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ASYMMETRIC EFFECTS OF CRUDE OIL PRICES AND EXCHANGE RATE SHOCKS ON STOCK RETURNS: FIRM-LEVEL EVIDENCE FROM PAKISTAN

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Abstract

Background: *Pakistan's listed oil and gas exploration companies earn revenues tied to world oil prices and the US dollar, yet little is known about whether their share prices respond differently to rising and falling oil prices or to rupee depreciation and appreciation.*

Objectives: *The study tests whether positive and negative changes in oil prices and the exchange rate have asymmetric effects on the stock returns of Oil & Gas Development Company Limited (OGDC), Pakistan Petroleum Limited (PPL), and Pakistan Oilfields Limited (POL), whether these sensitivities differ across the three firms, and whether oil and exchange-rate information improves return forecasts.*

Methods: *We use 574 weekly observations from January 2015 to December 2025 obtained from the Pakistan Stock Exchange, the U.S. Energy Information Administration, and the State Bank of Pakistan. We estimate firm-level regressions with Newey–West standard errors, Wald tests, quantile and GARCH-t models, a pooled model with Driscoll–Kraay errors, and walk-forward forecasts from Elastic Net, random forest, and XGBoost models.*

Results: *A 1% rise in Brent rises in the same week returns by 0.19% to 0.22% for all three firms. On average, responses to oil price increases and decreases are statistically equal, and rupee shocks show no asymmetric effect. Asymmetry appears for OGDC, which barely reacts to falling oil prices, in the upper tail of the return distribution, and in a post-2020 decline in sensitivity to oil price decreases. Oil and exchange-rate predictors improve directional accuracy, but forecast gains are small and concentrated in crisis weeks.*

Conclusion: *Oil exposure in Pakistani energy stocks is strong, mostly symmetric, and time-varying, so investors and regulators should rely on state-dependent rather than constant measures of oil risk.*

Keywords: Oil Price Shocks, Exchange Rate, Asymmetric Effects, Stock Returns, Machine Learning

JEL Codes Classification: G12, G17, Q43, F31

1. Introduction

1.1 Background

The price of crude oil is one of the most important prices for an emerging economy. Hamilton (1983) established that oil price booms had a lead over most U.S. postwar recessions, and Kilian (2009) found that the economic effect of an oil price change is tied with its effect on global demand. It's not a shock when you look at equity prices, depending on when and where you look. Oil shocks have diverse effects on the stock market that evolve over time and vary across countries depending on whether they are oil-importing or oil-exporting countries (Atif et al., 2022; Mokni, 2020); whether the shock is a supply shock or demand shock

(Castro et al., 2023; Das et al., 2022); and whether the shock occurs during a market or a crisis scenario (Jiang et al., 2020; Kielmann et al., 2022). Bashir (2022), who looked at 684 studies, observes limited sector-level analysis.

These are questions that have a very acute focus in Pakistan. Between 2015 and 2025, Brent crude fell to US$15.87 per barrel in April 2020 and rose to US$127.44 in June 2022, while the rupee weakened from about 100.5 to 280.4 per US dollar, a 179% increase in the USD/PKR rate. Certain movements were sudden and in the last seven days of January 2023 alone, USD/PKR gained 12.2% in log terms. The shocks are centered on the listed exploration and production companies of the country. They receive their revenues from oil prices in foreign markets, publish their reports in rupees and have significant proportion in the KSE-100 index. Weekly news on companies can uncover trends that are not apparent in market averages, as firm-specific news and regulated prices, as well as payment arrears, determine how the value of a firm responds to oil and currency volatility.

1.2 Statement of the Problem

The oil sensitivity of an energy company is frequently regarded as a single number by investors and risk managers. The assumption is convenient, but not tested in the case of Pakistan, as a majority of estimates are based on monthly or annual data at the market level and models that have the same response for rising and falling. A symmetric oil beta will misrepresent risk in just the times it is most critical if gains from rising oil prices are not equal to losses from falling prices. The same goes for the rupee whose sharp deprecations are large and abrupt, compared to its gradual appreciations. Another question is whether the three key exploration companies are all exposed, or whether they differ in terms of their ownership, their product mix and/or their delays in payment from gas utilities. Lastly, merely because there is a significant relation in the sample, it does not imply that oil and currency data can help investors to predict returns (Goyal et al., 2024).

1.3 Significance of the Topic

There are several groups who care about the question. The valuations of the largest listed companies such as OGDC, PPL and POL have an impact on public wealth as well as private portfolios, with the first two being majority state owned. Investors' understanding of the difference between downside and upside exposure to oil influences the size of positions they open, and the choices they make when hedging. The relationship between world oil prices, the rupee and energy-sector valuations are of relevance to the policymakers in the context of the regulated gas pricing and resolving the energy-sector arrears. In practice both shocks discussed here are closely linked because Pakistan must import most of the oil it consumes, which in turn has a deleterious impact on the trade balance and the rupee. For researchers, firm level evidence from an oil importing frontier market adds to the large exporter and developed markets literature.

1.4 Research Objectives

The study pursues three objectives.

RO1: To estimate and compare the short-run responses of OGDC, PPL, and POL stock returns to positive and negative changes in Brent crude oil prices and the USD/PKR exchange rate during 2015–2025.

RO2: To determine whether the size and direction of these sensitivities differ significantly across the three firms after controlling for the market return.

RO3: To evaluate whether oil-price and exchange-rate indicators improve out-of-sample forecasts of weekly stock returns compared with models that use stock-market information alone.

1.5 Aim of the Study

The aim is to establish how, and how reliably, world oil prices and the rupee are transmitted into the share prices of Pakistan's oil and gas exploration companies, and to judge whether this transmission is stable enough to be useful for forecasting. In doing so, the study links asymmetry theory, firm-level econometrics, and machine learning in a single design.

1.6 Contribution and Scope of the Study

The study has three contributions. It offers first-of-its-kind tests of oil and exchange-rate asymmetry on a firm basis for Pakistani energy stocks, based upon weekly data and inference which is invariant to heteroskedasticity, autocorrelation, fat tails and crisis episodes. Second, it formally tests if the three firms have the same sensitivities under a pooled model which has common shocks to all three firms. Third, it considers

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Volume 5 Issue 5, 2026

whether the same information helps forecasts of the returns for the following week, when evaluated purely out of sample. Its scope has been limited to the three largest listed E&P companies, weekly frequency, and January 2015–December 2025 which includes the 2020 oil price collapse, the 2022 energy shock, and the 2022–2023 rupee crisis.

1.7 Organization of the Study

Theory and evidence is reviewed and hypotheses developed in Section 2. The data and models are detailed in Section 3. The results are presented and discussed in Section 4, and recommendations, limitations and directions for future study are presented in Section 5.

2. Literature Review

2.1 Theoretical Review

The study is based on three theories. The first is the model of present value, with the price of a share being the discounted value of the cash flows the share is expected to generate. Oil pricing goes into both cash flows and discount rates (Jones & Kaul, 1996). With a higher oil price, the cost of oil to consumers would increase, while the revenue to the producers would increase, and the model would predict a positive correlation between oil prices and the returns of the companies examined in this paper.

The second is that of asymmetric oil shocks. Mork (1989) demonstrated that the economy of the U.S. is very sensitive to oil price increases, and scarcely responsive to decreases, while Hamilton (2003) suggested that the economy responds primarily to the increases above the peaks of the last few years. The source of a price change also plays a role, as supply shocks, global demand shocks and oil-specific demand shocks have different effects on activity, adds Kilian (2009). Other sources of firm-level asymmetry exist, such as investors being more responsive to bad news or increases and decreases being passed through unequally through the regulated price.

The third is the theory of exchange-rate exposure. Adler and Dumas (1984) defined exposure as the sensitivity of the value of a firm to movements in the currency, and Jorion (1990) demonstrated that exposure increases as a firm's exposure to foreign activity increases. For a producer whose revenue is denominated in dollars, but the share price is in rupees, the depreciation would be beneficial but a substantial and rapid depreciation could also indicate macroeconomic stress, which would reduce share prices.

2.2 Empirical Review

The oil-stock relation is unstable. Overall, Jiang et al. (2020) do not detect a general link between decomposed oil shocks and G7 stock returns, while Castro et al. (2023) prove that the reaction of the euro area to each type of oil shock evolves over time. Das et al. (2022) determines that in 24 emerging markets, oil shocks associated with higher demand are correlated with positive returns whereas oil shocks associated with lower supply are correlated with negative returns, and that this correlation is stronger for oil shocks that occur during bear markets. Time-varying dependence between oil shocks and BRICS returns is reported by Ji et al. (2020) and Kielmann et al. (2022).

