

# **THE DETERMINANTS OF BIODIESEL PRICE IN INDONESIA: A VAR MODEL ANALYSIS**

**Thesis**

**Submitted to meet the Graduation Requirements of  
Master's Degree (M.A. in Economics)**



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بِسْمِ اللَّهِ الرَّحْمَنِ الرَّحِيمِ

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MA in Economics

## ABSTRACT

As the world's largest biodiesel producer, Indonesia has undoubtedly made remarkable progress in biodiesel and gasoil fuel blending. Yet, despite the progress it makes, the country surprisingly still experiences significant volatility in biodiesel prices. This phenomenon raises a critical question about the factors driving these fluctuations, which apparently are still not adequately addressed by the existing literature. Notwithstanding, this study delves into the relationships between biodiesel prices and various potential determinants, namely crude palm oil (CPO), crude glycerin, catalyst, gasoil, methanol, and palm fatty acid distillate (PFAD). To investigate these complex relationships, the Vector Autoregressive (VAR) model was employed, given its robustness in capturing dynamic interdependencies between multiple time series. As for the data collection, the study relies on monthly data provided by Indonesia's Ministry of Energy and Mineral Resources (MEMR) and Independent Commodity Intelligence Service (I.C.I.S) from 2016 to 2022. The VAR analysis reveals the nuanced influences of these variables on biodiesel prices. Specifically, it suggests that an increase in the prices of CPO, crude glycerin, catalyst, and PFAD positively affects biodiesel prices, whilst price shocks in gasoil and methanol inversely impact biodiesel prices. These findings provide valuable insights into the intricate dynamics governing biodiesel pricing in Indonesia, highlighting the necessity for a multi-factor approach when formulating pricing strategies. Consequently, this study's results inform policy decisions and industry practices to foster price stability, drive the growth of the biodiesel sector, and facilitate Indonesia's transition towards sustainable energy.

**Keywords:** *Biodiesel Pricing, Price Determinants, Biodiesel Components, VAR Analysis, Biofuel Economics, Sustainable Energy.*

## **DEDICATION**

I dedicate this work to my wonderful parents, who were the first people in my life to set a good example and serve as a point of reference; they were the ones who made it possible for me to support and be supported by others throughout all of these years; they were also the ones who instilled true values in me and allowed me to become the person I am today.

In addition, I would like to dedicate this work to: My siblings, who motivate me by providing a positive example to advance along the appropriate professional and personal path effectively. My closest friends and colleagues for the intensity of the things we share, which all revolve around the concept of love and allow us to have profound conversations based on mutual regard.

Throughout the years we have received an education, all instructors and teachers have been extremely helpful and liberal with their time and expertise. They have also expressed their passion for instructing.

***Safiullah Junejo***

*07<sup>th</sup> June 2023*

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***Safiullah Junejo***

*07<sup>th</sup> June 2023*

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## **LIST OF ABBREVIATIONS**

ADF	Augmented Dickey-Fuller
AIC	Akaike Information Criterion
ARIMA	Autoregressive Integrated Moving Average
BPD	Barrels Per Day
CAD	Current Account Deficit
CAGR	Compound Annual Growth Rate
CPO	Crude Palm Oil
FAME	Fatty Acid Methyl Ester
FAO	Food and Agriculture Organization
FFA	Free Fatty Acid
FPE	Final Prediction Error
HQ	Hannan-Quinn
IEA	International Energy Agency
IRENA	International Renewable Energy Agency
IRF	Impulse Response Function
KPBN	Kharisma Pemasaran Bersama Nusantara
LR	Likelihood Ratios
MEMR	Ministry of Energy and Mineral Resources
ICIS	Independent Commodity Intelligence Services
MOI	Ministry of Industry
MOT	Ministry of Trade
MSW	Municipal Solid Waste
OECD	Organization for Economic Co-operation and Development
OLS	Ordinary Least Square
P.P	Philip-Perron
PFAD	Palm Fatty Acid Distillate
RBDDPO	Refined Bleached Distillates Palm Oil
RBPO	Refined Bleached Palm Oil
SC	Schwarz Information Criterion
USDA	United States Department of Agriculture

VAR      Vector Autoregressive  
VEC      Vector Error Correction

# CHAPTER 1

## INTRODUCTION

### 1.1 Background

Over the past decades, the Indonesian biodiesel (Fatty Acid Methyl Ester (FAME)) mixture has sharply increased from 2.5 percent to 30 percent blending composition, which leads the country as the world's highest blending mixture for FAME in gasoil fuel. In terms of capacity, Indonesia is also regarded as the world's largest biodiesel producer, with a production capacity of 137,000 barrels per day (BPD) in 2017 (Kusumawardhani, 2022). This is 20 percent more than the United States' biodiesel production as the second largest. In contrast, the third largest production is given to Brazil (99,000 BPD). Indonesian biodiesel production will be expected to rise significantly as the blending rate of biodiesel (FAME) for domestic use increases. At the same time, the trend in crude palm oil (CPO) exports is negligible. The blending rate for domestic usage has been at a 30 percent level since January 1, 2020, which is expected to increase from 35 percent (B35) to 40 percent (B40) in the short run.

The development of the biodiesel industry aims to create a balanced energy policy that will bring advantages to Indonesia, not only by substituting petroleum-based diesel. One of its main benefits is that it increases the longevity and cleanliness of diesel engines and the usefulness of petroleum. Marco Mangelsdrof (2000) argued, "*Our fleet of trucks and vans will be converted to run entirely on biodiesel manufactured in Hawaii, which is cleaner, biodegradable, free of sulfur and aromatics, increases engine longevity, and lessens our state's reliance on fossil fuels.*" (Pacific Business News, 2008). As a result of the community-based biodiesel production strategy, the community will become more self-sufficient and stronger. In Indonesia, local firms produce and supply the fuel to consumers, while farmers who raise the feedstock also get benefit from a community-based biodiesel distribution program. The money stays in the community while lowering its adverse effects on the local environment and boosting energy security.

Theoretically, biodiesel is an option to achieve the renewable energy target. Therefore, many countries around the world have set renewable energy targets as part of their efforts to reduce greenhouse gas emissions and combat climate change. These targets typically aim to increase the share of renewable energy sources in the overall energy mix (REN21, 2020). It suggests that biodiesel can be a viable option for meeting renewable energy targets due to its renewable nature and potential to replace fossil fuels in the transportation sector (Hossain et al., 2018; Demirbas, 2008). However, its positive impact on decarbonization is dubious, as Indonesia's biodiesel production is solely sourced from CPO as its feedstock. One of the reasons is that CPO's implementation as a biodiesel feedstock competes with food and turns it into an export commodity because of high demand and a promising price. Oil World (2007) reports that the average annual oil yield for CPO is roughly 3.74 tons/ha, compared to 0.38 tons/ha for soybean oil, 0.48 tons/ha for sunflower oil, and 0.67 tons/ha for rapeseed (FAO, 2020), making CPO one of the most promising vegetable oils for use as a feedstock in biodiesel. Indonesia is one of the world's largest CPO producers; thus, it has great potential to meet domestic biodiesel demand.

In Indonesia, CPO is used as the primary input/feedstock for biodiesel production; however, the quality of CPO determines the quality of biodiesel as a whole (Mayasari et al., 2019). Thus, CPO specifications must not contain a high level of acid compounds. Biodiesel producers in Indonesia adopted the transesterification method to convert CPO into biodiesel; additionally, it fulfills economic scale due to its advantage of quick reaction speed using a base catalyst rather than an acid catalyst, even at low temperatures. Hence, it is considered the most effective and efficient method in the process compared to others (Ambat, 2018).

Converting CPO into biodiesel has various advantages, including less dependence on nonrenewable resources and lower carbon emissions. However, biodiesel conversion from CPO requires several important steps in the process. The first step is to prepare the CPO, or, in other words, refine the CPO. In the refining process, impurities (gum and mucus) are separated from CPO by degumming and

bleaching. Refined bleached palm oil (RBPO) is generated but still contains low-quality mixed oil with impurities from spent bleaching earth (Ambat, 2018). This can cause the CPO to smell and taste bad because acid remains in it. Thus, producers need to fix this problem and then process RBPO to refine it again through degumming and bleaching. Then the oil gets cleaner after the second stage of the refining process, and the end product produced is called Refined Bleached Deodorized Palm Oil (RBDPO). However, in order to ensure the best quality biodiesel, the CPO must be refined until it yields RBDPO.

Notably, the process of refining crude palm oil (RBDPO) has a significant impact on biodiesel performance; this process enhances odor and taste while removing impurities and acids. This advancement makes biodiesel a more appealing and sustainable option. In order to take full advantage of the potential benefits of biodiesel production, the appropriate refining processes must be implemented to generate high-quality RBDPO. Indonesian biodiesel industries can help create a more sustainable and ecologically friendly future by supporting a cleaner and healthier planet for us and future generations. Nevertheless, during the RBDPO refinement process, an additional valuable byproduct (palm fatty acid distillate (PFAD)) is generated.

In contrast, it generates alkaline residue after degumming and bleaching, and PFAD has a significant economic value due to its ability to yield an assortment of bioactive chemicals. Vitamin E, phytosterols, and squalene are examples of these chemicals. As a result, PFAD has enormous potential to manufacture these beneficial compounds. The next step in the process involves further processing the RBDPO to generate biodiesel through transesterification, which contains fatty acid triglycerides. To maximize the reaction process, the transesterification process is carried out on a commercial scale at 55-60 degrees Celsius in the main reactor (Demirbas, 2008). In the transesterification process, producers add two chemicals, methanol and a catalyst, with specific volume amounts. The combination of methanol and catalyst ensures the conversion of CPO into biodiesel by fostering the transesterification process. However, methanol provides the alcohol component required for the process, while the catalyst enhances the reaction rate, resulting in

the desired final product of biodiesel. Indonesia imports both chemicals to fulfill the demand for biodiesel production.

Nevertheless, producers get two outputs during this process: crude fatty acid methyl ester (Crude FAME) and glycerol. Glycerol is another by-product that is generated during this process. Economically, glycerol has a crucial economic value because it can be used as a raw material for various manufacturing and food industries. In addition, the crude FAME moves on to the next step: it separates impurities such as unreacted methanol residue, remaining catalyst, residual glycerol, unconverted fatty acid compounds, and remaining soap (Demirbas, 2008). The final step is to purify the biodiesel through washing and drying (Ambat, 2018). After that, the final product, FAME or biodiesel, can be used as motor fuel.

Indonesia can potentially replace fossil fuels with biodiesel because it is the leading producer of CPO, the primary biodiesel feedstock. In contrast, the conversion process incurs high costs for inputs and feedstocks such as CPO, methanol, and catalyst. The Indonesian government has fixed the conversion price, but on the other hand, they import chemicals (methanol and catalyst), which are more costly. Some authors found that high feedstock costs significantly impact the biodiesel production processes (Mulugella, 2009; Apostolakou, 2009; Haas, 2006; Santana, 2010).

## **1.2 Problem Statement**

Biodiesel is a highly preferable renewable energy source in Indonesia, and it has the potential to reduce the country's dependence on fossil fuels and mitigate the environmental impact due to transportation. However, the price of biodiesel in Indonesia has been subject to considerable fluctuation, and there is a need to understand better the factors that influence this variability. For instance, prior studies (Alghifari et al., 2022; Reichenberg et al., 2018; Siregar et al., 2020) have suggested that production costs, crude oil prices, and governmental policies all affect the cost of biodiesel. In addition, supply and demand dynamics have impacted biodiesel pricing in other countries (Kang et al., 2018).

