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Asymmetric responses of industrial output to oil price volatility: A GARCH approach in East Asia-Pacific developing countries

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ABSTRACT

Crude oil represents a vital energy source essential for sustaining economic manufacturing activity and growth. Energy reliability is an absolute requirement for economic growth and development to occur. Widespread transmission across the economy becomes more complicated and nonlinear because of both business cycle patterns and policy changes. This study examines the asymmetric responses of industrial output to oil price volatility in East Asia-Pacific developing countries. The research utilizes monthly data from January 1997 to December 2024 on Brent oil prices and industrial production in these countries. It employs DCC and CDCC-GARCH models for symmetric analysis, while advanced asymmetric GARCH models (GJR-GARCH, FIEGARCH, HYGARCH) are used to detect asymmetric relationships. The results reveal significant differences in the effects of positive versus negative oil price shocks on industrial output growth. Symmetric GARCH models show weak correlations between oil price volatility and output, whereas asymmetric GARCH models uncover significant nonlinear and asymmetric relationships. The findings indicate that industrial output in East Asia-Pacific developing economies responds more strongly to oil price increases than decreases. The study concludes that the relationship between oil price volatility and industrial output growth is asymmetric, characterized by persistent and clustered volatility patterns. Furthermore, asymmetric GARCH models significantly outperform their symmetric counterparts in capturing these dynamics.

Contribution/Originality: This study is the first to integrate DCC/cDCC with long-memory asymmetric GJR-GARCH, FIEGARCH, and HYGARCH specifications, using monthly data (1997–2024) for energy-import-dependent East Asia-Pacific developing economies. It was found from the analysis that asymmetric GARCH, especially the FIEGARCH model, which other literature has ignored, does a better job in explaining actual economic changes compared to symmetric ones.

1. INTRODUCTION

Understanding the influence of global oil price fluctuations on the growth of industrial production is crucial for economies at all development stages. Unexpected shocks in wealthy economies have worldwide repercussions, especially in energy and productivity markets (Chuang & Yang, 2022; Hamilton, 1983). The significance of oil in manufacturing and industries will decrease in the upcoming years because various nations are introducing policies to minimize fossil fuel utilization (Dong, Li, Li, Liu, & Zheng, 2022; Liu & Chao, 2022; Meckling & Nahm, 2019). The research investigates how oil price volatilities shape output growth patterns within developing countries from the East and Asia Pacific regions, which the World Bank and United Nations have identified as Thailand, Malaysia, China, the Philippines, Indonesia, and other members. This field of investigation matters because symmetric models prove inadequate to reproduce entire economic cycle impacts as well as policy adjustments (Donayre & Wilmot, 2016). Their study shows an increasing interest in using nonlinear asymmetric models to analyze oil price volatility patterns.

Our investigation has two main research objectives. First, it analyzes the symmetric relation between oil price volatility and output growth for the industry. The research investigates the asymmetric impacts that oil price volatility has on the economy. This method evaluates industrial production growth through the divergent impacts of oil price volatilities, whether they are positive or negative. The large amounts of imported oil that East and Asia Pacific developing economies consume serve as essential contributors to their economic development and constant industrial and manufacturing energy availability. The region contains Malaysia and Indonesia as its essential oil exporters because Thailand and the Philippines, together with Vietnam, function as major oil importers (Kimura, Phoumin, & Purwanto, 2023).

The available scholarly literature provides insufficient information about oil price movements and industrial output in East and Asia Pacific developing economies, with other advanced GARCH models. Equity market responses are the main focus of existing studies on oil price volatility. While some studies have explored the asymmetric impact of oil price volatility on macroeconomic aggregates such as inflation and GDP, few have examined sector-specific impacts, particularly on industrial output. Moreover, much of the existing literature relies on linear or symmetric models, which may understate the influence of volatility when effects differ between rising and falling oil prices. Overlooking these asymmetries can result in incomplete or misleading policy prescriptions, especially in oil-importing economies seeking to insulate their manufacturing base from energy market instability.

The study will make an impactful contribution to the growing literature on the resultant effect of oil prices on industrial output in East Asia-Pacific developing countries. It will apply advanced asymmetric GARCH models (GJR-GARCH, FIEGARCH, HYGARCH) that capture nonlinear dynamics and long-memory volatility, which symmetric models miss. The rest of the study has the following structure: Section Two provides a literature review, and Section Three presents the data and methodological framework. Section Four displays the empirical results, while Section Five offers policy recommendations.

