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How do exchange rate and oil price volatility shape Pakistan's stock market?

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ABSTRACT

Changes in oil prices and currency values significantly influence economic systems worldwide, with pronounced effects on equity markets. This study specifically examines the consequences of oil price changes and currency value fluctuations on the volatility of Pakistan's stock market, exploring both direct and indirect pathways. Employing the Tobit regression model, it investigates how the volatility of oil prices and exchange rates impacts the volatility of stock returns in the Pakistani context. The findings underscore the importance for investors and policymakers in Pakistan to consider the implications of oil and currency volatility when assessing investment risks and opportunities in the stock market. This research contributes to the understanding of the intricate relationships between oil price volatility, exchange rate fluctuations, and stock market dynamics in Pakistan, offering valuable insights for informed decision-making.

1. Introduction

In an increasingly interconnected global economy, the intricate relationship between oil prices, exchange rates, and stock markets has gained heightened significance. As a fundamental input in economic production, oil exerts a profound influence on inflation, consumer spending, and overall economic growth, making it a key driver of macroeconomic stability (Ahmed et al., 2023). Simultaneously, exchange rate fluctuations shape the competitiveness of a nation's trade, directly impacting on corporate earnings and stock market performance (Engel and West, 2005). Given this interdependence, disruptions in any one of these domains can trigger far-reaching ripple effects, amplifying volatility across financial markets worldwide (Shen et al., 2025). Understanding these complex interactions is paramount for investors, policymakers, and researchers striving to navigate the evolving financial landscape.

Examining the interplay between oil price and exchange rate volatility and their cascading effects on stock market dynamics offers valuable insights into economic resilience and market predictability. Given the stock market's appeal as a high-return investment

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avenue, comprehending these relationships becomes even more critical. However, despite its attractiveness, forecasting stock market movements remains an intricate challenge due to the multifaceted nature of market forces (Fang et al., 2023). As a result, empirical investigations into these financial linkages are essential for developing more effective risk management strategies and enhancing investment decision-making in volatile economic environments.

Emerging markets are particularly sensitive to the volatility of oil prices and exchange rates (Lv et al., 2018). Many emerging economies are either major oil exporters or importers, making their stock markets highly reactive to changes in oil prices (Basher et al., 2018). Similarly, because these economies often have less mature financial systems, their currencies and stock markets can be more volatile in response to exchange rate fluctuations. Recent studies have highlighted how emerging markets need to enhance their financial and economic policies to mitigate the adverse effects of these volatilities (Banerjee et al., 2024). Similar to developed countries, emerging economies' stock markets have been shown to be highly impacted by currency exchange rates or oil prices (Wen et al., 2019).

Looking at the oil market and its relevance to emerging economies, it is observed that these markets require more energy in the form of oil, coal, gas, etc. As a result, the pace of economic growth, industrial structure, financial earnings, and stock markets are all directly impacted by changes in oil prices. Thereby any consumer demand decline brought on by the rise in oil prices may impact the firm's earnings negatively, and stock prices and markets may become unstable (Waheed et al., 2018). Central banks and policymakers are increasingly acknowledging the importance of understanding and responding to the dynamics between oil prices, exchange rates, and the stock market. Monetary policy tools, including interest rate adjustments and foreign exchange interventions, are being used to stabilize markets and shield economies from the adverse effects of volatility. The effectiveness of these tools, however, varies, and recent discussions emphasize the need for a coordinated international approach to address these global market interdependencies.

The study emphasizes Pakistan's specific vulnerabilities, particularly its dependence on oil imports and the pronounced impact of exchange rate volatility on its stock market. Pakistan's economy is highly sensitive to fluctuations in global oil prices due to its reliance on imported energy, which accounts for a significant portion of its import bill. This dependence exacerbates inflationary pressures and strains the current account deficit, which has been a persistent challenge for the country. Recent events, such as the surge in global oil prices during geopolitical tensions in 2022, further highlighted the economic fragility, as Pakistan faced soaring inflation and dwindling foreign exchange reserves. Exchange rate volatility compounds these issues, as the depreciation of the Pakistani rupee, seen during the 2023 currency crisis, led to higher import costs and uncertainty in the stock market, deterring both foreign and domestic investors. The stock market's performance reflects these macroeconomic stresses, with increased volatility observed during periods of sharp currency fluctuations. By situating these findings within Pakistan's unique economic landscape, the study provides a deeper understanding of the interconnectedness between oil price shocks, exchange rate movements, and their cascading effects on the country's stock market.

The conceptual framework for analyzing the relationship between stock prices and exchange rates has a solid basis, particularly rooted in the pioneering work of Fischer (1980) and their "flow-oriented" model of exchange rates. The interconnection of economic factors highlights the importance of understanding the relationships among oil prices, exchange rates, and stock markets for several reasons. For instance, multinational corporations can gauge their vulnerability to overseas contracts through this knowledge; investors can better evaluate their investment portfolios; oil-importing countries might see an impact on their trade balance and position in net foreign assets due to oil price volatility; and, for the general public, shifts in oil prices can influence their disposable income and the profitability of companies.

To identify the nexus comprehensively this study adopts a step-by-step approach where the impact of oil and exchange rate volatility on Stock market volatility is analysed. In the subsequent step, the mediating effect of stock market volatility on the relationship between oil and exchange rate volatility has been estimated. In the final step, the study employs probit regression to comprehend whether volatility is more intense for positive or negative returns since recent research have shown increased interest in directional forecasting (Zhong and Enke, 2019). This research seeks to utilise a censoring method to the data to analyse volatility impact and use a binary approach of the likelihood of a decrease or gain in price/return to analyse the directional affects (Amore and Murtinu, 2021). In this way, the purpose of this work in this context is to investigate how fluctuations in oil price volatility and currency rate volatility affect stock markets and its volatility. The majority of studies on oil price shocks and stock markets concentrate on the potential effects of various oil/exchange rate/ interest rate increases or on stock returns (Bhowmik and Wang, 2018; Wen et al., 2019). However, there have not been many studies which examine how the volatility of oil prices and exchange rate volatility, indirectly affect the stock return in presence of stock volatility and the directional effect of volatility on return.

Building on these academic blocks, the current study makes significant contributions to the existing body of literature by examining the intricate dynamics between oil price fluctuations, currency exchange rate volatility, and stock market behavior. *First,* this study provides a comprehensive understanding of how oil price volatility and exchange rate fluctuations impact stock markets, both directly and indirectly. By examining these relationships, the research illuminates the intricate ways in which external economic variables influence stock market volatility, thus offering a more detailed map of market dynamics. Second, despite the critical impact of oil and exchange rate volatilities on stock markets, there has been a relative paucity of comprehensive studies in this area. The current research addresses this gap by providing empirical evidence on the indirect effects of these volatilities on stock returns. Thus, it contributes to the academic literature by expanding our understanding of financial market volatilities and their implications for stock market performance. Third, employing advanced statistical models like the Tobit regression model and the Baron and Kenny approach, this research introduces innovative methodological frameworks to analyze the impact of volatility where these models allow for a more accurate and concrete analysis of the threshold effects and the directional impact of volatility on stock returns, thereby enhancing the precision of empirical research. Furthermore, the study's exploration of mediation effects using the Baron and Kenny approach adds depth to existing research by uncovering the mechanisms through which oil and exchange rate volatility influence stock return volatility.

