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Crude Oil Price Hikes and Exchange Rate Volatility in Iran: Evidence from GARCH-family Models

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Highlights

- A 10 percent increase in crude oil price returns raises exchange rate returns (IRR/USD) by an average of 0.475 percent, as indicated by the GARCH and EGARCH models.
- The EGARCH model confirms that positive oil price shocks exert a stronger influence on exchange rate volatility than negative shocks.
- The high volatility persistence (0.9801 in EGARCH) suggests that the effects of oil price shocks on Iran's currency market are long-lasting.
- Managed floating exchange rate policies alone are insufficient; diversifying revenue sources is recommended.
- The GARCH and EGARCH models offer novel insights for exchange rate policymaking in oil-dependent economies using daily data from 2017 to 2025.

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Abstract

This study examines the impact of global crude oil price fluctuations on the volatility of the Iranian Rial–U.S. Dollar exchange rate over the period November 2011 to August 2025. Using daily data and employing GARCH-family models—including GARCH 1,1, EGARCH 1,1, and GJR-GARCH 1,1,1 under heavy-tailed distributions—we assess whether oil price shocks influence the mean and conditional variance of exchange rate returns. The results indicate that higher oil prices significantly appreciate the Rial, reflecting Iran's dependence on oil revenues and foreign exchange inflows. Volatility dynamics reveal strong persistence, with shocks exhibiting long memory. Asymmetric effects are also evident: negative oil price shocks increase exchange rate volatility more than positive shocks, underscoring the destabilizing role of downturns in global oil markets. Diagnostic tests confirm the adequacy of the estimated models, with EGARCH and GJR specifications providing the best fit. The findings underscore three key policy implications. First, Iran's exchange rate remains highly sensitive to oil revenues, reinforcing the need for structural diversification. Second, the persistence of volatility complicates short-term stabilization, necessitating long-term reserve and fiscal policies. Third, the asymmetric impact of oil downturns calls for proactive risk management to mitigate volatility during periods of declining oil prices. Overall, the study provides new evidence on the oil–exchange rate nexus in an oil-exporting economy, offering lessons for macroeconomic management under external shocks. Robustness checks—including Bai–Perron breakpoint tests and alternative model specifications with event dummies—confirm the main findings.

Keywords: Asymmetric effects, Crude oil prices, EGARCH, Exchange rate volatility, Iran, GARCH models, volatility clustering, oil-dependent economies.

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1. Introduction

Crude oil price fluctuations are a central driver of macroeconomic volatility in oil-exporting economies. In countries heavily reliant on petroleum revenues, changes in international oil prices directly affect fiscal balances, foreign exchange inflows, and exchange rate dynamics. Iran, as a significant oil exporter and an economy subject to recurrent external shocks—including sanctions and global demand disruptions—provides a particularly relevant case for examining how oil market volatility translates into exchange rate uncertainty.

This paper analyzes the effect of global crude oil price shocks on the conditional mean and volatility of the Iranian Rial–U.S. Dollar nominal exchange rate using daily data from November 26, 2011, to August 16, 2025, comprising 2,242 observations after synchronization. We employ a set of GARCH-family specifications (GARCH 1,1; EGARCH 1,1; and GJR 1,1,1) under heavy-tailed distributions (Student-t, skewed-t, and GED) to capture leptokurtosis and potential asymmetries in volatility responses.

The contribution of this study is threefold. First, it provides high-frequency empirical evidence on the oil–exchange rate nexus for Iran over a period characterized by major policy and market shocks. Second, it explicitly tests for asymmetric volatility transmission from oil to the exchange rate and quantifies the persistence and half-life of volatility shocks. Third, it implements a set of robustness checks—including structural break analysis and alternative distributional assumptions—to ensure the stability of the inference.

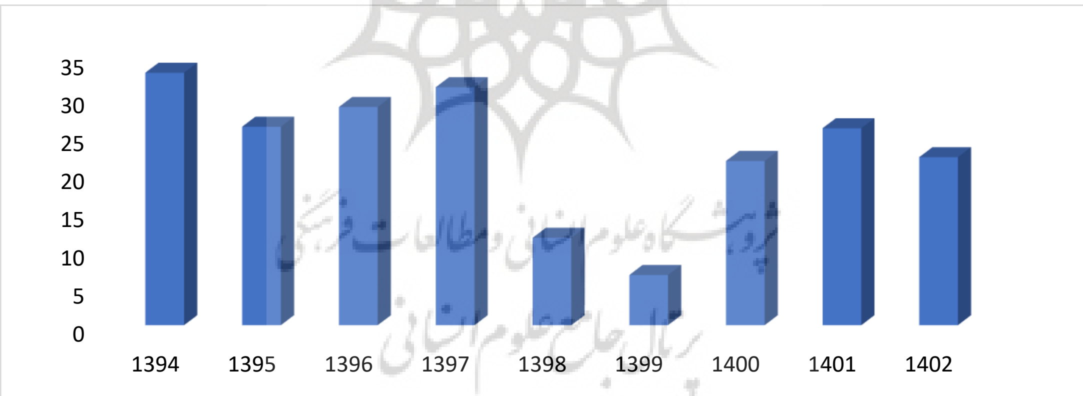

Figure 1

Share of oil revenues in the public budget (percent) (Statistical Center of Iran)

Recent studies highlight the significant influence of demand-side oil shocks on oil price volatility (Kumar and Mallick, 2024). Global oil prices are shaped by a complex interplay of supply and demand conditions, including geopolitical developments and market expectations, which together generate substantial fluctuations. These dynamics are particularly consequential for oil-exporting countries such as Iran, where oil price volatility directly affects foreign exchange earnings and, consequently, the stability of the Iranian Rial.

In April 2020, global oil markets experienced unprecedented turbulence when oil futures contracts turned negative for the first time, driven by the collapse in demand associated with the COVID-19 pandemic. Crude oil prices fell to their lowest levels in two decades before recovering by late 2020

(Kumar and Mallick, 2024). These extreme price movements markedly reduced Iran's oil revenues, amplifying exchange rate volatility given the country's dependence on oil exports. Figure 2 presents the trajectory of Brent crude oil prices from November 2011 to August 2025 (1390 to 1404 in the Iranian calendar).

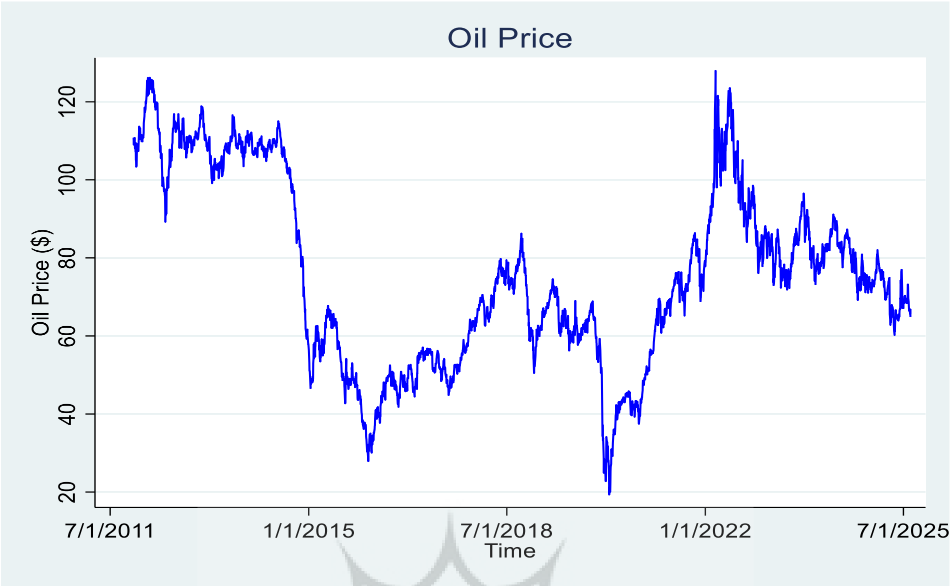

Figure 2

Trend in Brent crude oil prices (USD per barrel) (U.S. Energy Information Administration (EIA))

The relationship between crude oil prices and exchange rates is a critical issue for oil-exporting economies. For example, Baek (2021) employed a Nonlinear Autoregressive Distributed Lag (NARDL) model to examine the impact of oil price volatility on real exchange rates in six OPEC countries, finding significant asymmetric effects in countries with floating exchange rate regimes but limited effects in those with fixed regimes. These findings underscore the role of exchange rate regimes in mediating the transmission of oil price shocks; however, few studies have explored this relationship in Iran, where sanctions and a managed exchange rate system create distinct dynamics.