2. LITERATURE REVIEW

2.1. Theoretical Foundations

The theoretical basis for analyzing asymmetric responses to oil price changes originates with Hamilton (1983), who argued that oil price increases have disproportionately negative effects on macroeconomic indicators such as GDP and industrial output. Hamilton (1996) and Hamilton (2003) pointed out that price increases in oil result in major output drops for the economy, but price decreases produce weaker positive outcomes. This asymmetry is sometimes attributed to the impact of uncertainty on consumer and business spending, reallocation costs (shifting resources away from energy-intensive activities), and psychological or behavioral factors affecting spending decisions. The concept behind this analysis centers on oil price increases creating production-related expenses, which push businesses to alter their manufacturing procedures to handle rising relative oil expenditures. The modifications to production systems made by firms when oil prices rise stay in place when prices decrease, resulting in an unusual market scenario. In line with the Hamilton hypothesis, Mendoza and Vera (2010) the findings indicate that oil shocks positively and significantly affect output in Venezuela, using data from 1984 to 2008. Kim and Roubini (2000) pointed out that a negative price shock in oil does not decrease output in nations that combine diversified economies with domestic refining capabilities. These researchers show that nations with weak economic variety, combined with weak refining facilities, fail to reap output gains when oil prices increase. Currency appreciation does not occur when oil-producing nations rely on imports to meet refined petroleum demands, along with other goods, even though they generate higher revenues from oil production. Kriskkumar, Naseem, and Azman-Saini (2022) indicated that oil price fluctuations influence Malaysia's output growth asymmetrically, with both increases and decreases in oil prices positively affecting economic growth output. In contrast, Mishra, Tripathy, and Debasish (2021) established that changes in oil prices, along with their volatility, do not have significant effects on industrial production growth within rapidly emerging Asian economies.

2.2. Empirical Review

Various studies have focused on the nexus between oil price volatility and the production performance of oil-exporting and importing countries, which have yielded contradictory results. The results from Chuang and Yang (2022); Pinno and Serletis (2013) and Maghyereh, Awartani, and Sweidan (2019) deliver complete findings about oil price volatility effects using symmetric and asymmetric GARCH models to understand oil price volatility effects. Sun, Cai, and Huang (2022), along with Emenogu, Adenomon, and Nweze (2020); Yang and Zhou (2020) and Alao and Payaslioglu (2021), present various findings about the subject through their application of different GARCH models. Research by Hamilton (1983) shows that rising price volatility tends to precede economic recessions in the United States. The work by Mork, Olsen, and Mysen (1994) shows that changes in oil prices create asymmetric responses in output levels across the economies of the U.S., Canada, Japan, Germany, France, and the UK, with negative output effects prevailing. Investigations into the impact of oil price volatility on output growth in East and Asia Pacific developing countries employ linear ARDL and nonlinear ARDL models in studies conducted by Mishra et al. (2021); Khan, Husnain, Abbas, and Shah (2019); Nusair and Olson (2021); Rafiq and Salim (2014) and Kisswani (2021). They confirmed economic activity in China, South Korea, and other countries, including Bangladesh, India, and Pakistan. The analysis showed no evidence of a long-term association with oil price shock fluctuations but observed symmetric market reactions to oil price changes, although some results were asymmetric. Mishra et al. (2021) investigated how increasing oil prices affected industrial output, price levels, and currency values in China, India, South Korea, Singapore, and Japan using ARDL and SVAR models. Their results show a bidirectional causal relationship between Asian industrial output and global oil trends and indicate that the impact of oil price fluctuations on macroeconomic variables within Asian economies was minimal.

According to Kriskkumar et al. (2022), oil price uncertainties create asymmetrical effects on Malaysian output expansion. Similarly, Le, Nguyen, and Tran (2024) examined the relationship between oil and stock prices employing a complex EGARCH model, covering the period from 2000 to 2022. The results indicate an asymmetric pattern, with oil price changes having a negative impact on Thailand's stock markets but a positive effect on Indonesian stock markets. Based on the theoretical discussion and empirical review, the following hypotheses are proposed:

H_1: Industrial output growth in East Asia-Pacific developing economies responds asymmetrically to oil price volatility.

H_2: Asymmetric GARCH models (such as GJR-GARCH, FIEGARCH, and HYGARCH) significantly outperform symmetric GARCH models in capturing the volatility transmission from oil prices to industrial output.