Fourth, by uncovering how fluctuations in oil prices and currency rates affect stock markets, this work provides vital insights for investors, financial analysts, and policymakers. Understanding these dynamics enables more effective risk management strategies, as stakeholders can better anticipate and mitigate the effects of external volatilities on investment portfolios and economic policies. Finally, on a broader scale, this study's findings contribute to the discourse on global financial stability. By understanding how key economic indicators like oil prices and exchange rates influence stock markets, the research aids in the development of more robust financial systems that can withstand and adapt to the volatilities of the global economy. This is crucial for maintaining economic growth and stability in an increasingly interconnected world.

The findings of this research have significant implications for monetary and fiscal policy. By demonstrating the indirect effects of oil and exchange rate volatilities on stock returns in Pakistan, the study suggests that policymakers need to consider these external factors in their economic forecasts and policy formulations. This could lead to more stable financial markets and a more resilient global economic environment. Stock market investment decisions are directly and indirectly affected by a market causal linkages and volatility spill over effect, which has significant value for market investors and policymakers. In Pakistan, the volatility of oil prices and fluctuations in exchange rates exert an exceptionally pronounced influence on stock market returns. This dynamic stems from the country's reliance on imported energy and the limited capacity of its domestic industries to withstand external economic shocks. The analysis indicates that, in contrast to more diversified economies, Pakistan's stock market is particularly vulnerable to these macroeconomic variables. This heightened sensitivity complicates efforts by policymakers to control inflation and maintain market stability.

Hence, emerging stock markets may find this study helpful in getting a better understanding of the relationship between the oil shock, exchange rate volatility, stock market volatility, and stock market return. The demonstrated statistically significant influence of both oil and exchange rate volatility on stock return volatility highlights the need for a careful consideration of these factors when assessing risks and potential returns in stock market investments. In doing so, this research not only contributes to the academic literature by enriching our understanding of the complex interplay between oil volatility, exchange rate volatility, and stock return volatility but also offers actionable insights for real-world decision-making in the financial landscape.

The structure of the study has been organised as follows: Section 2 reviews earlier empirical literature; Section 3 sheds light on data and methodology; Section 4 explains results and discussion; Section 5 concludes the study along with implications.

2. Literature review

2.1. Oil price and stock volatility

Following the oil crisis of the 1970s, there has been an abundance of research on the impact of oil prices on macroeconomic dynamics, affecting both oil-rich and non-oil economies alike. Bhatia and Basu (2021) regard oil as the cornerstone of contemporary economic systems, noting that oil demand escalates with industrial advancement. Essentially, oil influences the trade conditions of nearly all modern economies through its global trade. The repercussions of sudden changes in oil prices can be both negative and uneven, spreading through multiple pathways. Bhatia and Basu, (2021) observed that stock price of non-oil producing companies also gets affected by oil price, because, decreasing/increasing oil price influences company profits via changing cost. Regarding the impact of oil price shocks on stock market volatility, Mensi et al., (2023) demonstrates that there is inter-market dependence in volatility between stock market and oil markets and report a significant impact. (Arouri et al., 2012) report that there is volatility transmission from oil to European stock markets. According to (Degiannakis et al., 2014) supply-side shocks and demand shocks that are particular to oil do not have an impact on stock market volatility. However, a spike in oil prices accompanied by an increase in aggregate demand does (Akkoc and Civcir, 2019). Based on this it is hypothesized;

H1. : Oil volatility has significant positive impact on Stock Volatility

2.2. Exchange rate

Research findings on the impact of exchange rates on stock prices have been varied. Özlen and Ergun (2012) identified exchange and interest rates as key factors affecting stock price fluctuations. The susceptibility of stock returns in any sector to variations in these rates is significant. Simbolon and Purwanto (2018) noted that a combination of interest rates, inflation rates, exchange rates, and GDP growth rates significantly influences stock prices, highlighting the critical effects of these economic indicators on equity valuations. Sari et al. (2010) examined the interplay and co-movements between the spot prices of certain precious metals, the USD/euro exchange rate, and oil prices, finding a limited long-term equilibrium relationship but notable short-term interactions. Basher et al. (2012) analyzed the connections between oil prices, exchange rates, and stock markets, observing that upward shifts in oil prices tend to negatively affect stock prices in emerging markets and the USD exchange rate in the short term, while positive oil production shocks decrease oil prices and boosts from real economic activity increase them. Based on the above arguments it is hypothesized;

H2. : Exchange Rate Volatility has significant positive impact on Stock Volatility

2.3. Volatilities and return

Stock returns can be influenced by various volatilities, which may also cause indirect effects through spill-over mechanisms, as noted by Dhaoui and Khraief (2014). The impact on stock returns can vary with the level of stock return volatility. A lower volatility is often preferred because it enables investors to liquidate their positions without causing significant price fluctuations, thereby reducing the undue risk that investors face. As volatility increases, risks escalate, and potential profits diminish. Risk is gauged by the deviation of returns from their mean; a wider spread of returns around the mean indicates a greater risk and a consequent reduction in compound returns, according to Easterling (2017). Akter and Nobi (2018) found that higher volatility is associated with a greater likelihood of market downturns, suggesting that understanding the relationship between market volatility and index values can aid investors in developing long-term investment strategies for portfolio construction, as indicated by Ang and Liu (2007).

Numerous studies have explored the connection between oil prices and stock markets. Huang et al. (1996) found no significant relationship between oil prices and stock returns. Conversely, Gogineni (2008) showed that the extent and direction of stock market responses depend on the magnitude of oil price changes, observing that supply-driven oil price changes negatively affect stock returns. However, when oil price shifts result from changes in aggregate demand, they positively influence market returns on the same day, as noted by Fang and You (2014). Oil price shocks have a proven adverse effect on real economic activity and, by extension, on stock returns, as demonstrated by Cunado et al. (2015). Wei and Guo (2017) further elucidated that stock markets react differently to oil shocks, with the nature of these reactions closely tied to the underlying reasons for oil price changes. Moreover, oil price volatility has been linked to stock market volatility, affecting the stock price index. Adjasi et al. (2008) identified a negative relationship between exchange rate volatility and stock market returns, concluding that increased volatility in a domestic currency's exchange rate, leading to financial instability, may be perceived as a sign of uncertainty, thereby influencing the stock price index

Based on these researches it is hypothesized that;

H3. : Stock price volatility impact the direction of stock price positively

2.4. Directional impact

Andersen et al. (2007) and Christoffersen and Diebold (2006) argue that even though stock market returns themselves are unpredictable, it may be possible to predict the sign of those returns. Models with continuous dependent variables have formed the foundation for the arguments used to support this viewpoint. For instance, the aforementioned studies have demonstrated that the sign predictability of the returns is implied by the predictability of stock return volatility. The purpose of this study is to evaluate sign predictability based on historical value. The time series models for the excess stock return form the foundation of the earlier conclusions about directional predictability. For instance, Christoffersen and Diebold (2006) explored the theoretical link between the volatility of asset returns and the predictability of the direction of asset returns, demonstrating that volatility and higher-order conditional moments of returns significantly contribute to forecasting the direction of returns. While prior research in this area is limited, binary dependent time series models emerge as a novel approach for predicting the direction of excess stock returns. The following hypothesis has been formed based on above statement;

H4. : Stock market volatility mediates the impact that oil price volatility has on Stock Return Direction

H5. : Stock market volatility mediates the impact that Exchange rate volatility has on Stock Return Direction

3. Data & methodology

In this research, data on stock market indicators were compiled on a monthly basis through daily figures. The study focused on the Pakistan stock market, specifically utilizing daily returns from the KSE100 index, a value-weighted portfolio of prime stocks, covering the period from January 2013 to March 2023. This high-frequency data was employed to develop covariance measures of returns, aligning with methodologies in existing literature for constructing indicators of implied and conditional volatility. Additionally, daily oil prices were tracked using the West Texas Intermediate (WTI) benchmark, and the daily exchange rate was monitored between the US dollar (USD) and the Pakistani rupee (PKR), with WTI price information sourced from the U.S. Energy Information Administration.