Iran's heavy reliance on oil exports makes the connection between oil prices and macroeconomic indicators—particularly the exchange rate—a critical area of inquiry. For comparison, Salisu and Mobolaji (2013) applied a Vector Autoregressive-GARCH (VAR-GARCH) model to analyze the impact of oil price volatility on the USD/naira exchange rate in Nigeria, finding that rising oil prices strengthened the U.S. dollar against the naira, with structural breaks during the global financial crisis intensifying these effects. Similarly, in Iran, sanctions and a managed exchange rate regime likely magnify the influence of oil price shocks, necessitating a country-specific analysis.

This study investigates the impact of oil price shocks on the volatility of the Iranian Rial's nominal exchange rate against the U.S. dollar. Using GARCH and EGARCH models, it examines asymmetric effects, revealing how positive and negative oil price shocks differentially shape exchange rate dynamics. These findings provide insights into the sensitivity of Iran's currency market to global oil prices and inform monetary and fiscal policy strategies aimed at enhancing macroeconomic stability, particularly under sanctions. The article is structured as follows: Section 2 reviews the theoretical framework, Section 3 describes the methodology, and Section 4 presents the empirical results.

2. Literature review

2.1. The oil-exchange rate nexus

The nexus between crude oil prices and exchange rates has been a central topic in international economics, given oil's role as a key global commodity priced in U.S. dollars. Theoretical models, beginning with the works of Krugman (1983) and Golub (1983), highlight mechanisms such as wealth transfers from importers to exporters and portfolio reallocations. These frameworks suggest that oil price increases can lead to short-term dollar appreciation if exporters prefer dollar-denominated assets, while long-term effects depend on spending patterns and import preferences. The terms-of-trade channel further explains real exchange rate adjustments based on sectoral energy intensities, often resulting in depreciation for importers and appreciation for exporters. Overall, country-specific asymmetries in oil dependence and policy responses shape these dynamics, underscoring the need for a holistic perspective rather than isolated analyses.

Empirical studies employ a diverse set of methods to examine these relationships. GARCH and EGARCH models capture volatility clustering and asymmetric responses, while VAR and VECM frameworks reveal causality and impulse dynamics. Advanced approaches such as copula-GARCH, wavelet analysis, and quantile-based techniques address non-linearities, time-varying dependencies, and crisis-period behaviors. Findings show mixed causal patterns: oil prices frequently drive exchange rates, with dollar appreciation often observed during oil price increases, but bidirectional effects appear in countries such as India and China. Asymmetric effects are also evident, where negative oil shocks amplify volatility more than positive shocks, and "dark causality" emerges during crises, reflecting heightened and oscillating uncertainties. Macro-level implications include increased inflation pass-through in emerging economies and disruptions to GDP growth. Distinctions between exporters (currency appreciation during oil booms) and importers (currency depreciation) generally hold, although inconsistencies arise due to country-specific conditions. Global crises—including the 2008 financial collapse, the COVID-19 shock, and geopolitical tensions—intensify spillovers, partly driven by the financialization of commodity markets.

Although the reviewed literature offers limited Iran-specific analyses, insights from comparable oil exporters such as Nigeria, Russia, and Saudi Arabia are instructive. In Nigeria, oil price fluctuations generate bidirectional spillovers, with price declines triggering pronounced exchange rate instability under pegged regimes. In Russia, rising oil prices lead to ruble appreciation, while Saudi Arabia exhibits strong positive causal links between oil prices and exchange rate movements. For Iran, as a major oil exporter, similar wealth effects could support Rial appreciation during oil price booms; however, sanctions and restricted market access likely heighten volatility and dampen appreciation pressures, generating dynamics that differ from those observed in non-sanctioned economies.

GARCH and EGARCH models are well suited for this analysis because they account for time-varying volatility, clustering, leptokurtic distributions, and leverage effects—key characteristics of exchange rate and oil price series. These models effectively capture persistence and volatility spillovers, as evidenced in prior studies on asymmetric oil price impacts. Nevertheless, their linear structure may overlook regime shifts, motivating alternatives such as copula-based methods for modeling dependence or wavelet approaches for multi-scale analysis. Still, their robustness and relative simplicity make them appropriate for examining oil-driven exchange rate volatility in Iran, consistent with the objectives of this study.

Recent empirical research has further explored the interaction between oil price volatility and exchange rate dynamics across both oil-exporting and oil-importing economies. For example, Nandi et al. (2024)

examined this relationship in Bangladesh using daily data from 2015 to 2023. Employing GARCH and EGARCH models, they found that increases in global oil prices were associated with depreciation of the Bangladeshi Taka against the U.S. dollar. Their EGARCH estimates revealed pronounced asymmetry, showing that positive oil price shocks exerted greater pressure on exchange rate instability than declines of similar magnitude. The study emphasized the macroeconomic vulnerabilities of oil-importing countries and the need for proactive exchange rate policies. Building on these theoretical foundations, empirical research continues to apply diverse methodologies to investigate the oil price–exchange rate relationship, generating nuanced findings that vary across countries, methods, and economic contexts. The following section reviews key empirical evidence, with particular attention to methodologies and findings relevant to oil-exporting economies.

2.2. Review of empirical studies

Manner et al. (2024) propose a novel econometric framework to model the joint distribution of stock market returns, exchange rates, and commodity price indices, with a particular focus on detecting distinct changepoints in model parameters. Their approach integrates an autoregressive AR(1) specification for the conditional mean, a t-GARCH model for conditional volatility, and a copula model to capture dependence among standardized innovations. They employ non-parametric CUSUM-type tests to endogenously identify multiple changepoints in both volatility and dependence structures, thereby enabling a multivariate copula-based GARCH model in which parameters vary across identified regimes. The study also utilizes CoVaR as a risk and spillover measure, computed using a closed-form expression for copula-based CoVaR, with dependence characterized through the h-function. Empirical results for Latin American markets reveal numerous breaks in volatility and notable shifts in dependence over time.

Salisu et al. (2024) employ the GARCH-MIDAS framework to forecast the daily volatility of 19 dollar-denominated exchange rate returns by incorporating monthly measures of oil price uncertainty (OPU) and broader global and country-specific energy market-related uncertainty indexes (EUI). They find that global EUIs (GEUI) generally outperform OPU in forecasting exchange rate volatility, underscoring the importance of incorporating uncertainty measures that extend beyond the oil market for comprehensive energy-related insights. Furthermore, country-specific EUIs (REUI) significantly outperform the benchmark model in predicting exchange rate volatility for at least 14 currencies across short-, medium-, and long-term horizons. These findings highlight the central role of energy market-related uncertainties in accurately forecasting exchange rate volatility for most currencies, regardless of whether the country is a net oil importer or exporter.