3. DATA AND METHODS

The following sections provide detailed information regarding data collection methods and explain how the analysis was conducted to achieve our research objectives.

3.1. Data

Monthly data (1997-2024) on Brent oil prices and industrial production for East Asia and the Asia-Pacific developing countries were sourced from the IMF (FRED) and the World Bank (GEM). Data were log-transformed and differenced to compute returns (Log (st/st-1)), where st represents the time-based value of the series.

Table 1. Definition of variables.

Variables	Meaning	Source
Oil	Oil price	Global Price Brent, International Monetary Fund via International Monetary Fund (2024)
IPQ	Industrial production output (IPQ) of East and Pacific developing countries in US dollars	Global Economic Monitor (GEM), The World Bank (2024)
lnOil	Log of oil price	Log transformation
lnIPQ	Log of East and Asia Pacific developing countries IPQ	Log transformation
rOil	Returns on oil price	Growth
rIPQ	Returns on the East and Asia Pacific developing countries' IPQ	Growth

Table 1 presents the study's key variables, their definitions, and data sources. The Brent crude oil is obtained from the IMF Primary Commodity Prices database, whereas the industrial production output of East Asia Pacific developing economies (IPQ) is represented by the Global Economic Monitor of the World Bank. Both series have been transformed into natural logarithms (lnOil, lnIPQ) to stabilize variance, and the first differences of the two provide growth rates per month (rOil, rIPQ), which are interpreted as returns.

Figure 1 depicts graphical data showing the level and growth of oil prices together with industrial production output patterns in developing East and Asian Pacific nations. The level of oil prices lacks long-term persistence, but volatility clustering appears in the return series. Industrial production output shows an increasing trend over time while revealing random peak points that indicate changes in short-term outcomes.

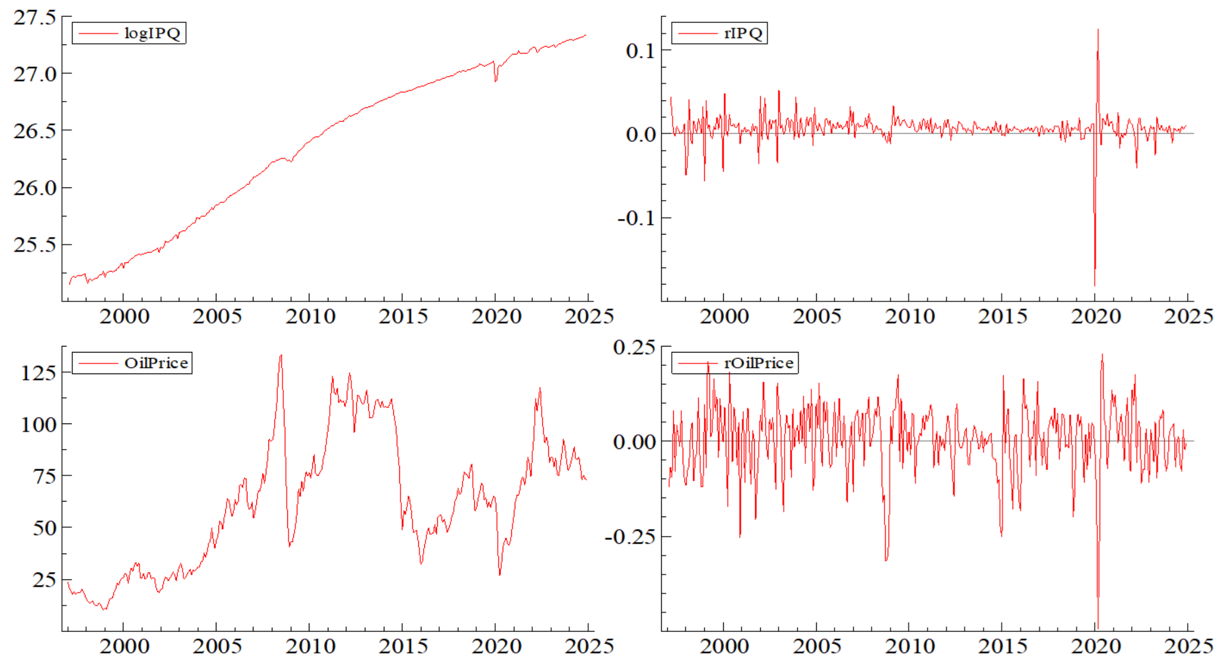

Figure 1. Brent oil price, IPQ, and their growth rates (1997:01–2024:12).

