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The Determinants of Biodiesel Price In Indonesia

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Abstract

Research Originality: Indonesia is one of the leading producers of biodiesel globally. Despite this progress, the country surprisingly still experiences significant volatility in biodiesel prices. This phenomenon raises a critical question about the factors driving these fluctuations, which the existing literature still does not address adequately.

Research Objectives: This study delves into the dynamic relationships between biodiesel prices and various potential determinants.

Research Methods: The Vector Autoregressive model was employed, given its robustness in capturing dynamic interdependencies between multiple time series. The analysis utilized monthly data spanning Jan. 2016 to Dec. 2022 collected from the Ministry of Energy and Mineral Resources, Indonesia.

Empirical Results: The VAR analysis reveals the nuanced influences of these variables on biodiesel prices. It suggests that an increase in the prices of CPO, crude glycerine, catalyst, and PFAD positively affects biodiesel prices, while price shocks in gasoil and methanol inversely impact them.

Implications: The findings highlight the necessity for a multi-factor approach to formulating pricing strategies. They inform policy decisions to foster price stability and drive the growth of the biodiesel sector.

Keywords:

biodiesel pricing; price determinants; biodiesel components; biofuel economics; sustainable energy

How to Cite:

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INTRODUCTION

Climate change poses a threat to the sustainability of the planet. It is mainly caused by the excessive consumption of fossil fuels by companies, sectors, governments and households. Nevertheless, the fuel explosion releases carbon emissions into the Earth's atmosphere, causing global temperatures to rise faster than required for human and non-human species (Azni et al., 2023; Nunes, 2023). According to the Intergovernmental Panel on Climate Change (2018), approximately one million species are at risk of extinction if global temperatures are assumed to rise by 1.5°C. To mitigate these impacts, environmentally friendly technologies and switching to renewable energy sources are crucial. Biofuels play a critical role in promoting renewable energy and reducing the global impact of fossil fuels (Damian et al., 2024). Based on current trends in biodiesel production, a global biodiesel market was forecast to be $34.1 billion in 2016 and is expected to reach $42.1 billion by 2021.

The biodiesel sector is growing due to the desire for a sustainable environment free of fossil fuel pollution. This is in line with the international agreement and national commitments to reduce greenhouse gas emissions. This situation has led numerous governments to adopt plans to accelerate the production and use of biofuels as a possible answer to achieving global net-zero emissions by 2050. In recent decades, Indonesian biodiesel or fatty acid methyl ester (FAME) blend composition has risen sharply from 2.5% to 35%, making the country have the highest FAME blend in gasoil fuel in the world. In terms of capacity, Indonesia is also considered the world's largest biodiesel producer with an installed capacity of around 18.1 million kiloliters in 2023 (Wirawan et al., 2024). That's 20% more than U.S. biodiesel production, which is the second largest. Indonesia's biodiesel production is expected to increase significantly due to the GDP growth trend and increasing blending rate of biodiesel for domestic use. As a form of biofuel, the use of biodiesel is considered one of the most important solutions to achieve the renewable energy mix target of 23% in 2025 and 31% by 2050 (Syahtaria, 2023). According to its nationally mandated program, the blending of biodiesel with gasoil products is required. On the other hand, the trend of its primary raw material, i.e. the global crude palm oil price (CPO), is determined exogenously (MEMR, 2023).

Indonesia's rich palm oil resources provide a competitive advantage in biodiesel production. CPO has an advantage over other feedstocks for biodiesel production because it contains a variety of phytonutrients that can be removed before synthesis. These phytonutrients have significant economic benefits and reduce the overall production cost of palm biodiesel. Alternative edible oil crops were not expected to have such a significant benefit. Lopresto (2024) also suggests that FAME could be a viable alternative to diesel or other fuels given high subsidies and variable costs of fossil oil. Blending and producing palm oil is a realistic option for the Indonesian government's energy transition goal. However, the cost implications are significant due to global fossil prices (Halimatussadiah et al., 2021). Therefore, cost is an important aspect of biodiesel production as it directly determines production volume in response to market demand. Significantly, the procurement of critical components such as methanol and catalysts for

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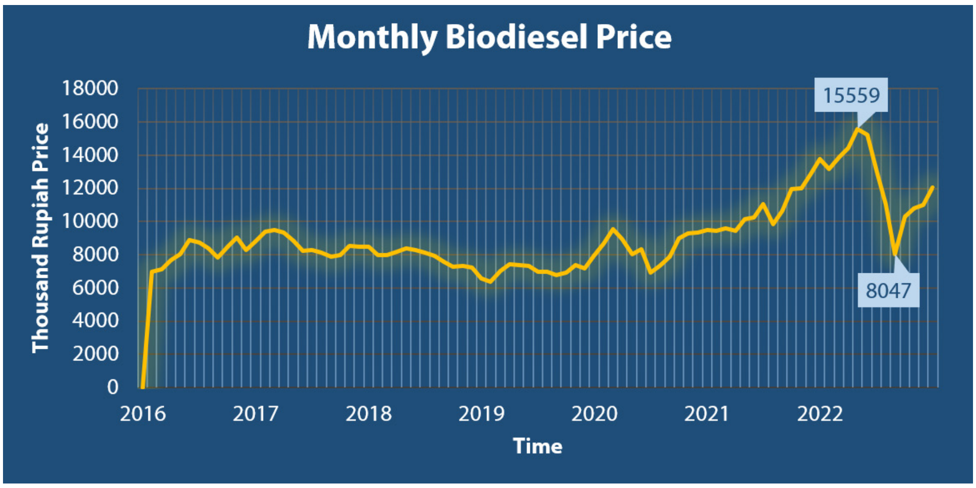
biodiesel synthesis is dependent on imports, making them vulnerable to the influence of exchange rate shifts (Hossain & Majumder, 2018). Market prices are determined by the production cost per kiloliter, which is influenced by government subsidies aimed at achieving net-zero emissions and mitigating the impact of volatile fossil fuel prices on the national economy (Harahap et al., 2019). Indonesia can potentially replace fossil fuels with biodiesel as it is the leading CPO producer.