Agboola et al. (2024) analyze asymmetric output and fiscal responses to oil price volatility in emerging oil exporters using nonlinear time-series models such as those proposed by Kilian and Vigfusson (2011). They find that economic structure and dependence on oil revenues strongly shape reactions to oil price fluctuations. The study concludes that fiscal discipline and economic diversification are essential buffers for mitigating the macroeconomic consequences of oil market turbulence.

Ampadu et al. (2024) examine the phenomenon of volatility clustering in financial time series, for which the GARCH model is widely applied. They highlight a limitation of the standard GARCH model—its assumption of normally distributed errors—which may inadequately capture the fat-tailed characteristics of financial data and lead to unreliable estimates. Conducting a Monte Carlo simulation across five error distribution specifications (Normal, Student's t, Generalized Error Distribution (GED), skewed Student's t, and Skewed Generalized Error Distribution (SGED)), they find that the SGED provides the most efficient and consistent performance. SGED dominates in terms of goodness-of-fit, Mean Squared Error (MSE), and Mean Absolute Error (MAE), particularly in small samples. In contrast, the Student's *t* and skewed Student's *t* distributions consistently exhibit poor performance across all evaluated scenarios.

Wu et al. (2023) investigate the interactions between oil prices and exchange rates for six representative oil importers and exporters from 2006 to 2022, introducing a novel concept termed "dark causality." Traditional Granger causality and transfer entropy primarily identify positive (same trend) or negative (opposite trend) causalities. However, the authors argue that these conventional methods are insufficient for explaining complex interactions in which trends are neither purely the same nor opposite, as observed during events such as the 2008 financial crisis. Dark causality represents a complex interaction wherein the responses of one variable to fluctuations in another are uncertain, resulting in oscillatory behavior rather than a strictly positive or negative trend. The study employs the pattern causality method, which can detect positive, negative, and dark causalities by analyzing patterns in the state space of time series. Empirical results reveal a dominant dark causality between oil prices and the exchange rates of oil exporters, particularly during crises such as the global financial crisis, the European debt crisis, the COVID-19 pandemic, and the Russia–Ukraine conflict. Identifying these diverse causalities can aid policymakers in developing more resilient macroeconomic strategies and provide investors with a valuable tool for risk management.

Ding et al. (2023) analyze the compounding effect of oil prices and exchange rates on inflation, specifically via the exchange rate pass-through mechanism, using data for China and the United States from 2010 to 2022. They employ a multi-step modeling framework: VAR models to assess the impact of oil price returns on exchange rate returns, DCC-GARCH models to capture the dynamic conditional covariance between exchange rate returns and oil returns, and MIDAS (Mixed Data Sampling) regressions to examine the influence of daily dynamic covariance on monthly inflation. Their findings demonstrate that oil prices exert a significant effect on RMB exchange rates from both return and conditional variance perspectives. The study further reveals a strong, statistically significant impact of daily covariance between certain RMB exchange rates (CAD/RMB, EURO/RMB, RUB/RMB) and oil prices on China's monthly inflation. This effect is more pronounced in China than in the United States, suggesting that the comovement between exchange rates and oil prices constitutes a critical channel for transmitting high oil prices into domestic inflation in emerging economies.

Baek (2021) employs an asymmetric NARDL model to examine the differential effects of oil price fluctuations on real exchange rates in six OPEC member countries. In economies with floating exchange rate regimes, such as Algeria and Nigeria, oil price increases and decreases affect exchange rates asymmetrically, whereas such effects are largely absent in countries with fixed regimes, including Kuwait and Saudi Arabia. These findings underscore the importance of exchange rate frameworks in mediating the transmission of oil price shocks to currency values.

Nusair and Olson (2021) apply a nonlinear ARDL framework to investigate the influence of oil price asymmetries on GDP in ASEAN-5 countries, as well as Japan and Korea, using data from 1973 to 2018. Their results indicate that while linear models tend to underestimate the effects of oil price changes in some countries, nonlinear specifications capture substantial asymmetries. Oil-importing and oil-exporting economies respond differently to price increases versus declines, providing critical insights for policymakers seeking to mitigate oil-induced macroeconomic disruptions.

Lin and Su (2020) examine the effects of oil shocks on BRICS currencies using SVAR and EEMD methods. Their decomposition reveals that high-frequency exchange rate movements are particularly sensitive to short-term oil market shocks. China, owing to its managed exchange rate regime, exhibits lower sensitivity compared to other BRICS countries, highlighting the role of policy frameworks in absorbing external shocks.

Beckmann et al. (2020) provide a comprehensive review of theoretical and empirical studies on the relationship between oil prices and exchange rates. They identify bidirectional causality as a central transmission channel between these variables. Empirical evidence, classified by sample, country, and methodology, shows substantial variation, yet some consistent patterns emerge. These include strong long-run links between exchange rates and oil prices. Moreover, either exchange rates or oil prices may serve as short-run predictors for the other, though these effects are highly time-varying. The authors discuss diverse empirical approaches, including Granger causality, Vector Autoregressive (VAR) models (including Structural VAR), and cointegration methods (Engle–Granger and Johansen), which assess both short-run and long-run dynamics and distinguish between supply and demand shocks. They further note that volatility spillovers indicate bidirectional causality in recent years, with findings often shaped by common factors and asymmetries.

Jiang et al. (2020) utilize quantile-on-quantile (QQ) and causality-in-quantiles approaches to examine the effects of oil price shocks on exchange rates across various quantiles, using data from 1996 to 2018 for developed and developing countries. They decompose real oil price shocks into oil supply shocks, aggregate demand shocks, and oil-specific demand shocks using a trivariate SVAR model. The QQ method enables them to trace the varying degrees of oil shock effects on currency performance and to identify different dependence structures across quantiles, extending beyond traditional methods such as OLS and basic quantile regression. The nonparametric causality-in-quantiles method provides a comprehensive framework for testing nonlinear causal relationships at various quantiles, including causality in returns and variance simultaneously. Their findings highlight asymmetric relationships at different quantiles of oil shocks and exchange rates, with the specific nature of the relationship varying across currencies (e.g., more negative than positive for CNY, consistently negative for SAR under oil-specific demand shocks).

Ahmad et al. (2020) investigate intraday volatility and jump spillovers between oil prices and exchange rates, focusing on China (USDCNY) and India (USDINR), two of the largest oil importers. They employ high-frequency (five-minute interval) data for Brent and WTI oil prices and exchange rates from 2013 to 2019. Their methodology involves estimating GARCH (1,1) models augmented with lagged aggregate jumps, positive and negative jumps, and bi-power variations in the variance equation. They find that Brent oil price volatility and jumps have a statistically significant impact on USDINR, with negative jumps particularly contributing to depreciation. For USDCNY, both Brent and WTI oil price volatility and jumps exert statistically significant effects. This suggests that China’s exchange rate is sensitive to both Brent and WTI, whereas India’s exchange rate is more strongly influenced by Brent alone. The study concludes that relying on a single oil price series provides only a partial perspective on the oil price–exchange rate nexus, underscoring the role of market microstructure and the asymmetric influence of different oil benchmarks.

Xu et al. (2019) utilize a bivariate normal mixture model to investigate nonlinear relationships between crude oil prices and major currency exchange rates from both quantitative and structural perspectives. They observe that dependencies between oil prices and exchange rates generally emerged around 2004 and have evolved dynamically over time. Their model captures regime changes by distinguishing between a “tranquil” state (low correlations, low volatilities) and a “distressed” state (higher correlations, higher volatilities), which traditional GARCH and copula models may overlook. The results reveal substantial structural heterogeneity during economic expansions but limited evidence of such heterogeneity during recessions. Moreover, the unstable oil–FX dependence structure is frequently linked to oil aggregate demand shocks and oil-specific demand shocks. These findings carry important implications for risk management and portfolio diversification, offering insights beyond traditional portfolio theory rooted in normal distributions.