Figure 1.1: Biodiesel Blending Policy Development

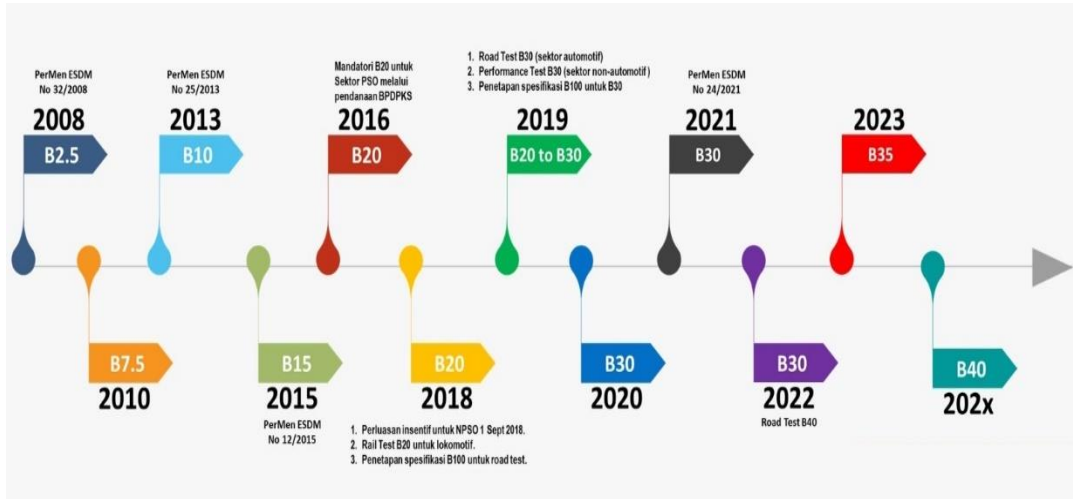


Figure 2.1 presents the policy implementation for blending biodiesel with fossil fuel. In 2008, it was implemented for the first time with a 2.5 percent blending rate, and it continuously developed over time and got government attention. Recently, Indonesia's government planned to blend 35 percent biodiesel with fossil fuel in 2023. Thus, the Indonesian government allocated incentives for converting biodiesel from CPO. Currently, in Indonesia, biodiesel prices are based on the price of CPO plus the conversion and distribution costs.

$$P_{biodiesel} = P_{CPO} + C_{conversion} + \varepsilon_{Distribution}$$

$C_{conversion}$  is constant, which is USD 85;  $P_{CPO}$  is based on the domestic price released by KPBN (Kharisma Pemasaran Bersama Nusantara) officially;  $\varepsilon_{Distribution}$  is the transportation cost from the supply point to the blending point. We argue that the above equation may not describe the actual price relationship between the input and the biodiesel output. Therefore, this research investigates the price relationship between the required inputs and the corresponding product, biodiesel. By identifying these factors, this study can provide insights into how biodiesel pricing in Indonesia can be stabilized, which could ultimately facilitate the biodiesel industry's growth and contribute to sustainable energy development.

### 1.3 Research Questions

- What is the relationship between the price of inputs, i.e., CPO, methanol,

catalyst, PFAD, crude glycerin, and the price of biodiesel?

- What are the most significant factors driving the fluctuations in biodiesel prices in Indonesia, and how can they be addressed to ensure a stable and sustainable biodiesel industry?
- To what extent can government policies be well designed to improve the implementation of biodiesel in Indonesia in the context of its market price?

## **1.4 Study Objectives**

The main objectives of this study are to analyze the factors that influence biodiesel prices in Indonesia and recommend potential solutions to mitigate their impact. Specific objectives include:

1. To examine the relationship between the price of inputs, including CPO, methanol, catalyst, PFAD, crude glycerin, and the price of biodiesel in Indonesia.
2. To identify the most significant factors driving the fluctuations in biodiesel prices in Indonesia and to recommend strategies that can be implemented to ensure a stable and sustainable biodiesel industry in the country.
3. To evaluate the effectiveness of government policies in improving the implementation of biodiesel in Indonesia, focusing on their impact on the market price of biodiesel.

When it comes to tackling complex problems, having a clear plan of action is critical. In order to address the first question, it is crucial to focus on the initial objective. Doing so can establish a solid foundation and understanding of the issue, enabling us to move forward with greater clarity and purpose. The second objective, on the other hand, is equally crucial to answering the second question. To continue this, the third objective is to answer the third question. Finally, the fourth objective considers answering the fourth question. These objectives build upon the initial groundwork and provide more specific guidance and direction regarding implementation and resolution. Therefore, it is critical to consider all four objectives to address the problem comprehensively and effectively. By dividing our

efforts into these clear and distinct categories, we can maximize our chances of success and ensure we handle all aspects of the issue.

## **1.5 Research Hypotheses**

The following hypotheses are developed based on the research questions and objectives:

- H<sub>1</sub>:** The prices of the primary raw materials used in the production of biodiesel in Indonesia—CPO, methanol, and catalyst—have a positive impact on the price of biodiesel.
- H<sub>2</sub>:** The price of biodiesel in Indonesia is negatively influenced by the price of PFAD (Palm Fatty Acid Distillate), glycerin, and gasoil. As these byproducts and alternatives compete with biodiesel as feedstock sources for biofuels, their presence in the market can drive down the demand and value of biodiesel, affecting its market price negatively.
- H<sub>3</sub>:** The market price of biodiesel will be significantly impacted by the execution of government initiatives intended to promote biodiesel in Indonesia and will eventually either decline or stabilize.

## **1.6 Significance of the Study**

The significance of this study can be attributed to several reasons. First, the fluctuation of biodiesel prices in Indonesia is critical for the biodiesel industry's growth. By identifying the factors influencing biodiesel pricing, this study can provide insights into how biodiesel pricing can be stabilized in Indonesia. This could ultimately facilitate the biodiesel industry's growth and contribute to sustainable energy development.

Second, this study expands upon the foundation of the following prior studies (Alghifari et al., 2022; Reichenberg et al., 2018; Siregar et al., 2020; Sari et al., 2018). But it provides new insights into the impact of government policies and regulations, supply and demand dynamics, and other key factors on biodiesel pricing.

Furthermore, biodiesel derived from CPO may replace diesel in Indonesia (Bell, 2011) due to abundant renewable energy sources. However, three key objectives in Indonesia's national energy mix may be accomplished by increasing the use of CPO in biodiesel production as part of the biological feedstock. First, using biodiesel blends is a great way to save money on imports and exports. Second, the need for domestic biodiesel provides a stable market for palm oil prices. Last but not least, it may boost the share and importance of biofuels in meeting the renewable energy portfolio standard. Together, these three objectives may increase the currency rate, reduce the current account deficit (CAD), and mitigate the predicted risk net energy importers face in 2027 (Brown, 2013). These advantages may be maintained permanently if the investment is put into renewable palm oil sources.

As a result of its focus on the elements that may boost the renewable energy sector and lessen the effects of climate change, the research has broader implications for renewable energy and sustainable development.

## **1.7 Outline of the Study**

The second chapter of the dissertation is devoted to the literature review. It overviews relevant academic works and identifies key concepts and definitions related to biodiesel production processes and price mechanisms. Additionally, this chapter highlights the existing gaps in the literature, which will help the reader to understand the significance of the current research. The third chapter of the dissertation is the research methodology chapter. In this chapter, we explain the methods used to gather data and analyze it. This chapter will include a detailed explanation of the research design, the research instruments used, the sampling techniques employed, and the data analysis techniques employed.

The fourth chapter is the results and discussion chapter. Here, we will present the data analysis results and discuss the findings. To facilitate easy comprehension, the results will be delivered using tables, graphs, or charts. The discussion section will provide an interpretation of the results and examine their implications for the research questions and hypotheses. The fifth and final chapter of the dissertation will be the conclusion and recommendations. This chapter will summarize the

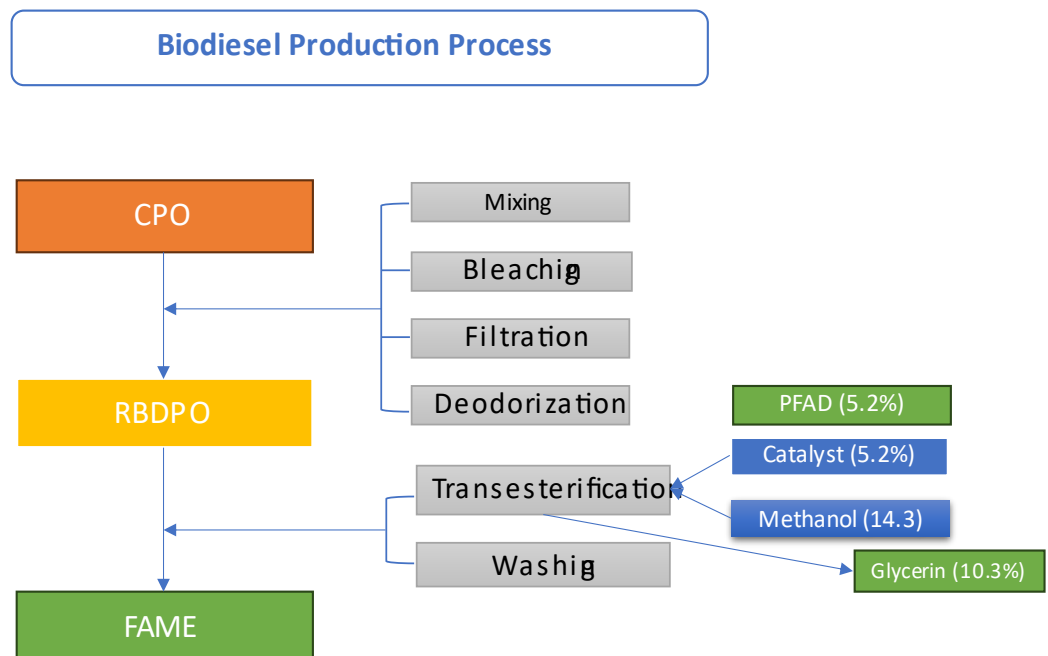
study's main findings, evaluate the research hypotheses, and conclude. Additionally, we will provide recommendations for future research in this area, highlighting the study's limitations and suggesting avenues for further investigation.

# CHAPTER 2

## LITERATURE REVIEW

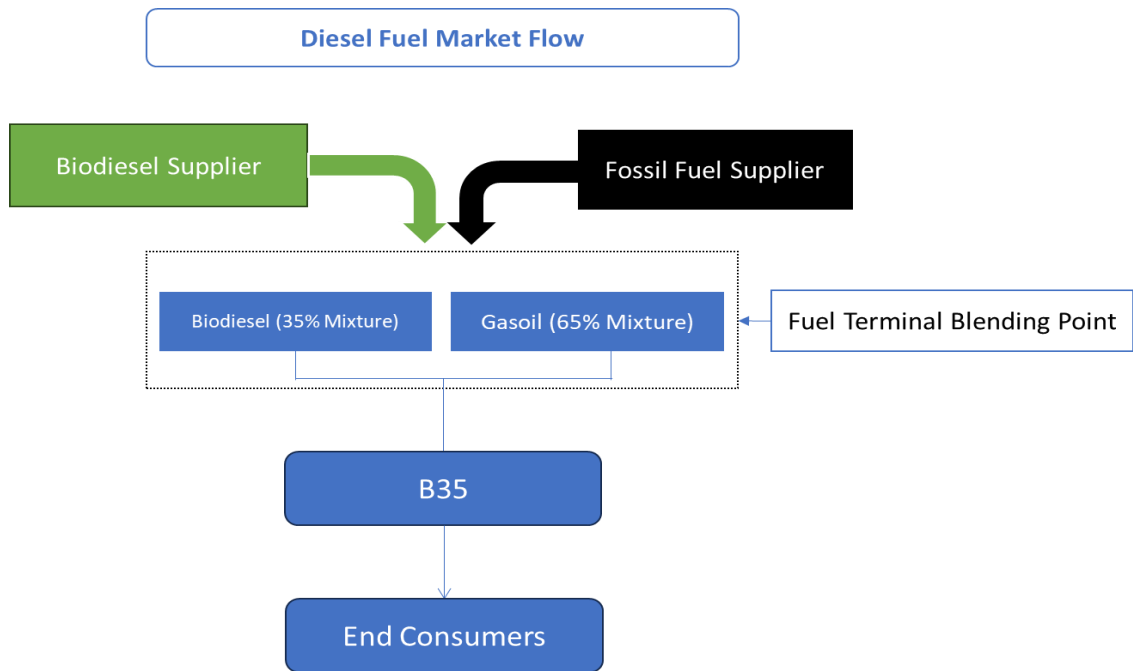
This chapter presents an in-depth review of the available biodiesel literature. Biodiesel has emerged as a promising renewable energy source and an appropriate replacement for conventional fossil fuels. Our review focuses on biodiesel's components, relationship with renewable energy, production process, price mechanisms, previous study findings, and research gaps. We aim to establish a solid foundation for our study by assessing the present level of knowledge in these areas and identifying areas that require further investigation. This literature review will help us understand biodiesel's potential as a sustainable energy solution. Additionally, we can understand the flow of study from the theoretical framework that is shown in Figure 2.1 and 2.2.