In contrast, the conversion process incurs high costs for inputs and raw materials such as CPO, methanol and catalysts. The Indonesian government has set the conversion price but imports more expensive chemicals. Some authors found that high raw material costs have a significant impact on biodiesel production processes (Acevedo et al., 2015; Elgharbawy et al., 2021; Gülşen et al., 2014). Currently, biodiesel prices in Indonesia are based only on the CPO price plus conversion and distribution costs. The conversion costs are now at $85 per ton (MEMR, 2023). In recent years, the method of pricing HIP biodiesel has undergone several changes. The price of biodiesel was initially set at $125 per ton in 2015. In 2017, the Indonesian government reduced the price to $100. However, the MT price dropped to $80 in May 2020. Finally, the exchange rate used to determine the price was changed to US$85 per MT in September 2020 (MEMR, 2022). This phenomenon or cost structure may not be able to capture and balance market demand and supply due to the sensitivity of input costs. This study is motivated by such a critical aspect of the biodiesel pricing approach.

Figure 1 demonstrates the mean monthly price fluctuations of biodiesel in Indonesia, indicating a certain degree of volatility in reaction to market dynamics. Following a strong surge in 2016, prices remained stable between 7,000 and 9,000 IDR till 2020. A massive growth happened in 2021, with a high of 15,559 IDR in early 2022, followed by a sharp dip to 8,047 IDR. Prices started to recover at the end of the year. These swings might be attributed to market dynamics, policy shifts, and global economic issues (MEMR, 2023).

Figure 1. The Average Monthly Price of Biodiesel in Indonesia



Source: Authors work based on MEMR data

In 2008, it was implemented for the first time with a blending rate of 2.5%, and it continued to evolve, attracting the government's attention. Recently, the Indonesian government planned to blend 35% biodiesel with fossil fuels in 2023 (Soebroto et al., 2021). Therefore, as part of the required mandate, the government has incentivized the conversion of biodiesel from CPO and fixed the market price every month. Nevertheless, according to state agricultural trading company KPBN (Kharisma Pemasaran Bersama Nusantara), biodiesel was produced at prices higher than domestic molasses prices in 2016. Before 2016, prices were based on Argus (commodity pricing and trading benchmarks). Numerous factors, such as the installed capacity of the biodiesel industry of 12.06 million kiloliters (KL), contribute to the effectiveness of the mandatory biodiesel policy. In addition, the government provides financing incentives to cover the difference between the biodiesel market index price and the diesel market index price, as well as monthly program monitoring. According to Wirawan et al. (2024), Although biofuels, particularly ethanol, are not a novel technology, the government's emphasis on achieving net-zero emissions has increased interest in renewable energy. Enforcing mandatory blending rates for diesel and gasoline helped mitigate the impact of the oil price shock on the domestic economy. In line with Abila (2015), biofuel production is crucial to combat climate change and promote energy security and a green economy. This served as the basis for repeated changes in biofuel policy. Nevertheless, increased production increases demand for raw materials and food. In summary, the approach may contradict energy and food security (De Lucia & Bartlett, 2014).

Research by Habibi et al. (2023) used bottom-up equilibrium optimization to analyze the supply chain of the biofuel market. Researchers believe the emerging biofuel business has a chance to reduce carbon emissions in the transportation sector. Additionally, agricultural subsidies negatively impact biofuel production by reducing biomass sales prices for biofuel producers. Biofuel production has always been associated with economic development (Sandaka & Kumar, 2023). Popp et al. (2023) found a high connection between biomass production and economic growth. Research on G-7 countries by Shahzad et al. (2023) showed that the use of biomass had a strong positive impact on the economy. Another study by Sandaka and Kumar (2023) examines how economic, social, political, and environmental issues impact environmental sustainability in the MENA region. They showed that the biofuel system of renewable energy leads to a green civilization in the long term. Indonesia's preferred renewable energy source is biodiesel, which could reduce the country's dependence on fossil fuels and reduce the impact of transportation on the environment. However, biodiesel prices have fluctuated in Indonesia, and the causes of this unpredictability need to be better understood. According to previous studies (Alghifari et al., 2022; Reichenberg et al., 2018; Siregar et al., 2020), production costs, crude oil prices, and government policies influence biodiesel prices. Biodiesel prices in other countries have also been influenced by supply and demand.

Despite the rapidly growing body of knowledge about biodiesel production, consumption, and economic impacts, there is a lack of comprehensive understanding of the dynamic interplay between input costs (such as CPO, methanol, and catalyst) and

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biodiesel price volatility in Indonesia. Most studies have either focused on static assessment or have unfortunately failed to effectively assess the impact of surrogate variables such as gasoline prices and the positive impact of by-products such as crude glycerol and PFAD. This created a critical gap in understanding the interplay of various input and output factors that impact biodiesel prices in a developing country that relies heavily on biofuels to achieve its renewable energy goals. The study contributes in two ways. First, this study is one of the pioneers of empirical analysis of the dynamic interplay between input and replacement costs and biodiesel prices in Indonesia using a novel vector autoregressive (VAR) methodology. Interestingly, using this complex modeling technique, the study provides a new comprehensive perspective on how input costs and market factors influence biodiesel volatility, providing insights that static models cannot capture. Second, this study presents policy recommendations based on the results of the dynamic VAR model that help stabilize biodiesel prices, thereby promoting the sustainable growth of Indonesia's biodiesel industry and contributing to the broader goals of renewable energy development. The main objectives of this study are to identify the most critical inputs and substitute factors affecting the dynamics of Indonesian biodiesel prices and to provide strategies to ensure a stable and sustainable biodiesel industry. This study closes the gap by achieving these critical goals and provides important insights for policymakers and industry stakeholders in Indonesia and beyond.

METHODS

This study employs a robust quantitative research design to analyze the factors that influence biodiesel prices in Indonesia comprehensively. The study utilizes monthly time series data from Jan. 2016 to Dec. 2022; the data was gathered from the Ministry of Energy and Mineral Resources Indonesia. This study ensures a comprehensive and rigorous analysis by incorporating existing research on the determinants/factors of biodiesel prices worldwide. Moreover, the selected variables for inclusion in the investigation have been identified in prior literature (Alberto Fuinhas et al., 2023; Braga et al., 2020; Deka et al., 2022; Rosyadi et al., 2021; Wang, 2020; Xu et al., 2020) as a crucial role in the fluctuation of biodiesel prices. These variables were not explored and examined collectively in a study. Thus, this study is among the first to adopt such input factors and substitutes to examine biodiesel price dynamics. Including these variables is expected to provide valuable insights into the determinants of biodiesel prices in Indonesia and contribute to the development of effective policies and strategies in the biofuel industry.