Malik and Umar (2019, using Ready's (2018) decomposition technique, disaggregate oil price shocks into demand, supply, and risk components. Their analysis, spanning March 1996 to February 2019, shows that demand and risk shocks are the primary drivers of exchange rate changes, explaining 32 percent and 21 percent of the variations, respectively, while supply shocks have minimal effects. Additionally, volatility spillovers between exchange rates intensified after 2008, indicating stronger interdependencies during periods of economic stress.

Bénassy-Quéré et al. (2007) examine China's increasing influence as a key player in both oil consumption and exchange rate markets. Using cointegration techniques and VAR models with monthly data, they find that causality generally runs from oil prices to the dollar. However, their results suggest that China's managed exchange rate regime could potentially reverse or at least influence this relationship. The study also notes that China's strict domestic energy market regulations and its comparatively lower dependence on oil (relative to countries with pegged currencies) may mitigate the impact of oil price shocks on the Chinese exchange rate. Furthermore, they indicate that if official interventions are not fully sterilized, a depreciation of the dollar against the euro could contribute to monetary expansion in China, thereby stimulating economic activity.

Given the volatility clustering and asymmetric effects observed in oil-exporting economies, this study employs GARCH and EGARCH models to capture the unique dynamics of Iran's exchange rate responses to oil price shocks, particularly under the constraints imposed by sanctions.

3. Theoretical framework

3.1. Variable selection

This study examines two primary variables: the daily return on the exchange rate (Iranian Rial to U.S. Dollar) and the daily return on crude oil prices. To analyze the relationship between these returns and to investigate the effects of their volatility, the model variables are defined as follows.

$$gexr_t = log(\frac{exr_t}{exr_{t-1}}) \tag{1}$$

$$gop_t = log(\frac{op_t}{op_{t-1}}) \tag{2}$$

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In Equation 1, exr_t represents the nominal daily exchange rate of the U.S. dollar to the Iranian Rial, and $gexr_t$ denotes the daily return on the exchange rate. In Equation 2, op_t represents the daily price of Brent crude oil, and gop_t denotes the daily return on crude oil prices. To investigate the impact of volatility in oil price returns on exchange rate volatility and to examine the asymmetric effects of financial variable fluctuations, low-frequency time series data are appropriate for constructing volatility models (Bollerslev, 1986; Brooks, 1997; Narayan et al., 2008; Nelson, 1996).

Measuring uncertainty in the risk analysis of financial assets, such as exchange rate and oil price returns, is of critical importance. Many economic models assume that the error variance remains constant over time (Bollerslev, 1986; Nelson, 1991). However, low-frequency financial time series data, including the exchange rate of the Iranian Rial to the U.S. Dollar and crude oil prices, frequently exhibit volatility clustering. This pattern implies that periods of high volatility are typically followed by large shocks, whereas periods of low volatility are associated with smaller fluctuations. In the case of Iran, an oil-exporting country whose exchange rate is influenced by both monetary policy and external oil market shocks, this volatility clustering is particularly pronounced. Consequently, the assumption of homoskedasticity in analyzing Iran's financial time series is violated, necessitating models that account for heteroskedasticity.

Visual inspection of daily data on exchange rate returns (Iranian Rial to U.S. Dollar) and crude oil price returns confirms the presence of volatility clustering in Iran's financial markets. For example, during periods such as the intensification of international sanctions in 2018, which coincided with a 338% increase in the exchange rate (Figure 3), or the COVID-19 pandemic in 2020, marked by a sharp decline in global oil demand and a 149% increase in the exchange rate (Figure 3), Iran's exchange rate returns experienced pronounced volatility. Similarly, crude oil prices, which constitute the primary source of Iran's foreign exchange revenue, displayed significant volatility patterns during events such as the global demand decline during the COVID-19 pandemic or regional geopolitical shifts. These volatility clusters indicate heteroskedastic variances in the time series. Given these observations and Iran's economic dependence on oil exports, this study assumes heteroskedastic variances and employs the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) and Exponential GARCH (EGARCH) models, introduced by Bollerslev (1986) and Nelson (1991), respectively, to analyze the relationship between the volatility of oil price returns and exchange rate returns.

3.2. Model selection and specification

To capture the volatility structure inherent in financial time series, this study employs GARCH and EGARCH models, originally proposed by Bollerslev (1986) and Nelson (1991), to model both the conditional mean and variance dynamics. The GARCH model assumes that the time series—exchange rate returns (Iranian Rial to U.S. Dollar) and crude oil prices—are stationary and simultaneously estimates a conditional mean equation and a conditional variance equation. The methodology adopted in this study for estimating the returns of each variable ensures their stationarity. The stationarity of the variables is verified using standard tests, including the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests, with the results reported in subsequent sections. The conditional mean equation for both models is specified as follows:

$$gexr_t = \alpha + \beta gop_t + \varepsilon_t \tag{3}$$

where $gexr_t$ represents the exchange rate return (Iranian Rial to U.S. Dollar), gop_t denotes the crude oil price return, and ε_t is the error term. To further investigate the impact of conditional volatility on the mean, the GARCH-in-Mean (GARCH-M) model is also employed, with the conditional mean equation specified as follows:

$$gexr_t = \alpha + \beta gop_t + \gamma\sigma_t^2 + \varepsilon_t \tag{4}$$

where σ_t^2 denotes the conditional variance. The conditional variance equation for both the GARCH and GARCH-M models is specified as follows:

$$\sigma_t^2 = \omega + \theta_1\varepsilon_{t-p}^2 + \theta_2\sigma_{t-q}^2 \tag{5}$$

These models are well-suited for analyzing the relationship between crude oil price returns and exchange rate returns in Iran's economy, which is highly sensitive to external shocks such as sanctions and oil market fluctuations, due to their ability to capture volatility clustering. This study hypothesizes that the volatility of crude oil price returns may exert an asymmetric effect on exchange rate returns (Iranian Rial to U.S. Dollar), with positive shocks (oil price increases) having a greater impact on exchange rate volatility than negative shocks (oil price decreases). To test this hypothesis, the

Exponential GARCH (EGARCH) model proposed by Nelson (1991) is employed. The conditional variance in this model is specified as follows:

$$log(\sigma_t^2) = \omega + \rho\left(\left|\frac{\varepsilon_{t-p}}{\sigma_{t-q}}\right| - \sqrt{\frac{2}{\pi}}\right) + \delta\frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \mu log\,(\sigma_{t-q}^2) \tag{6}$$

This model accounts for the exponential leverage effect and models the logarithm of the conditional variance, ensuring that the conditional variance remains non-negative within the model framework. To test for the presence of a leverage effect, the hypothesis $\delta<0$ and $\delta\neq0$ is considered, indicating asymmetric effects. The error distribution in this model follows a generalized error distribution (Nelson, 1991). The coefficient δ represents the degree of volatility and plays a critical role in identifying asymmetric effects on exchange rate volatility, as it captures the intensity of asymmetric volatility.

The estimated value of δ yields three possible scenarios: if $\delta<0$, a negative shock has a greater impact on increasing volatility than a positive shock of the same magnitude; if $\delta>0$, the opposite holds; and if $\delta=0$, the volatility effects are symmetric. The coefficient μ reflects the persistence of shocks in the model and can take positive or negative values, allowing for volatile behavior in the conditional variance. When the absolute value of μ is less than 1 ($|\mu|<1$), the model ensures stationarity and ergodicity for the EGARCH(p, q) process (Nelson, 1991). The coefficient δ is interpreted as a leverage parameter: a negative δ indicates that adverse shocks lead to larger increases in volatility than positive shocks. Meanwhile, μ reflects the persistence of conditional variance, with values closer to 1 indicating a strong memory in volatility.