3.1. Variable measurement

3.1.1. Stock return

Daily stock return is a commonly used metric in finance that measures the percentage change in a stock's closing price from one day to the next. In this section, we will discuss the formula for calculating daily stock returns and use a recent finance journal article to explain variable measurement. Following the method extended by (Ji et al., 2020) the research used the following formulae to calculate the daily returns of the stock.

Daily Stock Return = [(Today's Closing Price - Yesterday's Closing Price) / Yesterday's Closing Price] x 100

3.1.2. Stock market volatility

Assessing stock market volatility presents a considerable challenge for analysts, primarily because volatility demonstrates a tendency to be autocorrelated; that is, high levels of volatility today often predict similar levels tomorrow, yet this phenomenon has also proven to be predictive of significant financial upheavals. The development and application of Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models have significantly advanced over the past three decades, offering robust tools for analyzing market data volatility (Reddy and Narayan, 2016). This study employs the GARCH model to explore the persistence of volatility, wherein the model posits that the current variance is influenced by its own past variances.

3.1.3. GARCH (1.1) model

The foundational GARCH model was introduced by Bollerslev in 1986. It includes both a mean and a variance equation. Below is the equation for the mean.

$$\mathbf{R_t = R_{t-1} + \pi_t\, \varepsilon_t}$$

Rt = stock return at time t,

$\mathbf{R_{t-1}}$ = return in lagged time frame,

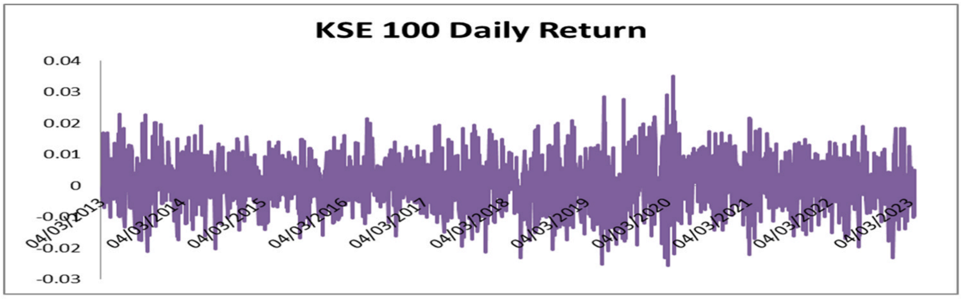
π = mean stock return,

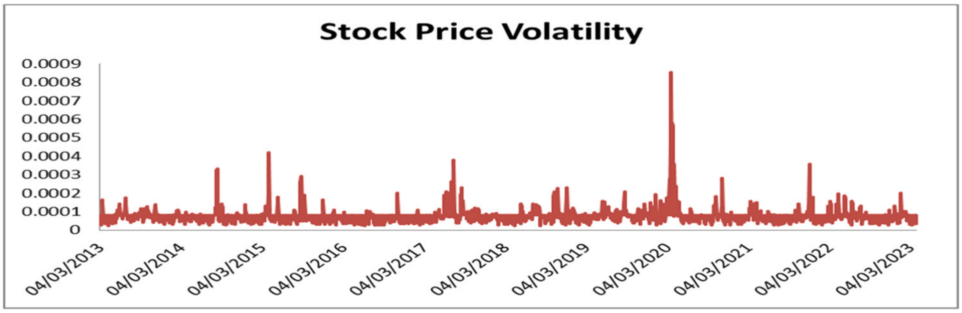
ε_t = return residual.

The GARCH variance equation is given below:

$$\mathbf{VarR_t^2 = \alpha + \omega_1\, \varepsilon_{t-1}^2 + \lambda_1\, \sigma_{t-1}^2}$$

$\mathbf{VarR_t^2}$ denotes conditional variance. Stationarity is presumed when the sum of the coefficients for past volatility and the conditional variance totals one. This approach ensures that the impact of volatility from any previous periods is balanced, facilitating the use of oil volatility as an effective measure (Arashi and Rounaghi, 2022; Lin, 2018). The equation for conditional variance captures the fluctuating nature of volatility in the residuals derived from the mean equation. In the context of finance, this method is typically understood as a process where a financial analyst or trader estimates the current period's variance by calculating a weighted average of a long-term mean (the constant), and the variance predicted from the previous period (the GARCH term). Should there be an unexpected large return on an asset, either positive or negative, the trader is then likely to adjust their variance estimate upwards for the forthcoming period.





3.1.4. Oil price

The study uses West Texas Intermediate (WTI) crude oil prices as a benchmark due to its prominence as a global standard for oil price volatility and its wide usage in academic research analyzing the impact of oil price fluctuations. Although Brent crude is often considered more relevant for Pakistan's oil imports due to its greater global market share, WTI remains a valid and impactful choice for several reasons. First, WTI prices are closely correlated with Brent crude prices, ensuring that trends and volatility patterns captured by WTI provide meaningful insights into global oil market dynamics, which indirectly affect Pakistan. Second, the global oil market is highly interconnected, and WTI prices often act as a leading indicator, influencing the price trajectories of other benchmarks, including Brent. Third, the accessibility and granularity of WTI price data allow for robust empirical analysis, particularly in studies where oil price volatility is a critical variable. By using WTI prices, the study ensures consistency with existing literature while capturing the broader implications of oil price shocks on Pakistan's stock market.

Haque and Shaik (2021) evaluated the ARIMA and GARCH models, discovering that the AR(1) MA(1) GARCH(1,1) model excels in capturing volatility due to its ability to account for non-constant conditional variance. Similarly, Aamir and Shabri (2015), in their comparison of ARIMA and GARCH models for forecasting Pakistan's monthly crude oil prices from February 1986 to March 2015, observed that the GARCH model demonstrated a lower Mean Absolute Error (MAE) than the ARIMA model, indicating superior performance. Consequently, this study also adopts the ARMA-GARCH model for estimating volatility, adjusting the MA and AR to a one-period lag based on partial autocorrelation and autocorrelation for improved volatility forecasting. This research follows the ARMA-GARCH specification for modeling exchange rate volatility, a method previously applied in studies such as Chen et al. (2020).

Here too, the ARMA (1,1) and GARCH (1,1) configuration is employed, with a focus on a one-period lag for both AR and MA components.