Sims (1986) developed vector auto-regressive models as a superior alternative to classical dynamic simultaneous equation models to investigate the dynamic interactions among correlated time series data. These models integrate an equation for each variable that explains how it emerged, considering its lags associated with other variables, ensuring that all variables are treated symmetrically as endogenous. Conversely to the "incredible identification restriction" encountered in the different structural models, a VAR model offers a theory-free approach to finding economic interactions (Sims, 1980). This feature has been significantly employed in investigating the relationship among macroeconomic factors related to energy (Shah et al., 2018; Hu et al., 2020; Alsaedi & Tularam, 2020). Therefore, the specification of the VAR model for this study is critical to providing robust results for volatility in biodiesel prices in Indonesia; this dynamic interplay was only able to be captured through VAR. Therefore, after careful consideration, we chose VAR over VECM and other dynamic models.

Table 1. Data Description

No	Variable	Acronyms	Description	Source
1	Biodiesel	biopr	Indonesian rupiah per liter	MEMR
2	Crude Palm Oil	cpo	Indonesian rupiah per kilogram	MEMR
3	Catalyst	ctl	Indonesian rupiah per kilogram	MEMR
4	Methanol	mtn	Indonesian rupiah per kilogram	MEMR
5	Crude Glycerin	crd	Indonesian rupiah per kilogram	MEMR
6	Palm Fatty Acid Distillate	pfad	Indonesian rupiah per kilogram	MEMR
7	Gasoil	goil	Indonesian rupiah per liter	MEMR

Note: MEMR (Ministry of Energy and Mineral Resources)

Most of the macroeconomic parameters in the time series exhibit a non-stationary nature, including cycles, trends, random walks, or a combination of all those, displaying them unpredictably (Junejo et al., 2024). Initially, we employed Augmented Dicky-Fuller (ADF) and Phillip-Perron (PPF) tests to identify variables' integration order prior to adopting the VAR model, which is the primary assumption for such model that all variables should be integrated into I(0) or I(1). Afterward, the appropriate lag length (h) for the VAR model is determined by the Schwarz-Bayesian information criterion (SBIC) test results. Considering the best option for the lag is crucial before constructing the VAR model for any study since determining the number of lags always carries a trade-off.

The VAR model is developed based on the suggested lag order. We then employed VAR analysis to evaluate whether variables are significantly associated. This is validated and critically tested on the residuals. The residual serial correlation Lagrange multiplier (LM) and portmanteau were employed, which rely on the VAR with a null hypothesis that no serial correlation occurs in the residuals for the lag order (h). Furthermore, forecasting performance, Granger causality testing (Granger, 1969), impulse response function, and forecast variance decomposition are employed to examine short-run relationships. As a result, we provide the VAR model specifications for each variable below, which will act as the basis for the following analysis.

$$\Delta lnbiopr_{1_t} = \alpha_1 + \sum_{j=1}^{p} \beta_{1t} \Delta lnbiopr_{1_{t-1}} + \sum_{j=1}^{p} \beta_{2t} \Delta lncpo_{i_{t-1}} + \sum_{j=1}^{p} \beta_{3t} \Delta lnctl_{i_{t-1}} + \sum_{j=1}^{p} \beta_{4t} \Delta lnmtn_{i_{t-1}} + \sum_{j=1}^{p} \beta_5 \Delta lncrd_{i_{t-1}} + \sum_{j=1}^{p} \beta_{5t} \Delta lnpfad_{i_{t-1}} + \sum_{j=1}^{p} \beta_5 \Delta lngoil_{i_{t-1}} + \varepsilon_t \quad (1)$$

$$\Delta lncpo_{2_t} = \alpha_2 + \sum_{j=1}^{p} \beta_{2t} \Delta lncpo_{i_{t-1}} + \sum_{j=1}^{p} \beta_{1t} \Delta lnbiopr_{1_{t-1}} + \sum_{j=1}^{p} \beta_{3t} \Delta lnctl_{i_{t-1}} + \sum_{j=1}^{p} \beta_{4t} \Delta lnmtn_{i_{t-1}} + \sum_{j=1}^{p} \beta_5 \Delta lncrd_{i_{t-1}} + \sum_{j=1}^{p} \beta_{5t} \Delta lnpfad_{i_{t-1}} + \sum_{i=1}^{p} \beta_5 \Delta lngoil_{i_{t-1}} + \varepsilon_t \quad (2)$$

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$$\Delta lnctl_{3_t} = \alpha_3 + \sum_{j=1}^{p} \beta_{3t} \Delta lnctl_{i_{t-1}} + \sum_{j=1}^{p} \beta_{2t} \Delta lncpo_{i_{t-1}} + \sum_{j=1}^{p} \beta_{1t} \Delta lnbiopr_{1_{t-1}} + \sum_{j=1}^{p} \beta_{4t} \Delta lnmtn_{i_{t-1}} + \sum_{j=1}^{p} \beta_5 \Delta lncrd_{i_{t-1}} + \sum_{j=1}^{p} \beta_{5t} \Delta lnpfad_{i_{t-1}} + \sum_{j=1}^{p} \beta_5 \Delta lngoil_{i_{t-1}} + \varepsilon_t \quad (3)$$

$$\Delta lnmtn_{4_t} = \alpha_4 + \sum_{j=1}^{p} \beta_{4t} \Delta lnmtn_{i_{t-1}} + \sum_{j=1}^{p} \beta_{3t} \Delta lnctl_{i_{t-1}} + \sum_{j=1}^{p} \beta_{2t} \Delta lncpo_{i_{t-1}} + \sum_{j=1}^{p} \beta_{1t} \Delta lnbiopr_{1_{t-1}} + \sum_{j=1}^{p} \beta_5 \Delta lncrd_{i_{t-1}} + \sum_{j=1}^{p} \beta_{5t} \Delta lnpfad_{i_{t-1}} + \sum_{j=1}^{p} \beta_5 \Delta lngoil_{i_{t-1}} + \varepsilon_t \quad (4)$$

$$\Delta lncrd_{5_t} = \alpha_5 + \sum_{j=1}^{p} \beta_5 \Delta lncrd_{i_{t-1}} + \sum_{j=1}^{p} \beta_{4t} \Delta lnmtn_{i_{t-1}} + \sum_{j=1}^{p} \beta_{3t} \Delta lnctl_{i_{t-1}} + \sum_{j=1}^{p} \beta_{2t} \Delta lncpo_{i_{t-1}} + \sum_{j=1}^{p} \beta_{1t} \Delta lnbiopr_{1_{t-1}} + \sum_{j=1}^{p} \beta_{5t} \Delta lnpfad_{i_{t-1}} + \sum_{j=1}^{p} \beta_5 \Delta lngoil_{i_{t-1}} + \varepsilon_t \quad (5)$$

