullahi (2025) applies multiple asymmetric models including GJR-GARCH, APARCH, and PARCH to assess volatility following a currency swap agreement. The asymmetric PARCH model outperforms others in capturing leverage effects and market dynamics, highlighting the relevance of accounting for asymmetry in policy-sensitive exchange rate environments.

Chinese exchange rate behavior is analyzed through a GARCH model augmented with a jumping process by Liu et al. (2023), revealing that including jumps allows better representation of thick tails and volatility clustering. The study demonstrates that models with double exponential jumps more accurately capture return fluctuations, providing practical tools for risk management.

Furthermore, Dritsaki (2019) studies the Euro/USD exchange rate using ARIMA-EGARCH models with various error distributions. The findings indicate that ARIMA (0,0,1)-EGARCH (1,1) with generalized error distribution effectively captures leverage effects and provides superior static forecasting results. Similarly, in the Khmer Riel/USD exchange rate context, the ARIMA (3,0,3) model is identified as the best-fitting model, with significant impulse response patterns confirming the reliability of forecasted volatility by Ky (2025).

A panel study of nineteen Arab countries investigated by Abdalla (2012) finds that for ten currencies, GARCH (1,1) indicates explosive volatility, while for seven currencies, volatility remains persistent and mean-reverting. Asymmetrical EGARCH (1,1) reveals significant leverage effects for most currencies, emphasizing that negative shocks increase subsequent volatility more than positive shocks.

Additionally, Wang (2021) highlights that the exchange rate is crucial for global financial markets, yet the impacts of search index on volatility have been largely overlooked. By integrating a search index into Heterogeneous Autoregressive (HAR) models, the study finds that the new model outperforms the original in forecasting efficiency. While RMB/USD daily volatility is unaffected by RMB indices, USD has a negative impact on daily realized volatility. Weekly and monthly models indicate significant contributions from search indexes, suggesting that these factors can help investors better understand market dynamics.

A study on nine ASEAN member countries by Kongwiriyapisal (2023) applies five forms of GARCH models using daily data from October 2018 to October 2022. Among the currencies analyzed, GARCH (1,1), TGARCH (1,1), and PGARCH (1,1) are found most appropriate, with leverage effects observed at certain exchange rates. The study emphasizes the importance of monitoring relevant news for investors and maintaining up-to-date policy measures to stabilize exchange rates.

Research focusing on Nigeria, Ghana, Niger, Gambia, and Sierra Leone by Maihulla et al. (2025) examines exchange rate volatility from 1999 to 2022 using both traditional time series models (ARIMAX, GARCH) and machine learning techniques (LSTM, hybrid models). The study finds that in conventional models current volatility is influenced by previous performance, but the hybrid ARIMAX-LSTM model achieves lower mean squared error, highlighting the superior predictive performance of combining econometric and machine learning approaches.

Furthermore, Bosnjak et al. (2016) analyze EUR and USD against HRK from 1997 to 2015 using several ARCH models. The findings reveal that GARCH (2,1) best fit the EUR/HRK, while GARCH (1,1) best describes USD/HRK daily volatility. No significant differences are observed between the impacts of positive and negative shocks, suggesting symmetric responses in these markets.

A study on USD/KES exchange rates by Omari et al. (2017) applies both symmetric and asymmetric GARCH models to daily data from 2003 to 2015. The results show that asymmetric models such as EGARCH (1,1), GJR-GARCH (1,1), and APARCH (1,1) with Student's t-distribution provide the most accurate estimation of volatility, capturing stylized facts like volatility clustering and leverage effects.

The hybrid NN-MS Beta-t-EGARCH model is proposed by Liao et al. (2020) to enhance forecasting of advanced and emerging market currencies. By combining neural networks with Markov-switching EGARCH, the study demonstrates improved in-sample and out-of-sample forecasts compared to traditional volatility models, addressing nonlinear and time-varying characteristics of exchange rates.

Additionally, Friedman & Vandersteel (1982) examine the statistical properties of daily foreign exchange rate changes for nine currencies and find that these changes are distinctly leptokurtotic, exhibiting sharp peaks and long tails. The study shows that such leptokurtosis does not stem from a Paretian stable distribution or a stationary mixture of normal distributions, but rather from normal processes with time-varying parameters. This casts doubt on the validity of many standard techniques, such as t-statistics and ARIMA models, and the paper also proposes moving statistics for estimating these time-varying parameters.