$\mathbf{R_t = \mu + \varepsilon_t}$

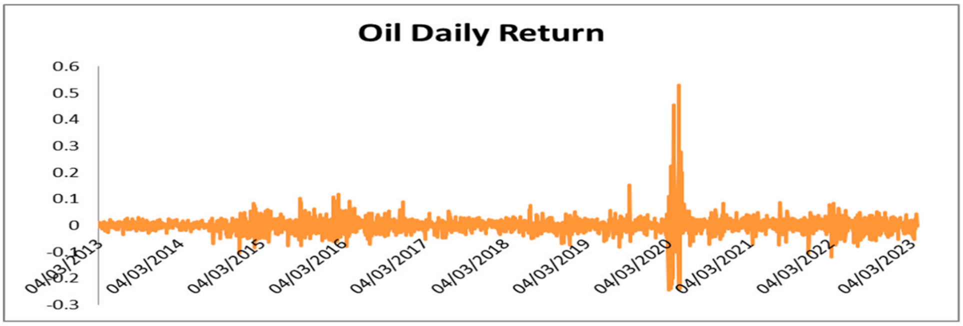
$\boldsymbol{\varepsilon_t = \sigma_t * e_t}$

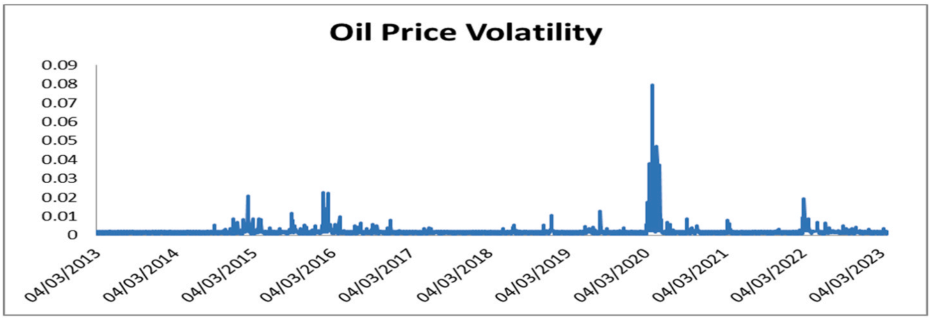
$\boldsymbol{\sigma_t^2 = \alpha + \omega_1 \varepsilon_{t\text{-}1}^2 + \ldots + \omega_p\, \varepsilon_{t\text{-}p}^2 + \beta_1\, \sigma_{t\text{-}1}^2 + \ldots + \beta_q\, \sigma_{t\text{-}q}^2}$

Where:

R_t represents the oil price return at time t, μ is the mean of the oil price, $\boldsymbol{\varepsilon_t}$ is the error term (or the residual) at time t, $\boldsymbol{\sigma_t}$ is the conditional standard deviation (or volatility) of the exchange rate at time t, $\mathbf{e_t}$ is the standardized error term (or the standardized residual) at time t, α is the constant term in the GARCH equation, ω _1,…,α_p and β_1,…,β_q are the coefficients of the GARCH model, which capture the autoregressive and moving average properties of the volatility, p and q are the order of the autoregressive and moving average terms in the GARCH model, respectively.

The ARIMA-GARCH model combines the ARIMA model for the oil price (R_t r) with the GARCH model for the conditional variance ($\boldsymbol{\sigma_t^2}$). The ARIMA part captures the short-term dynamics of the exchange rate, while the GARCH part models the volatility of the exchange rate, which is assumed to be time varying and dependent on its own past values as well as the past values of the error terms (Diaz et al., 2016).





3.1.5. Exchange rate volatility

Exchange rate volatility has been measured through a GARCH model (Rakshit and Neog, 2022).

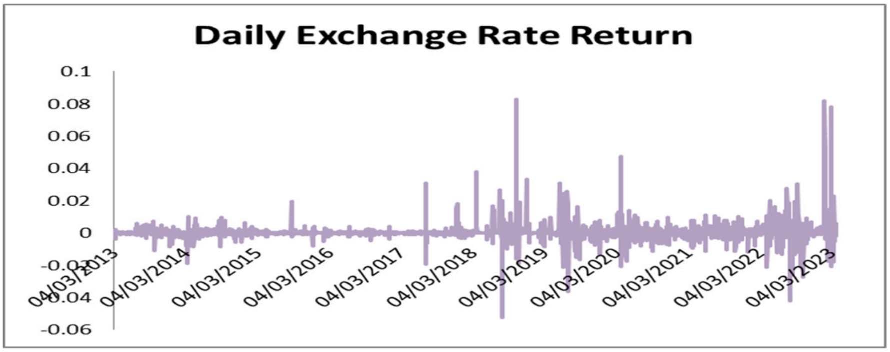
The general formula for a GARCH model for exchange rate volatility can be written as:

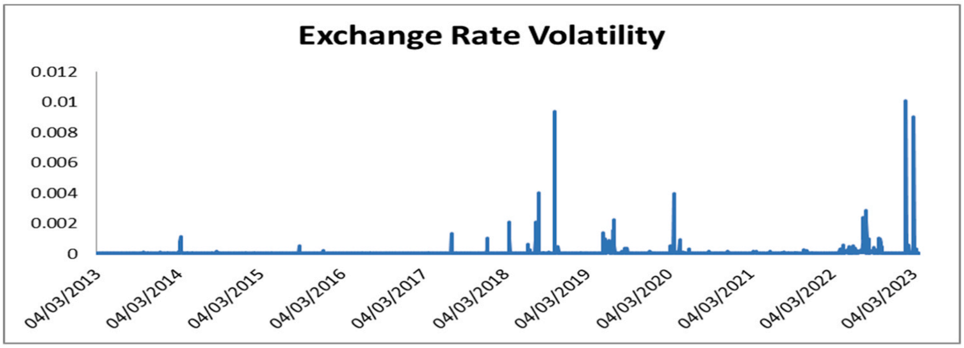
$\mathbf{Exchange\ Rate_t = Exchange\ Rate_{t\ -1} + \boldsymbol{\pi}\ \boldsymbol{\varepsilon}}$

Here π ε is change in Exchange rate (Exchange Rate return), which is defined in below Garch model

$\mathbf{VarE\ _t^2 = \boldsymbol{\alpha} + \boldsymbol{\omega_1}\ \boldsymbol{\varepsilon_{t\text{-}1}^2} + \boldsymbol{\lambda_1}\ \boldsymbol{\sigma_{t\text{-}1}^2}}$

In this context, $\boldsymbol{\alpha}$ denotes the long-term average variance rate of the Exchange Rate, $\boldsymbol{\omega_1}$ symbolizes a parameter that quantifies the responsiveness of Exchange Rate volatility to the most recent change in Exchange Rate, and $\boldsymbol{\lambda_1}$ quantifies the responsiveness to the historical variances of Exchange Rate. Utilizing the mentioned GARCH model, we estimate the time series of conditional volatility for each specified Exchange Rate (Huq et al., 2013; Takaishi, 2018).