3.2. Empirical Modelling

The empirical modelling procedure includes two essential components, which are GARCH estimation techniques for symmetric and asymmetric models.

3.2.1. Symmetric Estimation

To account for the impact of fluctuations in oil prices on industrial production, we start with a symmetric model in which positive and negative oil shocks are considered to have equal but opposite effects.

$$Y_t = \alpha + \delta O_t + \varepsilon_t \qquad (1)$$

Where:

Y_t is the industrial output growth (return) at time (t), O_t is the oil price volatility (return), δ is the impact coefficient, and ε_t is the error term. Meanwhile, this study incorporates the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family of models to capture volatility clustering and persistence in oil price fluctuations and their output transmission, and these are discussed as follows.

3.2.1.1. DCC-GARCH Model

The research utilizes Engle (2002) proposed methodology for determining dynamic relationships between industrial production and oil prices, along with spillover effects. Previous applications of this methodology appear in Lin, Wesseh, and Appiah (2014); Aydoğan, Tunç, and Yelkenci (2017); Alao and Payaslioglu (2021) and Alao et al. (2023). The GARCH model's conditional specification establishes its variance expression as follows.

$$\delta^2 = \theta + \delta\varepsilon_{t-1}^2 + \beta\delta_{t-1}^2 \qquad (2)$$

The DCC model expresses variance-covariance matrices through the following specification.

$$H_t = D_t R_t D_t \qquad (3)$$

Where,

$$D_t = diag\{\sqrt{h_{it}}\}$$

$$R_t = D_t^{-1} H_t D_t^{-1} = \varepsilon_{t-1}(\varepsilon_t \varepsilon_t')$$

$$\text{Since } e_t = D_t r_t \qquad (4)$$

Here, *h* represents univariate GARCH models with the correlation matrix denoted by *R*. R refers to the unconditional correlation matrix. The DCC estimator constructs an estimable positive-definite covariance matrix for its application, Qt:

$$IP_{IP,Oil_t} = \frac{qIP,Oil_t}{\sqrt{QIP,IP_t q_{oil} oil_t}} \qquad (5)$$

$$Q_t = L + \sigma\epsilon_{t-1}'\epsilon_{t-1}' + \beta Q_{t-1} \qquad (6)$$

Where L = (1-σ-β)$\bar{Q}$; $\bar{Q}$ = E ($\varepsilon_t\varepsilon_t'$) is an n-by-n unconditional variance matrix of ε_t and must satisfy the less than one condition (σ+β<1 and σ+β>0) to establish that the DCC model is mean-reverting, and β are not negative scalar parameters. the DCC model is specified as below:

$$Q_t = (1 - \sigma - \beta)\bar{Q} + \alpha\epsilon_{t-1}'\epsilon_{t-1}' + \beta Q_{t-1} \qquad (7)$$

Qt represents a symmetric positive definite matrix.

3.2.1.2. CDCC-GARCH Model

The study uses the CDCC method developed by Aielli (2013) to build upon Engle's (2002) initial model framework. The CDCC model stands out because it offers better estimation properties together with consistent dynamic correlation detection features. The main benefit of this methodology concerns its ability to fix the estimation bias of correlation patterns Aielli (2013) developed the specification of an improved CDCC model, which describes its formulation as follows:

$$Q_t = (1 - \sigma - \beta)\bar{Q} + \alpha \epsilon^{*\prime}_{t-1} \epsilon^{*\prime}_{t-1} + \beta Q_{t-1} \quad (8)$$

In line with Equation 7, the parameters and β share the same less-than-one condition (σ+β<1) models (7) and (8).

3.2.2. Asymmetric (GARCH) Estimations

However, theoretical and empirical literature (e.g., (Hamilton, 1983; Mork, 1989)) suggests that this response is likely asymmetric. We therefore extend the model to allow for differential effects of oil price increases and decreases:

$$Y_t = \alpha + \beta_1 O_t^+ + \beta_2 O_t^- + \varepsilon_t \quad (9)$$

Where:

O_t^+ captures positive oil price changes (shocks), and O_t^- captures negative oil price changes, while β_1 and β_2 measure their respective effects. However, to account for the possibility that negative oil shocks (e.g., price increases) create more volatility than positive shocks (price drops), we use asymmetric GARCH models as discussed below:

3.2.2.1. GJR-GARCH Model

Proposed by Glosten, Jagannathan, and Runkle (1993), the model correctly demonstrates how returns respond differently to shocks of equal size depending on whether they are positive or negative. Economists and financial experts extensively use this model when detecting supplementary asymmetric risks in their studies. GJR, which is third from the right-hand side Equation 10, typically performs better than GARCH and enhances forecasting capacity (Alao & Payaslioglu, 2021; Ali, Zhang, Abbas, Draz, & Ahmad, 2019; Jiang, Jiang, Nie, & Mo, 2019). The GJR model is represented below after transforming Equation 10 as:

$$\sigma_t^2 = \varphi + \alpha \epsilon_{t-1}^2 + n \epsilon_{t-1}' d_{t-1} + \beta \sigma_{t-1}^2 \quad (10)$$

In this model, d_{t-1} represents the dummy variable: >> 0, dt-1 = 1; otherwise, dt−1 =0. If n(gamma) ≠ 0, fulfilling non-negativity, then a leverage effect exists, but if n(gamma) = 0, from Equation 8, no leverage effect is present, and the model can be simplified and taken to a symmetric form. Under this specification, the assumption made by the model is that past shocks, whether positive or negative, affect current volatility equally. The main strength of the present model resides in the ease with which it can measure leverage effects and their presence or absence.

3.2.2.2. FIGARCH Model

The FIGARCH model developed by Brunetti and Gilbert (2000) provides a model for conditional variance, which enables an easy explanation of observed market volatility dependencies through unrestricted processes. Standard GARCH elements remain intact in this model, as it offers fractional integration functionality to handle long-term effects.

$$\sigma = \frac{a}{1-\beta(L)} + 1 - \frac{(1-\theta(L)(1-L)^d}{1-\beta(L)} \quad (11)$$

In this equation, d depicts the degree of geometric or hyperbolic decomposition. Meanwhile, we have three cases for d: 0, 1, and (0<d<1). First, there is a geometric decomposition if d=0; second, we have infinite persistence if d=1; and third, if d falls between the first and second scenarios, then there is an intermediate range of persistence.

3.2.2.3. EGARCH Model

The Exponential GARCH (EGARCH) model, which Nelson (1991) introduced as one of the most frequently used models for modeling asymmetrical volatility patterns, has the asymmetric EGARCH model's ability to respond to symmetrically distributed shocks, along with its capacity to model leverage effects, making it superior to standard ARCH/GARCH models. The parameter γ indicates the presence of an asymmetric effect. To be more specific, in Equation 12, a statistically significant γ, the γ means that negative shocks tend to increase volatility more than positive ones that are of the same magnitude. Conversely, if $\gamma = 0$ γ=0, symmetry of the model exists; thus, there is no asymmetry of the effect of shock direction on volatility.

$$In(\sigma_t^2) = a + \beta \left| \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}}} \right| + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}}} + \theta In(\sigma_{t-1}^2) \qquad (12)$$

3.2.2.4. FIEGARCH Model

FIEGARCH is the result of FIGARCH and EGARCH. The Fractionally Integrated Exponential GARCH (FIEGARCH) model, which Bollerslev and Ole Mikkelsen (1999) developed, operates with identical estimation approaches to EGARCH models. FIEGARCH provides a simultaneous analysis of shock magnitude alongside their persistence effects for both positive and negative events. The FIEGARCH model demonstrates exceptional capability for calculating long-term shock effects on market volatility, together with market deviation dimensions. The parameter γ within the model definition of Equation 12 preserves its function as an indicator for shock response differences between negative and positive events.

$$In(L)(1-L)^d In(\sigma_t^2) = a + \beta \left| \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}}} \right| + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}}} + \theta In(\sigma_{t-1}^2) \qquad (13)$$

The stationarity of the FIEGARCH model is in between zero and one stationarity conditions.

3.2.2.5. HYGARCH Model

Through its extension of GARCH, FIGARCH, and FIEGARCH models, the HYGARCH model includes enhanced derivations and refined notational structures. The model addresses volatility and long-term persistence features effectively because it was specifically designed to analyze these phenomena beyond standard asymmetric model capabilities. The performance of HYGARCH emerges superior to other GARCH methods for describing extended memory, together with complex volatility patterns (Ñíguez & Rubia, 2006). The model, propounded by Davidson (2004) and presented in a reduced form by Conrad (2010), is given thus:

$$\theta_i^{HY} = \pi\theta_i^{FI} + (1-r)\theta_i^{GA} \qquad \text{for i=1,2,3} \qquad (14)$$

Where HY, FI, and GA are HYGARCH, FIGARCH, and GARCH, respectively.