Asymmetry is becoming an established fact. Escobari and Sharma (2020) find significant asymmetries in the stock price response to oil that are explained mainly by recessions and partly by the size and sign of the price change. Rahman (2022) and Hashmi et al. (2021) argue that oil effects are asymmetric in the United States and in oil-exporting and oil-importing countries, respectively, while İmamoğlu (2026) reveals that Kazakhstan, an oil exporter, is particularly sensitive to oil price declines. The study by Aruna and Acharya (2023) at the firm level reveals that there is an asymmetric impact between net positive and negative changes in oil prices on Indian firms, with 1,168 firms being impacted by a net increase in oil prices and 1,127 firms being affected by a net decrease.

Oil exposure is confirmed as positive in studies of energy companies. Kushwah and Siddiqui (2023) reveal that there is a significant positive correlation between oil price movements and oil-sector returns in the top five oil-importing economies, while M. H. Khan et al. (2023) report that oil price shocks increase the returns of major oil and gas companies, even during the 2020 Saudi Russian price war. Yurteri Kösedagli et al. (2021) find positive, time-varying oil exposure in the oil-gas sectors of the fragile five economies other than Indonesia, Hoque et al. (2020) find that exposure among Malaysian oil and gas firms varies with sub-industry, size, and volatility state, and Adekunle et al. (2020) study the oil-return link firm by firm in Nigeria.

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Volume 5 Issue 5, 2026

The exchange-rate channel is typically weak or state-dependent. Cuestas and Tang (2021) could not detect any long-run Granger causality from the exchange rates to the stock returns of China, but they do detect contemporaneous spillovers; Long et al. (2021) find that the renminbi influences the stock prices of China only after the commodity prices enter the model. Previous studies, such as Sikarwar (2020), illustrate that interventions by the central bank affect the currency exposure of firms in an asymmetric way, while Asif and Frömmel (2022) examine the difference in currency exposure of exporting and domestic firms. Strong interaction with a nonlinear nature are observed between oil and currency prices in many countries, and especially with equity prices (Bagchi & Paul, 2023; Chkir et al., 2020; Hashmi et al., 2022; Kumeka et al., 2022).

Predictability is fragile. Goyal et al. (2024) demonstrate that over one-third of the equity premium predictors that have been proposed in recent years are insignificant even in the sample and half of the rest are insignificant out of sample. Nonejad (2022) and Alqahtani et al. (2020) discuss the nonlinear and regional impacts of oil, while Zhang et al. (2021) show that the impact of oil on stock returns in Japan was reduced by approximately 89.5% during the COVID-19 period. Gu et al. (2020) find large machine learning gains for U.S. equities, while Hanauer and Kalsbach (2023) generalize this approach for emerging markets.

The evidence in Pakistan is quite summative. Shabbir et al. (2020) study showed that gold and oil prices significantly influence the stock market, Sheikh et al. (2020) study indicated that there are asymmetric responses of the stock market to macroeconomic shocks around the 2008 crisis, while M. I. Khan et al. (2021) study found that oil prices have positive effect on stock market development and exchange rate has negative effect on stock market development. In this regard, Ali et al. (2022) discovered that the effects of oil on banking, power, chemical, and fertilizer stocks are asymmetric; M. Khan et al. (2025) discussed the impact of exchange-rate and oil-price volatility on the overall market; and Ullah et al. (2025) and Rehman and Gul (2026) employed machine learning on the Pakistan Stock Exchange.

2.3 Research Gap

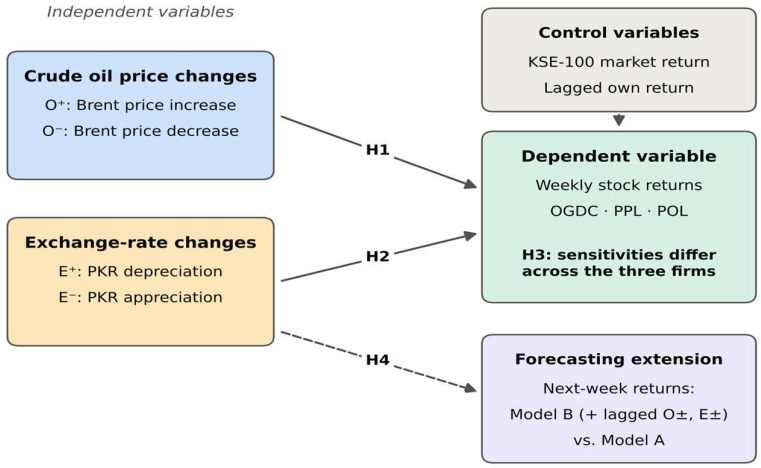
Three gaps emerge. First, Pakistani studies examine the aggregate market or broad sectors, and none tests asymmetric oil and exchange-rate effects for individual exploration and production companies; Ali et al. (2022) explicitly left the oil and gas sector out. Second, no study tests whether the sensitivity of these firms differ from one another while accounting for shocks

2.4 Conceptual Framework

The framework is summarised in Figure 1. The independent variables are changes in oil prices (both positive and negative) and rupee appreciation and depreciation, while the dependent variables are oil price returns of OGDC, PPL, and POL, and KSE-100 returns and lagged own returns are the controls. H1 and H2 are related to the asymmetry of each channel, H3 is related to differences in the firms, and H4 is an extension of the framework to out-of-sample forecasting.

Figure 1

Conceptual Framework of the Study



INVERGE JOURNAL OF SOCIAL SCIENCES
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Volume 5 Issue 5, 2026

Note. H1 and H2 test the asymmetry of oil and exchange-rate effects, H3 tests differences across firms, and H4 tests the out-of-sample value of lagged oil and exchange-rate shocks. Source: Authors' construction.

2.5 Hypotheses Development

Asymmetric oil theory (Hamilton, 2003; Mork, 1989) and recent evidence for individual firms (Aruna & Acharya, 2023; Escobari & Sharma, 2020) suggest that producers may respond differently to rising and falling oil prices.

H1: Positive and negative crude oil price changes have significantly different effects on the stock returns of Pakistani oil and gas exploration companies.

Exposure theory implies that dollar-linked revenues gain from depreciation, but the abrupt nature of rupee depreciation and the asymmetric effects of currency interventions (Sikarwar, 2020) point to unequal responses.

H2: Positive (depreciation) and negative (appreciation) changes in the USD/PKR exchange rate have significantly different effects on the stock returns of Pakistani oil and gas exploration companies.

Differences in ownership, product mix, and receivables, together with evidence of heterogeneous exposure among oil and gas firms (Hoque et al., 2020; Yurteri Kösedagli et al., 2021), motivate the third hypothesis.

H3: The sensitivities of OGDC, PPL, and POL stock returns to oil-price and exchange-rate changes differ significantly across the three firms.

If oil and currency shocks carry information that prices absorb with a delay (Dai et al., 2021), adding them should improve forecasts.

H4: Models that include oil-price and exchange-rate indicators produce significantly lower out-of-sample prediction errors for weekly stock returns than models using stock-market information alone.

3. Research Methodology

3.1 Study Area

The study is related to the Oil and Gas Exploration and Production Sector of the Pakistan Stock Exchange (PSX). The three biggest listed companies of the sector, OGDC, PPL and POL, form the backbone of the listed upstream sector in the country and are the sample.

3.2 Data Collection Techniques

This study is based on secondary data. Data on daily closing prices was obtained from PSX data portal, the Brent spot price (in USD/barrel) from the U.S. Energy Information Administration and the USD/PKR rate (the daily average bank floating rate) from the SBP EasyData portal for the three stocks along with KSE-100 index. The data in all series were weeklyised (last observation in each Saturday to Friday week) to eliminate the nonsynchronous-trading problem caused by the time lag between the oil markets in Karachi and London and New York. Bonus issues in the prices have been adjusted according to the announcement made by the official stock exchanges: October 2018, PPL 15% bonus; October 2019, PPL 20% bonus; September 2018, POL 20% bonus. The KSE-100 is a total return index while cash dividends are not reinvested and thus, stock returns are price returns. There are no values interpolated and the week ending May 14, 2021 is left missing due to markets being closed for an extended Eid holiday.

