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FROM BLACK GOLD TO GREEN ENERGY: GARCH-BASED FORECASTING OF INDIAN CRUDE OIL PRICE VOLATILITY IN THE ERA OF ENERGY TRANSITION

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Abstract

This study investigates the volatility of crude oil prices in India from 2000 to 2025, a period marked by significant market uncertainty and the nation's transition toward renewable energy sources. Given India's substantial dependence on imported crude oil, accurate forecasting of price volatility is essential for effective risk management and policy formulation. Monthly crude oil price data are analyzed using a range of Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family models, including both symmetric and asymmetric specifications, and integrated with Autoregressive Integrated Moving Average (ARIMA) frameworks. Statistically significant lag structures are identified, and model selection is guided by information criteria to ensure the best fit. The ARIMA (2,1,6) - GARCH (1,1,1) model is found to be optimal, demonstrating strong statistical adequacy and effectively capturing volatility clustering. In-sample forecasts confirm the model's accuracy in tracking actual price movements during periods of heightened uncertainty. The findings highlight the persistence of crude oil price volatility in India and provide valuable insights for policymakers and market participants as the country navigates the ongoing shift from fossil fuels to renewable energy.

Keywords: *Crude oil price volatility, Indian crude oil basket, GARCH modelling, Energy transition, green energy*

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INTRODUCTION

Crude oil remains the backbone of the global economy, powering transportation systems, industrial production, and electricity generation while serving as a fundamental raw material for plastics, chemicals, fertilizers, medicines, and electronics(worldbank.org). This pervasive dependence on oil makes price volatility a critical concern for both developed and emerging economies, with far-reaching implications for economic stability, investment decisions, and policy formulation.

India's Evolving Energy Security Challenge

India exemplifies the complex dynamics of oil dependency in the modern era. As the world's third-largest oil consumer and importer, India's reliance on crude oil imports has reached unprecedented levels, with dependency climbing to 89.1% in March 2025, up from 87.8% in FY24. This escalating dependence far exceeding the government's initial target of reducing import dependency to 67% by 2022 (PPAC.gov) exposes the Indian economy to significant vulnerabilities from global oil price fluctuations.

Macroeconomic Implications of Oil Price Volatility

India's crude oil imports, totaling $161 billion in FY25 (25% of total imports), underscore a major economic dependency. The Indian crude basket—comprising 75–80% sour grades (Oman, Dubai) and 20–25% sweet (Brent)—dropped to a 47-month low of $68.34/barrel in April 2025, reflecting high market volatility. A $10/barrel price rise adds $13–14 billion to the import bill and widens the current account deficit by 0.3% of GDP. Such fluctuations impact inflation, exchange rates, trade balance, and overall macroeconomic stability. Historically, a 100% oil price surge can cut industrial production growth by around 1% (PPAC.gov).

The Energy Transition Paradigm

India is rapidly advancing its green energy goals, having committed at COP26 to achieve net-zero emissions by 2070 with ambitious interim targets such as 500 GW of non-fossil fuel capacity and 50% renewable energy share by 2030((Ministry of Power). As of March 2025, India's renewable energy capacity has reached over 220 GW, accounting for nearly 47% of its total installed power capacity(pib.gov). This growth is driven primarily by significant expansions in solar and wind energy, reflecting India's strong progress toward a cleaner, more sustainable energy future.

This study employs Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models to analyse and forecast the volatility of Indian crude oil basket prices during this critical transition period from April 2000 to March 2025. GARCH models have proven effective in capturing the dynamic nature of oil price volatility, including the clustering and persistence characteristics that are typical of financial time series. By examining historical data and projecting future volatility patterns, this study aims to provide valuable insights for policymakers, energy companies, and financial institutions navigating India's complex journey from heavy reliance on "black gold" to an increasingly "green energy" future.

LITERATURE REVIEW

Evolution of Oil Price Volatility Research

Oil price volatility has been the subject of extensive academic research for decades, with studies consistently highlighting the unpredictable nature of oil markets and their far-reaching economic implications. Early foundational work by Kuper (2002) applied GARCH models to analyse Brent crude oil price volatility, establishing that time-varying volatility patterns exist and that heightened uncertainty leads to wider price fluctuations. This seminal contribution laid the groundwork for subsequent volatility modelling research in the oil market.