4. RESULTS AND DISCUSSION

4.1. Preliminary Analysis

In Table 2, Panel A shows negative skewness, along with positive excess kurtosis values, indicating that the data series follows a leptokurtic distribution. The stationarity tests presented in Panel B demonstrate that the analyzed series remains stationary. The diagnostic test results are shown in Panel C, and the unconditional correlation matrix appears in Panel D. Results from the ARCH (5) and ARCH (10) tests indicate that autoregressive conditional heteroskedasticity (ARCH effects) exists in the growth series, which is statistically significant at 5%, confirming the presence of volatility in the series of returns. The Box-Pierce test provides Q^2 statistics that help detect serial correlation in squared residual data. The combined analytical findings support the application of GARCH-type models for further analysis.

Table 2. Descriptive statistics.

Variables	rIPQ	rOilPrice
Panel A: Summary statistics		
Mean	0.0065	0.0043
Max	0.1253	0.2313
Min	-0.1824	-0.495
Standard deviation	0.0173	0.0914
Skewness	-3.2362	-1.0115
Excess Kurtosis	49.248	3.0342
Jarque-Bera statistic	547.58	42.73
Panel B: Unit root tests		
ADF (Lag 0)	-20.56**	-13.69**
ADF (Lag 1)	-18.15**	-11.67**
ADF (Lag 2)	-12.45**	-10.15**
ADF (Lag 3)	-10.73**	-9.337**
Panel C: Diagnostic tests		
Q^2(5) (Box-Pierce)	45.38 (0.0000) **	49.91 (0.0000) **
Q^2(10) (Box-Pierce)	45.52 (0.0000) **	50.26 (0.0000) **
ARCH (5)	12.21 (0.0000) **	9.14 (0.0000) **
ARCH (10)	6.14 (0.0000) **	4.54 (0.0000) **
Panel D: Unconditional correlation		
rIPQ	1	0.1
rOilPrice	0.1	1

Note: The p-values are in parentheses. Q^2 represents serial correlation tests. ARCH (5) and (10) tests for autoregressive conditional heteroskedasticity up to 5 and 10 lags. The ADF test for stationarity is known as the ADF. Levels of significance: ** p <.05.

4.2. Symmetric Analysis

Table 3 reports the symmetric GARCH results for the East Asia and Pacific Developing countries.

Table 3. Symmetric GARCH.

Parameters	Symmetric GARCH	
	DCC	***cDCC***
Mean (Oil)	0.00375*	0.00375*
Mean (IPQ)	0.00658***	0.00658***
Cst (Oil)	0.005396***	0.005396***
Cst (IPQ)	3.99E-05**	3.99E-05**
Alpha (Oil)	0.417649***	0.417649***
Alpha (IPQ)	3.672022	3.672022
Beta (Oil)	-0.06912	-0.06912
Beta (IPQ)	0.042278	0.042278
Conditional correlation	0.104512	0.039465
Log likelihood	1278.61	1278.55

Note: This research presents the p-values at 0.1 (***), 5 (**), and 10 (*) levels of significance. Oil indicates Brent oil price; IPQ indicates industrial production output; Cst depicts the constant term; Alpha represents the short-run impact of previous shocks; Beta describes the persistence of volatility; DCC refers to dynamic conditional correlation; cDCC represents corrected dynamic conditional correlation; and HYGARCH denotes hyperbolic GARCH.

The analysis in Table 3 shows that oil price volatility in the DCC and cDCC models has a mean return of 0.00375, yet industrial production growth (IPQ) generates a higher mean return of 0.00658, which demonstrates that IPQ has a slightly elevated average return compared to oil prices. The baseline variance described by Cst equals 0.005396 for oil price data, while industrial production growth has a lower volatility measure at 0.0000399. The values for alpha reveal industrial production's stronger sensitivity to past volatility events than oil prices, where alpha equals 0.417649 for oil and 3.672022 for industrial production. The beta coefficients indicate that oil price volatility decays at a rate of -0.06912, but industrial production volatility fluctuates at 0.042278. This demonstrates that oil price changes do not maintain their level across periods, although industrial output volatility persists and responds following past shocks. The DCC model demonstrated a low level of 0.104512 conditional correlation between oil price volatility and production growth, but the cDCC model showed an even more restrained value of 0.039465. Under the symmetric model framework, alteration of oil prices proves unable to significantly affect industrial production growth in these economies. The fit assessment between the two models through log-likelihood values shows identical values at 1278.61 for DCC and 1278.55 for cDCC. The evidence gathered from these outcomes indicates that oil price movements show a weak linkage and short-term impact on industrial output growth based on a symmetric GARCH model analysis.