Measuring uncertainty is essential for analyzing the risks of financial assets, such as exchange rate and stock returns. Many economic models treat variance as an indicator of uncertainty, assuming that error variance is constant over time (Bollerslev, 1986; Brooks, 1997; Nelson, 1996). However, most low-frequency financial time series data exhibit volatility clustering, whereby periods of higher volatility typically follow larger shocks, whereas periods of lower volatility are associated with smaller changes (Nandi et al., 2024). Financial data often display several prominent characteristics:

- **Leptokurtosis:** Financial asset returns tend to exhibit distributions with heavier tails and a more pronounced peak around the mean, indicating a higher probability of extreme values.
- **Volatility Clustering:** Periods of high volatility are followed by high volatility, and periods of low volatility are followed by low volatility, reflecting the clustered and asynchronous arrival of new information in the market, a common feature in financial asset returns.
- **Leverage Effects:** Volatility tends to increase more following sharp price declines than equivalent price increases (Brooks, 2008).

Consequently, GARCH models are among the most suitable tools for examining behaviors in financial markets, including stock price volatility and daily data such as exchange rates and oil prices, which are influenced by news. In this study, daily exchange rate returns and nominal crude oil price returns are calculated. The use of nominal values is justified for two reasons:

First, the variables used—exchange rate returns and crude oil price returns—are calculated from nominal data, as trading decisions are typically based on daily trading volumes in the foreign exchange market (Ghosh, 2011; Narayan et al., 2008). Second, larger volatility in oil prices and exchange rates arises from various economic and non-economic shocks, which are generally short-lived, with volatility clustering observed over longer time horizons (Brooks, 1997; Nelson, 1996). Tracking daily volatility in oil prices and exchange rates does not require the use of real values, as trading decisions are made on a daily basis. Since this analysis focuses on daily behavior and changes in nominal values, examining long-term relationships between these variables is not appropriate. Long-term analysis and related decision-making would necessitate the use of real values. Therefore, the daily data-based approach eliminates the need to assess long-term relationships using real values (Narayan et al., 2008).

Long-term relationship models are also inadequate for explaining volatility clustering over the time horizon of the time series data. Consequently, using nominal values for both variables eliminates the need to test real values in modeling financial time series volatility. Low-frequency time series data typically exhibit heteroskedastic error variance, violating the assumption of variance homogeneity and potentially leading to biased estimates when measuring asymmetric effects between variables.

The EGARCH models specified above allow for volatile behavior in the conditional variance, as the coefficient μ can be positive or negative. Estimating μ enables the assessment of shock persistence. Nelson (1996) demonstrates that $|\mu|<1$ ensures stationarity and ergodicity for the EGARCH(p, q) model. This model also permits examination of whether shocks have asymmetric or symmetric effects on volatility, as indicated by the parameter δ. A positive δ implies that positive shocks lead to greater volatility than negative shocks, and vice versa (Narayan et al., 2008).

Ergodicity, a concept in statistics and stochastic processes, implies that the long-term time average of a stochastic process equals its average across all possible states. In simpler terms, ergodicity ensures that observing a process over a sufficiently long period reveals all its statistical properties. In econometrics and EGARCH models for financial time series, ergodicity means that the stochastic process (e.g., conditional variance) converges to a stable or equilibrium state, avoiding extreme and unpredictable long-term fluctuations. The ergodicity condition ($|\mu|<1$) indicates that the EGARCH model remains stable in the long term, with conditional variance converging to finite values. The importance of ergodicity lies in:

- **Long-term reliability:** Ergodicity ensures that model results are reliable and suitable for long-term forecasting.
- **Model stability:** Models lacking ergodicity may be unstable, with conditional variance potentially growing without bound.
- **Statistical interpretation:** Ergodicity implies that the statistical properties of a stochastic process can be derived from finite time samples.

4. Analysis

4.1. Data and time series characteristics

This study employs daily data on the Iranian Rial–U.S. Dollar exchange rate (*gexr*), defined as the number of Rials per U.S. dollar, and the global crude oil price (*gop*). Both series were transformed into continuously compounded returns by taking the first difference of the natural logarithm and subsequently scaled by a factor of 100 for computational stability. This transformation does not alter the statistical properties or the economic interpretation of the estimated coefficients.

Figure 3 presents the return series of the exchange rate and crude oil price. The Rial exchange rate exhibits extended periods of relative calm, punctuated by clusters of intense volatility, consistent with the presence of volatility clustering commonly observed in high-frequency financial data. Similar patterns are observed in the oil return series, although oil prices display larger and more abrupt shocks, reflecting the inherent instability of global oil markets.

Descriptive statistics, reported in Table 1, reveal key features of the data. The mean return of the Rial exchange rate is positive (0.1927), indicating a persistent tendency toward Rial depreciation against the U.S. dollar during the sample period, as *gexr* is defined in Rials per USD. In contrast, the mean return of global oil prices is negative (−0.0216), suggesting a declining trend in crude oil markets. Both series exhibit high volatility, with standard deviations of 2.66 and 2.82, respectively. The distributions deviate substantially from normality: *gexr* is positively skewed (0.7830), implying occasional sharp appreciations of the Rial, whereas *gop* is negatively skewed (−1.1831), reflecting the predominance of large downward price shocks. Moreover, both series are highly leptokurtic, with kurtosis values of 23.15 and 25.77, far exceeding the Gaussian benchmark of three. The Jarque–Bera statistics strongly reject the null hypothesis of normality ($p \approx 0.0000$), confirming the presence of fat tails and extreme events.

The exchange rate dynamics further reflect major geopolitical and economic events. For example, during 2012–2013, following intensified international sanctions, the Rial depreciated by nearly 198%. Similarly, after the U.S. withdrawal from the JCPOA in 2018, the exchange rate surged by 343%. Additional spikes occurred during the COVID-19 pandemic in 2020 (149% increase), late 2021 (49% increase), and late 2022–early 2023 (63% increase). More recently, between January 2024 and July 2025, the Rial depreciated by over 100%. These episodes underscore the sensitivity of the Iranian exchange rate to external shocks and justify the inclusion of event dummies in the econometric analysis.