Hamilton (2008) provided comprehensive insights into the multifaceted nature of oil price determination, examining various factors including global demand, supply restrictions, OPEC pricing strategies, and market speculation. His analysis concluded that no single factor fully explains oil price movements; instead, price dynamics result from complex interactions among multiple causes acting simultaneously on the market.

GARCH Models in Oil Price Volatility Analysis

The application of GARCH-type models has become increasingly sophisticated over time, with researchers exploring various specifications to capture the different aspects of oil price volatility. Kuncoro (2011) investigated the volatility of world crude oil prices using GARCH models, finding evidence of asymmetric leverage effects in some markets while establishing that volatility processes exhibit mean-reverting behavior. This study highlights the importance of considering different oil benchmark characteristics when modeling volatility patterns.

Ural (2016) conducted a comprehensive comparison of volatility models during different crisis periods, demonstrating that asymmetric GARCH models (APGARCH and FIAPGARCH) outperform symmetric variants in capturing oil price volatility. This study provides evidence of leverage effects in oil markets, indicating that negative shocks generate higher subsequent volatility than positive shocks of equivalent magnitude.

Advanced GARCH modeling approaches have continued to evolve, with Herrera, Hu, and Pastor (2018) comparing various specifications, including Risk Metrics, GARCH, EGARCH, FIGARCH, and MS-GARCH models. Their findings suggest that simpler models, such as Risk Metrics, excel in short-term forecasting, whereas more sophisticated models demonstrate superior performance for longer-term predictions.

Crisis-Specific Volatility Patterns

Research has related to the impact of different types of crises on oil price volatility has been extensive. Zavadska, Morales, and Coughlan (2018) analysed volatility patterns during four major crises: the Gulf War, the Asian Financial Crisis, the September 11 attacks, and the Global Financial Crisis. Their findings revealed that direct oil supply/demand disruptions generate higher volatility spikes than financial crises, which tend to produce more persistent, long-term volatility.

The COVID-19 pandemic provided additional insights into crisis-driven volatility patterns. Rizvi and Itani (2021) compared oil market dynamics during COVID-19 with those during previous crises and found that the pandemic created unprecedented volatility characteristics with negative skewness and positive kurtosis. Their analysis using symmetric and asymmetric GARCH models confirmed significant spillover effects and asymmetric responses during the pandemic.

Indian Context Research

Limited research has specifically addressed Indian crude oil price volatility and its unique features. Punati and Raju (2018) examined the determinants of crude oil prices in India and found that a combination of financial, macroeconomic, and international variables significantly influenced domestic oil price fluctuations. Their analysis highlighted the importance of exchange rates, inflation, and international benchmark prices in determining the Indian oil price dynamics.

Agarwal et al. (2019) applied GARCH-M VAR models to analyse crude oil price fluctuations in the Indian context, focusing on the relationship between oil markets and stock exchanges. The study confirmed that speculation plays a critical role in driving oil price changes, with the speculative component of oil price shocks negatively affecting macroeconomic growth.

RESEARCH GAP

Although crude oil price volatility has been widely studied, important gaps persist in relation to the Indian crude oil basket. Much of the existing literature focuses on global benchmarks such as WTI and Brent, thereby neglecting the unique composition and sour-sweet grade weighting of the Indian basket, which can produce distinct volatility patterns. Furthermore, limited research spans the extended period from 2000 to 2025, a timeframe that captures multiple global financial crises, oil market disruptions, and the accelerating energy transition, all of which could significantly reshape volatility characteristics. In addition, prior studies predominantly employ multivariate GARCH models with macroeconomic or financial variables, leaving insufficient attention to univariate GARCH approaches that isolate and assess the inherent, price-driven volatility dynamics of the Indian crude oil basket.

SIGNIFICANCE OF THE STUDY

This study is vital to India's energy transition and economic planning from 2000–2025, a period marked by surging energy demand and a shift toward sustainability. With India importing 85–88% of its crude oil—ranking as the third-largest global consumer and importer—its economy is highly exposed to oil price volatility, affecting GDP, inflation, current account deficits, and macroeconomic stability. By focusing on the Indian crude basket (a mix of sour grades like Oman and Dubai, and sweet Brent), the study addresses a key research gap often overlooked in global benchmark analyses. Using univariate GARCH models, it forecasts volatility patterns during this pivotal phase, offering crucial insights for policymakers to strengthen energy security, manage economic risks, and support India's net-zero goals by 2070.