*Figure 2.1: Show First Scheme of Theoretical Framework*



*Source: Authors' Framework*

*Figure 2.2: Shows Second Scheme of Theoretical Framework*



*Source: Authors' Frame working*

## 2.1 Biodiesel and Its Components

This section presents comprehensive details on the biodiesel background and its components. Biodiesel is a renewable and environmentally friendly alternative fuel derived from natural resources such as vegetable oils, animal fats, and waste cooking oils (Rincoin, 2014). It is biodegradable, non-toxic, and produces lower emissions than traditional diesel. Rudolf Diesel first demonstrated using vegetable oils as fuel in 1900 when he ran his engine on peanut oil at the World Exhibition in Paris (IEA, 2021). Although biodiesel was demonstrated as early as the 1900s, it did not become popular until the early 21st century. This was mainly because fossil fuels were more widely available and cheaper than biodiesel (Bala, 2005).

Early in the 1990s, Germany and Austria saw a rise in the usage of biodiesel to reduce reliance on imported fossil fuels and cut greenhouse gas emissions. In the United States, the Energy Policy Act of 2005 offered tax incentives for the production and use of biodiesel. Still, it wasn't until the Renewable Fuel Standard was implemented in 2007 that things took off. The Renewable Fuel Standard

requires a certain amount of renewable fuel to be mixed into the transportation fuel supply, which helped promote the production and use of biodiesel in the U.S. (Owolabi et al., 2012).

Biodiesel has been identified as a potential solution to address the issue of increasing global demand for fuel and reducing greenhouse gas emissions (Gui, Lee, & Bhatia, 2008). Nowadays, many countries worldwide, including Indonesia, the United States, Brazil, and Europe, produce and use biodiesel. The demand for biodiesel is expected to grow as governments and industries seek to reduce dependence on fossil fuels and decrease greenhouse gas emissions (IEA, 2020). In Indonesia, biodiesel has gained significant attention and importance due to its potential to reduce dependence on fossil fuels and promote energy security. Historically, Indonesia started producing biodiesel in the early 2000s using palm oil as the primary feedstock. In 2005, the government mandated that all diesel fuel sold in the country contain at least 5 percent biodiesel (B5). Then the mandate was increased to B10 in 2015, requiring all diesel fuel to include at least 10 percent biodiesel. As of 2021, Indonesia's biodiesel market is growing rapidly. The government has set a target for 20 percent of all diesel fuel used in the country to be biodiesel by 2025 and a target to increase it to 30 percent by 2030 (MEMR, 2020).

Indonesia is the world's largest biodiesel producer, with a production capacity of 9.5 billion liters in 2021 (Sonnichsen, 2022). However, the biodiesel industry in Indonesia has been growing rapidly due to government support and favorable policies. Demirbas (2008) and Lueng (2010) found that transesterification is the primary and most important way to make biodiesel from CPO. This method involves reacting triglycerides with alcohol in the presence of a catalyst and methanol to make alkyl esters, fatty acids, biodiesel, and crude glycerol. Fuels are mandatory, which has increased the demand for biodiesel in the transportation and energy sectors (Indonesia Investment, 2022). However, the choice of feedstocks is an essential component of biodiesel production, accounting for at least 80 percent of the production costs (Azizian & Kramer, 2005). In Indonesia, palm oil is the dominant feedstock used for biodiesel production, accounting for approximately 90

percent of the total production volume (Sonnichsen, 2022). Other feedstocks, such as jatropha, microalgae, tallow coconut, and waste cooking oil, are also used in smaller volumes (Rincoin, 2014).

Therefore, in recent years, due to concerns over food shortages and the negative impact of using edible oils for fuel production, using non-edible oils as feedstocks for biodiesel production has gained popularity (Balat, 2011). In Indonesia, CPO (crude palm oil) is a significant source of feedstock for biodiesel production due to its high productivity and abundance (Indonesia Investment, 2022). However, the use of CPO as a feedstock for biodiesel production has been controversial due to its negative impact on the environment, particularly deforestation and habitat destruction (Wicaksono, 2017). However, Indonesia has put effort into planting more palm oil to reduce its negative impact on the environment. Also, biodiesel production from CPO will be a crucial step in reducing gas emissions generated due to fossil fuel use in transportation and industries.

Demirbas (2008) and Lueng (2010) found that transesterification is the primary and most important way to make biodiesel from CPO. This method involves reacting triglycerides with alcohol in the presence of a catalyst and methanol to make alkyl esters, fatty acids, biodiesel, and crude glycerol. In addition, Elgharbawy (2007) also suggested that transesterification is the most commonly used method in the biodiesel industry due to its speed and ease of use. However, this method requires careful optimization of the reaction parameters, including temperature, mixing rate, and catalyst concentration, to achieve maximum yield and quality of biodiesel (Lueng, 2010).

Additionally, one of the benefits of producing biodiesel from crude palm oil is the increase in value and price beyond the original commodity, which can help diversify the palm oil industry and increase its added value (Indonesia Investment, 2022). Nevertheless, biodiesel production also offers economic opportunities for rural communities in Indonesia, particularly for those who are involved in small-scale palm oil production (Wicaksono, 2017). Biodiesel has been used as a variable in many studies, such as (Smith., et al., 2015; Cako et al., 2022; Mohammadshirazi

et al., 2014; Mondala et al., 2009; Yusuf et al., 2011). These studies examined the costs and benefits of producing and using biodiesel as an alternative to diesel engines. The author looked at how it impacts the prices of agricultural commodities, whether it is possible to produce biodiesel from different feedstocks, and how it helps the environment when used as a transportation fuel. However, they showed biodiesel has a positive impact on environmental quality.

In previous studies, biodiesel is often used for its properties, such as its chemical composition, how it burns, and how much pollution it gives off. Most scientists are also looking for better, more sustainable ways to make biodiesel (Cako et al., 2022). In the past few years, the world has been paying attention to biodiesel as a possible solution to the global energy crisis and the environmental problems of using fossil fuels. In addition, scientists are also looking into how biodiesel can be used to reduce greenhouse gas emissions, improve energy security, and help rural development in developing countries (Smith et al., 2015; Cako et al., 2022). In this regard, we argue that biodiesel has the potential to replace diesel and reduce carbon emissions in Indonesia.

### **2.1.1 CPO (Crude Palm Oil)**

Crude palm oil (CPO) is a vegetable oil obtained from oil palm plants' fruit. The world's most popular oil crop is palm oil, which is primarily grown in tropical areas. A common agricultural product in Malaysia and Indonesia is palm oil. However, the top producers and exporters of palm oil worldwide are Indonesia and Malaysia. According to reports, Indonesia and Malaysia produced 83 percent of the world's palm oil in 2015 (Mielke, 2018), with Indonesia contributing 51 percent and Malaysia contributing 34 percent. In 2021, they'll contribute to the production and export of palm oil globally. Palm oil was produced worldwide in the marketing year 2021–2022 in an estimated 73.8 million metric tons. In terms of contribution, Malaysia had 19.6 million metric tons, compared to Indonesia's 48.8 million metric tons (IEA, 2023). According to this, about 93 percent of the palm oil produced globally in 2021 was generated in Indonesia and Malaysia.

Furthermore, CPO is used for various purposes all around the world,

including as an ingredient in food products, as a biofuel, and as a raw material in producing other products such as soap, shampoo, and cosmetics (Silalahi et al., 2020; Mahlia, 2019). In many countries, CPO is also used as a feedstock for biodiesel production. According to estimates, Indonesia will use 9.48 million metric tons of crude palm oil (CPO) to produce biofuels 2022. CPO processing and derivatives contribute considerably to Indonesia's state revenue, and developing and enhancing these industries requires knowledge and technological expertise (Latifah, 2016). This will help the people of Indonesia compete with other countries in developing renewable energy industries worldwide.

According to the Indonesia Palm Oil Statistics, CPO production in Indonesia increased by 5.38–8.42 percent from 2011 to 2015, reaching 33.2 million tons in 2016 (Indonesia Statistics Bureau, 2016). In addition, raw and refined CPO exports accounted for approximately 70.18 percent of Indonesia's total CPO production in 2016, with refined CPO dominating exports. The remaining CPO was used domestically for food, oleochemicals, and biodiesel, with an average domestic consumption rate of 22.5 percent. In 2016, India emerged as the largest importer of CPO from Indonesia, acquiring 55.71 percent of the country's total CPO exports (Korindo, 2018).

Supply and demand, production costs, and governmental regulations affect CPO prices in Indonesia. As a result, factors like weather, crop yields, labor costs, and transportation costs can also impact the cost of production, which in turn affects the price of CPO in Indonesia. The increasing demand for palm oil, its byproducts, biofuels, and other industrial uses worldwide drives the demand for CPO. As a result, factors like weather, crop yields, labor costs, and transportation costs can also impact the cost of production, which in turn affects the price of CPO in Indonesia. Consequently, government regulations can also impact the price of CPO by imposing export taxes and tariffs on CPOs, setting price controls, or implementing subsidies to keep the costs of certain CPOs low (Korindo, 2018). Additionally, because CPO is closely related to the price of other vegetable oils and the demand for these goods on a global scale, global market conditions also impact its price. Overall, a complex set of variables that can change over time have an

impact on the price of CPO in Indonesia.

We found that CPO has been considered a variable in several studies (Kanchymalay et al., 2017; Khalid., et al., 2018; Applanaidu., et al., 2011; Shamsudin and Arshad, 2000) because of its importance in the palm oil industry worldwide. Additionally, since CPO is the primary raw material used as the feedstock in the conversion process, its price directly impacts biodiesel price. Khalid., et al. (2018) showed in their study that CPO prices change significantly depending on global supply and demand, weather conditions, crop production levels, and geopolitical events. However, if the price of CPO increase, the price of converting biodiesel from CPO will also increase, which means that the price of the final product (biodiesel) will be high. On the other hand, if the price of CPO decreases, the price of converting biodiesel will also decrease, which means that the final product will be cheaper. This shows how important it is to track and predict the cost of CPO to keep the cost of conversion of biodiesel under control.

### **2.1.2 Methanol**

Alcohol plays a significant role as a raw component for biodiesel conversion from CPO in Indonesia. Therefore, many alcohols have been investigated for biodiesel production all around the world. Thus, methanol and ethanol are the process's most commonly used acyl acceptors. However, methanol is preferred due to its physical and chemical properties, including its rapid interaction with triglycerides and rapid dissolution in NaOH (Sodium Hydroxide). In addition, methanol is also more accessible than ethanol (Avagyan & Singh, 2019). Methanol is a colorless liquid chemical that is used in thousands of items, such as plastics, paints, pharmaceuticals, and fuels. It is also an emerging renewable energy resource that is biodegradable, clean-burning, and composed of four parts hydrogen, one part oxygen, and one part carbon (Mahmud, 2019). Methanol's environmental and economic benefits make it an increasingly desirable alternative energy for power generation, ships, cooking meals, and heating houses.

Although methanol is typically generated from natural gas, its production methods have diversified as interest in sustainability has increased. Therefore,

many projects are using renewable feedstocks such as agricultural waste, municipal solid waste (MSW), sewerage, renewable electricity, and captured CO<sub>2</sub> to reduce the intensity of greenhouse gas emissions and support the energy transition (Mahmud, 2019). Sustainably produced methanol promotes the expansion of the green chemical industry. It is used as a drop-in replacement fuel in shipping, commercial vehicles, and electricity production to reduce overall emissions and environmental effects.