The results conform to the work of Mishra et al. (2021) along with Rafiq and Salim (2014), who demonstrated that oil price variations do not create significant changes in macroeconomic factors across Asian economies in the long run while working with symmetric models. The research by Khan et al. (2019) indicated that oil price uncertainty does not create significant effects on industrial production in developing Asian countries over the long term (this result agrees with the low correlation levels measured during symmetric analysis).

4.3. Asymmetric Analysis

From asymmetric GARCH estimations, namely GJR-GARCH, FIEGARCH, and HYGARCH estimations, the results presented in Table 4 follow.

The estimations conducted in Table 4 utilize three asymmetric GARCH models: GJR-GARCH, FIEGARCH, and HYGARCH models. The oil price mean return appears different among the three models, as GJR-GARCH predicts 0.00375, while FIEGARCH predicts 0.003208, but HYGARCH estimates the highest at 0.010821. The mean industrial production (IPQ) returns value equals 0.00658 in every model run due to stable output growth independent of the chosen asymmetric specification.

The constant term (Cst) for oil prices exhibits a wide range between 0.004746 for GJR-GARCH and -4.89191 for FIEGARCH, with 0.001382 for HYGARCH, demonstrating different volatility structures in these models. FIEGARCH computes an extremely negative variance value (-67849.9) in its evaluation of industrial production, while HYGARCH generates a significantly higher variance at 0.516711, illustrating how different models determine volatility persistence differently. HYGARCH displays stronger shock-based volatility effects than FIEGARCH and GJR-GARCH because Alpha reveals values of 0.90045 for oil and 0.996998 for IPQ, whereas FIEGARCH reports 0.321127 for oil and 1.069514 for IPQ, and GJR-GARCH shows 0.074485 for oil and -0.06766 for IPQ. The high values for HYGARCH indicate an intense reaction from industrial production towards oil price volatility, especially when persistent shocks exist. The Beta values estimate that industrial output (IPQ) exhibits high volatility persistence under GJR-GARCH, but HYGARCH results in negative volatility persistence (-0.09985).

The GJR, d-FIEGARCH, and EGARCH Theta reveal additional information about asymmetric responses. The values of 0.525799 and 0.082941 in the GJR term indicate that oil and industrial production experience increased volatility when faced with negative shocks compared to positive shocks. FIEGARCH shows that oil prices have a fractional integration parameter of 0.321127, while IPQ exhibits a value of 1.069514, indicating long-term memory in industrial output volatility. Results show that oil price volatility spreads negative shocks at a stronger rate than industrial production volatility, according to the values of -0.2321 and 0.353374 for oil and IPQ, respectively. For conditional correlations, the DCC method produces varying values starting from 0.081386 in GJR-GARCH up to 0.165123 in FIEGARCH, along with 0.10431 in HYGARCH, but the cDCC approach demonstrates lower correlation rates at 0.062372 (GJR-GARCH), 0.134495 (FIEGARCH), and 0.038785 (HYGARCH). The oil price volatility measures suggest a weak relationship with industrial production growth based on the estimation results from FIEGARCH, which indicates that fractional integration methods lead to superior estimation of oil price impacts on industrial production.

Table 4. Asymmetric GARCH.