RESEARCH METHODOLOGY

Research Objectives

1. To analyse Indian crude oil price volatility patterns (2000–2025), focusing on key events, their price behavior, and market impact.
2. To develop and evaluate various univariate GARCH-based models for forecasting Indian crude oil basket price volatility, including symmetric and asymmetric specifications.
3. To assess the implications of oil price volatility forecasts for India's energy security and economic planning during the transition period.
4. To provide policy recommendations for managing oil price volatility risks during the energy transition period.

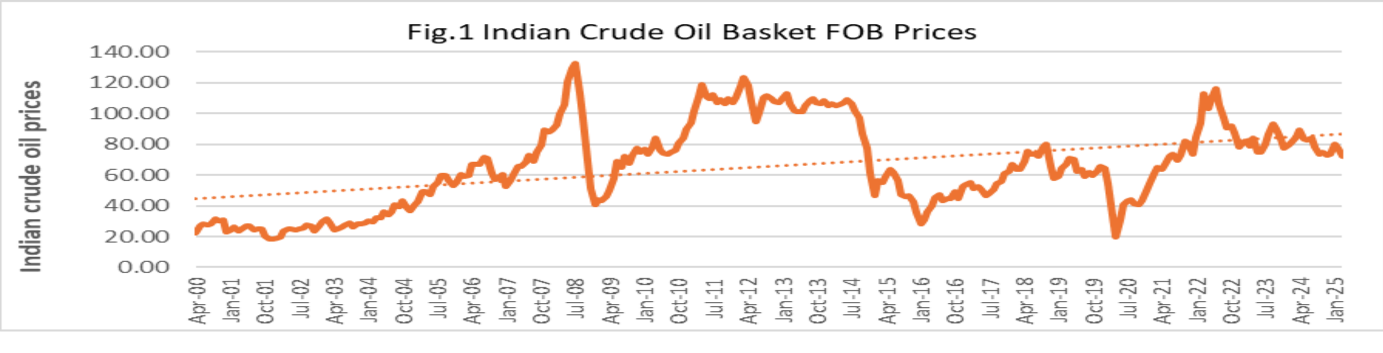
Data Sources and Collection

This study utilizes monthly Free on Board (FOB) price data for the Indian crude oil basket spanning from April 2000 to March 2025, comprising 300 observations sourced from the Petroleum Planning and Analysis Cell (PPAC).

DATA ANALYSIS AND INTERPRETATION

Volatility Pattern Analysis (2000-2025)

Figure 1 illustrates Indian crude oil basket price movements, revealing significant fluctuations over the 25-year period. The graph demonstrates several distinct volatility clusters and major price shocks, with prices ranging from approximately $20 to peaks exceeding $130 per barrel. While the overall trend shows a gradual upward trajectory (as indicated by the dotted trend line), the series is characterized by pronounced periods of instability in some years.



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Historical volatility patterns of Indian crude oil basket prices showing major crisis periods and energy transition dynamics from April 2000-March 2025

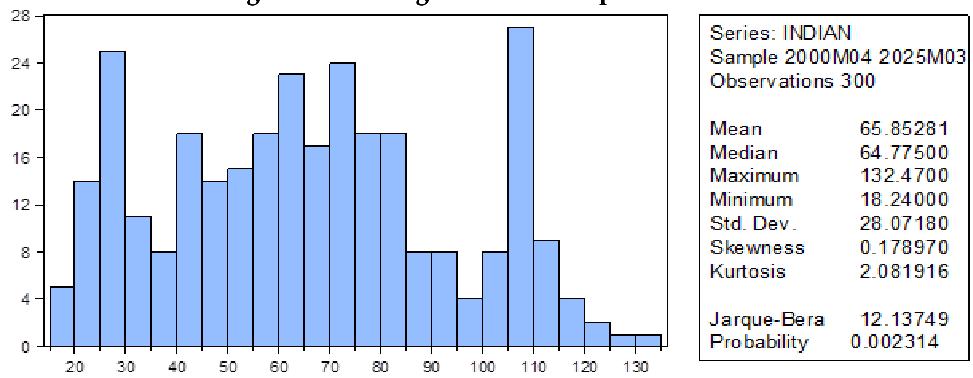
The analysis reveals distinct volatility clustering patterns consistent with stylized facts of financial time series. The study period encompasses multiple crisis events that significantly impacted volatility dynamics:

Table 1: Major Events Influencing Indian Crude Oil Price Volatility (2000–2025)

Period	Event Description	Price Behavior & Impact
2004–2008	Demand Boom in Emerging Economies	Prices rose steadily due to rapid industrialization, especially in China & India.
2008–2009	Global Financial Crisis	Prices surged to \$130, then collapsed to < \$40 as demand crashed during recession.
2011–2013	Middle East Instability (Arab Spring)	Prices remained elevated (~\$100–120) amid geopolitical tension and supply uncertainty.
2014–2015	OPEC Supply Glut vs. US Shale Boom	Sharp decline in prices as oversupply overwhelmed market (\$100 to < \$50).
2020	COVID-19 Pandemic	Historic crash (\$20) driven by lockdowns and global demand collapse.
2020–2022	Post - Pandemic Recovery & Supply Bottlenecks	Prices rebounded strongly, exceeding \$110 due to pent-up demand and supply lags.
2022–2025	Energy Transition & Russia–Ukraine War	Prices stabilized in the \$70–90 range; initial spikes followed the 2022 war onset, then moderated amid decarbonization policies and strategic reserves.

Figure 2 highlights the high volatility of Indian crude oil basket FOB prices from April 2000 to March 2025.

Figure 2. – Histogram and Descriptive statistics



Crude oil prices are ranging from \$18.24 to \$132.47 per barrel with a substantial standard deviation of 28.08. The distribution is nearly symmetric (skewness = 0.18) and slightly platykurtic (kurtosis = 2.08), yet the Jarque-Bera test ($p = 0.0023$) strongly rejects normality—signalling structural breaks due to global shocks and regime shifts. The histogram reveals several distinct price clusters, highlighting periods of both low and high prices, which underscores the need for robust risk management and advanced volatility modeling in India's energy sector

GARCH Model Development and Evaluation

To accurately apply a GARCH model, it is essential that the underlying time series is stationary, to check stationarity ADF test has been applied in E-views which shows result in Figure 3:

Table 2: ADF Test Result of Indian Crude Oil Price

Null Hypothesis: INDIAN has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=15)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.767661	0.0642
Test critical values:	1% level	-3.452141	
	5% level	-2.871029	
	10% level	-2.571897	

Table 2 presents the ADF test results, which indicate that Indian crude oil prices are non-stationary. The test statistic (-2.7677) and p-value (0.0642) fail to reject the null hypothesis of a unit root at the 5% significance level. This implies the series exhibits trending behavior and lacks mean reversion, necessitating first differencing or log transformation for econometric modeling.
This confirms that the Indian crude oil price series requires transformation (such as first differencing or logarithmic transformation) before being used in econometric analysis. Therefore, we use the first-differenced values of the Indian crude oil basket price, as this transformation ensures stationarity in the data.

Table 3: ADF Test Result of 1st Difference of Indian Crude Oil Price

Null Hypothesis: DINDIAN has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=15)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-11.81964	0.0000
Test critical values:	1% level	-3.452141	
	5% level	-2.871029	
	10% level	-2.571897	

Table 3 shows the ADF test results on the first-differenced crude oil price series, with a test statistic of -11.8196 and a p-value of 0.0000. This value is far more negative than the critical values at the 1%, 5%, and 10% levels, leading to the rejection of the null hypothesis of a unit root and confirming that the differenced series is stationary. Therefore, the data is now suitable for further econometric analysis.

Fig.3 - '1st Diff' has outliers at 'Month': Oct-08 and Mar-22.