3.3 Duration of the Study

The sample runs from January 2, 2015, to December 26, 2025, giving 574 weekly observations. For forecasting, 2015–2019 serves as the initial training period and January 2020 to December 2025 (309 weeks) as the out-of-sample test period.

3.4 Theoretical Model

Following the present value framework, the price of firm $i$equals the discounted value of expected cash flows, and an exploration company's cash flow depends on its output, the oil price, and the exchange rate:

$$P_{i,t} = \Sigma_k E_t\left[CF_{i,t+k}\right]/(1+r_i)^k,\ CF_{i,t} = Q_{i,t} \times Oil_t \times \mathrm{FX}_t - C_{i,t} \quad (1)$$

where $Q$is production, $Oil$is the world oil price, $FX$is rupees per dollar, and $C$is cost. Taking logs and first differences implies that returns move with percentage changes in oil prices and the exchange rate.

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Volume 5 Issue 5, 2026

Asymmetry theory allows these responses to differ for increases and decreases. All changes are therefore measured as weekly log differences in percent:

$$R_{i,t} = 100\ln\left(P_{i,t}/P_{i,t-1}\right), \quad M_i = 100\ln(\mathrm{KSE}_t/\mathrm{KSE}_{t-1})$$
$$O_t = 100\ln(\mathrm{Brent}_t/\mathrm{Brent}_{t-1}), \quad E_t = 100\ln(\mathrm{FX}_t/\mathrm{FX}_{t-1}) \quad (2)$$

and each shock is split into positive and negative parts:

$$O_t^* = \max(O_t, 0), O_t = \min(O_t, 0), E_t^* = \max(E_t, 0), E_t = \min(E_t, 0) \quad (3)$$

A positive Emeans the rupee depreciated. Because $O^-$and $E^-$are never positive, a positive coefficient on either means that returns fall when oil prices fall or the rupee appreciates.

3.5 Empirical Model

For each firm, we estimate

$$R_{i,t} = \alpha_i + \beta_{1i}O_t^+ + \beta_{2i}O_t^- + \beta_{3i}E_t^+ + \beta_{4i}E_t^- + \gamma_i M_t + \phi_i R_{i,t-1} + \epsilon_{i,t} \quad (4)$$

by OLS with Newey and West (1987) standard errors and five lags (Newey & West, 1994). H1 is tested with the Wald restriction $\beta_{1i} = \beta_{2i}$and H2 with $\beta_{3i} = \beta_{4i}$. Stationarity is checked with the tests of Dickey and Fuller (1979) and Kwiatkowski et al. (1992), and conditional heteroskedasticity with the ARCH-LM test (Engle, 1982). Robustness checks include BIC selected distributed lags, quantile regressions (Koenker & Bassett, 1978), GARCH(1,1) errors with Student-t innovations (Bollerslev, 1986), exclusion of four crisis windows, HAC-robust Chow (1960) tests, the OLS-CUSUM test (Ploberger & Kramer, 1992), and 156-week rolling regressions. For H3, the three firms are stacked in a fully interacted regression with OGDC as the base:

$$R_{i,t} = \alpha + \Sigma_j \delta_j D_j + \Sigma_k \theta_k X_{i,t} + \Sigma_j \Sigma_k \lambda_{jk}\left(D_j \times X_{i,t}\right) + u_{i,t} \quad (5)$$

where $D_j$are dummies for PPL and POL and $X_{i,t}$collects the regressors of Equation 4. Driscoll and Kraay (1998) standard errors handle shocks common to the three firms, and H3 is the joint restriction that all eight shock interactions equal zero.

For H4, the target is next week's return. Model A uses two lags of the firm's own return and of the market return, and Model B adds two lags of O^+, O^-, E^+, and E^-. Elastic Net (Zou & Hastie, 2005), random forest (Breiman, 2001), and XGBoost (Chen & Guestrin, 2016) models are reestimated every 26 weeks on an expanding window, with hyperparameters tuned by time-series cross-validation on past data only. Accuracy is measured by the out-of-sample $R^2$of Campbell and Thompson (2008):

$$R_{\mathrm{OS}}^2 = 1 - \Sigma_t\left(R_{i,t} - \hat{R}_{i,t}\right)^2 / \Sigma_t\left(R_{i,t} - \bar{R}_{i,t}\right)^2 \quad (6)$$

where $\bar{R}$is the historical mean, and by directional accuracy with the Pesaran and Timmermann (1992) test. Model B is compared with Model A using the Diebold and Mariano (1995) test with the correction of Harvey et al. (1997) and the Clark and West (2007) test. H4 is supported when either test rejects at 5% and R_{OS}^2rises by at least 0.5 percentage points. SHAP values (Lundberg et al., 2020) show which predictors drive the XGBoost forecasts.

4. Results and Discussion

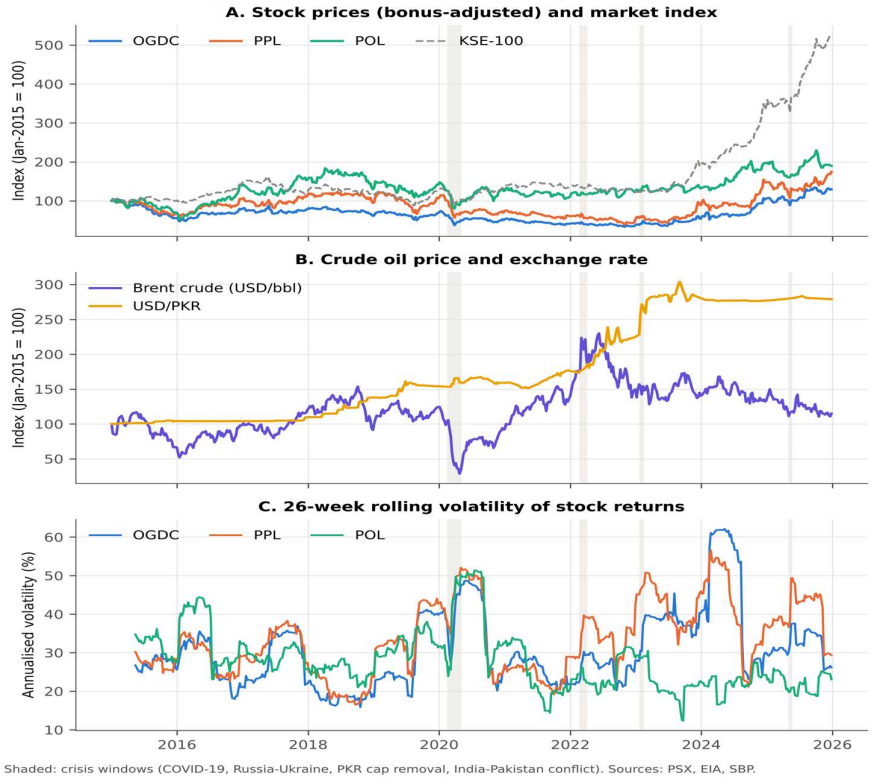
4.1 Graphical Analysis

Figure 2 traces the data. Over the sample, the bonus-adjusted prices of OGDC, PPL, and POL rose by 30%, 75%, and 90%, far behind the fivefold rise in the total-return KSE-100. Brent ended only 15% above its January 2015 level after its collapse in 2020 and its spike in 2022, while USD/PKR nearly tripled, with most of the rise in 2022–2023 and little movement after 2023. Rolling volatility peaked during the COVID-19 crash and again in 2024, when OGDC's annualized volatility reached 62%.