Methanol is an important part of turning CPO into biodiesel in Indonesia. Fatty acid methyl esters (FAME) use 14.3 percent of the methanol needed for the process. But Indonesia relies heavily on imports of methanol, which account for 75 percent of its consumption. This means that from 2016 to 2019, Indonesia will have a yearly trade balance deficit of about 216 million USD or 3.13 trillion IDR. Furthermore, the country's crucial downstream sectors depend heavily on methanol as a primary raw material for biodiesel production. The global demand for methanol has been gradually increasing, with imports hitting 29.91 million tons in 2019, a 10.81 percent increase over the previous year. The world's methanol imports have been rising at a CAGR of 5.45 percent from 2015 to 2019, indicating methanol's growing importance in various industries. China accounted for 28.87 percent of global methanol imports in 2017, while the United States and the Netherlands imported 9.37 percent and 9.0 percent of that substance, respectively. Therefore, Indonesia must explore alternative sources of methanol and reduce its dependency on imports to strengthen its economy and secure its energy needs (Report, 2021).

Some studies (Teo et al., 2015; Pellegrini et al., 2011; Puig-Gamero et al., 2021; Chen et al., 2018) have examined how important it is and how methanol affects the conversion properties of biodiesel. Methanol significantly impacts on the quantity and quality of biodiesel. However, the best concentration and conditions should be carefully chosen based on the feedstock and the properties we want the fuel to have. Furthermore, the price of methanol significantly impacts the conversion of CPO into biodiesel. If the price of methanol increases, the biodiesel price will also increase. This can make it harder for biodiesel manufacturers to compete with petroleum-based diesel. However, the price of methanol can also be

affected by specific changes in the global market for methanol, changes in the cost of the energy used to produce methanol, and changes in the demand for methanol in other industries (Chen et al., 2018). So, the price of methanol can be hard to predict and control, which makes it an essential factor in converting CPO into biodiesel. So, we argue that methanol significantly impacts biodiesel prices in Indonesia.

### **2.1.3 Catalyst**

A catalyst is a substance that speeds up the rate of a chemical reaction without sustaining permanent change. It works by providing a lower activation energy alternative pathway for the reaction, thereby improving the reaction rate. Catalysts are important in converting biodiesel from crude palm oil (CPO) in Indonesia. Transesterification is a process in which triglycerides found in CPO combine with an alcohol, usually methanol, in the presence of a catalyst to produce biodiesel. The triglycerides are converted into fatty acid methyl esters (FAME), which are the primary components of biodiesel, during this reaction. However, esterification and transesterification are currently the most widely used processes for biodiesel synthesis (Lem et al., 2010; Thanh, 2012).

Typically, sodium hydroxide (NaOH) and potassium hydroxide (KOH) are utilized as catalysts in this process, which uses an alkaline catalyst. By aiding the transesterification reaction, these catalysts enable the conversion of triglycerides into biodiesel. As a result of the catalyst, the reaction proceeds more quickly and effectively by requiring less activation energy. The choice of a catalyst, such as NaOH or KOH, depends on multiple factors, including the type of feedstock (in this case, CPO), reaction conditions, and desired biodiesel quality (Kansedo et al., 2009; Omkaresh et al., 2017). The choice of catalyst affects biodiesel's reaction rate, yield, and purity. It's important to know that the catalyst is only used in small amounts and is usually recovered and used again in the process. This lowers biodiesel's total cost and environmental impact (Lem et al., 2010).

According to Volza's Indonesia import data, catalyst import shipments in Indonesia accounted for 24.7K, with 774 suppliers worldwide. Most of Indonesia's

catalyst is imported from China, Japan, and India. However, the top three importers of catalysts are India (207,008 shipments), Vietnam (67,959 shipments), and the United States (52,717 shipments) (Vol., 2022). Several factors, such as supply and demand, production costs, and governmental regulations, affect the price of catalysts in Indonesia.

The country's expanding chemical and petrochemical industries and the increased use of catalysts in other sectors like the automotive and pharmaceutical industries are driving up catalyst demand in Indonesia. The cost of producing basic materials like metals and chemicals, labor, and transportation all have an impact on the price of catalysts in Indonesia (Harahap et al., 2019). The cost of research and development and the cost of adhering to environmental regulations can also affect the price of catalysts.

Harahap et al. (2019) found that government regulations can also impact the price of catalysts in Indonesia. Import tariffs, taxes, and other fees may be imposed on catalysts imported into the country, which can increase the product's price. Additionally, the government may set price controls or implement subsidies to keep the prices of specific catalysts low. Overall, several complex factors, such as supply and demand, production costs, and ever-changing government regulations, have an impact on the price of catalysts in Indonesia.

Previous studies (Shahbazi et al., 2012; Alkabbashi et al., 2009; Chen et al., 2018) suggest that the use of catalysts has been seen as a way to improve the efficiency of the reaction and the quality of the biodiesel. These studies show how essential catalysts are in converting biodiesel from CPO and suggest that the selection of catalysts can significantly impact the reaction and the quality of biodiesel. The catalyst is a key part of converting CPO into biodiesel because it reacts faster in the transesterification process and is more efficient and cheaper (Chen et al., 2018).

#### **2.1.4 Glycerin**

Glycerin is a colorless and odorless liquid with a sweet taste. It is also

known as glycerol or glycerin. It is a naturally occurring chemical found in various fats and oils, including crude palm oil (CPO). Glycerin is crucial in the biodiesel conversion process from CPO in Indonesia. Glycerin is made as a byproduct of the transesterification process that converts CPO into biodiesel. In the presence of a catalyst, the triglycerides in CPO combine with alcohol, usually methanol. This process converts the triglycerides into fatty acid methyl esters (FAME), which are the primary components of biodiesel and glycerin. Approximately 10 pounds of crude glycerol are produced for every 100 pounds of biodiesel. However, due to the rapid growth of the biodiesel industry, an excess of oil glycerol is being generated, leading to the need for alternative disposal methods (Harahap et al., 2019).

The glycerol produced during the biodiesel production process is referred to as crude glycerol or crude glycerol. It includes impurities and must be purified further before being used in various sectors, such as the food, pharmaceutical, or cosmetics industries. Crude glycerol, on the other hand, has its significance and applications. The percentage of glycerol in the crude stream can vary from 65percent to 85percent (w/w), depending on the glycerol purification method or feedstock used by biodiesel producers (Gonzalez-Pajuelo et al., 2005; Mu et al., 2006). For instance, Thompson & He (2006) noted that glycerol levels varied depending on the biodiesel feedstock utilized. They discovered that waste vegetable oil had the highest glycerol content (76.6 percent), then soy oil (67.8 percent), and mustard seed (62 percent).

Additionally, several factors affect glycerin prices in Indonesia, including supply and demand, production costs, and raw materials. The production of biodiesel, as well as the personal care and food industries, are what primarily drive glycerin demand. The availability of substitute raw materials and byproducts to produce biodiesel, such as grease and coconut oil, can also impact glycerol prices. The cost of glycerol is often closely tied to the price of crude oil and natural gas, as these are the primary raw materials used in biodiesel production (Harahap et al., 2019). The availability of substitute raw materials and byproducts to produce biodiesel, such as grease and coconut oil, can also impact glycerol prices. The prices of these agricultural materials can fluctuate depending on weather conditions and

crop yields. As a result, factors such as the price of raw materials, labor, transportation, and energy can also impact glycerin's price. In Indonesia, where CPO is a significant feedstock for biodiesel production, the utilization of glycerin is essential for the industry's overall economic viability and sustainability. Proper administration and utilization of the glycerin byproduct contribute to the efficient use of resources and the development of a circular economy.

In previous studies, glycerin was used as a variable. Abu-Baker et al. (2017) considered glycerin as a possible component for biofuels in Indonesia, and they suggested that glycerin affects biodiesel's price. The study found that glycerin could be a cheaper alternative to other biofuel materials. Shishido et al. (2018) did another study on how glycerin works as a fuel in internal combustion engines and how it affects engine performance and pollution. The results showed that glycerin could reduce engine emissions and make engines use less power, which causes to decrease in reliance on fossil fuel and reduces energy costs.

A D'Angelo et al. (2017) study examined how glycerin prices affect biodiesel's conversion cost. They found that as the price of glycerin increases, the cost of converting the cost of biodiesel also increases. Similarly, Chen et al. (2019) looked at the economic potential of making biofuels from glycerin, and they found that it could be an excellent alternative feedstock for producing biofuels. These studies show the importance of glycerin as a variable in energy economics and could help develop more sustainable energy-use methods.

### **2.1.5 PFAD (Palm Fatty Acid Distillate)**

PFAD is an abbreviation for palm fatty acid distillate. It is produced as a byproduct of refining crude palm oil (CPO). Handojo (2019) indicated that during the refining of crude palm oil (CPO), around 4 percent of palm fatty acid distillate (PFAD) would be produced. PFAD is essential in the biodiesel conversion process from CPO in Indonesia. The crude oil goes through a process called physical refining or steam distillation during the refining of CPO. This process removes impurities, free fatty acids, and other undesirable components from crude oil. As a result, PFAD is produced as a byproduct. PFAD contains a high concentration of

free fatty acids (FFA) and is a lower-grade product than CPO. However, it is a valuable feedstock for biodiesel production (Gapor et al., 1988).

In Indonesia, where palm oil production is significant, the use of PFAD in the production of biodiesel helps to optimize the country's resources while also boosting the country's bioenergy ambitions. Furthermore, PFAD can help lessen the environmental impact of this byproduct's disposal. It is crucial to note that using PFAD as a feedstock for biodiesel production may require particular process modifications and optimization to account for its increased FFA content (Lei, 2019). However, when handled effectively, PFAD can contribute to Indonesia's biodiesel industry's sustainability and economic viability. In 2018, PFAD output hit 1.6 million tons, and approximately 1 million tons of this quantity was exported. However, PFAD has the potential to be used as a raw material to produce calcium fat, a supplement for ruminants. The use of PFAD in animal feed has additional value, including a 5-8 percent increase in milk supply, accelerated postpartum weight growth, a 23.6 percent increase in cow fertility, and a 0.2-0.1 percent increase in fat milk content (IEA, 2021).

Several factors, such as supply and demand, production costs, and governmental regulations, affect the price of palm fatty acid distillate (PFAD) in Indonesia. PFAD is a by-product of the palm oil refining process and is primarily used as a source of biofuel and animal feed. The growing biofuel industry and the demand for animal feed in the country drive the demand for PFAD. However, the cost of production can also have an impact on the price of PFAD in Indonesia. The price of crude palm oil, the raw material used to produce PFAD, can fluctuate depending on weather conditions and crop yields.

Additionally, the cost of the refining and distillation processes, transportation costs, and other factors can affect the price of PFAD. Government regulations can also impact the price of PFAD in Indonesia. For example, the government may impose import tariffs, taxes, and additional fees on imports.

However, due to its importance as a by-product, many researchers (Lokman et al., 2015; Cho et al., 2013; Chen et al., 2018; Abun Lei, 2019) have analyzed

PFAD as a variable in their studies. Additionally, several studies (Lokman et al., 2015; Embong et al., 2021; Abun Lei, 2019) have shown that there is a strong link between PFAD (Palm Fatty Acid Distillate) prices and the conversion of CPO into biodiesel. Meanwhile, CPO conversion into biodiesel depends on the price and availability of raw materials like PFAD. When the price of PFAD increases, the costs of biodiesel conversion will also increase. This causes a decrement in the demand for biodiesel. On the other hand, when PFAD prices decrease, the cost of converting biodiesel from CPO will lead to the decrease, which will cause an increase in demand for biodiesel (Lokman et al., 2015; Cho et al., 2013; Chen et al., 2018; Abun Lei, 2019).

Abun Lei (2019) found that biodiesel conversion from CPO influences the demand and price of PFAD. When the demand for biodiesel increases, the demand for PFAD also increases. This caused to increment in the price of PFAD. This makes a connection between the price of PFAD and the cost of biodiesel conversion from CPO. In this study, we wanted to find out how PFAD affects the price of biodiesel in Indonesia and the economic consequences of PFAD in the fluctuation in the price of biodiesel.