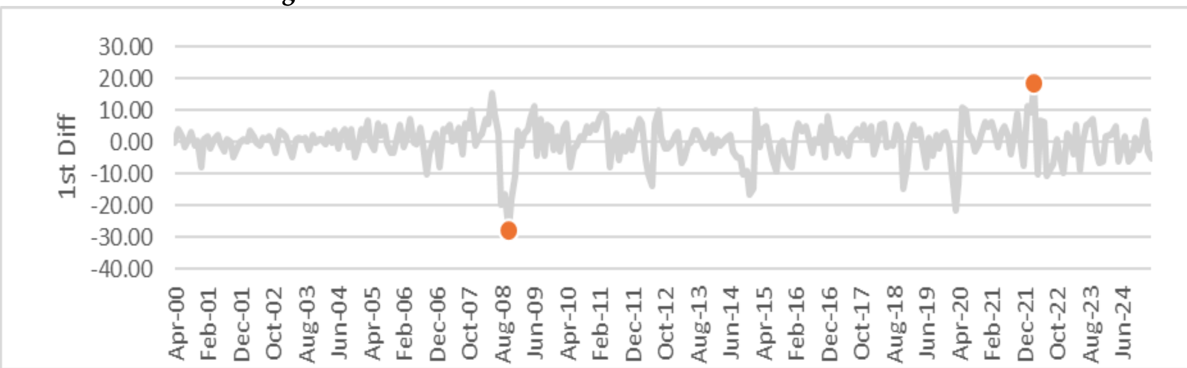


Figure 3 shows clear volatility clustering in 1st Difference monthly Indian crude oil price changes, with major outliers in Oct 2008 and Mar 2022 linked to global crises. These patterns suggest that current volatility shocks significantly influence expectations of future market risk.

GARCH Methodology Framework

The ARIMA model order selection for volatility analysis of the Indian crude oil basket was systematically guided by correlogram-based autocorrelation (ACF) and partial autocorrelation (PACF) diagnostics.

Figure 4: ADF Test Result of Indian Crude Oil Price

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.357	0.357	38.551	0.000
		2	0.089	-0.045	40.929	0.000
		3	-0.063	-0.092	42.124	0.000
		4	-0.073	-0.019	43.765	0.000
		5	-0.056	-0.018	44.725	0.000
		6	-0.118	-0.112	49.027	0.000
		7	-0.047	0.030	49.716	0.000
		8	-0.033	-0.026	50.055	0.000
		9	-0.076	-0.090	51.843	0.000
		10	-0.005	0.050	51.849	0.000

Figure 4 shows persistent and statistically significant spikes, particularly at the first and sixth lags, indicating strong serial dependence and volatility clustering in the first-differenced price series. Accordingly, the initial ARIMA equations included six AR and six MA terms to capture these dependencies. Subsequent stepwise significance testing led to the removal of statistically insignificant lag terms ($p > 0.05$),

and through trial-and-error refinement, four final ARIMA specifications were produced (ARIMA (2,1,6), ARIMA (2,1,5), ARIMA (4,1,6), and ARIMA (5,1,6)), each retaining only significant coefficients.
Before estimating the volatility models, Engle's ARCH test was conducted on the residuals of each selected ARIMA specification to formally detect the presence of conditional heteroscedasticity. The test results, summarized below, confirm significant volatility clustering, justifying the subsequent use of GARCH-family models.

Table 4: Engle's ARCH Test Result of 4 Selected Equations

Eq.	ARIMA Model Specification	ARCH Test F-Statistic	p-Value	Obs*R-squared	p-Value (Chi-Square)	Conclusion
1	ARIMA (2,1,6)-GARCH (1,1)	13.396	0.0003	12.903	0.0003	Strong presence of heteroscedasticity
2	ARIMA (2,1,5)-GARCH (1,1)	20.211	0.0000	19.047	0.0000	Strong presence of heteroscedasticity
3	ARIMA (4,1,6)-GARCH (1,1)	12.786	0.0004	12.340	0.0004	Strong presence of heteroscedasticity
4	ARIMA (5,1,6)-GARCH (1,1)	13.312	0.0003	12.825	0.0003	Strong presence of heteroscedasticity

Table 4 represents the ARCH-LM test results, which decisively reject the null hypothesis of no conditional heteroscedasticity across all four ARIMA specifications. The p-values are consistently below 0.001 for both the F-statistic and LM tests, confirming significant volatility clustering in the Indian crude oil basket price returns. These findings provide strong empirical justification for employing GARCH-family models (GARCH, TGARCH, EGARCH) to capture the time-varying conditional variance that standard ARIMA models cannot address. The rigorously selected lag structures, grounded in autocorrelation evidence, establish a robust and parsimonious foundation for systematic volatility modeling across 12 model specifications, ensuring improved volatility estimation and forecasting accuracy while maintaining methodological consistency and replicability.