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Volume 5 Issue 5, 2026

Figure 2

Stock Prices, Crude Oil, the Exchange Rate, and Return Volatility, 2015–2025

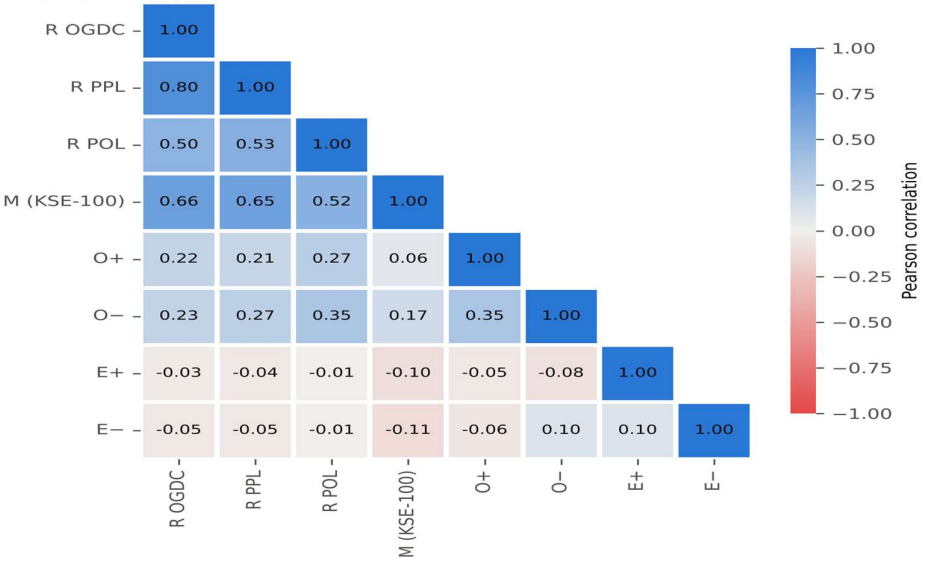


Note. Panel A indexes bonus-adjusted closing prices and the KSE-100 to 100 in January 2015. Panel B indexes the Brent spot price and USD/PKR. Panel C shows 26-week rolling annualized volatility of weekly returns. Shaded areas mark the four crisis windows. Data from the Pakistan Stock Exchange, the U.S. Energy Information Administration, and the State Bank of Pakistan.

Figure 3 shows the correlation structure. The three stocks move closely together (0.50 to 0.80) and with the market (0.52 to 0.67). Correlations with oil price increases and decreases are positive (0.21 to 0.35), while correlations with exchange-rate changes are close to zero.

Figure 3

Correlation Heatmap of Weekly Returns and Shocks



INVERGE JOURNAL OF SOCIAL SCIENCES
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ISSN (Online): 2959-4359, ISSN (Print): 3007-2018
Volume 5 Issue 5, 2026

Note. Pearson correlations over 2015–2025. Blue cells indicate positive and red cells negative correlation.

4.2 Descriptive Analysis

Table 1 shows that average weekly returns are small for all three firms, between 0.05% and 0.11%, against 0.29% for the KSE-100. Annualized volatility ranges from 28.7% for POL to 34.4% for PPL, compared with 18.8% for the market. Brent changes are more volatile still, with a weekly standard deviation of 5.58%. The exchange-rate series is extremely skewed (skewness 2.75, excess kurtosis 24.25), reflecting a few large depreciation weeks among many quiet ones; the rupee depreciated in 331 weeks and appreciated in 238. The Jarque–Bera test rejects normality for every series, and Table 2 confirms that stock returns are positively correlated with oil (0.28 to 0.38) but not with the exchange rate.

Table 1

Descriptive Statistics of Weekly Returns and Shocks

Variable	N	Mean	SD	Min	Max	Skewness	Kurtosis	JB
ROGDC	572	0.048	4.408	-29.58	16.21	-0.34	4.85	572.1***
RPPL	572	0.094	4.775	-17.45	21.63	0.27	2.00	101.9***
RPOIL	572	0.108	3.979	-23.85	15.07	-0.63	4.12	443.4***
M (KSE-100)	572	0.292	2.609	-16.20	11.77	-0.36	3.78	353.6***
O (Brent)	574	0.014	5.577	-34.64	27.04	-0.35	5.04	620.1***
E (USD/PKR)	572	0.178	1.245	-6.66	12.21	2.75	24.25	14,735.3***

Note. Weekly log changes in percent, January 2015 to December 2025. R =stock return; M =KSE-100 return; O =change in the Brent spot price; E =change in USD/PKR (positive = rupee depreciation). Kurtosis is excess kurtosis. JB =Jarque-Bera statistic. *** $p < .01$.

Table 2

Correlation Matrix of Weekly Returns and Shocks

Variable	ROGDC	RPPL	RPOIL	M	O	E
ROGDC	1					
RPPL	0.801***	1				
RPOIL	0.504***	0.532***	1			
M	0.665***	0.654***	0.521***	1		
O	0.276***	0.289***	0.377***	0.145***	1	
E	-0.05	-0.059	-0.017	-0.137***	-0.053	1

Note. Pearson correlations of weekly log changes. M =KSE-100 return; O =Brent change; E =USD/PKR change. * $p < .10$. ** $p < .05$. *** $p < .01$.

Table 3 reports the diagnostic tests. The ADF test rejects a unit root in every return series at the 1% level, and KPSS does not reject stationarity for PPL, POL, oil, or the exchange rate; it rejects narrowly for OGDC and the market ($p = .046$and .024). Given the strong ADF results, all returns are treated as stationary, whereas log price levels behave as unit-root processes. Ljung–Box and ARCH-LM tests detect volatility clustering in every series, which supports HAC inference and the GARCH robustness check.

Table 3

Unit Root and Conditional Heteroskedasticity Tests

Series	ADF	KPSS	$Q^2(10)$	ARCH-LM(4)
Returns				
ROGDC	-10.17***	0.483**	41.72***	31.28***
RPPL	-10.89***	0.243	37.04***	24.91***
RPOIL	-21.54***	0.046	19.60**	13.75***
M (KSE-100)	-10.18***	0.585**	98.66***	76.65***
O (Brent)	-8.64***	0.035	373.52***	119.43***
E (USD/PKR)	-8.20***	0.153	78.78***	31.79***
Log levels				

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ISSN (Online): 2959-4359, ISSN (Print): 3007-2018
Volume 5 Issue 5, 2026

ln POGDC	-1.05	0.604**	—	—
ln PPL	-1.11	0.448*	—	—
ln PPL	-1.88	1.345**	—	—
ln KSE-100	1.76	1.969**	—	—
ln Brent	-2.43	1.419**	—	—
ln USD/PKR	-0.27	3.345**	—	—

Note. ADF = augmented Dickey–Fuller test with a constant and AIC-selected lags (null: unit root). KPSS = Kwiatkowski–Phillips–Schmidt–Shin test (null: stationarity). $Q^2(10)$ =Ljung–Box statistic on squared demeaned returns at 10 lags. ARCH-LM(4) = Engle's test with 4 lags. Price levels for PPL and POL are bonus-adjusted. * $p < .10$. ** $p < .05$. *** $p < .01$.

4.3 Inferential Analysis

Table 4 presents the estimates of Equation 4. Oil price increases have a positive and highly significant effect on all three firms: a 1% rise in Brent is associated with same-week returns 0.22% higher for OGDC, 0.19% higher for PPL, and 0.21% higher for POL. The response to falling oil prices is also positive and significant for PPL (0.15) and POL (0.23), meaning that their returns fall when oil falls, but for OGDC it is only 0.08 and significant only at the 10% level. Market betas are 1.10, 1.15, and 0.74. The rupee coefficients are positive (0.13 to 0.22) but insignificant. The models explain 36% to 48% of weekly return variation, the residuals show no autocorrelation, and variance inflation factors stay below 1.2. Figure 4 plots the shock coefficients.

Table 4

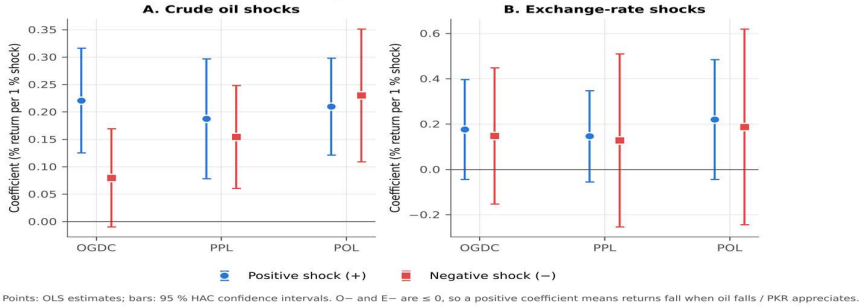
Asymmetric Effects of Oil and Exchange-Rate Shocks on Weekly Stock Returns

Variable	OGDC	PPL	POL
Constant	-0.592*** (0.193)	-0.345 (0.225)	-0.111 (0.222)
O^+ (oil increase)	0.221*** (0.049)	0.187*** (0.056)	0.210*** (0.045)
O^- (oil decrease)	0.080* (0.046)	0.154*** (0.048)	0.230*** (0.062)
E^+ (PKR depreciation)	0.176 (0.112)	0.146 (0.103)	0.220 (0.135)
E^- (PKR appreciation)	0.147 (0.153)	0.128 (0.195)	0.188 (0.220)
M (market return)	1.099*** (0.077)	1.155*** (0.080)	0.737*** (0.058)
Rt−1	-0.038 (0.040)	-0.013 (0.038)	0.015 (0.039)
N	570	570	570
R^2	0.482	0.467	0.369
Adjusted R^2	0.477	0.461	0.362
Durbin–Watson	2.09	1.98	2.02
Ljung–Box(10) p	.136	.861	.681
Maximum VIF	1.20	1.20	1.20

Note. OLS estimates of Equation 4. Newey–West HAC standard errors (5 lags) in parentheses. The dependent variable is the weekly log return in percent. Because $O^-$and $E^-$are never positive, positive coefficients mean that returns fall when oil prices fall or the rupee appreciates. VIF = variance inflation factor. * $p < .10$. ** $p < .05$. *** $p < .01$.