3.2. Methodology

3.2.1. Tobit regression

Tobin pioneered the use of the Tobit model, designed for analyzing situations where the dependent variable is subject to a lower or upper bound, in his study of household spending on durable goods, acknowledging that such expenditures cannot fall below zero. This model adjusts the probability function based on whether a latent dependent variable exceeds a certain threshold, aiming to account for potential uneven sampling across observations. Similar models, known as censored and truncated regression models, have emerged in fields like biometrics and engineering, evolving somewhat independently from their econometric origins. These models, also referred to as survival models, have been applied by sociologists and economists to study the duration of events such as unemployment, welfare dependence, and tenure in a specific job (Amore and Murtinu, 2021). In this research, the dependent variable is non-negative, continuous, and left-censored, displaying a concentration of zeros. Therefore, the Tobit regression model is employed to mitigate bias and inaccuracies in parameter estimation where the distribution is non-normal or constrained (Wu et al., 2022).

$$\mathrm{VarR_t} = \beta_0 + \beta_1 \mathrm{VarO_t} + \beta_2 \mathrm{VarE_t} + \epsilon \tag{1}$$

Here $\mathrm{VarR_t} = 0$ or $\mathrm{VarR_t} > 0$ for all Y, hence $\mathrm{VarR_t}$ is censored from below or left-censored, which is for stock volatility in the existing study

3.2.2. Mediation analysis

Once the result is drawn from the Tobit model, then volatility will be tested on the stock return and based on the effect that is drawn on stock volatility through Tobit model will then tested for mediation effect of stock volatility on effect that oil and price volatility has on Market return (Alswalmeh, 2021). In this research, the mediation analysis was conducted using the Baron and Kenny method for evaluating mediation effects (Mehmetoglu, 2018). Additionally, the study employed the Monte Carlo Method for Assessing Mediation (MCMAM), initially introduced and assessed by MacKinnon et al. (2004). This technique presupposes normal sampling distributions for the mediator (M) and the independent variable (X). It calculates confidence intervals for the mediation effect by generating random samples from the joint distribution of the mediator and independent variable coefficients, based on their estimated variances and covariances, then multiplying these samples together. This process is repeated extensively, and the distribution of the product of the mediator and independent variable is used to establish a confidence interval for the mediation effect observed. Although the MCMAM did not outperform the bias-corrected bootstrap in the MacKinnon et al. (2004) study, it proved more effective than the Sobel test, which is another method used in the study alongside simple delta analysis for mediation (Valente et al., 2020).

The equation for mediation has been explained below[1]

$$RETURN_t = \propto + C_1 \ VarO_t \ + \varepsilon M1$$

$$VarR_t = \propto + \beta_1 \ VarO_t \ + \varepsilon M2$$

$$RETURN_t = \propto + C_1 \ VarR_t + \beta_2 \ VarO_t \ + \varepsilon M3$$

Here M1 test the effect of oil on return then its effect on return volatility in equation 2 and the in equation three the effect on return mediated through volatility of return.

3.2.3. Probit or logit for directional study

For a binary variable widely used models of regression are the logit and probit models. The most glaring issue with the linear probability model, The probit model's normal errors and the logit model's logistic errors are frequently the options (Long, 1997).

The rule that a positive prediction indicates a potential positive return on stocks translates into the generation of sign forecasts. A key limitation of the linear probability model, which operates on a binary outcome, is its inability to consistently produce predicted probabilities that fall between "0" and "1". In situations where the dependent variable y_i is binary, *Pi* is formulated in the given equation.

$P_i = (y = 1|0) = \phi(x_i\beta)$

In this case, ϕ represents the cumulative distribution function and β signifies the maximum likelihood estimates associated with the standard normal distribution. The probit model posits that the underlying dependent variable follows a normal distribution, in contrast, the logistic model (reflected by the dependent variable *y*) suggests that the outcome is shaped following a logistic curve. This probit model is described through the following equation.

$y_i * = I_i = \alpha + \beta x_i$

Here, x_i is visible, but y_i * remains hidden. Similar to the Logit model's approach, y_i equals 1 if y_i * is greater than 0. Conversely, if y_i * falls below 0, then y_i is set to 0. In determining the outcome of the variable, τ is typically chosen as the cutoff point, often set to "0", though another value could be substituted. Given that y_i has an unseen cutoff value represented as y_i * , it's inferred that the occurrence happens when y_i surpasses y_i * , and fails to happen if it doesn't reach this threshold.

$$\text{Yt} = \begin{cases} \mathbf{1}, & \boldsymbol{y_t} > \mathbf{0} \\ \mathbf{0}, & \boldsymbol{otherwise} \end{cases}$$

$$\mathbf{Probit}(\boldsymbol{Return}) = \boldsymbol{\beta_0} + \quad \boldsymbol{\beta_1 VarO} + \boldsymbol{\beta_2 VarE} + \quad + \boldsymbol{\varepsilon_0}$$

In this model, Probit (PRET) is assigned a value of 1 if the Return exceeds 0, and it is set to 0 if the Return is less than 0. VarO denotes the volatility of oil returns, VarE represents the volatility in the exchange rate, β stands for the beta coefficient, and ε signifies the error term.Top of Form

3.2.4. Logit

The Logit model is employed to predict the probability of an event or category that has two possible outcomes (Long, 1997). If the value exceeds y_i * , it is classified as $y_i = 1$, whereas values that are less than or equal to y_i * are classified as $y_i = 0$. Within the structural framework of the model, the unseen variable y_i * is presumed to have a linear relationship with the observed x_i. The link between the latent variable y_i * and the observable binary outcome y_i is detailed in the subsequent equation:

$$\text{Yt} = \begin{cases} \mathbf{1}, & \boldsymbol{y_t} > \mathbf{0} \\ \mathbf{0}, & \boldsymbol{y_t} < \mathbf{0} \end{cases}$$

Hence the equation here will be,

$$\mathbf{Logit}(\boldsymbol{PRET}) = \mathbf{Log}\frac{\boldsymbol{p}}{\mathbf{1} - \boldsymbol{p}} = \quad \boldsymbol{\beta_0} + \quad \boldsymbol{\beta_1 VarO} + \boldsymbol{\beta_2 VarE} + \quad + \boldsymbol{\varepsilon_0}$$

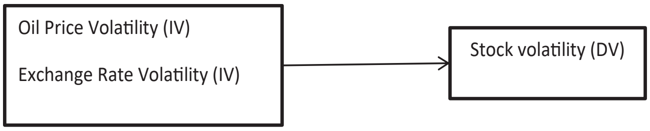
Where,

Logit (PRET)=Log p/(1-p) is 1, when Return is > 0 and 0, when return is < than 0, VarO is volatility in oil return, VarE is volatility of Exchange rate, B is beta coefficient and ε is error term.

3.3. Theoretical models

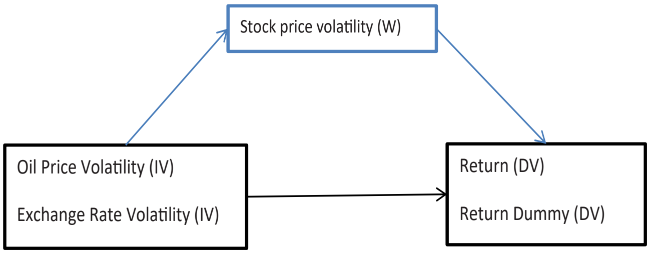
Step 1

[1] The same regression has been run for VarE as well



The above figure demonstrates the first step of research that will be conducted, which is to test the impact that Oil volatility and Exchange rate volatility has on stock market volatility.

Step 2



The above figure shows the second step of research which tests the impact of Oil volatility and exchange rate volatility on stock price return as well as direction of return (using dummy of '1' for positive direction and dummy of '0' otherwise. The mediation impact of stock volatility has also been analysed.