Model Specifications:
Equation 1: ARIMA (2,1,6)-GARCH (1,1) with AR (2,4,6) and MA (1,2,4,5,6) terms
Equation 2: ARIMA (2,1,5)-GARCH (1,1) with AR (1,2,4) and MA (1,2,4,5) terms
Equation 3: ARIMA (4,1,6)-GARCH (1,1) with AR (1,2,4,6) and MA (1,2,3,4,5,6) terms
Equation 4: ARIMA (5,1,6)-GARCH (1,1) with AR (1,2,4,5,6) and MA (1,2,4,5,6) terms
The general GARCH (1,1) specification follows the form:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$$

where σ_t^2 represents conditional variance, $\omega > 0$ is the constant term, $\alpha \geq 0$ captures the ARCH effect, and $\beta \geq 0$ represents the GARCH effect, with the persistence condition $\alpha + \beta < 1$ ensuring stationarity.

Model Selection
Model selection employed multiple information criteria including Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Research indicates that BIC performs best for GARCH model selection, particularly for capturing correct model order. In this study, four equations were estimated with GARCH, TGARCH, and EGARCH model specifications. To choose the best model, AIC, BIC, R-squared, and log-likelihood criteria were all considered.

Table – 5 Summary results of four ARIMA-GARCH model specifications

	GARCH				TGARCH				EGARCH			
Equation	AIC	BIC	Log-Likelihood	R²	AIC	BIC	Log-Likelihood	R²	AIC	BIC	Log-Likelihood	R²
1	5.953	6.103	-860.064	0.119	6.019	6.182	-868.716	0.119	5.956	6.119	-859.532	0.121
2	6.016	6.153	-876.288	0.101	6.017	6.167	-875.441	0.102	6.001	6.151	-873.189	0.100
3	6.013	6.189	-866.889	0.117	5.994	6.183	-863.154	0.119	5.988	6.177	-862.272	0.109
4	5.967	6.143	-860.117	0.115	5.978	6.166	-860.719	0.123	6.003	6.192	-864.489	0.100

Based on a comprehensive evaluation of Table 5 shows that Equation 1: ARIMA (2,1,6)-GARCH (1,1) with AR (2,4,6) and MA (1,2,4,5,6) terms was selected as the optimal model for analysing Indian crude oil price volatility, as it achieved the lowest AIC (5.952655) and BIC (6.103379) among all 12 configurations tested. This selection was made to ensure the most accurate and parsimonious representation of volatility dynamics in the data.

Diagnostic Tests Framework:
After selecting the best equation ARIMA (2,1,6)-GARCH (1,1) with AR (2,4,6) and MA (1,2,4,5,6) terms, diagnostic tests were performed to confirm its adequacy.

Table 6: Summary results of Diagnostic Tests

Diagnostic Test	Purpose	Test Statistic / Result	P-Value / Significance	Conclusion
ARCH LM Test	Detect remaining heteroskedasticity	F = 0.5991, Obs*R^2 = 0.60	p = 0.4396, 0.4378	No significant ARCH effects: model adequately captures volatility
Residual Autocorrelation	Check residual autocorrelation	Durbin-Watson = 1.993	p > 0.05 (from correlogram)	No residual autocorrelation: residuals are white noise
Normality of Residuals	Assess residual distribution	Histogram	p > 0.05 (from histogram)	Residuals approximately normal;

Table 6 presents the results of the ARCH LM test (for remaining ARCH effects), the Ljung-Box test (for autocorrelation in standardized and squared residuals), and the Jarque-Bera test (for normality of residuals). The results demonstrate the model's robustness: the ARCH LM test ($p = 0.4396$) confirms no remaining conditional heteroscedasticity, the insignificant lagged squared residual coefficient (-0.045390) validates the effective capture of volatility clustering, and the Durbin-Watson statistic (1.993) indicates no residual autocorrelation. These diagnostics support the model's suitability for risk management and volatility forecasting in the Indian crude oil market.

Methodological Justification
The estimated GARCH (1,1) model for Indian crude oil prices yields $\alpha = 0.519$ and $\beta = 0.366$, with both coefficients statistically significant ($p < 0.05$). The persistence parameter ($\alpha + \beta = 0.885$) is less than 1, satisfying the stationarity condition. This confirms that the standard GARCH (1,1) specification effectively captures volatility clustering in the series while ensuring a mean-reverting, stationary variance process.