Figure 4

Responses of Stock Returns to Positive and Negative Oil and Exchange-Rate Shocks



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https://invergejournals.com/
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Volume 5 Issue 5, 2026

Note. Points are OLS estimates from Table 4; bars are 95% confidence intervals based on Newey–West standard errors.

Table 5 compares the asymmetric model with a symmetric benchmark. BIC favours the simpler symmetric model for all three firms, in which a 1% oil price change moves returns by 0.15% to 0.22%. In economic terms, a one-standard-deviation oil price increase (3.6%) adds 0.67 to 0.79 percentage points to the week's return, and a one-standard-deviation decrease (4.2%) subtracts 0.33 points for OGDC, 0.65 for PPL, and 0.97 for POL.

Table 5

Symmetric Benchmark and Economic Magnitude of Shocks

Item	OGDC	PPL	POL
Panel A: Symmetric versus asymmetric specification			
β(O), symmetric model	0.145***	0.170***	0.220***
β(E), symmetric model	0.157*	0.139*	0.213*
Adjusted R^2, symmetric	0.475	0.463	0.365
Adjusted R^2, asymmetric	0.477	0.461	0.362
ΔBIC (asymmetric − symmetric)	8.42	12.49	12.60
Panel B: Return response to a one-standard-deviation shock (%)			
O^+ (+3.59%)	0.792***	0.673***	0.753***
O^- (−4.21%)	-0.335*	-0.649***	-0.968***
E^+ (+1.32%)	0.232	0.192	0.290
E^- (−0.85%)	-0.126	-0.109	-0.160

Note. Panel A compares Equation 4 with a model that uses $O$and Ewithout splitting them. A positive ΔBIC favors the symmetric model. Panel B multiplies each coefficient from Table 4 by the standard deviation of the shock over the weeks in which it is nonzero; significance refers to the underlying coefficient. * $p < .10$. ** $p < .05$. *** $p < .01$.

Table 6 compares the firms in the pooled model. Responses to oil price increases ($p = .594$)and to both rupee shocks ($p = .743$and .975) are statistically identical across firms. The exception is the response to falling oil prices: OGDC's coefficient (0.08) is significantly smaller than those of PPL and POL (both $p = .015$), and equality is rejected ($p = .016$). The joint test of all eight interactions, however, does not reject equality ($F, = 1.52p = .144$).

Table 6

Cross-Firm Comparison of Shock Sensitivities

Shock	Coefficient OGDC	Coefficient PPL	Coefficient POL	p PPL − OGDC	p POL − OGDC	p PPL − POL	Equality of all three
O^+ (oil increase)	0.221	0.187	0.210	.309	.828	.665	.594
O^- (oil decrease)	0.080	0.154	0.230	.015**	.015**	.176	.016**
E^+ (PKR depreciation)	0.176	0.146	0.220	.767	.790	.516	.743
E^- (PKR appreciation)	0.147	0.128	0.188	.888	.842	.823	.975

Note. Fully interacted pooled regression of the three firms ($N = 1710$firm-weeks) with OGDC as the base firm and Driscoll–Kraay standard errors (bandwidth 5). Coefficients for PPL and POL equal the base coefficient plus the firm interaction. Joint tests: all eight shock interactions, $F = 1.52, p = .144$; oil interactions only, $p = .054$; exchange-rate interactions only, $p = .957$; market beta, $p < .001$. * $p < .10$. ** $p < .05$. *** $p < .01$.

Table 7 reports the forecasting results for 309 test weeks. The Elastic Net with oil and exchange-rate

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https://invergejournals.com/
ISSN (Online): 2959-4359, ISSN (Print): 3007-2018
Volume 5 Issue 5, 2026

predictors is the only model that beats the historical mean for every firm ($R^2_{OS}$of 0.74% to 1.04%) and raises directional accuracy to between 55.7% and 57.0%, significantly so for OGDC and PPL. Its improvement over Model A, however, is not significant by the Diebold–Mariano or Clark–West tests. Tree-based models mostly underperform the historical mean (Figure 5). The only case meeting the H4 rule is XGBoost for OGDC, which gains 2.01 percentage points of R^2_{OS}(Clark–West $p = .006$), although both of its versions remain below the historical mean.

Table 7

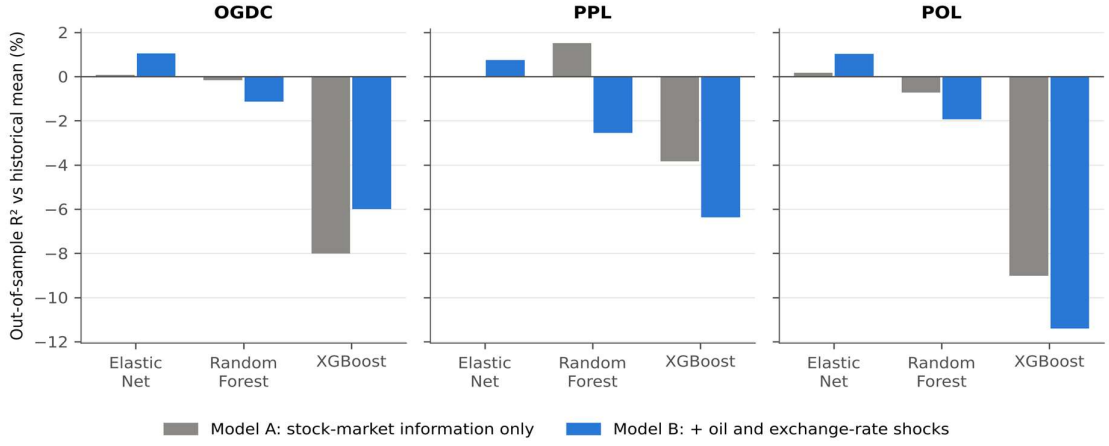
Out-of-Sample Forecast Performance, January 2020 to December 2025

Firm / learner	DA A (%)	DA B (%)	R²OS A (%)	R²OS B (%)	DM p	CW p	H4 supported
OGDC (historical-mean directional accuracy = 49.8%)							
Elastic Net	48.5	55.7**	0.0	1.04	.268	.166	No
Random Forest	52.4	52.1	-0.16	-1.14	.689	.165	No
XGBoost	54.4	48.5	-8.01	-6.00	.244	.006	Yes
PPL (historical-mean directional accuracy = 51.8%)							
Elastic Net	49.8	57.0***	-0.04	0.74	.284	.189	No
Random Forest	53.4	50.8	1.52	-2.56	.964	.613	No
XGBoost	52.1	49.2	-3.84	-6.38	.801	.086	No
POL (historical-mean directional accuracy = 54.0%)							
Elastic Net	55.3	56.6*	0.17	1.02	.377	.236	No
Random Forest	56.3	54.7*	-0.73	-1.94	.691	.100	No
XGBoost	52.8	51.5	-9.03	-11.41	.693	.037	No

Note. 309 weekly forecasts from an expanding window, with models re-estimated and re-tuned every 26 weeks. Model A uses two lags of the firm's own return and of the market return; Model B adds two lags of O^+, O^-, E^+, and E^-. $R^2_{OS}$is measured against the historical mean (Campbell & Thompson, 2008). Stars on Model B directional accuracy denote the Pesaran–Timmermann test. DM = Diebold–Mariano test with the Harvey et al. (1997) correction; CW = Clark–West test; both one-sided. H4 requires a significant test at 5% and a gain in $R^2_{OS}$of at least 0.5 percentage points. * $p < .10$. ** $p < .05$. *** $p < .01$.

