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ANALYSIS OF PRICE VOLATILITY AND DISCOVERY MECHANISMS IN PAKISTAN MERCANTILE EXCHANGE: FOCUS ON CRUDE OIL, COTTON, AND EXCHANGE RATES

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ABSTRACT

Commodity markets are pivotal for economic stability, particularly in emerging economies like Pakistan, where the Pakistan Mercantile Exchange (PMEX) serves as a critical platform for trading energy, agricultural commodities, and currencies. However, price volatility and interdependencies between key commodities like crude oil, cotton, and exchange rates remain underexplored, posing risks for investors and policymakers. This study examines volatility dynamics and price discovery mechanisms at PMEX to address this gap. Using daily data (2013–2022), we employ Vector Error Correction Models (VECM) to analyze long-run equilibrium relationships and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) to quantify volatility persistence. Results reveal a significant cointegrating relationship (trace statistic=43.66), with exchange rates acting as the primary adjustment mechanism (coefficient=0.08, $p<0.01$). Short-run dynamics show exchange rates strongly influence crude oil prices (coefficient = 38.74, $p < 0.01$) and cotton prices (coefficient=-0.08, $p=0.05$). The GARCH (1, 1) model confirms high volatility persistence ($\beta_1=0.78$) and shock sensitivity ($\alpha_1=0.20$), indicating prolonged volatility clusters. These findings underscore the centrality of exchange rates in PMEX's price discovery process and highlight actionable insights for hedging and policy formulation. The study contributes a novel framework for emerging markets by integrating volatility and cointegration analyses, offering traders strategies to mitigate currency-linked risks and guiding regulators in stabilizing commodity markets during external shocks.

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INTRODUCTION

Commodities play a vital role in the development of countries for creating employment, food security and export income, efficient utilization of resources, creating relationships between agriculture and other sectors (Koo and Kennedy, 2005). Globally, the commodities are categorized into six main groups: agricultural commodities, oilseeds, meat, cereal grains, soft commodities and dairy. The prices of commodities are the main mechanism for production, marketing, and processing in stabilizing and providing details to the market. (Yang and Latham 1999). In most years commodity market risk fluctuations have been high due to various reasons that include the crude oil prices, exchange rates and economic instabilities. From the beginning of 2006 the speculators increased in the size of the actual commodities derivatives. Prokopczuk et al. (2019) suggest that the knowledge about price and

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volatility effects must be understood able for investors and policy makers because it is very important for economy stability. It has been evidenced by several researched like Zhang et al., 2019 and Pal and Mitra, 2017, that the prices of agricultural commodities are very responsive to crude oil prices.

Pakistan Mercantile Exchange (PMEX) is the one only essential commodity trading market in Pakistan where nationally and internationally commodities are traded. This mercantile exchange was established in 2002 and was functionally started in 2007. The international products are sectorized into metals, energy, and agriculture, financial and liquid contracts while local products are sectorized into metal and agriculture products. PMEX intends to connect wholesale markets with international markets along with providing new ways of trading and hedging for speculators (Khan and Niazi, 2020). In 2020 commodity trading of PKR 1.3 trillion played a significant role to boost the economic activities but PMEX still holds a minor share in Pakistan economy (Ali and Shah 2021). For the stability and economic growth of the country, PMEX facilitates the price creation, hedging and market transparency for commodities (Farhan and Mehmood, 2023). The research results relating to volatility and the identification of price discovery mechanisms provide useful implications for policy decisions, as well as improve investment undertakings and shed light on the economic effects of variations in crude oil and cotton prices and exchange rates. Furthermore, it provides useful information for policymaking, sectoral participant and further research, and contributes to enriching knowledge databases and advanced strategical management in emerging markets.

METHODOLOGY

VAR model

The Vector autoregressive model (VAR) was introduced by great econometricians Christopher A. Sims and Clive W.J Granger. This model is used to capture the relationship between multiple variables over time. The general form of VAR model is given by:

$y_t = C + A\, r_{t-1} + \mu_t$

Where A is k x k transition matrix that expresses the dependence of r_t on r_{t-1}. The vector white noise process μ_t is assumed to multivariate normal with mean-zero and covariance matrix, E $(\mu_t \mu_t')$. The vector C = $(C_1, C_2, \dots \dots \dots, C_n)'$ appears as the constant in the regression setting.