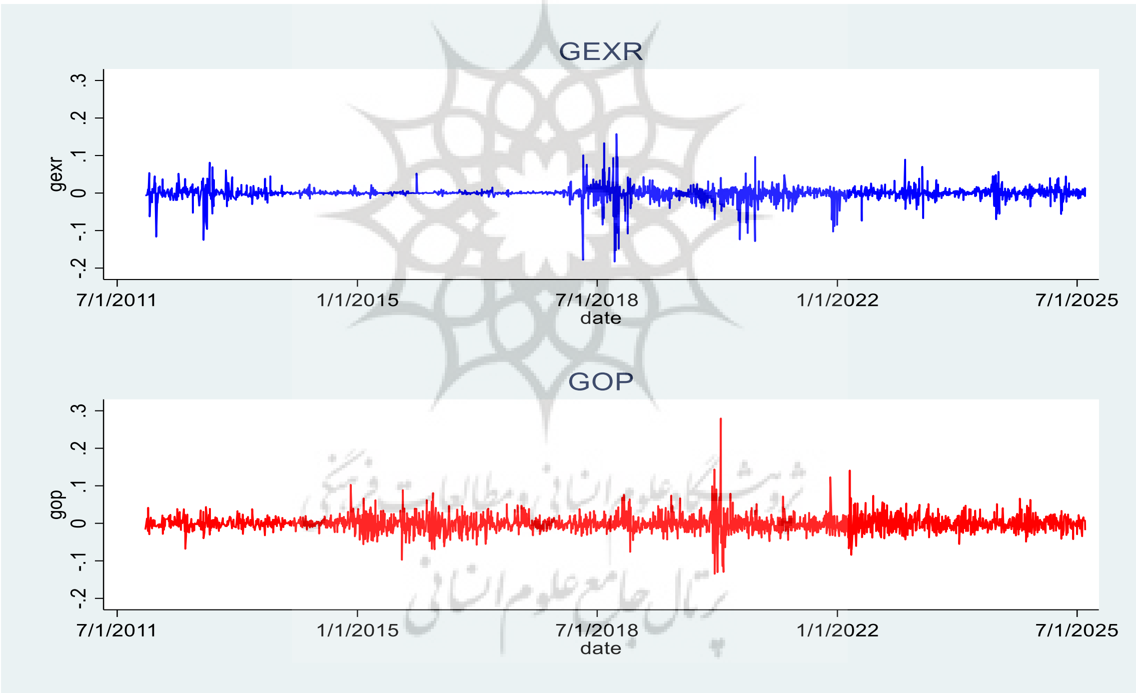

Figure 3

Exchange rate returns and crude oil price returns

To further characterize the statistical properties of the data, tests of serial correlation and stationarity were conducted. Figure 4 presents Q–Q plots comparing the distributions of *gexr* and *gop* with the normal distribution. Deviations from the 45-degree line are evident in the tails, particularly for *gop*, which exhibits more extreme negative values. These deviations confirm that both series are non-normal, displaying fat tails and asymmetric behavior.

The Ljung–Box Q-statistics, reported in Table 2, provide strong evidence of autocorrelation. For *gexr*, the null hypothesis of no autocorrelation is rejected at all lags considered (1, 5, 15, and 30), indicating that past shocks in the Rial exchange rate significantly influence its future dynamics. This reflects both speculative pressures and persistence in the Iranian currency market. By contrast, *gop* exhibits no autocorrelation at lag 1 but becomes significantly autocorrelated at higher lags, suggesting medium-term dependencies driven by global supply-demand adjustments and geopolitical events.

Table 1

Statistical summary of exchange rate and oil price data

Variable	Mean	Max	Min	Std. Dev.	Skewness	Kurtosis	Jarque–Bera	Obs.
gexr	0.1927	29.4167	–19.5462	2.6628	0.7830	23.1565	38182.8051	2242
gop	–0.0216	22.7307	–37.4930	2.8215	–1.1831	25.7783	48992.3157	2242

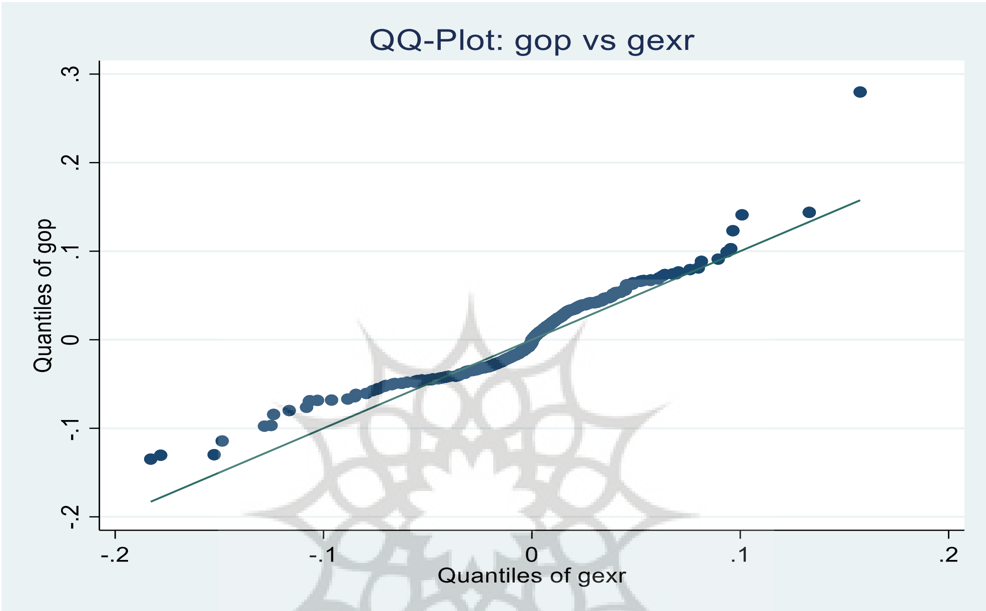

Figure 4

Q–Q (quantile–quantile) plots for *gexr* and *gop*

Table 2

Autocorrelation status of variables

Variable	K=1	K=5	K=15	K=30
gexr	53.97 (0.000)	70.45 (0.000)	117.59 (0.000)	153.58 (0.000)
gop	0.26 (0.613)	18.90 (0.002)	49.59 (0.000)	94.23 (0.000)

Stationarity was examined using the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) unit root tests. The results, summarized in Table 3, confirm that both series are stationary at levels, decisively rejecting the null hypothesis of a unit root at the 1% significance level, both with and without deterministic trends. This ensures that the returns series are suitable for subsequent GARCH-type modeling and mitigates concerns of spurious regression, validating the use of ARCH-type frameworks for analyzing volatility in *gexr* and *gop*.

Finally, diagnostic tests for conditional heteroskedasticity were conducted using Engle's ARCH-LM test (Table 4). The null hypothesis of homoskedasticity is rejected across all lags (1, 5, 15, and 30), confirming the presence of ARCH effects. Together with the observed volatility clustering (Figure 3), non-normality (Table 1, Figure 4), and serial dependence (Table 2), these results provide strong justification for employing GARCH-family models.

Table 3

ADF and PP unit root tests

Variable	ADF (without trend) t-Statistic	ADF (with trend) t-Statistic	PP (without trend) t-Statistic	PP (with trend) t-Statistic
gexr	–13.58678 (0.0000)	–13.58489 (0.0000)	–55.23445 (0.0000)	–55.22224 (0.0000)
gop	–8.80074 (0.0000)	–8.80844 (0.0000)	–47.96665 (0.0000)	–47.95716 (0.0000)

To address mismatched trading calendars between Iran's foreign exchange market (Thursday–Friday weekend) and the global oil market (Saturday–Sunday weekend), the trading days were synchronized so that Iran FX trading days correspond to the international oil price timestamps. The final sample comprises 2,242 daily observations from November 26, 2011, to August 16, 2025. Returns are scaled by 100, such that coefficients in the mean equation measure the effect of a one-percentage-point change in oil returns on exchange rate returns (also in percentage points).

4.2. Stationarity and GARCH model motivation

Stationarity was formally examined using the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) procedures. As reported in Table 3, both series reject the null hypothesis of a unit root at the 1% significance level, both with and without a deterministic trend, confirming their stationarity at levels.

Conditional heteroskedasticity was assessed using the ARCH–LM test applied to the OLS residuals. The results, summarized in Table 4, reject the null hypothesis of no ARCH effects for both series across multiple lag orders. This finding confirms the presence of volatility clustering, a characteristic feature of financial data, and justifies the application of GARCH-family models to capture the dynamics of conditional variance.