$$\Delta lnpfad_{6_t} = \alpha_6 + \sum_{j=1}^{p} \beta_{6t} \Delta lnpfad_{i_{t-1}} + \sum_{j=1}^{p} \beta_5 \Delta lncrd_{i_{t-1}} + \sum_{j=1}^{p} \beta_{4t} \Delta lnmtn_{i_{t-1}} + \sum_{j=1}^{p} \beta_{3t} \Delta lnctl_{i_{t-1}} + \sum_{j=1}^{p} \beta_{2t} \Delta lncpo_{i_{t-1}} + \sum_{j=1}^{p} \beta_{1t} \Delta lnbiopr_{1_{t-1}} + \sum_{j=1}^{p} \beta_5 \Delta lngoil_{i_{t-1}} + \varepsilon_t \quad (6)$$

$$\Delta lnpgoil_{7_t} = \alpha_6 + \sum_{j=1}^{p} \beta_5 \Delta lngoil_{i_{t-1}} + \sum_{j=1}^{p} \beta_{6t} \Delta lnpfad_{i_{t-1}} + \sum_{j=1}^{p} \beta_5 \Delta lncrd_{i_{t-1}} + \sum_{j=1}^{p} \beta_{4t} \Delta lnmtn_{i_{t-1}} + \sum_{j=1}^{p} \beta_{3t} \Delta lnctl_{i_{t-1}} + \sum_{j=1}^{p} \beta_{2t} \Delta lncpo_{i_{t-1}} + \sum_{j=1}^{p} \beta_{1t} \Delta lnbiopr_{1_{t-1}} + \varepsilon_t \quad (7)$$

Where *ln* with all variables represents the logarithmic form of biodiesel price, crude palm oil, catalyst, methanol, glycerin palm fatty acid distillate, and gasoil, we took the logarithm of all variables since it is a practical data transformation approach in statistics that can help to accomplish specific goals such as normalizing data distributions, heteroscedasticity issue, facilitating interpretation, and reducing the impact of outliers. Furthermore, α is a constant, β_j are matrices of coefficients and is a *Px1* vector of error terms. The number *p* is the model's lag order and represents the lagged values of the time series included as predictors.

RESULT AND DISCUSSION

This section discusses the results of a VAR model analysis of the factors that impact the dynamics of biodiesel prices in the Indonesian energy market, followed by a summary of the tests done, including the correlation matrix, stationarity test, cointegration test, VAR lag criterion test, VAR estimation, Granger causality test, impulse response function (IRF), and variance decomposition. Additionally, the section develops with a discussion about the most significant findings of the analysis, such as how important the factors that affect biodiesel prices in Indonesia are. Lastly, this will conclude with a discussion of what these findings mean and how policymakers, industry stakeholders, and researchers in the field might use them.

Table 3 presents key statistics for biodiesel price and its determinants, including CPO, Catalyst, Methanol, Glycerine, Gasoil, and PFAD for 84 observations for Indonesia, and it also presents the correlation matrix results. The data show that the average price of biodiesel is 9,070,810 with a standard deviation of 2,059,859, with prices ranging from 8.55 to 9.65 throughout the observation period. The other variables are also characterized by volatility, especially CPO and gasoil, suggesting that market conditions are ever-changing. The use of Methanol and glycerine price means are relatively lower, and their price standard deviations are relatively higher than other inputs, indicating their higher variability in affecting the price of biodiesel. The matrix shows moderate to significantly positive links between biodiesel price and all variables. The strongest correlations were found between biodiesel, PFAD, CPO, and Glycerine. To ensure the validity of time series analysis results, performing stationarity tests before adopting a dynamic model is essential. Thus, the Augmented Dickey-Fuller and Phillips-Perron tests are used to check stationarity in time series data. Table 4 presents the PP and ADF Test results to test stationarity in a time series.

Table 3. Descriptive Summary of Statistics and Correlation Matrix

	Mean	Median	Maximum	Minimum	Std. Dev.	Observations	
Biodiesel	9.070.810	8.442.500	15559.00	6.371.000	2.059.859	84	
CPO	9.072.037	8.361.000	16665.00	5.872.000	2.425.294	84	
Catalyst	7.975.565	8.036.500	9.375.000	6.510.000	7.226.916	84	
Methanol	3.524.137	3.571.250	4.925.000	2.060.000	7.113.695	84	
Glycerine	3.850.161	3.005.000	1.023.000	1.690.000	2.247.262	84	
Gasoil	6.555.579	6.172.890	15118.21	2.801.400	2.593.053	84	
PFAD	6.901.577	6.127.500	1.687.000	3.205.000	2.762.023	84	
	Biodiesel	**CPO**	**Catalyst**	**Methanol**	**Glycerine**	**Gasoil**	**PFAD**
Biodiesel	1.000	-	-	-	-	-	-
CPO	0.992***	1.000	-	-	-	-	-
Catalyst	0.387**	0.3782	1.000	-	-	-	-
Methanol	0.394***	0.3829	0.9922	1.000	-	-	-
Glycerine	0.839***	0.8476	0.5538	0.5711	1.000	-	-
Gasoil	0.509**	0.5104	0.4426	0.4462	0.4514	1.000	-
PFAD	0.938***	0.9444	0.3806	0.3815	0.8877	0.376055	1.000

The null hypothesis is that the time series has a unit root, while the alternative hypothesis is that the series is stationary. The PP and ADF tests show that the null hypothesis cannot be rejected at a 5% significance level when the series is leveled. Both tests show that the series becomes stationary after the first difference. Before VAR analysis, selecting VAR lags is crucial for precise forecasting and dynamic variable interactions. The lag order can be selected using parameters like AIC, BIC, and HQIC, with context and research issues influencing the lag selection criteria.

Table 5 presents the results of the Akaike, Schwarz, and Hannan-Quinn information criterion for lag orders ranging from 0 to 7. The optimal lag order is determined by the criterion's values, with SC suggesting a lag order of 0, HQ test statistic suggesting a

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lag order of 1, LR and FPE choosing a lag order of 2, and HQ indicating a lag order of 7. Therefore, we adopted a lag order of up to two lags. The Johansen approach and Engle-Granger test are widely used cointegration procedures developed by Sren Johansen and Robert Engle and Clive Granger, respectively (Johansen, 1988).