Figure 5

Out-of-Sample R² of Forecasting Models With and Without Oil and Exchange-Rate Information



Note. Out-of-sample R² relative to the historical-mean forecast over 309 weeks from January 2020 to December 2025. Model A uses lagged stock and market returns; Model B adds lagged oil and exchange-rate shocks.

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ISSN (Online): 2959-4359, ISSN (Print): 3007-2018
Volume 5 Issue 5, 2026

4.4 Results of Hypothesis Testing

Table 8 summarizes the hypothesis tests. H1 is not supported: equality of the oil coefficients is rejected for no firm at 5%, with OGDC closest ($p = .066$). H2 is not supported for any firm. H3 is not supported overall, although OGDC's weaker response to falling oil prices is a significant firm-specific difference. H4 is supported only partly, for OGDC with XGBoost.

Table 8

Summary of Hypothesis Testing

Hypothesis	Firm	Key evidence	Decision
H1: $\beta(O^+) \neq \beta(O^-)$	OGDC	$\beta^+ = 0.221$, $\beta^- = 0.080$, Wald p = .066; cumulative DL p = .093	Not supported
H2: $\beta(E^+) \neq \beta(E^-)$	POL	$\beta^+ = 0.187$, $\beta^- = 0.154$, Wald p = .693; cumulative DL p = .788	Not supported
		$\beta^+ = 0.210$, $\beta^- = 0.230$, Wald p = .821; cumulative DL p = .679	Not supported
H3: Sensitivities differ across firms	POL	$\beta^+ = 0.176$, $\beta^- = 0.147$, Wald p = .883; cumulative DL p = .818	Not supported
		$\beta^+ = 0.146$, $\beta^- = 0.128$, Wald p = .938; cumulative DL p = .886	Not supported
		$\beta^+ = 0.220$, $\beta^- = 0.188$, Wald p = .902; cumulative DL p = .834	Not supported
H4: Model B beats Model A out of sample	POL	Joint Wald F = 1.520, p = .144	Not supported
H5: Sensitivities differ across firms	POL	1/3 learners supportive; XGBoost: ΔR^2OS = 2.01 pp, DM p = .244, CW p = .006	Partly supported (1 learner)
		0/3 learners supportive; Elastic Net: ΔR^2OS = 0.78 pp, DM p = .284, CW p = .189	Not supported
	POL	0/3 learners supportive; Elastic Net: ΔR^2OS = 0.85 pp, DM p = .377, CW p = .236	Not supported

Note. Decisions at the 5% level. H1 and H2 use the Wald tests in Table 9 (baseline and cumulative distributed-lag models); H3 uses the joint Driscoll–Kraay test in Table 6; H4 uses Table 7. DL = distributed lag; DM = Diebold–Mariano; CW = Clark–West.

4.5 Empirical Estimation

Table 9 shows that the average symmetry is robust. OGDC's oil asymmetry weakens in the distributed-lag model ($p = .093$)and disappears under GARCH-t errors and when crisis weeks are excluded, and no specification detects exchange-rate asymmetry. The quantile regressions, however, show asymmetry in the tails. At the 75th percentile, the test rejects for all three firms and .005): in good weeks, a rise in oil lifts returns by 0.23 to 0.30 per 1% change, while a fall barely matters (about 0.06). At the 10th percentile, POL's response to falling oil (0.46) is more than three times its response to rising oil (0.13; $p = .028$). Figure 6 displays these patterns.

Table 9

Tests of Asymmetry Across Specifications

Specification	H1: β1 = β2 (oil) OGDC	H1: β1 = β2 (oil) PPL	H1: β1 = β2 (oil) POL	H2: β3 = β4 (exchange rate) OGDC	H2: β3 = β4 (exchange rate) PPL	H2: β3 = β4 (exchange rate) POL
Baseline OLS (HAC)	.066*	.693	.821	.883	.938	.902
Distributed lag, cumulative effect	.093*	.788	.679	.818	.886	.834
GARCH(1,1)	.595	.925	.376	.285	.417	.675

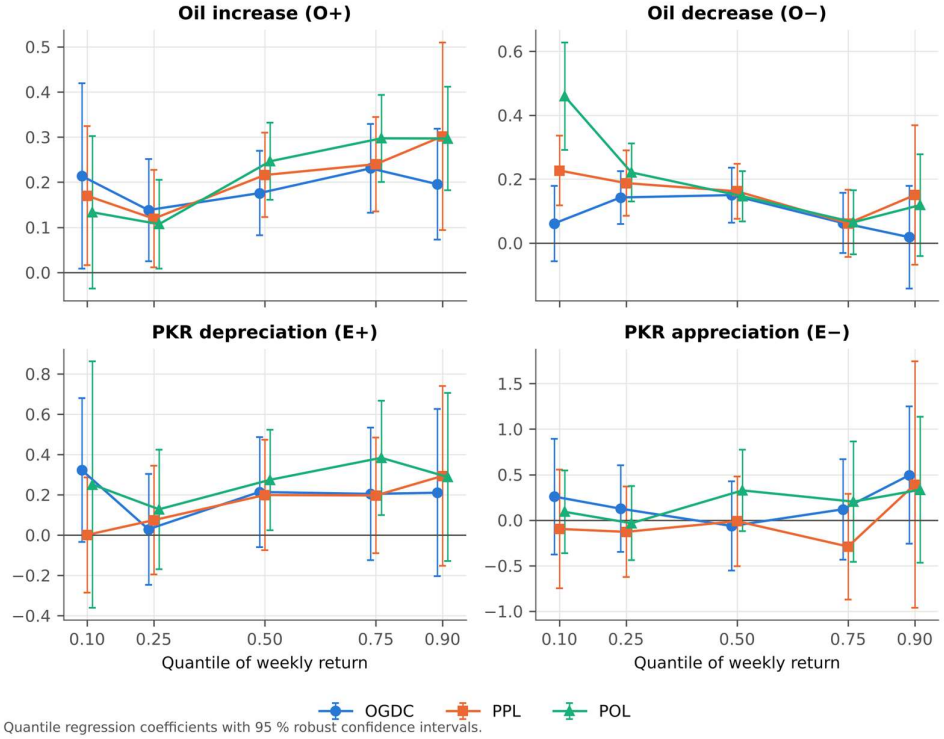
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Volume 5 Issue 5, 2026

with Student-t errors						
Excluding crisis weeks	.469	.874	.796	.963	.701	.929
Quantile regression τ = .10	.289	.615	.028**	.869	.796	.696
τ = .25	.956	.444	.159	.739	.494	.547
τ = .50	.731	.474	.146	.350	.481	.847
τ = .75	.040**	.043**	.005***	.804	.159	.634
τ = .90	.143	.410	.131	.535	.897	.924

Note. Entries are p-values of Wald tests that the coefficients on positive and negative shocks are equal. The distributed-lag model selects shock lags by BIC (zero lags chosen for all firms). Crisis windows: COVID-19 crash, Russian invasion of Ukraine, removal of the rupee cap, and the May 2025 India–Pakistan conflict ($N = 550$). Quantile regressions use robust covariance. * $p < .10$. ** $p < .05$. *** $p < .01$.

Figure 6

Shock Coefficients Across the Distribution of Weekly Returns



Note. Quantile regression estimates of Equation 4 at τ = .10, .25, .50, .75, and .90 with 95% robust confidence intervals. Low quantiles correspond to weak weeks and high quantiles to strong weeks.

The relationship has also shifted over time. Table 10 shows breaks in the shock coefficients at the COVID-19 crash for OGDC ($p = .005$)and PPL ($p = .034$), and broader changes for PPL and POL after the start of the war in Ukraine, while the CUSUM test finds no gradual drift. The rolling estimates in Figure 7 locate the change: sensitivity to oil price increases stays positive, mostly between 0.1 and 0.35, but sensitivity to decreases falls from about 0.3 in windows ending in 2018–2019 to near zero, or slightly below zero for OGDC and PPL, by 2024–2025.