Rapach & Strauss (2008) examine the importance of structural breaks in GARCH models of exchange rate volatility. Evidence indicates that accounting for structural breaks improved both in-sample and out-of-sample accuracy, highlighting the instability of GARCH processes across different periods.

A study on TZS/USD exchange rates in Tanzania by Epaphra (2017) applies ARCH, GARCH, and EGARCH models to capture clustering, nonstationarity, and leverage effects. Results indicate that past volatility influences current volatility, and positive shocks tend to generate higher subsequent conditional variance, emphasizing the policy relevance of accurate volatility forecasting.

Finally, research on EUR/USD realized volatility conducted by Plíhal & Lyócsa (2021) using HAR models augmented with implied volatilities finds that short-term option-implied volatilities better predicted future daily, weekly, and monthly volatility compared to historical realized volatility alone. The study also highlights the benefits of combining forecasts for improved predictive accuracy during periods of high volatility.

3. EMPIRICAL METHODOLOGY

3.1. AR(I)MA Models and Box & Jenkins Methodology

An ARIMA (p, d, q) model for a time series $\mathrm{Y_t}$ can be expressed in polynomial form as equation (1):

$$\Phi(\mathrm{L})(1-\mathrm{L})^{\mathrm{d}}(\mathrm{Y_t}-\mu_{\mathrm{t}}) = \Theta(\mathrm{L})\varepsilon_{\mathrm{t}} \qquad (1)$$

Where L denotes the lag operator, with $\Phi(\mathrm{L}) = 1 - \phi_1\mathrm{L} - \phi_2\mathrm{L}^2 - \cdots - \phi_{\mathrm{p}}\mathrm{L}^{\mathrm{p}}$ and $\Theta(\mathrm{L}) = 1 + \theta_1\mathrm{L} + \theta_2\mathrm{L}^2 + \cdots + \theta_{\mathrm{q}}\mathrm{L}^{\mathrm{q}}$ representing the lag polynomials. Additionally, μ_{t} is the intercept term, and ε_{t} is the error term. The methodology proposed by Box & Jenkins (1976) is widely employed to identify the most suitable ARIMA data generation process for empirical data. The core steps of this approach can be structured into four categories: i) Specification of the time series model [e.g., AR(p), MA(q), ARIMA(p, d, q)], ii) Estimation of the model's parameters, iii) Evaluation of model adequacy through diagnostic tests, and iv) Application of the model for forecasting purposes (Sevüktekin & Çınar, 2014:188–214).

3.2. Conditional Heteroscedasticity Models

The assumption of constant error term variance over time (homoscedasticity) in linear regression models is often challenged in models involving financial time series such as exchange rates, inflation rates, and interest rates (heteroscedasticity). Indeed, Engle (1982) demonstrates that the error term variance is not constant in a study using UK inflation data. This approach, which abandons the constant variance assumption in traditional time series models by allowing the error term variance to depend on the squares of previous error terms, is known in the literature as the autoregressive conditional heteroscedasticity (ARCH) model (Çil Yavuz, 2015:433–434). Engle (1982) emphasizes the necessity of detecting the presence of ARCH effects (or conditional heteroscedasticity) through the ARCH-LM test before initiating to model heteroscedasticity. Conditional heteroscedasticity models are typically categorized into two types: symmetric and asymmetric. Symmetric models assume that positive and negative news affecting the market have equal impacts on volatility; in contrast, asymmetric models are grounded in the observation that negative shocks (negative news) tend to increase volatility more significantly than positive shocks (positive news) due to the leverage effect. Among symmetric models, the ARCH model introduced by Engle (1982), the generalized ARCH (GARCH) model developed by Bollerslev (1986), the ARCH in Mean (ARCH-M) and the GARCH in Mean (GARCH-M) models developed by Engle et al. (1987) are included. Asymmetric models encompass the exponential GARCH (EGARCH) model developed by Nelson (1991), the threshold ARCH (TARCH) model introduced by Glosten et al. (1993), and the power ARCH (PARCH) model developed by Ding et al. (1993) (Çil Yavuz, 2015:436–467).