#### **2.1.6 Gasoil (Gasoline/Solar)**

Gasoil is a distillate fuel made from crude oil, often known as high-speed diesel, diesel oil, or diesel fuel. Diesel engines often utilize gasoline, such as those used in heavy-duty cars. A refining process divides crude oil into various components based on their boiling points to produce gasoline. However, gasoil has a greater boiling point than gasoline, often produced from heavier ingredients like gas and vacuum gas oils (Peri et al., 2022). Gasoline is a crucial fuel for transportation and power production due to its high energy density, portability, and ease of storage. It can provide more energy per unit volume since it has a greater energy density than gasoline. In diesel engines, gasoline is also more effective, which may result in improved fuel efficiency and reduced emissions.

However, burning gas or oil releases several hazardous gases and chemicals that may be hazardous to both the environment and human health. Environmentally,

among the pollutants released are nitrogen oxides (NO<sub>x</sub>), particulate matter (PM), sulfur dioxide (SO<sub>2</sub>), and other air toxics. When discharged into the atmosphere, these pollutants can cause respiratory issues, smog formation, and air pollution. Additionally, the extraction, manufacturing, and transportation of gasoil may have an adverse effect on the environment, resulting in oil spills and habitat destruction. In contrast, alternative fuels and technologies that help lessen the impact of transportation and energy production on the environment have attracted increasing attention in recent years. These include biofuels, electric vehicles, and renewable energy sources like wind and solar power. Even though gasoil will continue to play a significant role in the world's energy mix for as long as possible, its utilization will likely decrease as these alternatives gain traction (Edition, 2008).

Gasoil plays a crucial role in the biodiesel conversion process in Indonesia. A feedstock, such as CPO, combines with alcohol (often methanol) during transesterification to create biodiesel and glycerin as byproducts. Because it participates in the transesterification reaction as a co-solvent or co-reactant, gasoil is crucial to this process. By expediting the response and boosting biodiesel production, it helps with the conversion of feedstock (CPO) into biodiesel. Using gasoil in the biodiesel conversion process emphasizes the need for a consistent and stable supply of gasoil for Indonesia's biodiesel sector. The capacity and effectiveness of the nation's biodiesel facilities may be directly affected by the quantity and quality of gasoil available. The Indonesian government and biodiesel producers must ensure a sufficient supply of gasoil to support the development and sustainability of the renewable energy industries in Indonesia.

In Indonesia, initiatives are being taken to lessen the effects of gasoline on the environment and to encourage the use of cleaner, more environmentally friendly fuels. This includes putting biodiesel blending regulations into place, such as the B20 (20 percent biodiesel mix) and the B30 (30 percent biodiesel blend) programs, which are meant to reduce greenhouse gas emissions and encourage using renewable energy sources in the transportation industry.

However, several energy economics, transportation, and emissions studies have used gasoline as a variable due to its high demand. Peri et al. (2022) looked at

the link between the price of gasoline and the cost of shipping by sea. They found that the price of gasoil significantly affects the costs of running a shipping company. Another study by González et al. (2019) focused on how changes in the price of gasoil affect the carbon emissions of the transportation sector. They found that when the price of gasoil increases, carbon emissions decreases because fuel-efficient cars are cheaper to run, and less gasoil is used. These studies show how important gasoil is as a variable for understanding the economics of energy and the effects of the transportation sector on the environment. We argue that gasoil influences biodiesel prices because biodiesel is an alternative biofuel for gasoil, and they both impact each other.

## **2.2 Biodiesel and Renewable Energy Industry**

Indonesia's biodiesel and renewable energy industries have grown rapidly in recent years. The Indonesian government has set a target of 23 percent renewable energy in the national energy mix by 2025, prompting major investment in the area. Biodiesel has received significant attention, with the government implementing a mandatory blending program in 2006. This policy stipulates that all diesel fuel sold in the nation includes at least 30 percent biodiesel (B30), which has enhanced the country's demand for biodiesel. This thesis will also present an overview of Indonesia's biodiesel and renewable energy sectors, emphasizing relevant contemporary publications.

Indonesia is one of the world's greatest palm oil producers, which has resulted in the growth of a considerable biodiesel industry in the country. The United States Department of Agriculture (USDA) reported that Indonesia produced 6.2 billion liters of biodiesel in 2020 and more than 3.3 billion liters in 2019 (USDA, 2021). According to the research, the rise in output is due to the government's B30 mandate, which has helped to stabilize demand for biodiesel. Aside from the B30 mandate, the Indonesian government has enacted regulations that benefit the biodiesel industry. In this regard, the government has offered incentives for biodiesel producers, such as tax breaks and subsidies for developing biodiesel facilities in Indonesia (Yudha & Tjahjono, 2019). These regulations have helped

attract investment and contribute to the industry's development.

Indonesia has been constantly investing in renewable energy sources other than biodiesel, such as geothermal, hydroelectric, solar, and wind power. According to the International Renewable Energy Agency (IRENA), Indonesia's total installed renewable energy capacity was 11.4 GW in 2020, with hydropower accounting for 8.8 GW (IRENA, 2021). The government has set a 23 percent renewable energy target in the national energy mix by 2025, increasing investment in Indonesia. But in recent years, geothermal electricity has received particular attention in Indonesia. The country has the largest geothermal energy reserves in the world, with a potential capacity of 29 GW (Udin, 2020). Therefore, the government has implemented regulations encouraging geothermal energy development, such as a reduced tariff program and a risk guarantee fund (IRENA, 2021). These regulations have encouraged investment in renewable energy, and Indonesia is now one of the world's top geothermal energy producers.

Despite the rapid growth of Indonesia's biodiesel and renewable energy industries, the industry still faces challenges. One of the most significant challenges is a lack of finance. While the government has offered incentives for the industries, it still relies on private investment, which may be challenging to recruit. Furthermore, there are questions regarding the biodiesel industry's sustainability since there are difficulties with land usage and deforestation associated with palm oil extraction (Soebroto et al., 2021). Another challenge confronting industries is the need for infrastructural development. Moreover, there is a specific lack of infrastructure to support the distribution of biodiesel and renewable energy, making it difficult for these companies to compete with fossil fuels (Udin, 2020).

### **2.3 Biodiesel Production Process**

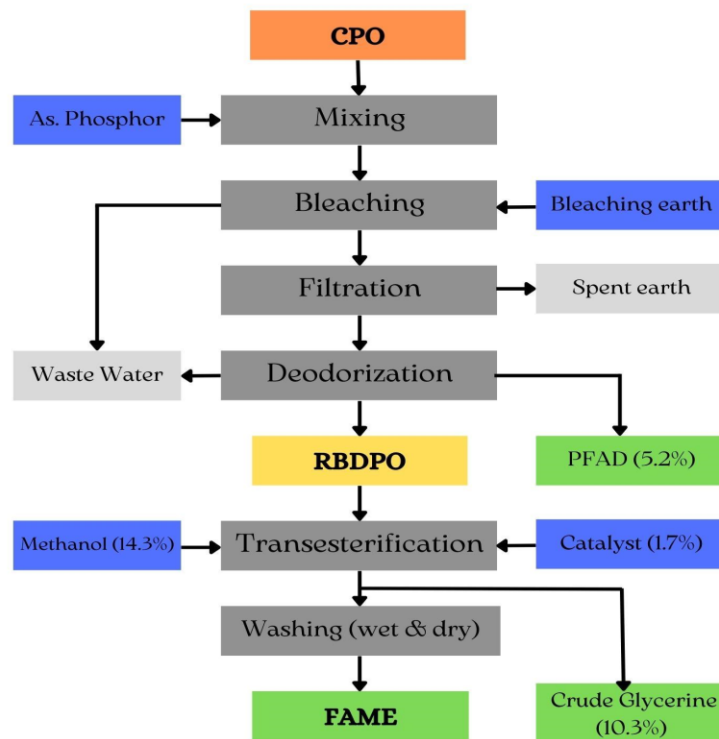
In Indonesia, the biodiesel production process from CPO (crude palm oil) feedstock generally consists of multiple stages, such as preparing raw materials. In the first stage, CPO (raw material) is brought in for the production process. The CPO is typically derived from palm oil mills, where it is produced from the palm oil tree's fruit. The CPO is then carried to the biodiesel conversion industries and

kept in tanks until it is ready for processing. However, transesterification is a crucial chemical process that converts CPO into biodiesel in the second phase. In a reactor, CPO is combined with an alcohol (usually methanol) and a catalyst (such as sodium hydroxide or potassium hydroxide). When the mixture is heated and stirred, the CPO degrades into glycerol and fatty acid methyl esters (FAME), which are biodiesel. The process usually takes 1 to 2 hours, and the resultant biodiesel is 95–98 percent pure (Mahmud, 2019; Alkabbashi, 2009).

The third stage is purification and washing, which involves purifying and washing the biodiesel converted during the transesterification process to eliminate any leftover impurities such as soap, water, and unreacted alcohol. Biodiesel is normally processed via a succession of filters, centrifuges, and distillation columns. The fourth process is drying and storage, which involves drying the purified biodiesel to eliminate any leftover water and storing it in tanks until it is ready to be delivered or blended with ordinary diesel fuel.

Furthermore, the fifth and last stage is blending, in which biodiesel is mixed with ordinary diesel fuel to produce B5 or B10 diesel in line with government requirements (U.S. IEA, 2021). Blending typically entails mixing biodiesel with diesel fuel in a blending tank before delivering the blended power to storage tanks or straight to distribution routes. Figure 1 depicts the manufacturing process.

*Figure 2.3: Biodiesel Production Process from CPO Feedstock*



It is crucial to note that the procedure may differ somewhat based on the facility's capacity and the technology employed. Nonetheless, the essential stages for most biodiesel manufacturing plants in Indonesia are identical (U.S. IEA, 2021). Furthermore, using CPO as a feedstock for biodiesel production is linked to environmental and social issues such as deforestation, habitat damage, and human rights abuses. We concentrate on chosen commodities such as CPO, methanol, catalyst, PFAD, glycerol, and gasoline in this research since they are all important in the unit production of biodiesel (Cako et al., 2022). Furthermore, other commodities such as phosphorus and bleaching earth have little bearing on the cost of biodiesel.

## **2.4 Price Mechanism**

The price mechanism is a fundamental economic concept that describes how prices in a market economy are determined. In a market economy, the interaction of supply and demand determines the prices of goods and services, with the equilibrium price occurring when the quantities demanded and supplied are equal. The price mechanism is critical for efficient resource allocation, signaling to producers what commodities and services to make and how much to produce and to consumers what goods and services to buy and at what price. Supply and demand, production costs, and governmental regulations are just a few of the factors impacting CPO, methanol, catalyst, glycerol, PFAD, and gasoline prices in Indonesia (Harahap et al., 2019). The increasing global demand for palm oil, its derivatives, biofuels, and other industrial uses, the growing use of methanol as a fuel, the expansion of the chemical and petrochemical industries, and the demand for biodiesel production and animal feed all contribute to the demand for these commodities.

However, the cost of production also considerably impacts the price of these commodities. Weather conditions, crop yields, labor expenses, transportation costs, raw materials, energy, and R&D costs are all elements that might affect production costs (Kharina et al., 2016). The expense of complying with environmental rules and certification criteria might impact the price of these commodities (USDA, 2022).

Government laws and policies also significantly impact the pricing of certain commodities. To keep prices low for consumers, the government may levy export taxes and tariffs on CPOs, establish price controls, or introduce subsidies. Therefore, the government may also set the official price of gasoline based on the cost of production, delivery, and other considerations. Still, it may also provide subsidies to keep consumer prices low (U.S. EIA, 2021). Furthermore, worldwide market movements can impact the prices of certain goods in Indonesia. In reaction to changes in the global market, the government may adjust subsidies or the official price of gasoline.

## **2.5 Previous Research**

The Indonesian government has mandated a minimum 30 percent biodiesel (B30) blend in all diesel fuel sold in the country, making biodiesel an increasingly significant renewable energy source. Consequently, the price of biodiesel in Indonesia has become a concern for producers and consumers. This section examines prior research on the determinants of biodiesel prices in Indonesia and related study aspects.