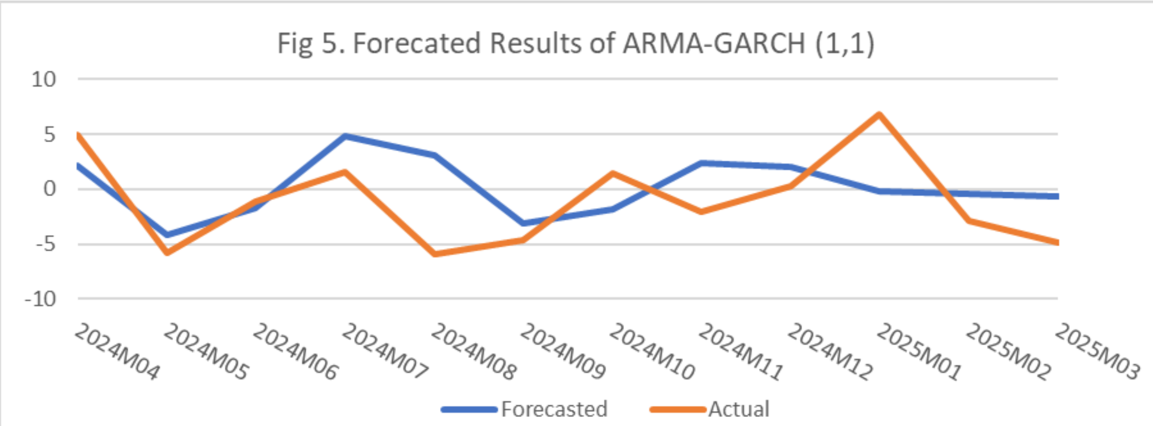


Figure 5 illustrates the performance of the ARIMA (2,1,6) – GARCH (1,1) model, selected using AIC and BIC, in forecasting Indian crude oil price volatility. The forecasted values closely track actual data for most of the period from April 2024 to March 2025, effectively capturing both trend direction and volatility clustering. This suggests the model is robust and reliable for short-term volatility forecasting in the crude oil market.

Implications of Oil Price Volatility Forecasts for India's Energy Security and Economic Planning
India's extreme vulnerability to oil price volatility stems from its 90% import dependency, making it the world's third-largest oil importer. Strategic Petroleum Reserves cover just 9.5 days of consumption far below the 90-day international standard and even with a planned expansion, coverage will only reach about 21 days, leaving India exposed to supply disruptions. Despite diversifying to 39 supplier countries, Russia now accounts for 35% of imports, followed by Iraq (19%) and Saudi Arabia (14%), while 40% of imports transit through the vulnerable Strait of Hormuz, heightening geopolitical risk (pib.gov).

Rising oil prices have a big impact on India's economy. For every $10 increase, GDP growth drops by 0.2–0.3%, inflation goes up by 0.49%, and the current account deficit widens by 0.3% of GDP (OPEC.org) High oil costs also limit government spending, as more money is needed for fuel subsidies. For example, during the Russia-Ukraine war, the government had to cut fuel taxes to ease public burden, exposing the country's fiscal vulnerability.

The BRICS initiative to promote the use of local currencies, including the Indian rupee, for international transactions—particularly in energy trade—implies a potential shift away from dollar-dominated crude oil pricing. This move may reduce India's exposure to exchange rate volatility and external shocks in global oil markets, thereby strengthening energy security and enhancing the country's resilience during the global energy transition. (spglobal.com)

Sectoral Vulnerability Assessment

Rising crude oil prices directly elevate fuel costs for India's transportation sector, which operates under strong market competition and limited flexibility in passing on price increases to consumers, resulting in squeezed margins (RBI.org). Manufacturing, especially energy-intensive industries, faces higher expenses from both direct petroleum inputs and indirect transportation inflation(worldbank.org). In agriculture, rising fuel prices increase costs for diesel-powered irrigation and the transport of produce. According to a UK–Gol case study, this often necessitates hikes of 10–12% in the Minimum Support Prices (MSP) to offset elevated input costs and preserve farmers' incomes.