The conditional variance equations and characteristics of symmetric and asymmetric models, where the error term $\varepsilon_t \sim N(0, \sigma_t^2)$ and the conditional variance σ_t^2, are explained below:

For ARCH(p) and ARCH(p)-M,

$$\sigma_t^2 = c + \sum_{k=1}^{p} \alpha_k \varepsilon_{t-k}^2 \qquad (2)$$

In equation (2), it is observed that the conditional variance of the ARCH(p) and ARCH(p)-M models depends on the squared error terms from previous periods.

For GARCH (p, q) and GARCH (p, q)-M,

$$\sigma_t^2 = c + \sum_{k=1}^{p} \alpha_k \varepsilon_{t-k}^2 + \sum_{m=1}^{q} \beta_m \sigma_{t-m}^2 \qquad (3)$$

In equation (3), it is evident that the conditional variance of the GARCH (p, q) and GARCH (p, q)-M models depend not only on the squared error terms from previous periods but also on the lagged values of the conditional variance itself. This characteristic makes these models superior to ARCH and ARCH-M models, as the inclusion of lagged conditional variance values as part of the model specification allows for more accurate volatility forecasting.

For EGARCH (p, q),

$$\ln(\sigma_t^2) = c + \sum_{k=1}^{p} \alpha_k \left|\frac{\varepsilon_{t-k}}{\sigma_{t-k}}\right| + \sum_{m=1}^{q} \beta_m \ln(\sigma_{t-m}^2) + \sum_{n=1}^{r} \theta_n \frac{\varepsilon_{t-n}}{\sigma_{t-n}} \qquad (4)$$

In equation (4), it is noted that the logarithm of the conditional variance is modeled for the EGARCH (p, q) model. This feature ensures that the non-negativity condition is directly satisfied, making it one of the most significant advantages of the EGARCH model over the GARCH model. The terms $\varepsilon_{t-k} / \sigma_{t-k}$ and $\varepsilon_{t-n} / \sigma_{t-n}$ in the conditional variance equation represent standardized error terms. The use of standardized errors instead of past error values in the EGARCH model provides information about the magnitude and persistence of shocks. The variable $\varepsilon_{t-n} / \sigma_{t-n}$, which is related to the parameter θ_n, imparts an asymmetric property to the EGARCH model. The parameter θ_n is defined as the asymmetric leverage coefficient, which quantifies the volatility leverage effect. This parameter typically takes negative values. In this context, if the negative θ_n parameter is statistically significant, it indicates that positive shocks cause less volatility compared to negative shocks. In other words, if θ_n is less than zero, the leverage effect is present.

For TARCH (p, q),

$$\sigma_t^2 = c + \sum_{k=1}^{p} \alpha_k \varepsilon_{t-k}^2 + \sum_{m=1}^{q} \beta_m \sigma_{t-m}^2 + \sum_{n=1}^{r} \theta_n \varepsilon_{t-n}^2 I_{t-n} \qquad (5)$$

In equation (5), the conditional variance equation for the TARCH (p, q) model is presented. The TARCH model is constructed by adding a variable that accounts for positive asymmetry to the GARCH model. Here, ε_t represents shocks occurring in financial markets, while I_{t-n} denotes a dummy (indicator) variable that takes the value 1 or 0 depending on whether the shocks are positive or negative. Specifically, if $\varepsilon_{t-n} < 0$ (negative news), $I_{t-n} = 1$; otherwise (positive news), $I_{t-n} = 0$. For the conditional variance to remain positive, the conditions $c > 0, \alpha_k \geq 0, \alpha_k + \theta_n \geq 0$ and $\beta_m \geq 0$ must be satisfied. Additionally, it was previously stated that the effects of positive and negative news on conditional variance differ. As seen in equation (5), the effect of positive news on conditional variance is captured by α_k, while the effect of negative news is represented by $\alpha_k + \theta_n$. The leverage effect is associated with the parameter θ_n, and the condition $\theta_n \neq 0$ signifies asymmetry. If $\theta_n > 0$ and the parameter is statistically significant, the leverage effect is present.

For PARCH (p, q),

$$\sigma_t^\delta = c + \sum_{k=1}^{p} \alpha_k \left(|\varepsilon_{t-k}| - \gamma_k \varepsilon_{t-k}\right)^\delta + \sum_{m=1}^{q} \beta_m \sigma_{t-m}^\delta \qquad (6)$$

Finally, in equation (6), the upper parameter δ of the PARCH(p, q) model is greater than zero ($\delta > 0$) and can be estimated within the model framework, unlike in previous models. The presence of asymmetric effects in the model depends on the parameter γ being different from zero ($\gamma \neq 0$). If $\delta = 2$ and $\gamma_k = 0$ for all k, the PARCH model reduces to the standard GARCH model (Çil Yavuz, 2015:461–465; Ding et al., 1993; Sarıkovanlık et al., 2019:149–153).