Table 4. Unit Root Test Results of Augmented Dicky Fuller and Phillips-Perron Test

	Variable	ADF Unit Root Test		PP Unit Root Test	
		Statistics	Probability	Statistics	Probability
At level (0)	Biodiesel	-2.1537	0.5085	-2.2838	0.4377
	CPO	-2.0546	0.5629	-2.2196	0.4724
	Catalyst	-2.5960	0.2833	-2.0010	0.5920
	Crude Glycerine	-1.7120	0.7371	-1.7040	0.7409
	Methanol	-2.1960	0.4853	-2.1960	0.4853
	PFAD	-2.1557	0.5073	-1.8990	0.6461
	Gasoil	-0.745465	0.8286	-0.407901	0.9021
At First Deference (I)	Biodiesel	-8.1106***	0.0000	-8.0536***	0.0000
	CPO	-7.7882***	0.0000	-7.7173***	0.0000
	Catalyst	-6.7825***	0.0000	-6.6517***	0.0000
	Crude Glycerine	-6.6318***	0.0000	-6.4652***	0.0000
	Methanol	-9.0122***	0.0000	-9.0249***	0.0000
	PFAD	-6.3280***	0.0000	-6.3280***	0.0000
	Gasoil	-6.999670***	0.0000	-6.863234***	0.0000

*, **, and *** shows significant at 1%, 5%, and 10% respectively.
Source: Author's Computation.

Table 6 presents the results of the Johansen cointegration test, revealing that the null hypothesis of no cointegration implies no relationship between variables. This could lead to economic consequences like instability, inaccurate forecasting, spurious regression, policy inefficiencies, and increased volatility. The table also shows each hypothesis's trace statistic and eigenvalue, as well as the likelihood of rejecting the null hypothesis. However, all hypotheses strongly support the cointegration of variables. The study uses the Granger Causality test to examine causal relationships between variables like biodiesel, CPO, methanol, crude glycerine, catalyst, PFAD, and gasoil. The test aims to determine if one variable caused another or if both had a cause over the other. Table 7 (appendix) indicates that certain variables are connected and explains their specific values. For instance, CPO Granger causes biodiesel, indicating that CPO strongly predicts biodiesel. However, there are no clear links between certain factors, such as gasoil and crude glycerine, indicating that gasoil and crude glycerine are not strong indicators of biodiesel in Indonesia.

The results obtained from the impulse response function provide essential insights into the relationship between the price of biodiesel and various inputs in the biodiesel production process. The results indicate that the prices of crude palm oil (CPO), methanol, catalyst, crude glycerin, and gasoil impact Indonesia's biodiesel prices. The response of biodiesel to shock/innovation in CPO and catalyst is shown in Figure 2. The figure 2

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shows that biodiesel prices increase when there is a shock/innovation in CPO prices. Initially, there was no response of biodiesel to changes in the CPO price.

Table 5. Lag Order Criteria Test Results for VAR Model

Lag	LogL	LR	FPE	AIC	SC	HQ
0	717.1072	NA	1.81e-17	-18.68703	-18.47236*	-18.60124
1	822.8530	189.2294	4.08e-18	-20.18034	-18.46296	-19.49399*
2	891.2944	109.8664*	2.52e-18*	-20.69196	-17.47187	-19.40505
3	933.7283	60.30090	3.26e-18	-20.51917	-15.79637	-18.63171
4	976.1499	52.46875	4.57e-18	-20.34605	-14.12054	-17.85803
5	1016.786	42.77518	7.62e-18	-20.12596	-12.39773	-17.03738
6	1084.717	58.99251	7.50e-18	-20.62413	-11.39320	-16.93501
7	1169.800	58.21474	6.32e-18	-21.57369*	-10.84005	-17.28401

Note: * indicates lag order selected by the criterion

However, biodiesel was found to respond positively in increasing ways until it reached its peak in the second period. After that, it started to go down and reached zero, and then it constantly decreased and stopped. Biodiesel responds positively to unit shock in the price of CPO because it is an essential feedstock in biodiesel production in Indonesia. When the price of CPO increases, the price of biodiesel also increases. This indicates that the CPO plays a significant role in determining biodiesel prices. However, there are reasons for this positive relationship, including a rise in the cost of raw materials and production, supply and demand dynamics, and competing markets because it is used for many other products as a feedstock and Chanthawong et al. (2016). We found that the hypothesis that the price of CPO influences the price of biodiesel has been accepted. These findings are aligned with those of (Muhammad & Hasudungan 2025).

Table 6. Cointegration Test Result

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.697235	294.9982	125.6154	0.0000
At most 1 *	0.477816	199.4143	95.75366	0.0000
At most 2 *	0.418306	147.4354	69.81889	0.0000
At most 3 *	0.387914	104.0906	47.85613	0.0000
At most 4 *	0.331866	64.81995	29.79707	0.0000
At most 5 *	0.207839	32.55862	15.49471	0.0001
At most 6 *	0.159696	13.91936	3.841465	0.0002

* Denotes rejection of the hypothesis at the 0.05 level.
Source: Author's Computation

The biodiesel price responded positively to the shock in the catalyst price; it increased and peaked. However, the figure shows that shock occurs again in the price of catalyst, and the price of biodiesel declined negatively to zero and stopped in the third period. Afterward, the biodiesel prices increased positively and went away. Catalysts positively

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influence the price of biodiesel in Indonesia. Catalysts play a significant role in biodiesel production by speeding up the chemical reaction known as transesterification, which turns raw materials such as CPO into biodiesel. Most of the time, catalysts are used in small amounts compared to raw materials (CPO), but they are used for the conversion process to work well and efficiently. When there is a sudden shock or increase in the price of catalysts, it immediately impacts the cost of producing biodiesel. This result shows that the cost of producing biodiesel increases when the price of catalysts increases. This is causing biodiesel prices to rise. Biodiesel producers must often pass on catalysts' extra expenses to consumers to stay profitable. These results agree with Maheshwari et al. (2022) and Ambat et al. (2018).