The VEC (vector error correction) model:

The extension of VAR model is VECM model which incorporates both short-term and long-term dynamics equilibrium relationships among variables. This model is often used when the variables in the system are found to be cointegrated, indicating long-run deviations from equilibrium and the adjustment process back to equilibrium in the long-run. This model was introduced by Soren Johansen and Katarina Juselius. The VEC (p,q) model is given as:

$\mathrm{VEC}(\Sigma_t) = \mathrm{C} + \sum_{i=1}^{q} A_i \,.\mathrm{VEC}(\varepsilon_{t-i}\, \varepsilon_{t-i}') + \sum_{j=1}^{p} B_i \,.\mathrm{VEC}\,(\varepsilon_{t-j})$......

Where A_i and B_j are parameters, matrices containing $(N^*)^2$ parameters [with N^* = N(N+1)/2], Whereas the vector C contains N^* coefficients. VEC is the column stacking operator. We assumed that all eigenvalues of the matrix $\sum_{i=1}^{q} A_i + \sum_{j=1}^{p} B_i$ have modules smaller than one, in which case the vector process, t is covariance stationary with unconditional covariance matrix given by the t.

Generalized Autoregressive Conditional Heteroskedastic (GARCH) Model:

General Autoregressive Conditional Heteroscedasticity (GARCH) model allows the conditional variance of the variable to be dependent upon previous lags; first lag of the squared residual from the mean equation and present news about the volatility from previous period which is as follows:

$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_t^2$

Where:

σ_t^2 is the conditional variance at time t

ε_{t-1}^2 is the lagged residual (error term),

α_0 , α_1 and β_1 are coefficients.

Augmented Dickey-Fuller (ADF) Test Equation:

The ADF test checks for stationarity in a time series by testing the null hypothesis that a unit root exists. The general form of the ADF regression is:

$\Delta Y_t = \alpha + \beta_t + \gamma Y_{t-1} + \delta_1 \Delta Y_{t-1} + \delta_1 \Delta Y_{t-2} + \ldots + \delta_p \Delta Y_{t-p} + \epsilon_t$

Where: $\Delta Y_t = \Delta Y_t - \Delta Y_{t-1}$ (first difference of the series), ΔY_{t-1} is the lag of series, ϵ_t is white noise, and γ is the coefficient that tests the presence of a unit root.

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Lag Order Selection Criteria

For selecting the optimal lag order, the criteria are computed as follows:

Akaike Information Criterion (AIC): $\boldsymbol{AIC = -2ln(L) + 2k}$

Bayesian Information Criterion (BIC): $\boldsymbol{BIC = -2ln(L) + kln(n)}$

Research Data

In this study, daily closing prices for Crude100 and Cotton were sourced from the official website of the Pakistan Mercantile Exchange (PMEX), while daily exchange rate data was obtained from Kaggle.com. The dataset covers the period from 2013 to 2022, comprising a total of 2,525 observations. The collected data was cleaned and prepared for analysis using MS excel. Python was used both data collection and analysis, ensuring efficient handling, manipulation, and visualization of the dataset.

RESULTS

Table 1 summarizes the results of the Augmented Dickey-Fuller (ADF) test for testing the stationarity of the crude oil (Crude100), cotton, and exchange rates variables, in their levels and first differenced. Employment of stationarity is crucial in analyzing time series since stationarity enables a consistent level of statistical properties when the data is taken over time. In studies at the level of each variable, the p-values are substantially greater than the traditional levels of significance (0.01, 0.05, and 0.10) which causes the rejection of the null hypothesis of unit root. This suggests that at their levels crude oil, cotton and exchange rates are non-stationary and contain trends or seasonality that rule out some forms of time series modelling.

The difference series yields very low p-values close to zero; hence, rejecting the null hypothesis confirms stationarity. For instance, the differences between Crude100, cotton, and exchange rates had ADF statistics of -11.7886, -32.8202, and -10.8142, respectively, while the p-values were less than 0.05. There is evidence herein that first order differencing aids in the stabilization of variance and eradication of trends, therefore making the series appropriate for VAR and VECM modeling. This step is essential in the case of volatility and price discovery research at the PME where external and consistent time series data plays an important role.