4. DATA AND EMPIRICAL ANALYSIS

4.1. Data and Unit Root Test Results

This study aims to investigate the exchange rate volatility of the Turkish lira using a monthly dataset spanning the period from January 1980 to September 2025, sourced from the CBRT electronic data delivery system. The dataset is structured to ensure temporal continuity and empirical relevance, reflecting historical exchange rate dynamics. Table 1 provides an overview of the variables included in the analysis; variable names, variable abbreviations and detailing their definitions. This systematic presentation of variables ensures clarity in the conceptual framework and facilitates reproducibility, aligning with methodological rigor in empirical research. The DOLLAR series is seasonally adjusted by using the Tramo/Seats method.

Table 1. Variables Used in the Study

Variable Name	Variable Abbreviation	Variable Definition
Dollar Rate	DOLLAR	USA Dollar (Foreign Exchange Selling Rate) (% Change)
Dollar Rate Uncertainty	CV-DOLLAR	The dollar rate uncertainty is the conditional variance series obtained as a result of TARCH modelling of the dollar rate.

To assess stationarity, the Augmented Dickey-Fuller (ADF) test is applied to all variables, considering three standard model specifications: intercept-only, intercept-and-trend, and no intercept/trend. This approach ensures robustness by accounting for potential structural components such as deterministic trends and level shifts. The results in Table 2 confirm that all variables are stationary [I(0)] at the 1% significance level across all model configurations. This uniformity in findings across different specifications strengthens the validity of the stationarity conclusion. The 1% significance level further underscores the statistical rigor, providing strong evidence against the presence of unit roots, which is critical for subsequent econometric analyses.

Table 2. ADF Unit Root Test Results (Level)

Variable	Model without Intercept and Trend	Model with Intercept, without Trend	Model with Intercept and Trend
DOLLAR	-5.674006* (0.0000)**	-15.95707* (0.0000)**	-17.41860* (0.0000)**
CV-DOLLAR	-13.85359* (0.0000)**	-14.11178* (0.0000)**	-14.11616* (0.0000)**
Notes: * and ** denote t-statistics and p-values, respectively.			

4.2. Model Estimations and Comparative Analysis

In this study, the DOLLAR variable is initially modeled using an autoregressive moving average [ARMA (p, q)] framework to capture the temporal dependencies inherent in exchange rate dynamics. The maximum likelihood estimation (MLE) method is employed to ensure robust parameter estimation, as it provides efficient and consistent estimates under standard regularity conditions. The empirical results of the ARMA (p, q) model, including coefficient estimates, standard errors, and diagnostic statistics, are systematically presented in Table 3.

Table 3. ARMA Model for the Dollar

C	2.9771 (0.0103)*
AR(1)	0.9890 (0.0000)*
MA(1)	-0.6108 (0.0000)*
MA(2)	-0.3361 (0.0000)*
Diagnostic Tests	
R^2	0.1698
$\overline{R}^2$	0.1637
F-Statistics	27.8101 (0.0000)*
AIC	6.0379
SIC	6.0771
SSR	13212.62
LR	-1652.402
Q-Statistics	Insignificant [1-36]*
ARCH-LM Test	[1]* (0.0000)*
Notes: (…)* and […]* denote p or $p-\chi^2$(in the ARCH-LM test) values and lag levels, respectively.	

The empirical results presented in Table 3 indicate that the DOLLAR variable is statistically explained by the AR(1), MA(1), and MA(2) components at the 1% significance level, highlighting the significant contribution of these lags in capturing the dynamics of exchange rate volatility. Additionally, the intercept term (C) is found to be statistically significant at the 5% level. The overall significance of the F-statistics further supports the model's ability to explain the variation in the DOLLAR variable and the R^2 is 0.1698. The Q-statistics, which tests for residual autocorrelation, is found to be insignificant, confirming the absence of autocorrelation in the residuals. To investigate the presence of heteroscedasticity, the ARCH-LM test is conducted, which serves as a critical diagnostic tool for identifying ARCH effects—a prerequisite for modeling conditional heteroscedasticity. The test's significance at the 1% level strongly suggests the presence of ARCH effects in the residuals, implying that the volatility of the DOLLAR variable is not constant over time but rather exhibits time-varying characteristics. This finding necessitates the use of conditional heteroscedasticity models to better capture the dynamic nature of exchange rate fluctuations.