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Volume 5 Issue 5, 2026

Table 10

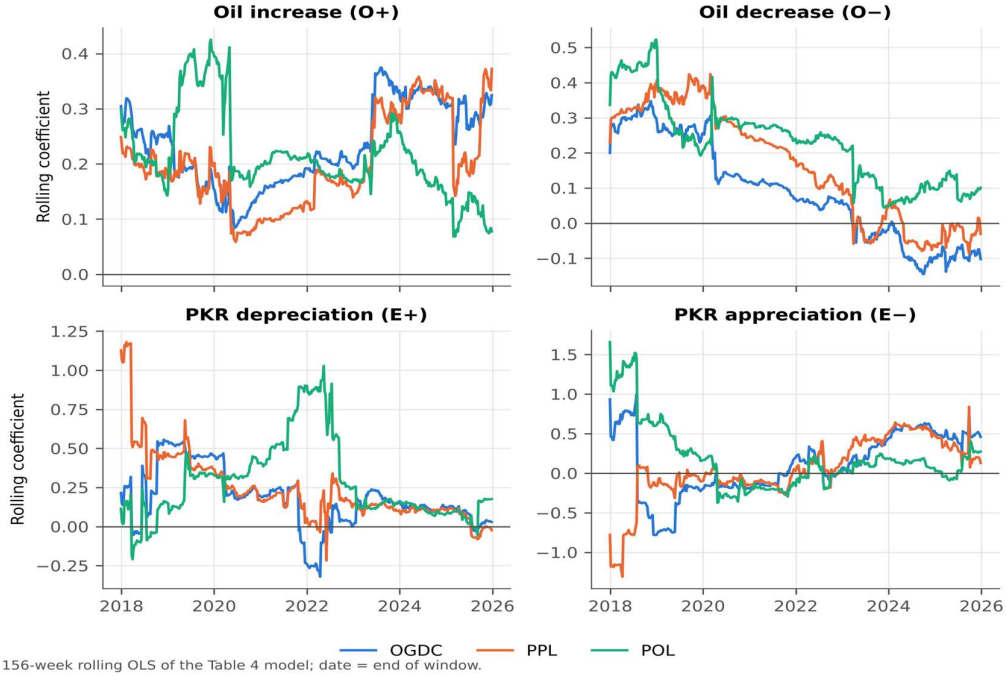
Structural Break and Parameter Stability Tests

Test	OGDC	PPL	POL
Chow test, COVID-19 crash (March 13, 2020): all coefficients	2.20 (.033)**	1.73 (.100)*	2.74 (.008)***
Shock coefficients only, p	.005***	.034**	.052*
Chow test, Russia–Ukraine war (February 25, 2022): all coefficients	0.80 (.592)	2.33 (.024)**	4.17 (< .001)***
Shock coefficients only, p	.494	.350	.071*
OLS-CUSUM stability test	0.62 (.836)	0.70 (.717)	0.72 (.680)

Note. Entries are test statistics with p-values in parentheses. The Chow tests are HAC-robust Wald tests that the intercept and all slopes of Equation 4 shift after the break date; the second row of each test restricts attention to the four shock coefficients. CUSUM null: stable parameters. * $p < .10$. ** $p < .05$. *** $p < .01$.

Figure 7

Rolling 156-Week Sensitivities to Oil and Exchange-Rate Shocks



Note. Coefficients of Equation 4 estimated over rolling three-year windows; each point is dated at the end of its window.

The forecasting gains are fragile. Table 11 shows that Elastic Net gains survive one lag but turn negative for POL with four lags, at a four-week horizon, and for all firms once crisis weeks are excluded. Figure 8 confirms that most of the gain accrued in early 2020. SHAP values in Figure 9 nonetheless show that oil predictors account for 33% to 39% of XGBoost feature importance and exchange-rate predictors for 17% to 22%, with last week's oil price decline the single most important predictor for OGDC and POL.

Table 11

Robustness of Out-of-Sample Forecast Comparisons

Firm	Check	Learner	RMSE A	RMSE B	ΔR²OS (pp)	DM p	CW p
OGDC	Lags = 1	Elastic Net	4.855	4.829	1.05	.287	.156
	Lags = 4	Elastic Net	4.854	4.833	0.86	.275	.178
	Horizon = 4 weeks	Elastic Net	9.070	9.102	-0.70	.737	.572
	Excluding crisis weeks	Elastic Net	4.411	4.429	-0.80	.765	.512

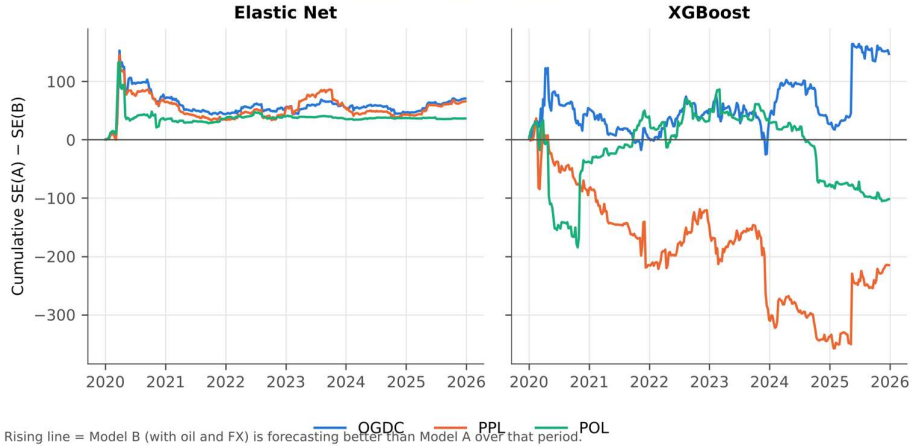
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ISSN (Online): 2959-4359, ISSN (Print): 3007-2018
Volume 5 Issue 5, 2026

	Excluding crisis weeks	Random Forest	4.419	4.471	-2.40	.871	.337
	Excluding crisis weeks	XGBoost	4.555	4.596	-1.91	.767	.064*
PPL	Lags = 1	Elastic Net	5.234	5.214	0.77	.300	.179
	Lags = 4	Elastic Net	5.248	5.237	0.43	.204	.148
	Horizon = 4 weeks	Elastic Net	10.638	10.710	-1.34	.925	.910
	Excluding crisis weeks	Elastic Net	4.719	4.738	-0.81	.805	.596
	Excluding crisis weeks	Random Forest	4.690	4.816	-5.39	.990	.724
	Excluding crisis weeks	XGBoost	4.815	4.920	-4.59	.948	.137
POL	Lags = 1	Elastic Net	3.711	3.698	0.68	.402	.243
	Lags = 4	Elastic Net	3.715	3.734	-1.02	.648	.409
	Horizon = 4 weeks	Elastic Net	8.264	8.292	-0.68	.900	.793
	Excluding crisis weeks	Elastic Net	3.303	3.326	-1.41	.758	.559
	Excluding crisis weeks	Random Forest	3.321	3.346	-1.55	.729	.073*
	Excluding crisis weeks	XGBoost	3.574	3.627	-3.46	.719	.049**

Note. ΔR^2 is Model B minus Model A in percentage points. Lag and horizon checks re-run the Elastic Net walk-forward exercise; the four-week horizon uses cumulative returns with HAC-adjusted tests. The crisis check removes the four crisis windows from the evaluation sample of Table 7. * $p < .10$. ** $p < .05$. *** $p < .01$.

Figure 8

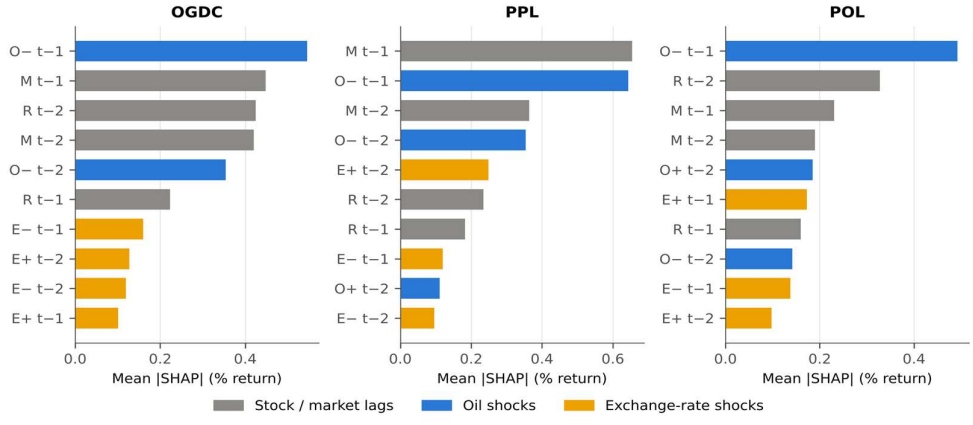
Cumulative Squared-Error Difference Between Model A and Model B



Note. Cumulative sum of the squared forecast error of Model A minus that of Model B. A rising line means that adding oil and exchange-rate predictors improved forecasts over that period.