Table 1. Augmented Dickey-Fuller (ADF) Test Results for Stationarity

Variable	ADF Statistic	p-value	Stationarity
Crude100 (Level)	-0.3196	0.9227	Non-Stationary
Cotton (Level)	-2.4286	0.1338	Non-Stationary
Exchange Rates (Level)	2.4353	0.999	Non-Stationary
Crude100 (Differenced)	-11.7886	0.000	Stationary
Cotton (Differenced)	-32.8202	0.000	Stationary
Exchange Rates (Differenced)	-10.8142	0.000	Stationary

Table 2. Johansen Cointegration Test Results.

Null Hypothesis	Trace Statistic	Critical Value (5%)	P-Values
0 Cointegrating Equations (r=0)	43.6573	29.7961	0.00
1 Cointegrating Equation (r<=1)	14.7776	15.4943	0.00
2 Cointegrating Equations (r<=2)	0.4791	3.8415	0.00

Table 2 shows the Johansen cointegration test results. Researchers examined the presence of a long-run relationship between crude oil, cotton prices, and the exchange rate at PMEX. For the trace test the result is $r \leq 1$ for a single equation cointegration at 5% level of significance meaning that the null hypothesis that there are no cointegrating equation ($r = 0$) has been rejected. This finding suggests that these variables share a long-run co-integrating relationship, at least in the current context. The establishment of cointegration supports the application of a VECM, which allows the analysis to examine short-run and long-run relationships in price discovery across these markets. The role of cointegration in this regard is critical since it identifies a valid long-term relationship between crude oil prices, cotton prices and exchange rates that may be useful for trading and risk management at PMEX. Cointegration evidence lends support to the fact that while there may be short-term differences in these markets, in the long run, they are in identical trends, indicating that exchange rates play an essential role in prices and transmission of volatility effects.

Table 3. Lag Order Selection for VAR/VECM Models.

Lag	AIC	BIC	FPE	HQIC
0	11.51	11.52	100000	11.52
1	11.49	11.52	98000	11.50
2	11.46	11.51	94800	11.48*
3	11.45	11.52	94200	11.48
4	11.45	11.54	93500	11.48
5	11.44	11.55	93100	11.48
6	11.44	11.57	92900	11.49
7	11.44	11.59	93000	11.50
8	11.45	11.62	93500	11.51
9	11.44	11.64	93000	11.51
10	11.43	11.65	92400	11.51
11	11.42	11.66	91000	11.50
12	11.42	11.67	90800	11.51
13	11.40*	11.68	89300*	11.50
14	11.40	11.70	89300	11.51
15	11.40	11.72	89600	11.52

* Shows significant at 95%

Table 3 shows the specifications for selecting the lag order for the VAR/VECM model for crude oil, cotton prices, and exchange rate on PMEX. In the table below, the models with different number of lag lengths are fitted to estimate the values of the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Final Prediction Error (FPE), and Hannan-Quinn Information Criterion (HQIC). The minimum AIC and FPE statistics are at lag 13, which suggests that this may be the most appropriate number of lags to use in modeling the volatility in the data set. However, the BIC and the HQIC propose lag 2 as the suitable one to use. Because these criteria involve the trade-offs between model fit and model simplicity, they suggest that lag 2 might be better where the concern is for the lack of overly complicated models. These indicators offer important clues concerning the right lag length for capturing the price discovery and the lead-lag relationships in the chosen commodities and exchange rates at PMEX.

VECM Results

The vector error correction model (VECM) in Table 4 outlines the coefficient estimates of crude oil, cotton, and exchange rates, showing the impact of these variables on crude oil prices.

Crude Oil (L1. crude100)

The coefficient for the lagged dependent variable, crude oil, is -0.04 with a borderline significance level as the p-value is 0.071, implying a weak influence of past crude oil prices on the current crude oil price. Although the p-value suggests near insignificance, it highlights some potential relationship with crude oil prices, although weak.

Cotton (L1. cotton)

Cotton is found to influence crude oil prices significantly. The coefficient of 8.33 ($p=0.016$), indicated that past values of cotton prices positively impact crude oil prices. The positive coefficient shows that the increase in cotton prices leads to increased crude oil prices.

Exchange Rates (L1. Exchange Rates)

Exchange rates have a strong, highly significant impact on crude oil prices. The coefficient is 38.74, with a p-value < 0.01, indicating that changes in exchange rates substantially influence crude oil prices. The high significance at the 5% level further reinforces that exchange rates play a critical role in determining crude oil price.