To address this, seven conditional heteroscedasticity models—four symmetric (ARCH, ARCH-M, GARCH, and GARCH-M) and three asymmetric (EGARCH, TARCH, and PARCH)—are estimated for the DOLLAR variable. These models account for both symmetric and asymmetric responses to shocks, reflecting the potential for volatility clustering and leverage effects in financial time series. The maximum likelihood estimation method is employed in all model specifications to ensure robust and efficient parameter estimation. The results of these models are systematically presented in Table 4, providing a comprehensive analysis of the volatility dynamics of the DOLLAR variable.

In the academic literature, the selection of the optimal conditional heteroscedasticity model among the various specifications (e.g., ARCH, GARCH, EGARCH, etc.) is typically guided by a combination of information criteria and statistical tests. The Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC), which balance model fit and complexity, are widely used to identify the model with the smallest values for these criteria. Additionally, the Likelihood Ratio (LR) test is employed to assess the relative fit of nested models, with the model exhibiting the largest LR statistic being preferred. However, these criteria are complemented by the significance of model parameters and the absence of diagnostic issues such as autocorrelation or heteroscedasticity in residuals, which are critical for ensuring the validity and robustness of the model.

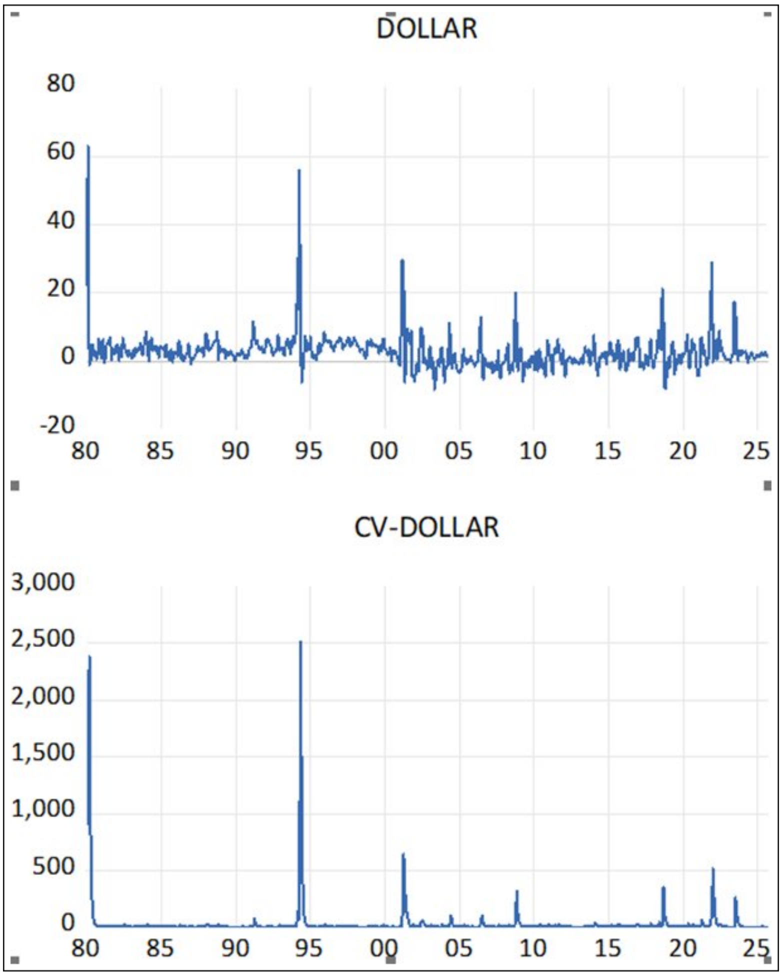
In the context of model selection for conditional heteroscedasticity analysis as it is represented in Table 4, the TARCH model is identified as the optimal specification based on the evaluation of key diagnostic criteria. The Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC), which balance model fit and parsimony, are critical for identifying the most efficient model. The TARCH model exhibits the smallest AIC (5.1295) and SIC (5.1923) values among all estimated specifications, indicating superior explanatory power while maintaining simplicity. Furthermore, the Likelihood Ratio (LR) statistic for the TARCH model (-1397.472) ranks second-highest, placing it closely behind the PARCH model (-1397.090), which underscores its relative robustness in capturing volatility dynamics. Diagnostic assessments further support the TARCH model's validity. Both the TARCH and PARCH models exhibit statistically insignificant Q-statistics, confirming the absence of residual autocorrelation and aligning with the assumption of independence in time-series analysis. Additionally, the TARCH model demonstrates no evidence of ARCH effects, as the residual variance is consistently modeled without conditional heteroscedasticity. This is complemented by the significance of the conditional variance equation parameters at the 1% level of confidence.