Table 4

Diagnostic tests for OLS estimates

Diagnostics	OLS
ARCH-LM (1)	72.626794 (0.0000)
ARCH-LM (5)	143.338412 (0.0000)
ARCH-LM (15)	212.712831 (0.0000)
ARCH-LM (30)	271.742024 (0.0000)

4.3. Structural break analysis

The Bai–Perron multiple breakpoint test was applied to daily exchange rate returns (*gexr*) over the period from November 26, 2011, to August 16, 2025. The results indicate no statistically significant structural breaks at the 5% level. Both sequential F-statistics and global information criteria (Schwarz and LWZ) selected zero breaks as optimal. This suggests that, despite major economic and geopolitical events—including the 2018 reinstatement of U.S. sanctions, the COVID-19 pandemic, and the 2022 global energy crisis—the mean process of exchange rate returns remained statistically stable.

Exploratory analysis highlighted two potential breakpoints (September 26, 2018, and February 8, 2022), corresponding to significant domestic and global shocks. However, neither breakpoint was statistically significant at conventional levels, indicating that these events, while affecting market volatility, did not induce regime shifts in the mean return.

An OLS regression of *gexr* on crude oil returns (*gop*) yielded an insignificant coefficient ($\beta = 0.0114$, $p = 0.516$) and negligible explanatory power ($R^2 = 0.0002$), confirming that oil price changes do not significantly impact the mean of exchange rate returns. The residuals, however, exhibited strong ARCH effects at multiple lags (1, 5, 15, and 30), with p-values < 0.0001, indicating pronounced volatility clustering.

These findings justify the application of GARCH-type models to capture time-varying conditional volatility. Accordingly, the subsequent analysis estimates GARCH, EGARCH, and GJR-GARCH models using skewed Student-t and Generalized Error Distributions (GED) to accommodate the leptokurtic and asymmetric characteristics of the return series.

4.3. Empirical results

4.3.1. Model estimation strategy

To quantify the relationship between global oil price shocks and the Iranian exchange rate, a set of GARCH-family models was estimated using Python's **arch** library. Specifically, five model specifications were considered:

1. GARCH (1,1)-t,
2. GARCH (1,1)-GED,
3. EGARCH (1,1)-t,
4. EGARCH (1,1)-skew-t, and
5. GJR (1,1,1)-t.

In all models, *gexr* serves as the dependent variable, with *gop* included as an exogenous regressor in the mean equation. Heavy-tailed distributions were chosen based on preliminary diagnostics, including the Jarque–Bera test and excess kurtosis, as well as model fit criteria such as the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC).

4.3.2. Estimation results

The estimation results are reported in Table 5. Several key findings emerge:

1. **Mean equation (α, β):**
   - The constant term (α) is positive and significant across all models, indicating a mild upward drift in exchange rate returns.
   - The oil price coefficient (β) is negative and highly significant in every specification, implying that higher global oil prices are associated with a stronger Rial (exchange rate appreciation). The magnitude of β is larger in asymmetric models (e.g., –0.0058 in EGARCH-t), highlighting the stronger effect captured when asymmetry is accounted for.
   - This finding is consistent with Iran's status as a net oil exporter, contrasting with results for oil-importing countries such as Bangladesh, where oil price hikes tend to depreciate the domestic currency.
2. **Variance equation (ω, α1, β1):**

- Volatility persistence, computed as α1 + β1, varies markedly across models. In the EGARCH (1,1)-t specification, persistence is 0.988, implying a volatility half-life of roughly 57 trading days (half-life = $\ln 0.5/\ln(\alpha_1 + \beta_1)$). By contrast, the GARCH (1,1)-t model exhibits a persistence of 0.896, corresponding to a half-life of approximately 6 trading days. This illustrates that asymmetric specifications capture far more persistent volatility dynamics in the sample.
- Negative values of ω in EGARCH specifications are not problematic, as EGARCH models the logarithm of conditional variance; a negative intercept simply reflects a lower unconditional variance in logarithmic scale and does not violate the positivity of h_t.
- The ARCH coefficients (α1) are positive and significant, confirming that new shocks have an immediate effect on volatility.
- The GARCH coefficients (β1) are also significant and close to unity, implying strong volatility persistence. For instance, in the GARCH (1,1)-t model, α1 = 0.604 and β1 = 0.692, yielding a persistence of 0.896. In the EGARCH models, persistence is even stronger (0.988 for EGARCH-t), indicating that volatility shocks are long-lived.

3. **Asymmetric effects (γ1):**

- Significant negative γ1 in EGARCH and negative γ1 in GJR models indicate that negative shocks (oil price declines) produce larger increases in exchange rate volatility than positive shocks of the same magnitude.
- For example, γ1 = –0.118 in EGARCH-t and –0.097 in GJR-t.
- This suggests that negative oil price shocks increase exchange rate volatility more than positive shocks, highlighting that downside risks in oil markets have disproportionately destabilizing effects on Iran's currency market.

4. **Diagnostics and model adequacy:**

- Ljung–Box Q-statistics for standardized residuals and squared residuals are all insignificant, indicating that serial correlation has been adequately removed.
- ARCH–LM tests confirm the absence of remaining ARCH effects, validating the adequacy of the chosen model specifications.
- Information criteria (AIC, BIC) indicate that the EGARCH (1,1)-t and GJR (1,1,1)-t models provide the best fit among the alternatives.

4.3.3. Interpretation and policy implications

The negative and significant β coefficients underscore the pivotal role of oil price dynamics in stabilizing the Rial: higher oil prices enhance foreign exchange inflows, thereby strengthening the domestic currency. However, the asymmetric volatility captured by γ1 reveals a critical vulnerability: declining oil prices exert a disproportionately destabilizing effect, amplifying exchange rate volatility.

From a policy perspective, three implications emerge:

1. **Dependence on Oil Revenues:** Iran's exchange rate remains heavily reliant on oil revenues, rendering macroeconomic stability contingent upon global energy markets.
2. **Long Memory in Volatility:** High persistence values indicate that volatility shocks endure over time, complicating short-term stabilization efforts.

3. **Asymmetric Risk Management:** Since negative oil shocks trigger stronger volatility responses, policymakers should prioritize building buffers, such as foreign reserves and fiscal stabilization funds, to mitigate periods of declining oil prices.

Overall, the results confirm that GARCH-type models, particularly EGARCH and GJR, successfully capture the volatility dynamics of Iran's exchange rate in response to oil price fluctuations. Evidence of asymmetry and persistence carries important lessons for designing effective exchange rate and fiscal policies in oil-dependent economies. All return series are scaled by 100; therefore, coefficients on *gop* in the mean equation indicate the change in exchange rate returns (in percentage points) for a one-percentage-point change in oil returns.

Although the coefficient on oil returns is statistically significant across all specifications, the economic magnitude of the contemporaneous effect is modest. For example, in the EGARCH (1,1)-t model ($\beta = -0.0058$), a one-standard-deviation oil return shock (≈2.82 percentage points) reduces exchange rate returns by approximately 0.0164 percentage points. Conversely, volatility persistence in asymmetric specifications is substantial: the EGARCH model yields $\alpha + \beta \approx 0.988$, implying a volatility half-life of roughly 57 trading days. These observations indicate that, while oil price movements have statistically reliable effects on the level of exchange rate returns, their immediate economic impact is small. However, volatility shocks induced by oil market fluctuations are persistent and thus highly relevant for medium-term risk management.