Previous research has identified several factors that affect biodiesel pricing in Indonesia. These factors include the price of crude fuels, the exchange rate, government policies, technological advancement, and the weather. In this regard, Sahirman et al. (2018) found that crude oil prices were the most influential factor in determining the price of biodiesel in Indonesia. This is due to the close relationship between the price of biodiesel and the price of petroleum oil, the primary input used in its production. Harahap et al. (2019) discovered that biorefinery technological advancements in Indonesia reduce the industry's reliance on government subsidies for biodiesel production and its susceptibility to fluctuations in fossil petroleum prices. The exchange rate is also a significant factor in determining the price of biodiesel in Indonesia. Since Indonesia is a net importer of petroleum oil, fluctuations in the exchange rate can have a substantial effect on the price of biodiesel. For instance, Habibie et al. (2019) discovered that exchange revenue was a significant predictor of biodiesel prices in Indonesia. In this regard, Purba et al. (2018) suggest that replanting policies can mitigate the negative impact

on foreign exchange revenues.

Indonesian biodiesel prices have also been found to be heavily influenced by government policies. For instance, the government mandate for B30 has increased demand for biodiesel, which has helped to maintain price stability. Concerns have been raised about the long-term viability of the biodiesel industry in Indonesia due to land use and deforestation issues associated with palm oil production (Soebroto et al., 2021). Consequently, the government has implemented policies to encourage the development of sustainable biodiesel, which may have a future impact on prices.

Silalahi et al. (2020) state that the recent Indonesian government mandate to blend 20 percent biodiesel with 80 percent fossil fuel has a favorable economic, social, and environmental impact. Despite all the challenges, this policy is still a work in progress that can be completed successfully. Indonesian biodiesel prices have also been found to be affected by weather conditions. For instance, a study by Suhariyanto et al. (2017) discovered that weather conditions, such as rainfall and temperature, significantly impacted the price of crude palm oil (CPO), the primary input used in Indonesia's biodiesel production. This suggests weather conditions could indirectly affect biodiesel prices by influencing CPO prices.

According to the study by Mundi et al. (2008), the development of biodiesel will reduce poverty levels. Therefore, biodiesel development should be accelerated by appointing government-owned companies in the CPO and energy industries by providing the sector with tax incentives and price subsidies (Mundi et al., 2008). Additionally, biodiesel production development is thought to assist society and regional and national economies by creating jobs, improving infrastructure, generating government revenue, reducing national reliance on fossil fuels, and minimizing the negative environmental effects of fossil fuels.

Halimatussadiah et al. (2021) found that the ambitious biodiesel policy must be supported by land expansion equal to 48 percent to 76 percent of the productive oil palm plantation area. This is because, despite the biodiesel policy lowering diesel imports, the potential loss of CPO exports outweighs the diesel import

savings. However, according to the study, the limited domestic market, particularly because of the uncompetitive price of diesel fuel, low and high prices, are obstacles to producing domestic biodiesel for absorption. Domestic political concerns associated with using biodiesel by government-designated parties are also vital in ensuring biodiesel's longevity (Kurniawan et al., 2021).

## **2.6 Literature Gap**

Indonesia is the world's largest biodiesel producer and has adopted several policies and incentives to boost the use of biodiesel as a transportation fuel. However, biodiesel prices in Indonesia have fluctuated significantly, threatening the profitability of the biodiesel business and limiting the use of biodiesel as a fuel. On the other hand, policymakers and stakeholders in the biodiesel industry must understand the factors that influence biodiesel prices in Indonesia. The Indonesian biodiesel sector has been extensively researched with an emphasis on feedstocks and price factors (Martin, 2017; Mayasari and Dalimi, 2017; Hardaya, Silveira, and Khatiwada, 2018; Ambat, 2018; Rincoin, 2014; Sahirman et al., 2018; Habibie et al., 2019; Suhariyanto et al., 2017). However, there is a gap in the research regarding assessing the relationship between the input and output of the Indonesian biodiesel industry. This gap indicates a lack of understanding of how feedstock supply and conversion processes affect biodiesel prices.

Furthermore, there is a lack of studies on the impact of international market conditions on Indonesia's domestic biodiesel industries. Although some studies have been conducted to examine the impact of global oil prices on biodiesel pricing, other international market variables such as currency exchange rates or trade agreements, technology innovation, and policy implementation have been overlooked (Purba et al., 2018; Silalahi et al., 2020; Sahirman et al., 2018; Habibie et al., 2019; Suhariyanto et al., 2017). The gap in research on this topic is significant since Indonesia's biodiesel business operates worldwide, and global market conditions can substantially impact the domestic industry.

Additionally, there is a considerable gap in the literature regarding research on the relationship between inputs such as CPO, methanol, catalyst, PFAD, and

glycerine and the output (biodiesel) of the Indonesian bioenergy market, as well as the impact of the foreign market circumstances on the domestic biodiesel industry. Filling these gaps will improve our understanding of the Indonesian biodiesel market and allow policymakers to build long-term plans to support the industry's growth. Further research focuses on time, variables, data, and appropriate models to fill this gap to reduce the projected results. This study aims to fill a gap in the literature by studying the factors that influence biodiesel pricing in Indonesia and providing feasible methods to lessen their impact.

## **CHAPTER 3**

# **RESEARCH METHODOLOGY**

This chapter explores the fundamentals of data collection, the Vector Autoregressive (VAR) model, and the VAR estimation procedure. The collection of accurate and pertinent data is essential for any empirical analysis, and we investigate various methods and considerations for effective data collection. The VAR model is a robust statistical framework extensively employed in time series analysis to comprehend the dynamic interrelationships between multiple variables. We investigate the fundamental principles of the VAR model, including its assumptions and ramifications for capturing the complex interactions of variables over time. All variables in this study are interrelated such that the standard demand model cannot capture the dynamic relationship of biodiesel prices. In addition, we explored the various estimation techniques used to adapt a VAR model to the data, enabling us to obtain precise parameter estimates. By the end of this chapter, you will have a thorough understanding of data collection techniques, the theoretical foundations of the VAR model, and the practical aspects of VAR estimation, enabling you to conduct sophisticated time series analysis and draw insightful conclusions from your data.

### **3.1 Data Collection Method**

This section presents detailed information about data collection methods. In order to comprehensively analyze the factors that influence biodiesel prices in Indonesia, this study employs a robust quantitative methodology that utilizes monthly time series data from a diverse range of sources, including biodiesel companies, governmental institutions, and agencies such as the Ministry of Energy and Mineral Resources (MEMR), Independent Commodity Intelligence Service (I.C.I.S), Ministry of Industry (MOI), Ministry of Trade (MOT), and the Central Bureau of Statistics, as well as international organizations such as the OECD (Organization for Economic Co-operation and Development) and EIA (Energy Information Administration).

This study ensures a comprehensive and rigorous analysis by incorporating existing research on the determinants of biodiesel prices in Indonesia. Moreover, the selected variables for inclusion in the investigation have been identified in prior literature (Amiruddin et al., 2005; Rosa and Vasciaveo, 2008; Abdullah and Wahid, 2010; Nazlioglu and Soytas, 2011; Kumar et al., 2014) as a crucial role in the fluctuation of biodiesel prices in Indonesia and other countries. The inclusion of these variables is expected to provide valuable insights into the determinants of biodiesel prices in Indonesia and thus contribute to the development of effective policies and strategies in the biofuel industry in Indonesia.

### 3.1.1 Data Description

This section explains the data description, which includes the nature of variables, codes, measurement units, and data sources. Table 3.1 shows a brief description of the data.

*Table 3.1: Data Description*

<b>Variable</b>	<b>Description</b>	<b>Source</b>
Biodiesel (BIO)	Rupiah (IDR) (Per Liter)	MEMR & I.C.I.S
Crude Palm Oil (CPO)	Rupiah (IDR) (Per Kilogram)	MEMR & I.C.I.S
Catalyst (CTL)	Rupiah (IDR) (Per Kilogram)	MEMR & I.C.I.S
Methanol (MTN)	Rupiah (IDR) (Per Kilogram)	MEMR & I.C.I.S
Crude Glycerin (CRD)	Rupiah (IDR) (Per Kilogram)	MEMR & I.C.I.S
Palm Fatty Acid Distillate (PFAD)	Rupiah (IDR) (Per Kilogram)	MEMR & I.C.I.S
Gasoil (GOIL)	Rupiah (IDR) (Per Liter)	MEMR & I.C.I.S

*Note: MEMR (Ministry of Energy and Mineral Resources), I.C.I.S (Independent Commodity Intelligence Service)*

Table 3.1 summarizes the data collection sources and descriptions. A dataset with useful information on commodity pricing in Indonesia's energy sector has been compiled. These prices, stated in Indonesian Rupiah (IDR) per liter or kilogram, provide insight into the market's dynamics. This dataset defines several variables, each representing a specific product and its related price. One such variable is biodiesel (BIO), which indicates the price of a renewable fuel derived from biomass, such as vegetable oils and animal lipids. Another significant variable is crude palm oil (CPO), which denotes the price of extensively used vegetable oil extracted from oil palm fruits. This oil is both a culinary ingredient and an essential

component in the biodiesel production process. A second variable, catalyst (CTL), represents the cost of a substance used to speed up chemical reactions.

Given its presence in the dataset, it is probable that this catalyst is essential to the biodiesel production process. Methanol (mtn) is yet another variable that reflects the price of a volatile liquid with various applications, including solvents, antifreeze, and fuel. Methanol can be utilized as a vital component in biodiesel production. In addition, the dataset contains the price of crude glycerin (CRD), a biodiesel production byproduct. This glycerin has a wide range of industrial applications. Palm fatty acid distillate (PFAD) is an additional variable that indicates the price of a byproduct of palm oil refining. This substance is utilized to manufacture cleansers, detergents, and numerous industrial processes. The dataset also includes the price of gasoil (GOIL), a diesel fuel commonly used in engines and heating systems. It is important to note that Indonesia's Ministry of Energy and Mineral Resources (MEMR) is the primary source for these price values, providing valuable insights into the energy market.

The government of Indonesia (GOI) sets the market price rate for biodiesel every month as a part of the required mandate. Nevertheless, based on what the government-owned agricultural trading company KPBN (Kharisma Pemasaran Bersama Nusantara) stated, biodiesel was produced at these prices about domestic molasses prices in 2016. Before 2016, prices were based on Argus (benchmarks for commodity pricing and trading). The GOI sets biodiesel prices based on the prices of CPO from the same state-owned enterprise. Numerous factors, such as the biodiesel industry's installed capacity of 12,06 million kiloliters (KL), contribute to the effectiveness of the mandated 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. The market price for the biodiesel market index price can be seen in the table below.

*The formula for the Biodiesel Market Index Price (HIP)*

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**HIP Formula (IDR/litter)**

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$$\text{Biodiesel} = (\text{CPO Price IDR/kg} + 85\$/\text{ton}) \times 870 \text{ kg/m}^3 + \text{Transportation Cost}$$

Source: Ministry of Energy Mineral Resource (MEMR)

In the past few years, the method for pricing HIP biodiesel has been changed several times. The price for biodiesel was initially set at USD125 per metric ton (MT) in 2015. In 2017, the Indonesia government cut the price to USD100 per metric ton (MT). Also, the price per MT went down to USD80 in May 2020. Lastly, the exchange rate used to determine the price was changed to USD85 per MT in September 2020 (MEMR, 2022).