Parameters	Asymmetric DCC GJR-GARCH	FIEGARCH	HYGARCH	Asymmetric cDCC GJR-GARCH	FIEGARCH	HYGARCH
Mean (Oil)	0.00375*	0.003208	0.010821**	0.00375*	0.003208	0.010821**
Mean (IPQ)	0.00658***	0.00658***	0.00658***	0.00658***	0.00658***	0.00658***
Cst (Oil)	0.004746**	-4.89191***	0.001382**	0.004746***	-4.89191***	0.001382**
Cst (IPQ)	2.80E-05	-67849.9***	0.516711*	2.80E-05**	-67849.9***	0.516711*
Alpha (Oil)	0.074485	0.321127*	0.90045***	0.074485	0.321127*	0.90045***
Alpha (IPQ)	-0.06766	1.069514***	0.996998***	-0.06766	1.069514***	0.996998***
Beta (Oil)	0.053426	0.039453	0.621605***	0.053426	0.039453	0.621605***
Beta (IPQ)	1.014882	0.563546***	-0.09985	1.014882	0.563546***	-0.09985
GJR (Oil)	0.525799**			0.525799*		
GJR (IPQ)	0.082941			0.082941		
d-FIEGARCH (Oil)	-	0.321127*		-	0.321127*	
d-FIEGARCH (IPQ)	-	1.069514***		-	1.069514***	
EGARCH Theta1 (Oil)	-	-0.2321*		-	-0.2321*	
EGARCH Theta1 (IPQ)	-	0.353374***		-	0.353374**	
EGARCH Theta2 (Oil)	-	0.519644***		-	0.519644***	
EGARCH Theta2 (IPQ)	-	1.045318***		-	1.045318***	
Log Alpha (HYGARCH Oil)	-		-0.30998	-		-0.30998
Log alpha (HYGARCH IPQ)	-		1.321986*	-		1.321986*
Conditional correlation	0.081386	0.165123	0.10431	0.062372	0.134495	0.038785
Log likelihood	1321.92	1375.2	1280.9	1321.82	1375.18	1280.81

Note: The p-values in 0.1 (***), 5 (**), and 10 (*) levels of significance are presented in this research. Oil indicates Brent oil price; IPQ indicates industrial production output; Cst denotes constant term; Alpha represents the short memory impact of past shocks on volatility; Beta describes the persistence of volatility; GJR indicates the Glosten-Jagannathan-Runkle (GJR) asymmetric parameter; Fractionally integrated exponential generalized autoregressive conditional heteroscedasticity is known as FIEGARCH; HYGARCH denotes hyperbolic GARCH.

The findings indicate that FIEGARCH (1375.2 for DCC and 1375.18 for cDCC) achieves the best fit. This suggests that the FIEGARCH model demonstrates the importance of using fractional integration mechanisms to analyze how long-memory processes influence the persistence of oil price changes, as well as their nonlinear impact on industrial output growth.

Moreover, research by Mork (1989), together with Kilian and Vigfusson (2011), discovered that oil price elevation produces magnified negative effects against the somewhat positive growth outcomes of oil price diminution. Kriskkumar et al. (2022) established that Malaysian output growth responds asymmetrically to oil uncertainty because both rising and declining petroleum prices produce positive GDP impacts. Research by Nusair and Olson (2021) and Yang and Zhou (2020) confirmed that oil-importing countries exhibit different reactions compared to oil-exporting nations regarding oil price movements, necessitating nonlinear modeling methods. The study confirms results from Le et al. (2024), which showed that economic crises magnified oil price effects on stock markets, indicating that economic uncertainty enhances oil price transmission pathways.

5. CONCLUSION AND POLICY RECOMMENDATIONS

The research analyzes how oil price volatility impacts industrial output growth within East Asian and Pacific developing countries using symmetrical and asymmetrical GARCH models. The outcomes demonstrate that using a symmetric approach leads to incorrect oil price volatility analysis because GARCH estimates indicate a weak oil-price-to-industrial production relationship. The asymmetric GARCH methodology reveals that industrial output behaves differently toward oil price volatilities of positive and negative varieties, thus demonstrating nonlinear relationships. Industrial output becomes more volatile during the periods of increasing oil prices based on the results from the GJR-GARCH, FIEGARCH, and HYGARCH models, which indicate that rising oil prices create more contractionary impacts than falling prices do for expansion.

Meanwhile, we recommend that alternative energy sources, including renewables and nuclear energy, receive more government financial support to decrease oil imports and protect industrial operations from oil price surges. The Philippines needs to accelerate its energy transition plans because its extreme dependence on imported oil creates vulnerabilities in both energy security and price management. Oil price risk management should be implemented by importing nations to protect industrial manufacturing from price instability, and governments in East Asian Pacific areas should develop stronger energy partnership systems to secure their oil supply networks and stabilize market energy. The governments of affected countries need to establish industrial energy efficiency programs, which will decrease oil usage, thus protecting industrial sectors from price shocks. Governments within these countries should establish institutionalized funds for oil price stabilization and hedging mechanisms, especially for energy-intensive industries, to manage short-term price shock effects. Industrial firms adopting alternative fuels and green technologies should be provided with financial incentives through tax benefits or subsidies to reduce their oil dependence.

Lastly, additional research is needed to study a larger variety of developing economies together with emerging countries to verify if these asymmetric reactions persist across different industrial distributions. Investigating oil price shocks in various industrial sectors requires future research to utilize sectoral GARCH models.

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