Table 4. Equation Crude100.

Variable	Coefficient	Std. Error	z-value	p-value	Lower Bound	Upper Bound
L1.crude100	-0.04	0.02	-1.80	0.07	-0.08	0.00
L1.cotton	8.33	3.47	2.40	0.02	1.54	15.12
L1.Exchange Rates	38.74	7.04	5.51	0.00	24.95	52.53

Table 5. Equation Cotton.

Variable	Coefficient	Std. Error	z-value	p-value	Lower Bound	Upper Bound
L1.crude100	0.00	0.00	2.81	0.01	0.00	0.00
L1.cotton	0.03	0.02	1.60	0.11	-0.01	0.07
L1.Exchange Rates	-0.08	0.04	-1.97	0.05	-0.16	0.00

Table 5 shows the VECM results for the cotton equation and how the lagged variables affect the current price of cotton.

Crude Oil (L1.crude100): The lagged coefficient of crude oil is statistically significant with a p-value of 0.005. This indicates that past crude oil prices have a significant positive impact on cotton prices, though the effect is relatively small as the coefficient is 0.00.

Cotton (L1.cotton): The lagged value of cotton prices is not statistically significant, as indicated by the p-value of 0.11. The coefficient of 0.03 shows an insignificant influence of past cotton prices on current cotton prices, suggesting that the cotton market is less dependent on its past values.

Exchange Rates (L1.Exchange Rates): Exchange rates have a near significant negative impact on cotton prices, as shown by the p-value of 0.048. The coefficient is -0.08, suggesting that an increase in past exchange rates tends to decrease cotton prices in the current period. This negative relationship highlights that cotton prices are inversely related to exchange rates in the short run.

Table 6. Equation Exchange Rates.

Variable	Coefficient	Std. Error	z-value	p-value	Lower Bound	Upper Bound
L1.crude100	0.00	0.00	0.71	0.48	0.00	0.00
L1.cotton	-0.03	0.01	-2.65	0.01	-0.05	-0.01
L1.Exchange Rates	0.08	0.02	3.85	0.00	0.04	0.12

The VECM results for exchange rates illustrate how the lagged values of crude oil, cotton, and exchange rates themselves affect the exchange rates.

Crude Oil (L1.crude100): The coefficient of crude oil on exchange rates is insignificant, with a p-value of 0.48. This shows that past crude oil prices do not significantly influence current exchange rates, with a coefficient of 0.00.

Cotton (L1.cotton): Cotton significantly negatively affects exchange rates, as seen by the p-value of 0.008. The coefficient is -0.03, indicating that past cotton prices have a distinct and negative influence on exchange rates, showing a crucial relationship between the two in determining currency movements.

Exchange Rates (L1.Exchange Rates): The lagged exchange rates have a highly significant positive impact on current exchange rates, with a p-value < 0.01 and a coefficient of 0.08. This suggests strong self-persistence, where the past values of exchange rates significantly influence their current level.

Table 7. Coefficients (alpha) for cointegration

Variable	Coefficient	Std. Error	z-value	p-value	Lower Bound	Upper Bound
E.C Crude100	0.00	0.00	-1.40	0.16	-0.01	0.00
E.C Cotton	0.00	0.00	-0.96	0.34	0.00	0.00
E.C Exchange Rates	0.00	0.00	4.00	0.00	0.00	0.00

E.C abbreviated as Error Correction

Table 7 explains the adjustment process toward long-run equilibrium, describing how each variable adjusts to deviations from the long-run cointegration relationship.

Crude100 (Error correction 1): The adjustment coefficient for crude oil is -0.00 with a p-value of 0.161, indicating that the deviation from long-run equilibrium does not significantly influence crude oil prices in the short run. Crude oil prices do not respond significantly to the correction mechanism, suggesting a low adjustment speed toward equilibrium.

Cotton (Error correction 1): The adjustment coefficient for cotton is also insignificant (P>0.05) reinforcing that cotton prices do not significantly adjust towards the long-run equilibrium. The coefficient is **0.00**, meaning cotton prices exhibit low reactivity to deviations from equilibrium.

Exchange Rates (Error correction 1): The adjustment coefficient is highly significant for exchange rates with a p-value < 0.01 and a coefficient of 0.00. This suggests that exchange rates quickly adjust to deviations from the long-run equilibrium, moving flexibly to correct any disequilibrium compared to crude oil and cotton.