Figure 9

SHAP Feature Importance of the XGBoost Model B



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ISSN (Online): 2959-4359, ISSN (Print): 3007-2018
Volume 5 Issue 5, 2026

Note. Mean absolute SHAP values for the ten most important predictors of each firm's weekly return, from XGBoost models fitted on the full sample. Labels show the variable and its lag (t − 1, t − 2).

4.6 Discussion

The exploration and production stocks are relatively well positioned in Pakistan, as are other markets in the country (Hoque et al., 2020; M. H. Khan et al., 2023; Kushwah & Siddiqui, 2023) in terms of positive oil exposure. Overall, however, the response is symmetric, unlike the macroeconomic response of Mork (1989) and Hamilton (2003) and recent evidence for oil exporters and individual firms, respectively, that is nonlinear (Aruna & Acharya, 2023; Escobari & Sharma, 2020; İmamoğlu, 2026). There seems to be no difference in the minds of the Pakistani investors between a dollar won and one lost per barrel, except in certain market scenarios.

The lack of sensitivity to falling prices at OGDC and the drop in this sensitivity among firms after 2020 aligns with an earnings composition explanation. The fall in oil prices becomes less significant when the revenues are derived from the sale of gas at regulated prices, or when depreciation of the rupee occurs alongside a fall in oil prices, thereby protecting the rupee revenues. The quantile results confirm evidence of the oil-stock link being stronger during bearish markets and different during market states (Das et al., 2022; Jiang et al., 2020) and the breaks around the crises are in line with the findings of Katsampoxakis et al. (2022) and Sheikh et al. (2020).

The lack of an exchange-rate effect is noteworthy, especially in the wake of the rupee's depreciation. Usually big depreciations have happened with market stress, thus much of the effect of the depreciations has already been built into the market's return, the negative correlation between the rupee and the KSE-100 (−0.14) shows this. This is in contrast with the asymmetric and negative exchange rate effect documented for the aggregate market (M. I. Khan et al., 2021; Sheikh et al., 2020). The result of forecasting is consistent with the broader literature (Campbell & Thompson, 2008; Goyal et al., 2024), as most of the forecasting power came during turbulent times that occurred during the COVID-19 collapse (Atif et al., 2022; Prabheesh et al., 2020; Salisu et al., 2020) and in the wake of the war in Ukraine that caused structural breaks in markets (Bagchi & Paul, 2023; Boungou & Yatié, 2022; Kumari et al., 2023).

4.7 Analysis

Table 12 asks whether the forecasts have economic value in a simple strategy that holds a stock in weeks with a positive forecast and cash otherwise, after a 0.10% trading cost. The Elastic Net Model B delivers higher Sharpe ratios than buy-and-hold for PPL (0.58 versus 0.35) and POL (0.59 versus 0.29), with much smaller maximum drawdowns (−43% versus −70% for PPL; −21% versus −46% for POL), but not for OGDC. Gains from tree-based models are inconsistent across firms. Oil and currency signals are thus most useful for limiting losses in turbulent periods.

Table 12

Economic Value of Forecasts in a Long-or-Cash Strategy, 2020–2025

Strategy	Model	Annual return (%)	Annual volatility (%)	Sharpe ratio	Maximum drawdown (%)	Time invested (%)
OGDC						
Buy and hold	—	15.9	35.0	0.46	−56.6	100
Elastic Net	A	0.0	0.0	—	0.0	0
Elastic Net	B	8.2	21.0	0.39	−32.8	36
Random Forest	A	2.9	20.7	0.14	−58.5	31
Random Forest	B	19.9	22.4	0.89	−32.1	46
XGBoost	A	13.9	25.0	0.56	−54.1	43
XGBoost	B	6.1	23.3	0.26	−50.2	47
PPL						
Buy and hold	—	13.4	38.3	0.35	−70.0	100

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Volume 5 Issue 5, 2026

Strategy	Model	Annual return (%)	Annual volatility (%)	Sharpe ratio	Maximum drawdown (%)	Time invested (%)
Elastic Net	A	−2.7	21.0	−0.13	−57.8	24
Elastic Net	B	15.9	27.6	0.58	−43.5	58
Random Forest	A	22.5	30.6	0.73	−47.0	47
Random Forest	B	4.7	25.0	0.19	−53.8	41
XGBoost	A	14.6	26.3	0.56	−44.4	38
XGBoost	B	7.3	27.4	0.27	−51.2	42
POL						
Buy and hold	—	7.7	26.4	0.29	−45.6	100
Elastic Net	A	7.7	26.4	0.29	−45.6	100
Elastic Net	B	12.1	20.5	0.59	−20.7	76
Random Forest	A	9.1	19.7	0.46	−29.0	58
Random Forest	B	9.0	16.1	0.56	−20.8	54
XGBoost	A	6.1	18.7	0.33	−45.4	55
XGBoost	B	10.1	17.3	0.58	−18.9	53

Note. The strategy holds the stock in weeks with a positive forecast and cash otherwise, with a 0.10% one-way trading cost. Cash earns zero, so Sharpe ratios ignore the risk-free rate. A dash in the Model column denotes buy-and-hold; Model A uses stock-market information only and Model B adds oil and exchange-rate predictors.

5. Conclusion and Recommendation

5.1 Major Findings

The oil sensitivity is positive and significant for all three companies: Same week returns increase by 0.19% to 0.22% in case of a 1% increase in Brent. The average responses to increases and decreases in oil prices are not significantly different and the direct and asymmetric effects of the rupee are not significant after controlling for the market return. There are three areas of weakness: an inadequate response by OGDC to the drop in oil prices, the top end of the oil price return distribution, and the lack of sensitivity to a fall in oil price following 2020. Outside of OGDC's lacklustre downside reaction, the firms are exposed to a similar level of risk. Oil and exchange-rate data adds value to determining a direction of change, and it is helpful when a crisis occurs, but does not consistently minimize forecast errors.

5.2 Conclusion

The study finds that on average oil price risk is real, large, and mostly symmetric for all listed exploration companies in Pakistan although the conditions vary by the market and have changed since 2020. The episodes when it is important are masked if it is treated as a single constant number.

5.3 Recommendations

Portfolio managers might consider OGDC, PPL and POL to be suitable alternatives that provide similar exposure to oil, though OGDC provides greater protection during a down oil move. Risk managers should not always use oil betas but rather use time varying / quantile based oil measures particularly for stress testing; and pay closer attention to oil and currency signals during the times when they can have the most predictive power that is during crisis periods. These signals should not be relied upon by investors for consistent profits in stable markets. The Pakistan Stock Exchange and brokerage research desks may release the roll-on sensitivity estimates of energy listed companies. It is important for policy makers to understand that regulated pricing of gas and energy-sector arrears settlement has now become a determinant of the valuation of these firms' response to world oil prices.

5.4 Limitations

Total returns may differ from the price returns analyzed here because returns do not include cash dividends, which are significant for these firms. The three-firm sample restricts the extent of cross-sectional

inference and analysis focuses on aggregate oil price changes, rather than breaking them down into supply and demand shocks as Kilian (2009) and Ready (2018) suggest.

5.5 Delimitations

The study deliberately excludes oil marketing and refining companies, excludes unlisted companies and intraday movements and only considers listed upstream producers, weekly data and the USD/PKR rate as the oil price benchmark.

5.6 Future Recommendations

Dividend adjusted returns, and extending the analysis to oil marketing and refining companies to compare producers with consumers, to identify the structural causes of oil shocks and to see if the sensitivity change in the post-2020 period remains as the energy pricing reforms in Pakistan continue, could be the next steps for further research. Daily or intraday data, alternative oil benchmarks, and models with time-varying parameters would also help to illustrate the speed of the oil and currency news pricing.

Conflict of Interest Statement

The authors declare no conflicts of interest.

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Informed Consent

Informed consent was obtained from all individual participants included in the study.

Ethical Approval

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Data Availability

The datasets generated during and analysed during the current study are available from the corresponding author on reasonable request.

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