Table 3.1: Price Input for Producing FAME Based on the HIP Formula

COST OF PRODUCING 1 TON FAME							
CPO	Main Raw Materials	\$715.01	100.00%	1,000.00	Kg	\$715.01	
Variable Cost						\$46,52	
Input Material	Explanation	Cost Per Unit	Rate	Need	Unit	Cost	
Bleaching Earth	Processing RBDPO	\$0.28	0.80%	8.00	Kg	\$2.24	
Phosphor	Processing RBDPO	\$1.05	0.05%	0.50	Kg	\$0.53	
Methanol	Processing FAME	\$390.72	14.30%	143.00	Kg	\$55.87	
Catalyst	Processing FAME	\$879.93	1.70%	17.00	Kg	\$14.96	
Oil Loss Conversion	Processing FAME	\$715.01	6.80%	68.00	Kg	\$48.62	
Glycerin	By Product	\$400.58	10.30%	103.00	Kg	-\$41.26	
PFAD	By Product	\$717.48	5.20%	52.00	Kg	-\$37.31	
Fuel	Processing RBDPO	\$0.82	0.35%	3.50	Liter	\$2.87	
Fixed Cost						\$38,36	
Input Material	Explanation	Cost Per Unit	Rate	Need	Unit	Cost	
<b>Direct Labor</b>							
Direct Labor Cost		\$113.13	1.30%	\$1.47	Per Ton Fame	\$1.47	
<b>Direct Overhead</b>							
Overhead Production (Operational cost)		\$113.13	14.27%	\$16.14	Per Ton Fame	\$16.14	
<b>Direct Depreciation Expense</b>							
Building	20	Years	\$113.13	16.53%	\$0.94	Per Ton Fame	\$0.94
Machine	10	Years	\$113.13	70.76%	\$8.01	Per Ton Fame	\$8.01
Others	5	Years	\$113.13	2.16%	\$0.49	Per Ton Fame	\$0.49
<b>Expected Margin</b>		\$113.13	10.00%	\$11.31	Per Ton Fame	\$11.31	
<b>Total Conversion Cost</b>						<b>85</b>	

Source: Author's computation according to MEMR data set and Process.

Table 3.1 presents comprehensive information on converting biodiesel from CPO in

Indonesia. We can see in detail how it works practically, and it is shown that a one-ton conversion of CPO into biodiesel requires 85 USD. That cost is based on the HIP pricing method.

## 3.2 VAR Model

### 3.2.1 Introduction

The Vector Autoregression model is fitted to investigate the factors influencing biodiesel prices in Indonesia. Because the VAR model is an econometric model used to analyze the relationship between multiple variables over time (Gujarati, 1987), we used this model to analyze comprehensively how changes in one variable can influence other variables and how these effects may evolve. In a biofuel-based economy, examining the pricing of relationships is critical for determining economic feasibility, optimizing supply chain efficiency, increasing market competitiveness, and encouraging sustainability. Stakeholders may make educated decisions that contribute to the success and long-term profitability of the biofuel business by successfully understanding and controlling relationship prices.

Simo Hall and Ragnar Frisch introduced the concept of using multiple variables in an econometric model in the 1930s. Christopher Sims formally developed VAR models in the 1970s and 1980s. Sims demonstrated that a system of equations representing the relationship between a variable and a set of lagged values of other variables could be used to analyze the dynamic relationships between multiple variables (Agung, 2011; Gujarati, 1987).

The VAR\_Lag p, which represents a regular VAR model with p lags, can be written as follows:

$$y_{i_t} = \alpha + \sum_{j=1}^p \beta_j y_{i_{t-j}} + e_t$$

Where  $y_{i_t}$  is a Px1 vector of the P time series being considered,  $\alpha$  is a constant,  $\beta_j$  are matrices of coefficients, and  $e_t$  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 that are included as predictors. The coefficients in the VAR model are estimated

using ordinary least squares (OLS) regression or maximum likelihood estimation. However, the estimated coefficients can be used to predict values of the time series, analyze the relationships between the time series, and test hypotheses about the interdependencies between the time series (Gujarati, 1987).

### 3.2.2 Model Description

This section discusses the several stages to implementing this methodology in this study for the purpose of investigating the factors that influence biodiesel prices in Indonesia.

#### 3.2.2.1 Model Specification

The model specification for this study is presented in this section. It is a crucial step in implementing the Vector Autoregression (VAR) model specification to choose it carefully. In order, the variables that will be included in the VAR model must be selected. However, while a wide variety of these models are available, we will concentrate on one that primarily consists of the features that these models frequently share. Thus, degrees of freedom may be constrained due to Indonesia's short sample period and the sizeable lags needed to produce well-behaved residuals in estimated VAR models. In order to ensure an accurate estimation, it is crucial to include the variables in the VAR model liberally.

To accomplish this, we will adopt the strategy suggested by Gujarati (1987) and incorporate as many pertinent variables as possible into the model. By doing this, we can make the most of the data information and better understand how the variables relate to one another. As a result, we provide the VAR model specifications for each variable below, which will act as the basis for the following analysis.

$$\begin{aligned} \Delta \ln bio_{1t} = & \alpha_1 + \sum_{j=1}^p \beta_{1t} \Delta \ln bio_{1t-1} + \sum_{j=1}^p \beta_{2t} \Delta \ln cpo_{it-1} + \sum_{j=1}^p \beta_{3t} \Delta \ln ctli_{t-1} + \\ & \sum_{j=1}^p \beta_{4t} \Delta \ln mtn_{it-1} + \sum_{j=1}^p \beta_5 \Delta \ln crd_{it-1} + \sum_{j=1}^p \beta_{5t} \Delta \ln pfad_{it-1} + \\ & \sum_{j=1}^p \beta_5 \Delta \ln goil_{it-1} + e_t \dots\dots\dots (Eq. 01) \end{aligned}$$

$$\Delta \ln cpo_{2t} = \alpha_2 + \sum_{j=1}^p \beta_{2t} \Delta \ln cpo_{it-1} + \sum_{j=1}^p \beta_{1t} \Delta \ln bio_{1t-1} + \sum_{j=1}^p \beta_{3t} \Delta \ln ctli_{t-1} +$$

$$\sum_{j=1}^p \beta_{4t} \Delta \ln mtn_{i_{t-1}} + \sum_{j=1}^p \beta_5 \Delta \ln crd_{i_{t-1}} + \sum_{j=1}^p \beta_{5t} \Delta \ln p f a d_{i_{t-1}} + \sum_{j=1}^p \beta_5 \Delta \ln g o i l_{i_{t-1}} + e_t \dots \dots \dots \text{(Eq. 02)}$$

$$\Delta \ln c t l_{3t} = \alpha_3 + \sum_{j=1}^p \beta_{3t} \Delta \ln c t l_{i_{t-1}} + \sum_{j=1}^p \beta_{2t} \Delta \ln c p o_{i_{t-1}} + \sum_{j=1}^p \beta_{1t} \Delta \ln b i o_{1t-1} + \sum_{j=1}^p \beta_{4t} \Delta \ln m t n_{i_{t-1}} + \sum_{j=1}^p \beta_5 \Delta \ln c r d_{i_{t-1}} + \sum_{j=1}^p \beta_{5t} \Delta \ln p f a d_{i_{t-1}} + \sum_{j=1}^p \beta_5 \Delta \ln g o i l_{i_{t-1}} + e_t \dots \dots \dots \text{(Eq. 03)}$$

$$\Delta \ln m t n_{4t} = \alpha_4 + \sum_{j=1}^p \beta_{4t} \Delta \ln m t n_{i_{t-1}} + \sum_{j=1}^p \beta_{3t} \Delta \ln c t l_{i_{t-1}} + \sum_{j=1}^p \beta_{2t} \Delta \ln c p o_{i_{t-1}} + \sum_{j=1}^p \beta_{1t} \Delta \ln b i o_{1t-1} + \sum_{j=1}^p \beta_5 \Delta \ln c r d_{i_{t-1}} + \sum_{j=1}^p \beta_{5t} \Delta \ln p f a d_{i_{t-1}} + \sum_{j=1}^p \beta_5 \Delta \ln g o i l_{i_{t-1}} + e_t \dots \dots \dots \text{(Eq. 04)}$$

$$\Delta \ln c r d_{5t} = \alpha_5 + \sum_{j=1}^p \beta_5 \Delta \ln c r d_{i_{t-1}} + \sum_{j=1}^p \beta_{4t} \Delta \ln m t n_{i_{t-1}} + \sum_{j=1}^p \beta_{3t} \Delta \ln c t l_{i_{t-1}} + \sum_{j=1}^p \beta_{2t} \Delta \ln c p o_{i_{t-1}} + \sum_{j=1}^p \beta_{1t} \Delta \ln b i o_{1t-1} + \sum_{j=1}^p \beta_{5t} \Delta \ln p f a d_{i_{t-1}} + \sum_{j=1}^p \beta_5 \Delta \ln g o i l_{i_{t-1}} + e_t \dots \dots \dots \text{(Eq. 05)}$$

$$\Delta \ln p f a d_{6t} = \alpha_6 + \sum_{j=1}^p \beta_{6t} \Delta \ln p f a d_{i_{t-1}} + \sum_{j=1}^p \beta_5 \Delta \ln c r d_{i_{t-1}} + \sum_{j=1}^p \beta_{4t} \Delta \ln m t n_{i_{t-1}} + \sum_{j=1}^p \beta_{3t} \Delta \ln c t l_{i_{t-1}} + \sum_{j=1}^p \beta_{2t} \Delta \ln c p o_{i_{t-1}} + \sum_{j=1}^p \beta_{1t} \Delta \ln b i o_{1t-1} + \sum_{j=1}^p \beta_5 \Delta \ln g o i l_{i_{t-1}} + e_t \dots \dots \dots \text{(Eq. 06)}$$

$$\Delta \ln p g o i l_{7t} = \alpha_6 + \sum_{j=1}^p \beta_5 \Delta \ln g o i l_{i_{t-1}} + \sum_{j=1}^p \beta_{6t} \Delta \ln p f a d_{i_{t-1}} + \sum_{j=1}^p \beta_5 \Delta \ln c r d_{i_{t-1}} + \sum_{j=1}^p \beta_{4t} \Delta \ln m t n_{i_{t-1}} + \sum_{j=1}^p \beta_{3t} \Delta \ln c t l_{i_{t-1}} + \sum_{j=1}^p \beta_{2t} \Delta \ln c p o_{i_{t-1}} + \sum_{j=1}^p \beta_{1t} \Delta \ln b i o_{1t-1} + e_t \dots \dots \dots \text{(Eq. 07)}$$

Where:

*lnbio* = Log of Biodiesel Price

*lncpo* = Log of CPO (Crude Palm Oil) Price

*lnctl* = Log of Catalyst Price

*lnmtn* = Log of Methanol Price

*lncrd* = Log of Glycerin Price

*lnpfad* = Log PFAL (Palm Fatty Acid Distillate) price

*lnpgoil* = Log Gasoil Price

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, facilitating interpretation, and reducing the impact of outliers. (Wooldridge, 2016; Greene, 2018; Osborne, 2010). Furthermore,  $y_{i_t}$  is a  $P \times 1$  vector of the  $P$  time series being considered,  $\alpha$  is a constant,  $\beta_j$  are matrices of coefficients, and  $e_t$  is a  $P \times 1$  vector of error terms. The number  $p$  is the model's lag order and represents the lagged values of the time series that are included as predictors.

### **3.2.3 Model Estimation**

This section discusses the employment of the well-known econometric program EViews 12 from IHS Markit for time series data analysis. However, EViews offers a variety of estimation techniques in multivariate time series models, such as vector autoregression (VAR), vector error correction (VEC), least squares estimates (L.S.) using a system of equations, and system equation estimation approaches (Agung, 2011). It is important to remember that different linear associations or structural equation models may be defined for a given multivariate dataset. Therefore, based on the time series properties of the endogenous variables considered in the analysis, we must decide the first level, first difference, and vector error-correction forms when estimating a Vector Autoregression (VAR) model. As a result, analyzing the time series properties of the endogenous variables is crucial as a first step.

The Augmented Dickey-Fuller (ADF) and Phillips-Perron (P.P) tests are generally used to assess the time series properties of the variable under investigation. These tests' results give us information about the unit root in the time series data. Thus, the variables' unit roots serve as the test's null hypothesis (Gujarati, 1987).

#### **3.2.3.1 Augmented Dickey-Fuller Test**

In this section, the Augmented Dickey-Fuller (ADF) test is explained. We can determine statistically whether the unit root exists by using the Augmented Dickey Fuller (ADF) test, which is a crucial presumption in many statistical models.