4. Results and discussion

4.1. Summary statistics

The variable PRET is a dummy variable that takes a value of 1 if there is profit and 0 otherwise. The mean of 0.529 indicates that in the sample, about 52.9 % of the observations had a profit. The standard deviation of 0.4993 indicates that there is a wide range of values for this variable. The minimum value of 0 indicates that there were some observations with no profit, while the maximum value of 1 indicates that there were some observations with a profit. The variable varR represents stock volatility. The mean of 0.00007595 indicates that the average daily stock volatility in the sample was very low. The standard deviation of 0.000035915 suggests that there is not much variability in the values of this variable. The minimum value of 0.000024 indicates that there were days with very low stock volatility, while the maximum value of 0.0422 indicates that there were days with very high stock volatility. The variable VarO represents oil price volatility. The mean of 0.002025383 indicates that the average daily oil price volatility in the sample was slightly higher than the volatility of the stock market. The standard deviation of 0.0031179012 suggests that there is more variability in the values of this variable compared to varR. The minimum value of 0.0003585 indicates that there were days with very low oil price volatility, while the maximum value of 0.0795367 indicates that there were days with very high oil price volatility.

The variable VarE represents exchange rate volatility. The mean of 0.00029505 indicates that the average daily exchange rate volatility in the sample was very low. The standard deviation of 0.000302777 suggests that there is not much variability in the values of this variable. The minimum value of −0.000036 indicates that there were days with a slight decrease in exchange rate volatility, while the maximum value of 0.0711 indicates that there were days with a significant increase in exchange rate volatility. In summary, the descriptive statistics suggest that VarO and VarE have a wider range of values and higher variability and varR have a narrower range of values and lower variability.

The correlation coefficient measures the strength and direction of the linear relationship between two variables. A coefficient of 1 indicates a perfect positive correlation, while a coefficient of −1 indicates a perfect negative correlation. A coefficient of 0 indicates no correlation. The correlation matrix above shows the pairwise correlations between the four variables, collinearity is likely to exist if values of correlation are out of the range of −8–8 (Young, 2018). The values in the upper triangle represent the correlation coefficients, while the values in the lower triangle in parentheses represent the standard errors of the coefficients.

PRET and varR have a positive correlation coefficient of −0.003, which is not statistically suggesting that there is a insignificant

Table 1
Descriptive Statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
RETURN	2499	.00728	.00754	−.0257	03519
varR	2499	.00007	.00004	.00002	.00042
VarO	2499	.00202	.00311	.00036	.07953
VarE	2499	.00007	.00039	0	.01010
PRET	2499	.52861	49928	0	1

Table 2
Pairwise correlations.

Variables	(1)	(2)	(3)	(4)	(5)
(1) RETURN	1.000				
(2) PRET	0.759	1.000			
	(0.000)				
(3) varR	0.038	−0.003	1.000		
	(0.054)	(0.900)			
(4) varO	0.062	0.029	0.275	1.000	
	(0.002)	(0.151)	(0.000)		
(5) varE	−0.002	0.008	0.111	0.031	1.000
	(0.936)	(0.706)	(0.000)	(0.125)	

Table 3
Tobit regression.

varR	Coef.	St.Err.	t-value	p-value	[95 % Conf	Interval]	Sig
VarE	.008	.002	14.22	0	.003	.004	* **
VarO	.021	.004	5.36	0	.013	.028	* **
Constant	0	0	77.26	0	0	0	* **
Constant	0	0	.b	.b	0	0	
Mean dependent var		0.000	SD dependent var			0.000	
Pseudo r-squared		0.016	Number of obs			2499	
Chi-square		155.002	Prob > chi2			0.000	

* ** p < .01, * * p < .05, * p < .1

Table 4
Structural Equation Model (SEM).

SEM (VarR varO →RETURN) (varO → VarR)

	Coef.	Std.Err.	Z	P > z	[95 %Conf.	Interval]
Structural						
RETURN < -						
varR	10.477 * *	4.311	2.430	0.015	2.028	18.926
VarO	0.004	0.050	0.090	0.932	−0.093	0.102
_cons	−0.000	0.000	−0.220	0.828	−0.001	0.001
varR < -						
VarO	0.003 * **	0.000	11.740	0.000	0.002	0.003
_cons	0.000	0.000	84.760	0.000	0.000	0.000
var(e.RETURN)	0.000	0.000		0.000	0.000	
var(e.varR)	0.000	0.000		0.000	0.000	

SEM (VarR varE →RETURN) (varE → VarR)

	Coef.	Std.Err.	Z	P > z	[95 %Conf.	Interval]
Structural						
RETURN < -						
varR	10.559 * *	4.216	2.500	0.012	2.297	18.822
VarE	0.002	0.389	0.000	0.996	−0.760	0.764
_cons	−0.000	0.000	−0.210	0.832	−0.001	0.001
varR < -						
VarE	0.009 * **	0.002	4.780	0.000	0.005	0.012
_cons	0.000	0.000	103.710	0.000	0.000	0.000
var(e.RETURN)	0.000	0.000		0.000	0.000	
var (e.varR)	0.000	0.000		0.000	0.000	

LR test of model vs. saturated: chi2(1) = 0.00, Prob > chi2 = 1.0000
LR test of model vs. saturated: chi2(1) = 0.00, Prob > chi2 = 1.0000

positive relationship between profit and stock volatility. PRET and VarE also have a positive correlation coefficient of 0.042, which is statistically insignificant. PRET and VarO have an insignificant positive correlation coefficient of 0.041. varR and VarE have a small positive correlation coefficient of 0.029, which is not statistically significant (t-statistic of 1.22). This suggests that there is no significant relationship between stock volatility and exchange rate volatility. VarR and VarO have a very small positive correlation coefficient of 0.004, which is statistically significant. Overall, there is no issue of multicollinearity in the data as given in Appendix A, when two independent variables have high collinearity then there could be biased results shown.

4.2. Tobit regression

The model described is a Tobit regression, designed to examine datasets with censoring. This means the dependent variable is subject to either a lower or upper threshold, beyond which observations are not possible. The model also includes two constant terms, which are not usually included in Tobit regression but can be added to account for the presence of censoring. The chi-square value is 135.669, with a p-value of 0, indicating that the model is significant overall.

The analysis reveals that VAROIL significantly influences the dependent variable positively, indicated by a coefficient value of 0.008 and a p-value of 0.00. This implies that any single-unit increase in VarO correlates with an adjustment in the stock price. Furthermore, Sadorsky (1999) observed that fluctuations in oil price volatility account for a considerable portion of the variability in stock returns, hinting at either changes in oil price volatility dynamics or shifts in economic structures. (Cunado et al., 2015) discovered that volatility shocks in oil prices result in an immediate and lasting decrease in economic activity by approximately 0.1 percentage points. Given the premise that increased volatility negatively impacts various economic activities, the findings of this study indicate that oil price volatility adversely affects the returns of G7 stock markets. Cuñado and de Gracia, (2005) noted that preceding behaviors of oil and stock movements, where significant declines in oil prices lead to increased volatility, demonstrate the effect of oil volatility on stock market volatility. Conversely, VarE's significance is also underscored by a coefficient of 0.003 and a p-value of 0.00, indicating a noteworthy positive impact of exchange rate volatility on stock returns, a finding echoed by Adjasi et al. (2011). Ultimately, the Tobit regression analysis concludes that both VarE and VarO exert significant positive impacts on stock return volatility (VarR).