Table 8 highlights the cointegration relations among the variables. The cointegration coefficients between the variables indicate how they share a long-run equilibrium relationship. The estimates of beta coefficients show the long-run interactions, with the results suggesting that exchange rates are the key component in maintaining long-run equilibrium. At the same time, crude oil and cotton are less responsive in the long-term adjustment process.

Table 8. Cointegration relations for coefficients.

Variable	Coefficient	Std. Error	z-value	p-value	Lower Bound	Upper Bound
beta.1	1	0.00	0.00	0.00	1	1
beta.2	-29.28	40.31	-0.73	0.47	-108.28	49.72
	-32.71	23.71	-1.38	0.17	-79.18	13.77

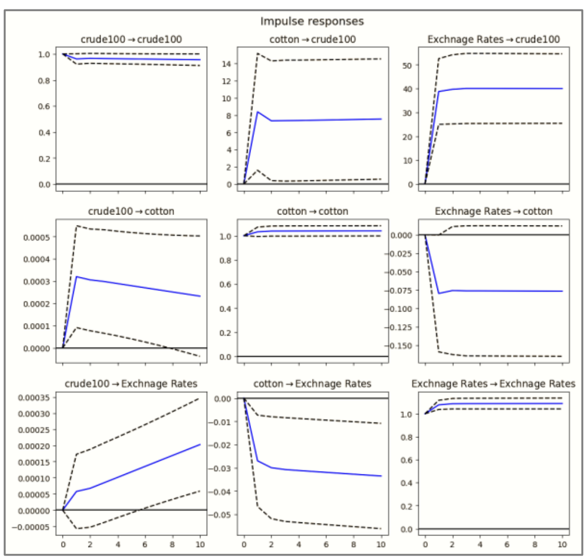

Figure 1. Impulse Responses

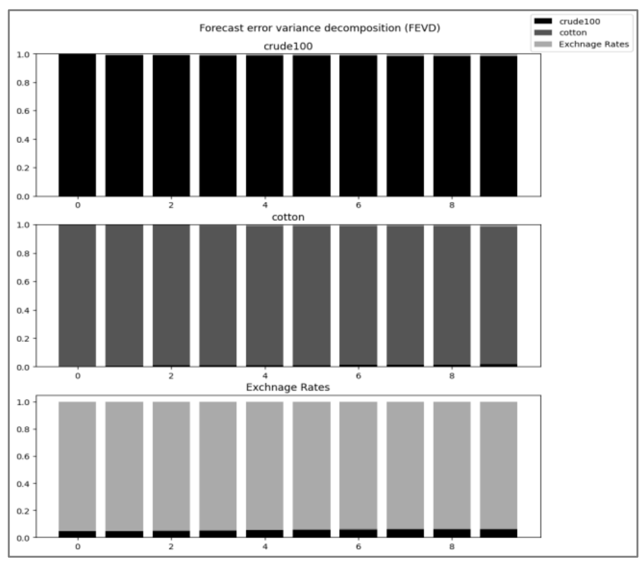

Figure 2. Forecasted error variance decomposition plot for crude, cotton, and exchange rates.

The impulse response functions show that the long-run effects of shocks to each variable are permanent and have a selective impact on the variables. There are some overlaps, but for the most part, the pertinent effects are not as interconnected. Importantly, the analysis shows that the Granger causality of crude oil price shocks on cotton prices is predominant than that of cotton price shocks on crude oil prices. Turning to exchange rates, while their responses to crude oil and cotton prices are harmful in the short run, they gravitate towards positive changes in the long run.

In summary, the relationships between the variables are interdependent while the shocks in the system are relatively enduring.

An inspection of the FEVD plot also shows that unpredicted change in crude oil prices is mainly attributed to the shock in crude oil prices; likewise, cotton is partially attributed to the shock induced by cotton prices. In the case of exchange rates, however, all three variables play a more powerful role. In this case, it is demonstrated that crude oil plays a significant role in contributing to the forecast error variance of all three variables. The prices of cotton and exchange rates are correlated in that the price of one affects the price of the other. Fluctuations in exchange rates are dependent on both crude oil and cotton and, also affect both.

Table 9. GARCH (1, 1) Component Mean Model.