Figure 2. Response of Biodiesel to CPO and catalyst

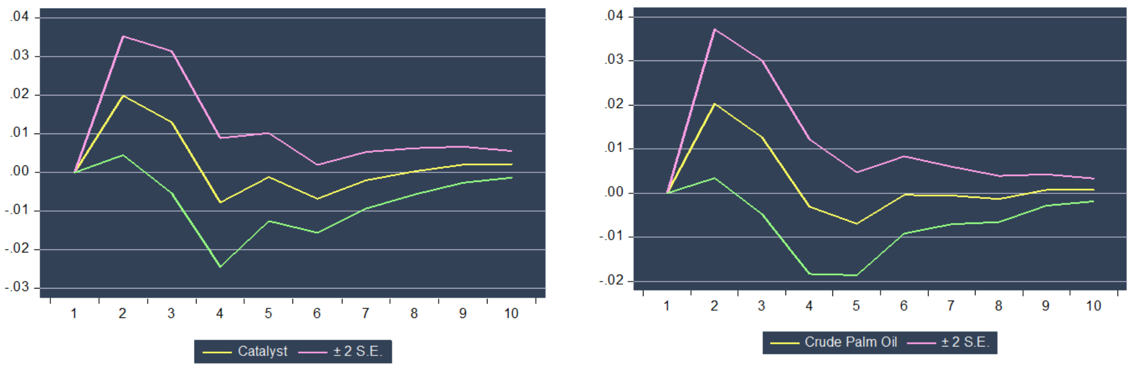
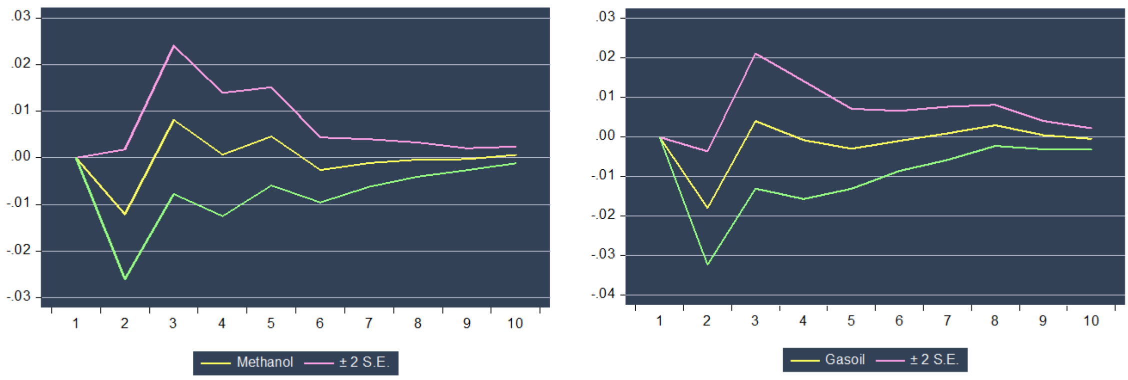


Figure 3 shows that methanol has a negative impact on the price of biodiesel. Biodiesel seemed hostile, decreasing until it reached the minimum response to methanol and stayed at the second period. After that, biodiesel responded positively to shock in methanol increasingly until it peaked. Again, biodiesel began to decline slightly negatively due to a shock in the price of methanol and stopped in the fourth period with inadequate response. The cost of dynamics of the biodiesel production process can explain this negative response of biodiesel prices to methanol price fluctuations. Methanol is a crucial ingredient in biodiesel synthesis and is frequently used as a reactant or solvent. Therefore, any increase in the price of methanol results in higher biodiesel production costs. When the price of methanol increases, biodiesel producers face more expenses in acquiring this essential input. Biodiesel producers frequently pass these increased expenses to consumers through higher biodiesel prices to maintain profitability. Canakci and Sanli (2008) presented the same results earlier.

The evident negative relationship between methanol and biodiesel pricing could be due to complex market dynamics, subsidy programs, supply chain factors, and time lag. Other factors influencing biodiesel pricing, such as feedstock supply, government legislation, and global market conditions, might overshadow the direct impact of methanol prices. For example, if biodiesel is in excess due to increased production, changes in methanol prices may have a minimal effect on the final price of biodiesel. Consider a scenario where the price of methanol significantly increases. Due to methanol's role in the production process, this increase will likely result in higher biodiesel prices. However, the impact of methanol prices on biodiesel prices could be mitigated because the primary feedstock CPO for biodiesel production is abundantly available in Indonesia. The accessibility and affordability of CPO can outweigh the effect of methanol prices, resulting in a reduced or even negative correlation between the two variables (Cako et al., 2022).

Figure 3. Response of Biodiesel to Methanol and Gasoil



Moreover, biodiesel was found to respond negatively in a decreasing manner until it reached a minimum response in the second period. Subsequently, it began to increase quickly due to the shock in gasoil price. According to the above impulse response function, gasoil has a negative impact on the price of biodiesel in Indonesia. This indicates that biodiesel and gasoil compete as alternative fuels in the market. When the price of gasoline increases, the price of biodiesel decreases. These results show that as gasoline prices have increased, people have become more interested in biodiesel, which has led to lower demand and reduced prices for biodiesel. In addition, increasing petroleum prices can increase the cost of conventional fossil fuels, thereby increasing demand for alternative fuels such as biodiesel. Consequently, there may be more competition for the raw materials used to produce biodiesel, which could cause their prices to increase and the price of biodiesel to decrease. Similar results are reported by Declerck et al. (2022) and contradicting findings reported by Mizik and Gyarmati (2021).

The fuel substitutability of biodiesel and gasoil drives competition. Both biodiesel and gasoil are energy sources for transportation, and consumers can choose between them based on cost-effectiveness and availability. This finding supports the hypothesis that the price of gasoline negatively influences the price of biodiesel in Indonesia. It emphasizes the significance of considering the pricing dynamics of competing fuels when analyzing biodiesel price movements. Understanding the relationship between biodiesel and gasoil prices enables biodiesel industry stakeholders to make informed decisions about production levels, market positioning, and pricing strategies.

From Figure 4, biodiesel responds positively quickly to a shock in the PFAD, and it reached its maximum response in the second period. After that, biodiesel was found to decline to no response and stayed constant, even though there was a unit shock in

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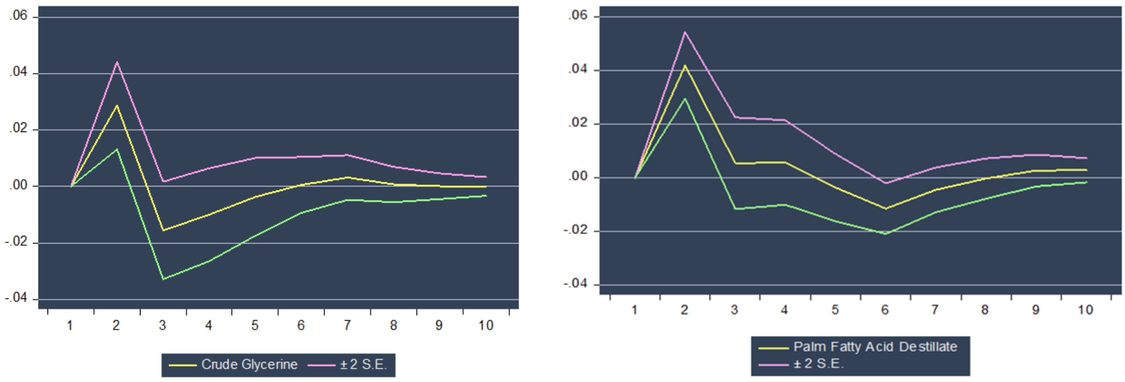
the price of PFAD. The impulse response trend shows that PFAD significantly impacts the price of biodiesel in Indonesia. PFAD is a byproduct usually made when biodiesel is produced from CPO. So, when the price of PFAD changes, biodiesel also changes; it directly impacts biodiesel prices.