4.3. Mediation impact on return

The above table shows the calculated through SEM (structural equation modeling) to assess the possible mediation impact that could be established for VarR on the relationship between varO and VarE on the RETURN. The results show the main effect of the volatility variable on return as well as the individual effect of VarO and VarE on VarR. Var E and VarO have shown significant impact on VarR, which confirms the results that were established in the Tobit regression as well. If the effect of varR is analyzed for its impact on RETURN, there is a significant positive impact. Whereas varE and varO has no significant impact on return, Pan et al. (2007) have demonstrated that there is no long-term co-integration between the exchange rate and the Malaysian stock market; rather, their pair-wise causality analysis demonstrates that there is only a short-term unidirectional causal relationship between the exchange rate and the stock market. However, it is possible that through mediation of varR the effect of varE and varO becomes significant upon RETURN. Hence, to analyze that, mediation impact was tested and has been displayed in below Table.

Utilizing the Baron and Kenny method for mediation analysis, multiple regression tests were performed to explore the dynamics between the independent variable (X), the mediating variable (M), and the outcome variable (Y). In the context of oil price volatility in Table 5, the initial step of the analysis uncovered a significant positive link between X and M, with a unit increase in varO leading to a 0.003 unit rise in varR, a statistically significant finding. Proceeding to the second phase, the analysis showed a significant positive connection between M and Y, where a unit elevation in M correlated with a substantial 10.477 unit increase in Y, further confirming the statistical significance of this relationship. Given these substantial connections in the first two steps and corroborated by the Sobel test—which evaluates the significance of the mediation effect—the evidence strongly suggests that there is a positive indirect influence of varO on RETURN through the mediator (M). This underscores the pivotal role of the mediator in channeling the effect of varO to RETURN. Supporting this conclusion, research by Ge et al. (2016) indicates that the impact of oil price volatility on the aggregate stock return in the Chinese market diminishes when market risk/volatility is considered, highlighting that it is the market volatility that transmits oil price volatility to stock returns. Further, a study by Xiao et al. (2018) on the effect of oil price fluctuations on comprehensive and sector-specific stock returns in China from 2007 to 2017 demonstrates that the crude oil volatility index significantly influences overall stock returns, especially under conditions of market turbulence and downturns.

Considering the exchange rate volatility, in the first step, the analysis revealed a significant positive relationship between X and M. For every one-unit increase in X, M increased by 0.019 units, and this relationship was found to be statistically significant. Moving to

Table 5
Mediation Regression Model.

MEDIATION EFFECT ON OIL PRICE VOLATILITY			
Estimates	**Delta**	**Sobel**	**Monte Carlo***
Indirect effect	0.028	0.028	0.028
Std. Err.	0.012	0.012	0.012
z-value	2.380	2.380	2.351
p-value	0.017	0.017	0.019
MEDIATION EFFECT ON EXCHANGE PRICE VOLATILITY			
Estimates	**Delta**	**Sobel**	**Monte Carlo***
Indirect effect	0.202	0.202	0.203
Std. Err.	0.086	0.086	0.089
z-value	2.342	2.342	2.279
p-value	0.019	0.019	0.023

the second step, the results indicated a significant positive relationship between M and Y. Each one-unit increase in M was associated with a 10.753-unit increase in Y. This relationship was also statistically significant. It can be concluded that mediation is present and results in a significant positive impact of exchange rate on stock market return based on the significant relationships seen in steps 1 and 2 as well as the significant results from the Sobel's test, which assesses the significance of the indirect effect. In the findings of (Narayan et al., 2010) it was stated that currency volatility has a positive effect on returns in China. In contrast to China, where currency appreciation has occurred over the years, Pakistan's depreciating currency causes people to have less faith in their cash and prefer to invest in stocks to preserve their money's value, which may have a positive effect on stock market returns. These findings indicate that the mediator (M) plays a crucial role in transmitting the effect of X to Y. Although the direct effect of X on Y was not significant, the indirect effect through the mediator was statistically significant, providing evidence of mediation.

4.4. Directional effect

This is a probit regression result, which is similar to a logistic regression as given in Appendix B, since these bother models have a binary dependent variable. The dependent variable in this case is denoted as PRET.

The independent variables include VarE VarR, and VarO. The coefficient for VarR is 527.171, however, the p-value for VarR is.469, indicating that this variable is not statistically significant at conventional levels. The coefficient for VarE is 32.24 where the results depict insignificance. The VarO has also shown an insignificant result for the directional impact on return. The pseudo R-squared value is 0.002, indicating that the independent variables explain very little of the variation in the dependent variable. The Chi-square value 2.135 and the associated p-value is 0.545, indicating that the model as a whole is not statistically significant at conventional levels. In summary, none of the independent variables are statistically significant at conventional levels and the model as a whole is not statistically significant. This concludes that there is not statistically significant directional impact and there is expected to be no mediation either, which can be seen in the results below.

The above Table 7 shows the results obtained using the Baron and Kenny approach to test mediation, several regression analyses were conducted to assess the relationships between the independent variable (X), the mediator (M), and the dependent variable (Y). there is no mediation impact of VarR on varO and varE when testing for its impact on the effect on directional movement in RETURN.

4.5. Discussion of results

The Tobit regression analysis reveals significant insights into the relationship between oil price volatility (VarO), exchange rate volatility (VarE), and stock return volatility (VarR). The positive and statistically significant coefficient for VarO aligns with Sadorsky's (1999) assertion that oil price volatility substantially impacts stock market performance. Recent studies, such as those by Gokmenoglu et al. (2021), confirm that oil price dynamics remain a critical determinant of stock market volatility, particularly in emerging markets. Similarly, Cunado et al. (2015) observed that volatility shocks in oil prices negatively impact economic activity, consistent with this study's findings that oil price volatility adversely affects returns in G7 markets. These results further emphasize the role of energy price shocks in shaping financial market outcomes, as highlighted by Zhang et al. (2022), who noted that oil price fluctuations significantly influence sectoral stock returns.

Regarding exchange rate volatility, the positive coefficient of VarE indicates its meaningful impact on stock return volatility. This outcome echoes Adjasi et al. (2011) and aligns with recent findings by Nain and Yadav (2023), who reported that exchange rate volatility influences investment decisions and portfolio adjustments in developing economies. The mediation analysis also substantiates the significance of VarR in transmitting the effects of VarO and VarE to stock market returns. Notably, studies by Ge et al. (2016) and Xiao et al. (2018) underline the intermediary role of volatility in the relationship between macroeconomic variables and financial market outcomes, which this study confirms.

The SEM results reveal a statistically significant indirect effect of VarO on returns. This supports the notion that market volatility mediates the influence of oil price shocks on stock market behaviour. Recent evidence by Lin and Chen (2021) corroborates this, emphasizing the importance of considering market risk when assessing oil price impacts. Similarly, the mediation analysis for VarE highlights its significant indirect effect on returns, resonating with the findings of Narayan et al. (2020) and Tian and Ma (2010). These studies illustrate how currency depreciation in emerging markets like Pakistan encourages investors to shift toward equities, enhancing stock market returns.

Table 6
Probit regression (Main Effect).