Coefficient	Std. Error	t-Statistic	p-value	95% Confidence Interval
0.000797	0.000427	1.868	0.0618	-0.000039, (0.001634)

Table 10. GARCH (1, 1) Volatility Model.

Component	Coefficient	Std. Error	t-Statistic	p-value	95% Confidence Interval
omega (ω)	2.59E-05	2.5E-06	10.38	0.00	0.000021, (0.000031)
alpha [1] (α1)	0.20	0.046	4.34	0.00	0.110, (0.290)
beta [1] (β1)	0.78	0.035	22.40	0.00	0.712, (0.848)

( ) shows upper values at 95%

Table 11. Model Fit and Coefficients

R^2	Adj R^2	L.L	AIC	BIC	Df_residual	Df_model
0.00	0.00	5927.73	-11847.50	-11824.10	2518	1

Table 9 contains information on GARCH model testing performed on the volatility in PMEX with the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. Mean values (mu) found a coefficient of 0.000797 with a p-value level being of 0.062, which suggests that it has a significant borderline effect. The two volatility parameters are very significant, with omega (ω) = 0.000026 ($p < 0.01$), which shows a long-run stable baseline volatility. The estimated coefficient of GARCH (β1) is 0.78, $p < 0.01$, which shows that the past volatility is persistently influencing the series, which is typical for financial time series. Likewise, the ARCH (α1) parameter is also significant ($p < 0.01$), showing that recent shocks contribute notably to current volatility. The observation of high persistence combined with large shock effects implies that volatility in the PMEX should be closely monitored since events in the past and the occurrence of shocks could have repercussions on the state of price stability. The GARCH model perfectly fits with the data, as can be detected through the model fit statistics. There is a good log-likelihood (5927.73) with lower AIC and BIC values, indicating model efficiency. The more generous covariance estimator lends confidence to the standard errors and confidence intervals, reinforcing the results' stability. Due to higher coefficient values of the volatility parameters and reasonable fitness, the obtained GARCH model is appropriate for the volatility of the commodities traded in the PMEX.

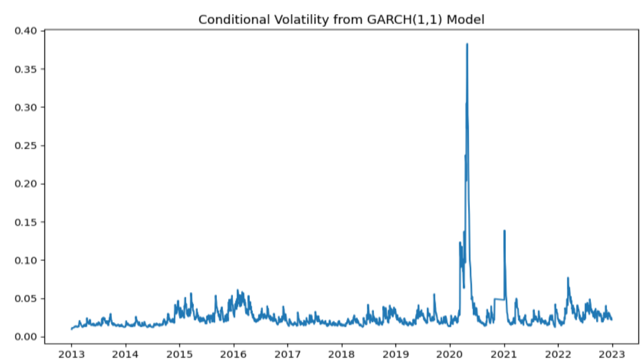

Figure 3. Conditional volatility from GARCH (1, 1) model.

The plot clearly shows another well-known feature of financial markets – volatility clustering. Testing for auto-correlation of the volatility reveals that high volatility periods are most likely followed by further high volatility periods, while low volatility periods are likely to be followed by low volatility periods. Implied volatility varies within conditional volatility, which shows the level as the risk level changes. The plot also may show some events that can cause high turbulence, such as economic upheaval, market instability, or revolutionary policies.

Suggested model performance evaluation

Thus from the above findings, the GARCH model yields a better estimate of volatility as compared to the boom or bust view in the PMEX. The level of ARCH and GARCH terms combined with the relative fitness of the fit statistics demonstrates its capacity to model volatility persistence and more suitedness to analyze short-term volatility for identifying the long-run co-integrating relations between the variables; the GARCH model is more suitable for analyzing short-term volatility, making it ideal for dynamic price discovery and dynamic volatility control in this case. Hence, based on these findings, the GARCH model is suggested for higher accuracy of volatility and price changes in the PMEX.

DISCUSSION

This study investigates the dynamics of crude oil prices, cotton prices, and exchange rates at the Pakistan Mercantile Exchange (PMEX) using advanced econometric techniques, including the Augmented Dickey-Fuller (ADF) test, Johansen cointegration test, Vector Error Correction Model (VECM), and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. The key findings are as follows:

Stationarity and Differencing

The ADF test confirmed non-stationarity at levels for all variables, requiring first differencing to achieve stationarity. This aligns with Hamilton’s (1994) assertion that economic time series often exhibit trends or unit roots, necessitating differencing for valid inference. For instance, Zhang et al. (2008) similarly found that crude oil prices required differencing to stabilize variance, a result echoed here for PMEX data. The stationarity of differenced series supports using VAR/VECM frameworks, as non-stationary data can lead to spurious correlations (Enders, 2015). This step is critical for PMEX, where external shocks (e.g., geopolitical events) may introduce non-stationarity, complicating price discovery analysis.