Table 4. Conditional Heteroscedasticity Models for the Dollar

	ARCH	ARCH-M	GARCH	GARCH-M	EGARCH	TARCH	PARCH
Mean Equation							
C	-2.8542 (0.3703)*	2.0873 (0.0000)*	-1.0679 (0.6637)*	-27.2938 (0.1724)*	3.2934 (0.0000)*	2.9564 (0.0000)*	2.7969 (0.0000)*
AR(1)	0.9928 (0.0000)*	-0.5810 (0.0000)*	0.9935 (0.0000)*	0.9989 (0.0000)*	0.8999 (0.0000)*	0.9209 (0.0000)*	0.9264 (0.0000)*
MA(1)	-0.7850 (0.0000)*	1.1278 (0.0000)*	-0.5888 (0.0000)*	-0.5866 (0.0000)*	-0.4276 (0.0000)*	-0.4195 (0.0000)*	-0.4338 (0.0000)*
MA(2)	-0.1566 (0.0000)*	0.3615 (0.0000)*	-0.3575 (0.0000)*	-0.3614 (0.0000)*	-0.1401 (0.0049)*	-0.2890 (0.0000)*	-0.2960 (0.0000)*
σ_t^2		-0.0240 (0.0000)*		-0.0098 (0.2372)*			
Conditional Variance Equation							
C	5.1778 (0.0000)*	6.1688 (0.0000)*	2.6632 (0.0000)*	2.8743 (0.0000)*	0.1884 (0.0023)*	3.1964 (0.0000)*	5.6966 (0.1843)*
ε_{t-k}^2	0.9473 (0.0000)*	0.7488 (0.0000)*	0.6722 (0.0000)*	0.7271 (0.0000)*		1.1179 (0.0000)*	
σ_{t-m}^2			0.3157 (0.0000)*	0.2776 (0.0000)*		0.3281 (0.0000)*	
$\left\|\frac{\varepsilon_{t-k}}{\sigma_{t-k}}\right\|$					0.5847 (0.0000)*		
$\ln(\sigma_{t-m}^2)$					0.7395 (0.0000)*		
$\frac{\varepsilon_{t-n}}{\sigma_{t-n}}$					0.3252 (0.0000)*		
$\varepsilon_{t-n}^2 I_{t-n}$						-1.0382 (0.0000)*	
$(\|\varepsilon_{t-k}\| - \gamma_k \varepsilon_{t-k})^\delta$							0.4940 (0.0000)*
σ_{t-m}^δ							0.2655 (0.0012)*
ε_{t-k}							-0.5088 (0.0000)*
δ							2.5642 (0.0008)*
Diagnostic Tests							
R^2	0.1290	0.3043	0.1661	0.1622	0.1203	0.1430	0.1463
$\bar{R}^2$	0.1242	0.2992	0.1615	0.1560	0.1155	0.1383	0.1416
AIC	5.2345	5.2787	5.1842	5.1851	5.1587	5.1295	5.1317
SIC	5.2817	5.3337	5.2392	5.2479	5.2216	5.1923	5.2024
SSR	13519.60	10798.25	12943.46	13005.16	13654.85	13301.92	13251.11
LR	-1428.266	-1439.364	-1413.458	-1412.705	-1405.496	-1397.472	-1397.090
Q-Statistics	Significant [1-36]*	Significant [1-36]*	Significant [1-36]*	Significant [1-36]*	Significant [1-36]*	Insignificant [1-36]*	Insignificant [1-36]*
ARCH-LM Test	[1]* (0.6733)*	[1]* (0.6136)*	[1]* (0.8172)*	[1]* (0.9096)*	[1]* (0.7118)*	[1]* (0.8392)*	[1]* (0.7818)*

Notes: (…)* and […]* denote p or $p - \chi^2$(in the ARCH-LM test) values and lag levels, respectively.