PRET	Coef.	St.Err.	t-value	p-value	[95 % Conf	Interval]	Sig
varRZ	527.171	727.782	0.72	.469	−899.255	1953.597	
VarOZ	−.463	8.333	−0.06	.956	−16.796	15.87	
varE	32.24	112.018	0.29	.773	−187.31	251.791	
Constant	.031	.059	0.52	.601	−.085	.147	
Mean dependent var	0.529	SD dependent var	0.499	Mean dependent var	0.529	SD dependent var	
Pseudo r-squared	0.002	Number of obs	2499	Pseudo r-squared	0.002	Number of obs	
Chi-square	0.683	Prob > chi2	0.877	Chi-square	0.683	Prob > chi2	
Akaike crit. (AIC)	3463.480	Bayesian crit. (BIC)	3486.774	Akaike crit. (AIC)	3463.480	Bayesian crit. (BIC)	

* ** p < .01, * * p < .05, * p < .1

Table 7
Mediation Regression Model.

Mediation impact on exchange rate volatility			
Estimates	**Delta**	**Sobel**	**Monte Carlo***
Indirect effect	3.825	3.825	3.903
Std. Err.	5.284	5.284	5.434
z-value	0.724	0.724	0.718
p-value	0.469	0.469	0.473
Mediation impact on oil price volatility			
Estimates	**Delta**	**Sobel**	**Monte Carlo***
Indirect effect	0.574	0.574	0.583
Std. Err.	0.754	0.754	0.765
z-value	0.761	0.761	0.763
p-value	0.447	0.447	0.446

The probit regression analysis, however, shows no significant directional impact of VarO or VarE on returns, suggesting that their effects may primarily operate through mediating factors such as VarR. This aligns with Nguyen et al. (2023), who found that macroeconomic variables often exert indirect rather than direct effects on market outcomes. Furthermore, the mediation effects calculated using the Sobel and Monte Carlo methods reaffirm the pivotal role of volatility as a conduit for macroeconomic shocks.

In the context of Pakistan, oil price volatility and exchange rate fluctuations have a disproportionately high impact on stock market returns, reflecting the country's import-heavy energy sector and the limited resilience of domestic industries to external shocks. The findings suggest that, unlike more diversified economies, Pakistan's stock market exhibits heightened sensitivity to these macroeconomic factors, amplifying the challenges for policymakers in managing inflation and market stability. The findings emphasize the critical roles of oil price and exchange rate volatilities in shaping stock market dynamics. The mediation analyses highlight the importance of considering indirect effects, as direct impacts may not always be apparent. Future research could explore the sectoral implications of these volatilities, particularly in economies with high dependence on energy imports or exports.

5. Conclusion

This research examined the effects of oil price and exchange rate fluctuations on the volatility of stock returns, employing the Tobit regression model for analysis. The results highlighted a substantial impact of both oil price and exchange rate volatilities on the volatility of stock returns, indicating that these factors play a significant role in the variability of stock market returns through their influence on stock volatility. Interestingly, the study found no meaningful effect on a dummy variable that represented positive stock returns, suggesting that while oil and exchange rate volatilities impact stock return volatility, they might not directly affect the direction of stock market movements regarding positive gains.

These findings enrich the body of knowledge by shedding light on the dynamics between oil price volatility, exchange rate volatility, and stock return volatility. They affirm the significant influence that market volatilities in these areas can exert on the stock market's behavior. This emphasizes the importance for investors and policy makers to carefully evaluate the repercussions of oil and exchange rate volatilities on stock market risks and potential returns. A notable limitation of this study was its general approach over a decade-long period without considering varying economic conditions, market structures, or regulatory environments that could affect these relationships. Additionally, the study's reliance on high-frequency data (daily observations) meant it did not incorporate macroeconomic indicators, pointing to areas for future research to explore further variables that could influence the relationships among oil volatility, exchange rate volatility, and stock returns. Future studies might also benefit from examining different time frames and geographical areas to test the consistency and applicability of these findings.

From an academic standpoint, the study makes several contributions to financial economics literature, especially by applying advanced statistical models like the Tobit regression and exploring mediation effects and directional influences through the Probit model regression. This methodological contribution provides researchers with enhanced tools for analyzing economic variable relationships.

Given the significant impact of exchange rate and oil price volatility on stock market performance in Pakistan, policymakers should prioritize strategies aimed at stabilizing the rupee and reducing dependence on oil imports. This could involve investing in alternative energy sources, enhancing domestic production capacities, and strengthening foreign exchange reserves to mitigate the impact of external shocks. Practically, the study's insights are vital for investors and policymakers, highlighting the critical need for comprehensive risk assessment strategies that account for the effects of oil and exchange rate volatilities on stock market volatility. These insights can guide informed portfolio management and risk reduction decisions, as well as aid policymakers in formulating policies that consider the impact of these economic factors on market stability. Ultimately, this research bridges theoretical analysis and practical application, offering valuable perspectives for navigating financial market complexities.

While the findings of this study are focused on Pakistan, they provide valuable insights into the broader dynamics of oil price and exchange rate volatility in emerging markets. However, given the unique economic challenges faced by Pakistan, such as its dependency on oil imports and vulnerability to external financial flows, the results may not be directly applicable to all countries. Future studies could explore how these interdependencies play out in other emerging economies with different economic structures and external vulnerabilities. In addition, future research could expand this analysis to other emerging economies in Asia, Africa, and Latin America, comparing how oil price and exchange rate volatilities affect stock markets in countries with varying levels of economic diversification. A comparative study could offer insights into the broader applicability of these findings and provide valuable policy recommendations for countries exploring similar economic challenges. Finally, future iterations could explore Brent crude prices to provide a comparative analysis and strengthen the alignment with Pakistan's specific oil market context.

CRediT authorship contribution statement

Naz Farah: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Karim Sitara:** Writing – original draft, Supervision, Software, Project administration, Methodology, Conceptualization. **Lucey Brian M.:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Data curation. **Khan Misbah:** Writing – review & editing, Writing – original draft, Visualization, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Multicollinearity

Multi-collinearity

VIF	1/VIF
1.250	0.800
5.860	0.171
6.370	0.157
3.940	0.254
4.010	0.249
4.290	

Appendix B. Logistic Regression

Logistic regression

DRET	Coef.	St.Err.	t-value	p-value	[95 % Conf	Interval]	Sig
varRZ	633.482	1280.495	0.49	.621	−1876.242	3143.206	
VarOZ	95.215	41.02	2.32	.02	14.818	175.611	* *
C	−652356.67	271421.72	−2.40	.016	−1184333.5	−120379.88	* *
VarE	−62.266	192.317	−0.32	.746	−439.2	314.668	
O	0	.	.	.	.	.	
C	169963.75	1323502.9	0.13	.898	−2424054.4	2763981.8	
Constant	−.237	.119	−1.99	.047	−.47	−.003	* *
Mean dependent var	0.471	SD dependent var	0.499	Mean dependent var	0.471	SD dependent var	
Pseudo r-squared	0.003	Number of obs	2499	Pseudo r-squared	0.003	Number of obs	
Chi-square	6.504	Prob > chi2	0.260	Chi-square	6.504	Prob > chi2	
Akaike crit. (AIC)	3459.131	Bayesian crit. (BIC)	3494.073	Akaike crit. (AIC)	3459.131	Bayesian crit. (BIC)	
probit/logit goodness of fit							

* ** p < .01, * * p < .05, * p < .1

Probit model for PRET, goodness-of-fit test

number of observations = 2499

number of covariate patterns = 1812

Pearson chi2(1806) = 1812.00

Prob > chi2 = 0.4559

Data availability

The data that has been used is confidential.

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