Figure 4. Response of Biodiesel to Palm Fatty Acid Distillate and Crude Glycerine



The positive reaction of biodiesel to a PFAD price shock can be attributed to the interdependence of the biodiesel and palm oil industries (Silalahi et al., 2020). The rising price of PFAD reflects higher costs for the raw materials used in biodiesel production. As a result, biodiesel prices increase to maintain profitability and cover the additional expenses (Embong et al., 2023 & Elgharbawy, 2021). Furthermore, the response of biodiesel to shock in the price of crude glycerine is also positive, and it is another byproduct generated in the biodiesel production process. This result shows that the price of crude glycerine influences the biodiesel market. This condition could mean that crude glycerine and biodiesel compete as biofuel feedstock sources. The impulse response function suggests that an increase/shock in the price of crude glycerine results in a rise in the price of biodiesel in Indonesia (Soebroto et al., 2021). The positive correlation between crude glycerine and biodiesel prices in Indonesia is caused by the dependence on crude glycerine as a feedstock, increased production costs, supply-demand dynamics, market competition, and market expectations. This study's results support Wicaksono's (2022) and Chilakamarry et al. (2021) findings.

Additionally, the variance decomposition analysis helps us learn more about the factors that affect the price of biodiesel in Indonesia. Table B (appendix) shows that biodiesel explains a big part of the price variation. Still, other input factors such as CPO, crude glycerine, catalysts, gasoil, and methanol also play a crucial role in the price variation (Khatiwada, 2018). Based on these results, biodiesel's price is affected by internal (things about biodiesel itself) and external (things about other inputs and the market) factors. In the end, the results of the VAR model analysis give us essential information about what affects biodiesel prices in Indonesia. Based on the results, the prices of CPO, methanol, catalysts, PFAD crude glycerine, and gasoil significantly impact the price of biodiesel. Understanding these factors is essential for policymakers and industry players

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who want to ensure Indonesia's biodiesel industry is stable and will last. Furthermore, the findings highlight the need to consider how input prices interact and change over time to develop successful government policies and market interventions.

CONCLUSION

Indonesia is the world's largest biodiesel producer; this complements global efforts towards net zero emissions. However, using a robust approach, we are motivated to examine input price spillovers to biodiesel prices. Insights from impulse response estimation and forecast error variance decomposition suggest that biodiesel prices increase as CPO, crude glycerol, catalyst, and PFAD prices increase. This result suggests that increasing prices for these inputs leads to increasing biodiesel prices. Accordingly, the study's central hypothesis is that increasing prices of the primary raw materials used to produce biodiesel in Indonesia - CPO, methanol, and catalyst - significantly influence prices. The result shows that biodiesel prices and profitability depend on tracking and regulating the prices of these inputs.

In contrast, biodiesel prices decrease when gasoline and methanol prices increase, suggesting that higher gasoline and methanol prices lead to a decrease in biodiesel prices. This result suggests that the price of biodiesel depends on how competitive biodiesel is compared to regular gasoline. Therefore, to ensure price volatility in the biodiesel market, government policy should focus on monitoring and regulating CPO, crude glycerin, catalyst, and PATH prices. Strategic measures are needed to maintain biodiesel's competitiveness against traditional fuels such as gasoline by considering subsidies or incentives for biodiesel production when methanol prices and gasoline increases are high to prevent biodiesel from taking market share. Strengthening the supply chain for biodiesel inputs by ensuring a consistent supply of CPO, methanol, and other key ingredients could help stabilize biodiesel prices and increase industry profitability. This way, Indonesia will become less dependent on fossil fuels and develop into a greener, more environmentally friendly energy sector. Additionally, the study highlights the environmental benefits of biodiesel, such as lower CO2 emissions and improved air quality. Biodiesel is critical to ensuring lubricant oil supplies and contributes to national sovereignty by reducing dependence on imported fossil fuels and promoting the use of renewable energy. The research results can be an important resource for policymakers and stakeholders working to ensure price stability, expand the biodiesel industry, and help Indonesia move toward a more sustainable energy future.

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APPENDIX

Table A. Granger Causality Test Result

Null Hypothesis	Obs.	F-Statistic	Prob.
LNCPO does not Granger Cause LNBIO	82	3.27457	0.0432*
LNBIO does not Granger Cause LNCPO		0.53324	0.5888
LNCRD does not Granger Cause LNBIO	82	1.22907	0.2982
LNBIO does not Granger Cause LNCRD		1.96652	0.1469
LNCTL does not Granger Cause LNBIO	82	4.17369	0.0190*
LNBIO does not Granger Cause LNCTL		0.16572	0.8476
LNGAS does not Granger Cause LNBIO	82	0.12769	0.8803
LNBIO does not Granger Cause LNGAS		2.45408	0.0926
LNMTN does not Granger Cause LNBIO	82	1.38664	0.2561
LNBIO does not Granger Cause LNMTN		0.05040	0.9509
LNPFAD does not Granger Cause LNBIO	82	50.8953	8.E-15
LNBIO does not Granger Cause LNPFAD		2.19326	0.1185
LNCRD does not Granger Cause LNCPO	82	0.64140	0.5293
LNCPO does not Granger Cause LNCRD		2.31849	0.1053
LNCTL does not Granger Cause LNCPO	82	4.50763	0.0141*
LNCPO does not Granger Cause LNCTL		0.17010	0.8439
LNGAS does not Granger Cause LNCPO	82	0.30238	0.7399
LNCPO does not Granger Cause LNGAS		1.51724	0.2258
LNMTN does not Granger Cause LNCPO	82	1.56181	0.2163
LNCPO does not Granger Cause LNMTN		0.48031	0.6204
LNPFAD does not Granger Cause LNCPO	82	55.5955	1.E-15
LNCPO does not Granger Cause LNPFAD		4.17986	0.0189*
LNCTL does not Granger Cause LNCRD	82	0.14031	0.8693
LNCRD does not Granger Cause LNCTL		1.96261	0.1475
LNGAS does not Granger Cause LNCRD	82	1.68899	0.1915
LNCRD does not Granger Cause LNGAS		8.94144	0.0003*
LNMTN does not Granger Cause LNCRD	82	0.14651	0.8640
LNCRD does not Granger Cause LNMTN		1.58831	0.2109
LNPFAD does not Granger Cause LNCRD	82	4.10180	0.0203*
LNCRD does not Granger Cause LNPFAD		0.12019	0.8869
LNGAS does not Granger Cause LNCTL	82	0.92095	0.4025
LNCTL does not Granger Cause LNGAS		9.10154	0.0003*
LNMTN does not Granger Cause LNCTL	82	0.63816	0.5310
LNCTL does not Granger Cause LNMTN		11.5836	4.E-05
LNPFAD does not Granger Cause LNCTL	82	1.37663	0.2586
LNCTL does not Granger Cause LNPFAD		2.31110	0.1060
LNMTN does not Granger Cause LNGAS	82	5.46192	0.0061*
LNGAS does not Granger Cause LNMTN		0.91382	0.4053
LNPFAD does not Granger Cause LNGAS	82	4.12365	0.0199*
LNGAS does not Granger Cause LNPFAD		0.83172	0.4392
LNPFAD does not Granger Cause LNMTN	82	4.01165	0.0220*
LNMTN does not Granger Cause LNPFAD		2.57692	0.0826