Cointegration and Long-Run Equilibrium

The Johansen test identified one cointegrating equation, indicating a long-run relationship among crude oil, cotton, and exchange rates. This mirrors Nazlioglu et al. (2013), who found cointegration between energy and agricultural markets, though their study focused on developed economies. The current results extend this to PMEX, highlighting exchange rates as a linchpin in maintaining equilibrium. This contrasts with Reboredo’s (2012) emphasis on crude oil as the primary driver in cointegrated systems. The divergence may reflect Pakistan's import-dependent economy, where exchange rate fluctuations disproportionately affect commodity pricing (Khan et al., 2020). For PMEX traders, this underscores the need to monitor currency trends alongside commodity fundamentals.

Short-Run Dynamics and VECM Insights

The VECM revealed asymmetric short-run interactions. Exchange rates significantly influenced crude oil and cotton prices, while cotton prices negatively affected exchange rates. This aligns with Zhang and Wei (2010), who noted bidirectional causality between exchange rates and oil prices in emerging markets. The dominance of exchange rates in PMEX’s short-run dynamics diverges from studies emphasizing agricultural supply shocks (Gilbert, 2010). Weak self-persistence of cotton ($p=0.11$) contrasts with robust autoregressive effects in U.S. cotton markets (Baffes, 2007). This suggests that PMEX traders may prioritize currency hedging over historical price trends for cotton.

Volatility Modeling with GARCH

The GARCH (1,1) model captured volatility clustering, with high persistence ($\beta_1 = 0.78$) and significant shock impacts ($\alpha_1 = 0.20$). This mirrors Engle’s (1982) foundational findings on ARCH effects in financial markets. However, the PMEX’s lower persistence than developed markets (e.g., $\beta_1 \approx 0.90$ in Kumar, 2017) suggests quicker mean reversion, possibly due to regulatory interventions or liquidity constraints. The model’s strong fit (AIC = -11847.50) validates its use for PMEX volatility forecasting, critical for derivative pricing and risk management. These results echo Mensi et al. (2016), who advocated GARCH models for emerging market commodities.

Synthesis with Prior Literature

While the stationarity and cointegration findings align with global studies, the centrality of exchange rates in PMEX’s dynamics offers a novel perspective. For instance, Zhang et al. (2008) and Nazlioglu et al. (2013) identified oil-agriculture linkages but underemphasized currency roles. The current study bridges this gap, contextualizing PMEX within Pakistan’s import-reliant economy. Similarly, the GARCH results extend Kumar’s

(2017) work by quantifying volatility persistence in a frontier market, offering practical benchmarks for traders.

CONCLUSION

The study revealed significant interdependencies and volatility patterns that are critical for understanding market behavior in Pakistan's commodity and financial sectors. The VECM analysis confirms a long-run cointegrating relationship among the variables, with exchange rates emerging as a pivotal driver of short-term price adjustments. Crude oil and cotton prices exhibit bidirectional interdependencies, emphasizing their endogenous nature and the interconnectedness of agricultural and energy markets in the PMEX. The GARCH (1,1) model results revealed strong volatility persistence ($\beta 1 = 0.78$) and significant shock impacts ($\alpha 1 = 0.20$), indicating that historical volatility and sudden market disruptions play a dominant role in shaping crude oil price movements. This volatility clustering is a hallmark of financial markets, and its presence in the PMEX underscores the need for robust risk management tools to navigate price instability. The model's ability to capture these dynamics makes it a valuable tool for forecasting and decision-making in the PMEX. Traders and financial institutions should prioritize hedging strategies that account for exchange rate fluctuations, given their significant influence on commodity prices. Utilizing derivatives such as futures and options can help mitigate risks associated with currency volatility.

Policymakers should enhance market stability by closely monitoring volatility clusters identified through GARCH models. Implementing early warning systems during periods of external shocks (e.g., geopolitical events or economic crises) can help stabilize the market and protect stakeholders.

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