Energy Transition Period Challenges

The combination of extreme import dependency (90%), inadequate strategic reserves (9.5 days), and concentrated supply routes (40% through Strait of Hormuz) creates systemic vulnerabilities during the critical energy transition period ((ISPRL Chief Jain, Reuters). This necessitates accelerated diversification, enhanced risk management strategies, and aggressive renewable energy transition to reduce structural oil dependence.

Policy Recommendations for Managing Oil Price Volatility Risks During Energy Transition

Short-Term Measures

Expand Strategic Petroleum Reserves (SPR): India should increase its oil storage (called Strategic Petroleum Reserves or SPR) so it can cover at least 45 days of the country's oil needs by 2030. These reserves can be used not just in emergencies, but also for commercial use or in coordination with other countries during global oil crises. It helps secure energy supply and manage price shocks (Ministry of Petroleum & Natural Gas).

Financial Hedging & Fiscal Tools: India should implement sovereign oil price hedging to cover 30–50% of annual crude imports, shielding the economy from sudden global price surges—an approach successfully tested by countries like Mexico. Additionally, promoting rupee-denominated oil derivatives would reduce reliance on the U.S. dollar, lowering currency risk and stabilizing import costs for Indian refiners. Finally, establishing an oil price stabilization fund, supported by variable excise duties, could smooth domestic price volatility and enhance fiscal resilience during oil shocks (RBI Annual Report, Ministry of Finance).

Medium-Term Actions

Accelerate Renewable: Fast-track achieving 500 GW renewable capacity by 2030, backed by grid modernization and smart technologies.

Promote Biofuels and Electric Mobility: Scale up ethanol blending to 20%, expand green hydrogen and biodiesel production, and target 30% EV sales by 2030 with robust charging infrastructure (Niti Aayog).

Long-Term Structural Reforms

Enhance Domestic Oil & Gas Production: India should increase its own oil and gas production by exploring more areas and using better technology to extract more fuel—even from unconventional sources like shale or deep-sea reserves. This will help reduce dependence on imports and improve energy security (Ministry of Petroleum & Natural Gas, IEA).

Boost Energy Efficiency and Green Finance: India should make factories and buildings use energy more efficiently by strictly applying energy-saving rules. At the same time, it should raise money for clean energy projects (like solar or wind) by using tools like green bonds and getting support from banks and financial institutions. This helps cut energy waste and support a greener economy (Ministry of Power, SEBI, World Bank).

Foster Innovation: India should invest more in research and development (R&D) for clean energy technologies, support local manufacturing of green equipment (like solar panels or batteries), and develop carbon markets where companies can trade emissions credits. This will drive innovation, reduce pollution, and support the transition to a low-carbon economy. (Ministry of New & Renewable Energy, NITI Aayog, SEBI).

Global Partnerships: Strengthen international cooperation on energy security, climate finance, and technology transfer, leveraging platforms like the International Solar Alliance and IEA partnerships (Ministry of External Affairs, IEA).

This streamlined framework balances immediate risk management with strategic energy transition goals, ensuring India's resilience to oil price volatility while accelerating its shift toward a sustainable energy future.

CONCLUSION

This study's findings reinforce the established literature on oil price volatility modeling, confirming that GARCH-type models effectively capture volatility clustering and time-varying risk, as demonstrated by Kuper (2002) and supported by Hamilton (2008) regarding the complex drivers of oil price movements. While international research (Kuncoro, 2011; Ural, 2016) often finds that asymmetric GARCH models best capture leverage effects our analysis of Indian crude oil prices reveals a notable divergence. Specifically, for the Indian market, symmetric GARCH models outperform their asymmetric counterparts in forecasting volatility. This difference likely arises from the use of the Indian crude oil basket as a benchmark, which blends WTI and Brent international grades and may dampen asymmetric responses seen in single-benchmark studies.

To mitigate these risks, a multi-pronged strategy is essential. In the short term, expanding Strategic Petroleum Reserves and adopting sovereign hedging can buffer sudden price surges. Medium-term focus should accelerate renewables and biofuel adoption, while long-term resilience demands boosting domestic oil and gas production, strengthening energy efficiency, financing green technologies, and fostering innovation. Global cooperation, especially through alliances like the International Solar Alliance and the IEA, will be vital in securing technology transfer and climate finance.

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