Source: Author's Computation.

Note: The asterisk (*) shows the null hypothesis is rejected.

Table B. Shows the Variance Decomposition of All Variables

Variance Decomposition of DLNBIO								
Period	**S.E.**	**DLNBIO**	**DLNCPO**	**DLNCRD**	**DLNCTL**	**DLNGAS**	**DLNMTN**	**DLNPFAD**
1	0.046150	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.077493	35.50580	6.873024	15.31045	6.612773	4.118947	2.436035	29.14297
3	0.081647	32.38412	8.603015	16.81968	8.517097	3.794861	3.189063	26.69216
4	0.083014	31.43945	8.458246	17.94226	9.096960	3.682810	3.092141	26.28813
5	0.083744	31.00303	9.005397	17.82141	8.957626	3.849381	3.340383	26.02278
Variance Decomposition of DLNCPO								
Period	**S.E.**	**DLNBIO**	**DLNCPO**	**DLNCRD**	**DLNCTL**	**DLNGAS**	**DLNMTN**	**DLNPFAD**
1	0.056667	47.06103	52.93897	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.091039	18.53435	21.75716	13.02544	6.589312	0.154105	0.539159	39.40048
3	0.094948	17.96809	20.11620	15.35255	8.161957	0.185990	1.313148	36.90207
4	0.096325	17.49428	19.56347	16.19788	8.770440	0.826239	1.293063	35.85462
5	0.097124	17.44215	19.53696	15.98372	8.793964	0.941878	1.514482	35.78685
Variance Decomposition of DLNCRD								
Period	**S.E.**	**DLNBIO**	**DLNCPO**	**DLNCRD**	**DLNCTL**	**DLNGAS**	**DLNMTN**	**DLNPFAD**
1	0.117597	0.302965	1.648461	98.04857	0.000000	0.000000	0.000000	0.000000
2	0.143432	0.573857	2.182485	93.56833	0.033686	0.017513	3.604749	0.019381
3	0.145542	0.675440	3.138529	91.23529	0.198454	0.423348	4.275879	0.053059
4	0.151394	1.684247	2.908973	87.04187	0.475968	0.487486	4.259405	3.142050
5	0.153764	1.913228	2.820848	84.74544	0.798938	0.555000	4.407238	4.759305
Variance Decomposition of DLNCTL								
Period	**S.E.**	**DLNBIO**	**DLNCPO**	**DLNCRD**	**DLNCTL**	**DLNGAS**	**DLNMTN**	**DLNPFAD**
1	0.034742	0.059095	0.497900	2.101868	97.34114	0.000000	0.000000	0.000000
2	0.037428	0.339889	0.447915	2.660112	90.08783	1.536798	0.285846	4.641605
3	0.038435	0.323006	0.447640	2.865104	85.82770	3.323510	1.402296	5.810746
4	0.039114	0.332943	1.041893	2.766936	84.56115	3.218507	1.547693	6.530880
5	0.039275	0.458369	1.042002	2.754550	84.19201	3.200549	1.538742	6.813783
Variance Decomposition of DLNGAS								
Period	**S.E.**	**DLNBIO**	**DLNCPO**	**DLNCRD**	**DLNCTL**	**DLNGAS**	**DLNMTN**	**DLNPFAD**
1	0.092250	0.443806	4.720655	0.906967	0.960537	92.96804	0.000000	0.000000
2	0.105681	0.949735	3.668082	1.726365	14.50448	73.05252	0.214479	5.884344
3	0.113827	1.519749	5.762498	1.549492	18.43505	63.31427	1.243658	8.175277
4	0.116726	1.456528	5.739101	3.165030	17.54353	63.06495	1.241827	7.789034
5	0.118838	1.688337	6.283327	3.749775	17.43155	61.05739	1.324675	8.464950
Variance Decomposition of DLNMTN								
Period	**S.E.**	**DLNBIO**	**DLNCPO**	**DLNCRD**	**DLNCTL**	**DLNGAS**	**DLNMTN**	**DLNPFAD**
1	0.081098	0.397390	0.732817	0.983036	85.54515	0.558391	11.78321	0.000000
2	0.092134	0.500986	3.261206	5.439420	68.87016	0.880962	18.34765	2.699615
3	0.096261	0.459380	2.998664	5.071222	65.48043	2.541599	20.45455	2.994159
4	0.097918	0.519108	2.911196	4.901331	66.15606	2.499855	20.01814	2.994308
5	0.098290	0.760990	3.007692	4.864866	65.68322	2.571948	19.86920	3.242080
Variance Decomposition of DLNPFAD								
Period	**S.E.**	**DLNBIO**	**DLNCPO**	**DLNCRD**	**DLNCTL**	**DLNGAS**	**DLNMTN**	**DLNPFAD**
1	0.092465	0.724963	5.042250	25.98460	7.476249	0.597159	0.038195	60.13659
2	0.102092	6.511856	10.79474	21.56838	6.865791	0.748893	0.188286	53.32205
3	0.105094	6.568717	10.89444	20.41664	6.624600	1.877527	0.457904	53.16017
4	0.106301	6.420753	10.78767	21.39674	6.570728	1.983224	0.724312	52.11657
5	0.107883	6.299854	10.51262	21.48644	7.408752	1.928930	0.721962	51.64144

Note: Cholesky Ordering: DLNBIO DLNCPO DLNCRD DLNCTL DLNGAS DLNMTN DLNPFAD
Source: Author's Computation

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