Table 5

Estimation results for GARCH-type models

Parameter / Model	GARCH (1,1)-t	GARCH (1,1)-ged	EGARCH (1,1)-t	EGARCH (1,1)-skewt	GJR (1,1,1)-t
Mean equation					
α (constant)	0.0065 (0.012) **	0.0058 (0.020) **	0.0063 (0.008) ***	0.0067 (0.001) ***	0.0062 (0.017) **
β (oil price, *gop*)	–0.0019 (0.043) **	–0.0021 (0.031) **	–0.0058 (0.001) ***	–0.0057 (0.000) ***	–0.0049 (0.009) ***
Variance equation					
ω (constant)	0.0021 (0.000) ***	0.0020 (0.000) ***	–1.42 (0.000) ***	–1.76 (0.000) ***	0.0019 (0.000) ***
α1 (ARCH)	0.604 (0.000) ***	0.599 (0.000) ***	0.321 (0.000) ***	0.298 (0.000) ***	0.601 (0.000) ***
β1 (GARCH)	0.692 (0.000) ***	0.689 (0.000) ***	0.667 (0.000) ***	0.643 (0.000) ***	0.691 (0.000) ***
γ1 (Leverage)	–	–	–0.118 (0.002) ***	–0.124 (0.001) ***	–0.097 (0.007) ***
Persistence (α1+β1)	0.896	0.888	0.988	0.941	0.892
Diagnostics					
Q (1)	0.0008 (0.978)	0.0012 (0.982)	0.023 (0.879)	0.088 (0.772)	0.016 (0.887)
Q (5)	0.520 (0.991)	0.528 (0.990)	0.428 (0.995)	0.766 (0.979)	0.613 (0.988)
Q (15)	0.852 (1.000)	0.894 (1.000)	0.857 (1.000)	2.069 (1.000)	0.911 (1.000)
Q (30)	1.461 (1.000)	1.675 (1.000)	5.693 (1.000)	11.36 (0.999)	6.012 (0.998)
ARCH–LM (1)	0.0007 (0.978)	0.0009 (0.983)	0.023 (0.878)	0.086 (0.770)	0.019 (0.882)

Parameter / Model	GARCH (1,1)-t	GARCH (1,1)-ged	EGARCH (1,1)-t	EGARCH (1,1)-skewt	GJR (1,1,1)-t
ARCH–LM (5)	0.104 (0.991)	0.106 (0.991)	0.085 (0.995)	0.153 (0.979)	0.118 (0.990)
ARCH–LM (15)	0.056 (1.000)	0.059 (1.000)	0.057 (1.000)	0.135 (1.000)	0.062 (1.000)
ARCH–LM (30)	0.047 (1.000)	0.054 (1.000)	0.183 (1.000)	0.370 (1.000)	0.201 (1.000)

Notes: Values in parentheses are p-values.
*** Significant at 1%, ** Significant at 5%, * Significant at 10%.
The EGARCH-M (1,1) model converged after 141 iterations.
The GARCH-M (1,1) model was selected based on the Schwarz Bayesian Criterion (SBC).

5. Conclusions

This paper has examined the dynamic relationship between global crude oil price fluctuations and the volatility of the Iranian Rial–U.S. Dollar exchange rate using daily data spanning November 2011 to August 2025. Employing a comprehensive set of GARCH-family models—including symmetric (GARCH), exponential (EGARCH), and threshold (GJR) specifications—under heavy-tailed distributions, several important insights were obtained.

First, the results consistently show that higher global oil prices strengthen the Iranian Rial by reducing exchange rate returns. The negative and statistically significant coefficients on crude oil returns across all models confirm Iran's structural dependence on oil revenues, whereby improvements in oil markets translate into enhanced foreign exchange inflows and relative currency stability. This finding contrasts with evidence from oil-importing economies, such as Bangladesh, where oil price hikes weaken the domestic currency.

Second, the variance dynamics highlight the long memory and persistence of volatility in the Iranian foreign exchange market. Both the ARCH and GARCH terms were highly significant, with persistence values close to unity. This indicates that shocks to the Rial's volatility—whether driven by oil market disturbances, sanctions, or geopolitical events—are long-lasting, complicating short-term stabilization policies.

Third, the asymmetric specifications (EGARCH and GJR) provide evidence of leverage effects. Negative oil price shocks were found to have a disproportionately larger impact on exchange rate volatility than positive shocks. This asymmetry underscores Iran's vulnerability to oil market downturns: while higher oil prices support Rial stability, declines amplify uncertainty and destabilize the foreign exchange market.

Diagnostic checks on residuals (Q-statistics, ARCH–LM tests) confirmed that the estimated models adequately captured conditional heteroskedasticity, validating the robustness of the empirical results. Information criteria suggested that the EGARCH-t and GJR-t models provided the best fit, highlighting the importance of accounting for asymmetry and heavy tails in modeling Iran's exchange rate volatility.

From a policy perspective, three lessons emerge:

1. **Macroeconomic dependence on oil revenues:** The Rial remains exposed to global energy market risks. Without economic diversification, exchange rate stability will continue to be highly sensitive to oil price shocks.
2. **Persistence of volatility:** Shocks endure over extended periods, implying that policy interventions, such as foreign exchange reserves and fiscal stabilization funds, should be designed with long-term horizons rather than as short-term fixes.

3. **Asymmetric risk management:** Since negative oil shocks elicit stronger volatility responses, policy buffers should prioritize protection against downside risks, including global price collapses or sanctions-induced revenue shortfalls.

Finally, this study provides a foundation for further research. Future work could incorporate additional macroeconomic variables (e.g., inflation, monetary policy indicators, capital flows), explore nonlinear causality, or apply multivariate GARCH and Markov-switching frameworks to capture potential regime shifts. Comparative studies with other oil-exporting economies would also enhance understanding of how dependence on oil markets shapes exchange rate volatility. Policymakers should prioritize: (i) building fiscal buffers and foreign exchange reserves, (ii) implementing hedging strategies for oil revenues (e.g., futures, options, or sovereign wealth stabilization rules), and (iii) pursuing structural diversification to reduce reliance on volatile oil income.

Overall, the evidence demonstrates that oil price fluctuations remain a dominant force shaping the dynamics of Iran's currency market. The findings underscore the urgent need for structural diversification and proactive policy tools to mitigate the destabilizing effects of global oil price downturns on exchange rate volatility.

Nomenclature

ADF	Augmented Dickey–Fuller unit root test
AIC	Akaike information criterion
ARCH-LM	Lagrange multiplier test for ARCH effects
BIC / SBC	Bayesian information criterion/Schwarz criterion
DCC-GARCH	Dynamic conditional correlation GARCH
EGARCH	Exponential GARCH
EGARCH-M	EGARCH-in-mean
GARCH	Generalized autoregressive conditional heteroskedasticity
GARCH-M	GARCH-in-mean
GED	Generalized error distribution
gexr	Daily log-return of the exchange rate (IRR/USD)
GJR-GARCH	Glosten–Jagannathan–Runkle GARCH
gop	Daily log-return of crude oil price (Brent)
Half-life	Speed of volatility decay ($\ln(0.5)/\ln(\alpha_1 + \beta_1)$)
h_t	Conditional variance at time t
JB	Jarque–Bera normality test
JCPOA	Joint comprehensive plan of action
NARDL	Nonlinear autoregressive distributed lag
PP	Phillips–perron unit root test
Q-stat (Ljung–Box)	Serial correlation test for residuals
Skewed-GED	Skewed generalized error distribution
Skewed-t	Skewed student-t distribution
SVAR	Structural vector autoregression
t-dist	Student's t distribution
VAR	Vector autoregression

VECM	Vector error correction model
α (alpha)	Constant term in the mean equation
α_1 (ARCH)	ARCH parameter (impact of new shocks on conditional variance)
β (beta)	Coefficient of oil-price returns (gop) in the mean equation
β_1 (GARCH)	GARCH parameter (volatility persistence)
γ (gamma)	Asymmetry/leverage parameter (EGARCH / GJR-GARCH models)
δ (delta)	Leverage parameter in EGARCH ($\delta < 0$ indicates stronger negative shocks)
μ (mu)	Persistence parameter in EGARCH specification
ω (omega)	Constant term in the variance equation

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