Graph 1. Dollar Rate and Dollar Rate Uncertainty



The conditional variance series (CV-DOLLAR) in this study is derived from the TARCH model specification applied to the DOLLAR variable, which captures the dynamic interplay between exchange rate fluctuations and underlying economic shocks. Time-series plots of both the DOLLAR and CV-DOLLAR variables, presented in Graph 1, visually illustrate the volatility dynamics of the Turkish lira. Notably, the CV-DOLLAR series exhibits more pronounced volatility patterns, reflecting the heightened uncertainty associated with exchange rate movements. Specific periods of significant volatility, such as 1980 M03, 1994 M05, 2001 M04, 2008 M11, 2018 M09, 2022 M01, and 2023 M07, correspond to historical episodes of economic instability, including currency crises, financial shocks, and structural reforms. These events underscore the sensitivity of the Turkish economy to exchange rate fluctuations, particularly during periods of macroeconomic fragility.

The empirical findings align with historical episodes of macroeconomic vulnerability in Türkiye, where exchange rate volatility has often been intertwined with broader economic crises. However, the observed intensification of volatility in recent years suggests a structural shift in the relationship between exchange rate dynamics and economic uncertainty. This trend implies that the volatility of the Turkish lira has become a persistent feature of the economic landscape, reflecting heightened risk perception and institutional fragility. The synchronization of these volatility spikes with major economic crises—such as the 1994 devaluation, the 2001 financial crisis, and the 2008 global downturn—highlights the deep-seated link between exchange rate instability and macroeconomic vulnerabilities.

Furthermore, the study underscores the critical role of exchange rate volatility in shaping Türkiye's economic trajectory. The persistence of volatility, even in the absence of overt crises, indicates a structural asymmetry in the response to positive and negative shocks, as captured by the TARCH model. These findings contribute to the broader discourse on exchange rate dynamics, offering empirical evidence of the interplay among exchange rate volatility, macroeconomic stability, and policy formulation. By contextualizing recent volatility patterns within a historical framework, the study provides a nuanced understanding of the Turkish economy's sensitivity to exchange rate fluctuations, offering valuable insights for policymakers navigating an increasingly uncertain global environment.

5. CONCLUSION

This study provides an examination of exchange rate volatility dynamics in Türkiye over the period from January 1980 to September 2025. We model the USD/TRY exchange rate by AR(I)MA specifications and conditional heteroscedasticity models consisting of symmetric (ARCH, ARCH-M, GARCH, GARCH-M) and asymmetric (EGARCH, TARCH, PARCH) models. Among these models, we choose the ARMA(1,2)-TARCH(1,1) model as the best model in view of model selection criteria. The finding that the dollar rate is best modeled by the TARCH model is consistent with Almisshal & Emir (2021). The fact to consider here is that it is assumed that positive and negative shocks (news) affecting the market have different (asymmetric) impacts on volatility in the TARCH model. Therefore, market agents and policymakers should not ignore this situation.

The empirical findings demonstrate that the exchange rate exhibits pronounced and recurrent volatility, with sharp spikes observed during critical historical episodes, including March 1980, May 1994, April 2001, November 2008, September 2018, January 2022, and July 2023. These episodes coincide with major macroeconomic crises, financial disruptions, currency regime transitions, and periods of intensified global uncertainty, thereby highlighting the strong linkage between exchange rate instability and Türkiye's underlying economic vulnerabilities.

The long-term perspective adopted in this study allows for a deeper understanding of the evolution of exchange rate dynamics in Türkiye, revealing a path shaped by financial liberalization, increasing integration into global capital markets, and repeated exposure to systemic risks. The persistence of high volatility, even outside explicitly defined crisis periods, suggests a structural shift toward greater sensitivity to both external financial conditions and domestic macroeconomic imbalances. This persistence indicates that exchange rate instability in Türkiye is not merely episodic but embedded within the broader economic framework. Measures that reduce uncertainty, reinforce monetary policy credibility, and mitigate excessive exchange rate pass-through effects are essential for containing volatility and supporting long-term economic stability. This study contributes to understanding of Türkiye's exchange rate behavior and offers valuable insights for policymakers seeking to balance currency stability, macroeconomic performance, and deeper integration into the global financial system.

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