A stationary time series has statistical characteristics like mean and variance that do not change over time. On the other hand, non-stationary time series are hard to model and predict because their mean or variance changes over time.

Furthermore, the ADF test also analyzes the significance of the regression coefficients by regressing the time series onto its lag values. We can say it is discovered that the coefficients are significantly different from zero. If the coefficients are significantly different from zero, the time series is deemed stationary; otherwise, it is assumed to be non-stationary. However, it is essential to remember that it is not the only test, and that stationarity can be verified using other techniques, such as the KPSS test (Gujarati, 1987). The regression equation used in the ADF test is as follows:

$$\Delta y_t = \beta_0 + \beta_1 \Delta y_{t-1} + \beta_2 \Delta y_{t-2} + \dots + \beta_p \Delta y_{t-p} + \mu_t$$

In the Augmented Dickey-Fuller (ADF) test,  $\Delta y_t$  represents the first difference in the time series  $y_t$ , where  $t$  is a time trend variable,  $\beta_0$  to  $\beta_p$  are coefficients, and  $\mu_t$  is the error term. However, the null hypothesis for the ADF test is that the time series has a unit root (i.e., is non-stationary), while the alternative hypothesis is that the time series is stationary.

To calculate the test statistic for the ADF test, the t-statistic of the  $\beta_1$  the coefficient is used to measure the strength of the linear relationship between the first difference of the time series and the time trend. Moreover, if the t-statistic of  $\beta_1$  is statistically significant, then the null hypothesis is rejected, and the time series is considered to be stationary. (Agung, 2011; Gujarati, 1987).

### 3.2.3.2 Philips-Perron Test

This section presents the Phillips-Perron test technique for determining whether a time series contains a unit root. This examination comes with the names of Pierre Perron and Peter C. B. Phillips (PHILLIPS & PERRON, 1988). Because many time series models, like ARIMA models, assume that the underlying data is stationary, stationarity is a crucial time series component. A time series unit root

can be tested using the P.P. test, a modification of the well-known Dickey-Fuller test. However, many econometric models can encounter issues due to a non-stationary time series' unit root property. Because it considers autocorrelation and heteroscedasticity in the time series residuals, the P.P. test is considered superior to the Dickey-Fuller test (PHILLIPS & PERRON, 1988; Gujarati, 1987).

The Phillips-Perron test is significant because it can produce reliable results when examining the stationarity of time series data. This is important because econometric models can produce inaccurate results and poor model fit if a time series is not stationary. The P.P. test is frequently employed, highly regarded in econometrics, and is still an essential resource for studying time series data. The Augmented Dickey-Fuller (ADF) regression model, which serves as the foundation for the test, is estimated using the following equation:

$$\Delta y_t = \beta_0 + \beta_1 \Delta y_{t-1} + \beta_2 \Delta y_{t-2} + \dots + \beta_p \Delta y_{t-p} + \mu_t$$

In the context of the Phillips-Perron (P.P.) test, the variable  $\Delta y_t$  represents the first difference of the time series  $y_t$ , where  $t$  is a time trend variable,  $\beta_0$  to  $\beta_p$  are coefficients, and  $\mu_t$  is the error term. The null hypothesis for the P.P. test is that the time series has a unit root (i.e., is non-stationary), while the alternative hypothesis is that the time series is stationary.

To calculate the test statistic for the P.P. test, the t-statistic of the  $\beta_1$  coefficient is used to measure the strength of the linear relationship between the first difference of the time series and the time trend. If the t-statistic of  $\beta_1$  is statistically significant, then the null hypothesis is rejected, and the time series is considered to be stationary.

### 3.2.3.3 Granger Causality Test

This section discusses the Granger Causality Test technique to establish a causal relationship between two-time series variables. It is used to estimate Vector Autoregressive (VAR) models. Regarding lagged values, the test compares the fit of two VAR models—one with lagged values for only one variable and another

with lagged values for both variables. If the second model fits the data better, the first variable may be caused by the second.

Furthermore, economics, finance, and other disciplines frequently use the Granger Causality Test to establish causal links between variables and shed light on the system's dynamics. The Granger Causality Test can be used in VAR models to help to decide which variables to include and the direction of their causal relationships. Making predictions and developing policies can both benefit from this information.

#### **3.2.3.4 Impulse Response Function (IRF)**

This section explained the Impulse Response Function (IRF) as a tool for calculating the dynamic response of a system to an exogenous shock. According to Wei (2006), it is frequently used when estimating Vector Autoregressive (VAR) models. A VAR model is a set of linear equations explaining how various time series variables interact. However, these variables may alter due to an exogenous shock, such as a change in demand or supply of CPO or government policies (Hamilton, 2020). The IRF provides a visual representation of the dynamic impact of a shock on the system while quantifying the size and timing of these changes. The IRF examines how one variable responds to a shock in another (Brockwell and Davis, 2002; Wei, 2006; and Hamilton, 1994).

Furthermore, all other variables' responses are recorded due to shock by a unit change and over a predetermined period. This procedure is repeated for each of the system's variables. The Impulse Response Function (IRF) shows how each variable reacts to a one-unit shock in another variable and can be represented graphically. The IRF is a useful tool for comprehending how shocks are transmitted through a system and can be used to assess the outcomes of various policy interventions. Additionally, it offers perceptions of the system's stability and aids in locating potential sources of instability (Gujarati, 1987).

#### **3.2.3.5 Forecasting**

This section defines the study's forecasting methodology and how we'll

apply this test. Forecasting in the estimation of VAR (Vector Autoregression) is a well-known process for predicting future values of a group of time-series variables based on their historical importance and relationships. The main goal of VAR modelling is to analyze the dynamic connections between the variables and how they affect one another. In order to forecast future values of the dependent variable, VAR models use past values of variables as explanatory variables. Therefore, forecasting is carried out by extrapolating the future values of the variables based on historical data using the estimated coefficients from the VAR model (Gujarati, 1987).

Furthermore, the accuracy by which the VAR model can forecast data depends on the length of the lag order, the selection of independent variables, the quality of the data, and the model's assumptions. Therefore, appropriate model selection and validation techniques should ensure the accuracy of the forecasting results.

# CHAPTER 4

## RESULTS AND DISCUSSIONS

This chapter discusses the results of a Vector Autoregression (VAR) model analysis of the factors that impact biodiesel prices in Indonesia. The chapter will start with a summary of the tests done, including the correlation matrix, stationarity test, cointegration test, Granger causality test, VAR lag criterion test, VAR estimation, impulse response function, and variance decomposition. The chapter follows 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 chapter will end with a discussion of what these findings mean and how policymakers, industry stakeholders, and researchers in the field might use them.

### 4.1 Results

#### 4.1.1 Descriptive Statistics

This section presents the summary statistics that refer to a set of descriptive measures that summarize the key features of a dataset, such as the mean, median, standard deviation, skewness, and kurtosis (Wonnacott & Wonnacott, 2012). Furthermore, these measures are essential in research because they provide a concise data summary and allow researchers to draw meaningful conclusions about their findings (Portney & Watkins, 2015). In addition, summary statistics can help readers better understand the data distribution and identify any outliers or variations. (Salkind, 2017).

*Table 4.1: Descriptive Summary of Statistics*

	<b>LN BIO</b>	<b>LN CPO</b>	<b>LN CRD</b>	<b>LN CTL</b>	<b>LN GAS</b>	<b>LN MTN</b>	<b>LN PFD</b>
Mean	9.090554	6.438681	5.815781	6.677438	8.721734	5.843731	6.470253
Median	9.041022	6.422585	5.705446	6.689164	8.727880	5.878078	6.417956
Maximum	9.652394	7.057456	6.930495	6.843217	9.623655	6.199494	7.430707
Minimum	8.759512	6.002837	5.129899	6.478509	7.937875	5.327876	5.769882
Std. Dev.	0.205856	0.234628	0.505291	0.091631	0.357127	0.209341	0.355713
Skewness	0.922440	0.628080	0.655978	-0.241278	0.452686	-0.345797	0.580391
Kurtosis	3.270332	3.190289	2.393844	2.110315	3.070984	2.200435	2.989208
Jarque-Bera	12.16833	5.649526	7.310283	3.585402	2.886580	3.911619	4.716365
Probability	0.002279	0.059323	0.025858	0.166510	0.236150	0.141450	0.094592
Sum	763.6066	540.8492	488.5256	560.9048	732.6256	490.8734	543.5012

Sum Sq. Dev.	3.517272	4.569181	21.19152	0.696886	10.58582	3.637374	10.50211
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*Source: Author's Computation.*

Table 4.1 summarizes variables in terms of natural logarithm form (LN) of prices, such as biodiesel price (LNBIO), Crude Palm Oil (LNCPO) price, Crude Glycerin (LNCRD) price, catalyst (LNCTL) price, gasoil (LNGAS) price, and Palm Fatty Acid Distillate (LNPAD). We used the natural logarithm form of prices instead of nominal prices because it can help us to address issues related to heteroscedasticity, non-normality, and nonlinearity of the data. Additionally, the logarithm form of values allows us to estimate elasticities, which are essential measures of demand and supply responsiveness to price changes. Therefore, we used the natural logarithm form of prices due to the statistical approach and the looking at the elasticity relationship.

Furthermore, the mean and median provide information about the central or typical values of the variable, whereas the range (maximum and minimum) reflects its variability/spread. However, we can see that LNBIO has the highest mean of 9.090554, indicating a higher trend, and LNCRD has the lowest mean of 5.815781, which shows a more downward direction in the group. On the other hand, we know that the median measures central tendency that is less sensitive to outliers than the mean, and it represents the values that separate the upper 50 percent of data from the lower 50 percent. In this regard, LNBIO reported having the highest median of 9.041022 and LNCRD having the lowest median of 5.704546. Therefore, we can deduce that the central values in the LNBIO group tend to be higher than those in the LNCRD group, and the LNBIO data distribution is skewed toward higher (positive) values compared to the LNCRD data distribution. We know that the standard deviation quantifies the data's dispersion around the mean; in contrast, LNCRD has the highest standard deviation with 0.505291, and LNCTL has the lowest standard deviation with 0.091631. That means the LNCRD group's observations are more spread out or dispersed around the mean than the LNCTL groups.

Furthermore, the skewness and kurtosis indicate the distribution's shape. According to the table above, LNBIO has a positive skewness of 0.922440, which

suggests that the distribution is skewed to the right. A positive skewness indicates the tendency to the right, whereas a negative skewness indicates skewed data to the left. In this sense, LNBIO, LNCPO, LNCRD, LNPFAD and LNGAS are positively skewed, whereas LNCTL and LNMTN are negatively skewed. Kurtosis measures the degree to which a distribution is peaked or flat compared to a normal distribution. Low kurtosis indicates a more balanced distribution with more dispersed data and extreme values. High kurtosis indicates a sharper peak with more data clustering around the mean and fewer extreme values. In addition, Kurtosis helps economists understand the shape of a variable's distribution and its stability or risk. In this case, LNBIO has the highest Kurtosis, which is 3.270332. This means it has a sharp peak with more values close to the mean and fewer values far from it.

On the other hand, LNCTL has the lowest Kurtosis, which is 2.110315. This means that its data are more spread out, and its values are more extreme. The normal distribution is shown by a value of 3. However, values above three show that the tails have more weight, which means more extreme values are in the data. Values less than three indicate that the tails have less weight, meaning there aren't as many extreme values as possible in the data. This study uses the Jarque-Bera test to see if the data is normal. If the p-value is less than 0.05, it means that the data are not spread out in a normal way. In this case, LNBIO, LNCPO, LNCRD, LNCTL, LNGAS, and LNPFAD have a high Jarque-Bera statistic and a low probability, which shows that they are not normally distributed. The sum and sum of squares of deviations from the mean also give more information about how the data is spread out.

#### **4.1.2 Correlation Matrix**

The correlation matrix coefficients between different variables are presented in this section. The correlation matrix also examines the relationship between variables and identifies data patterns or trends (Field, 2013). In this research, correlation matrices are essential because they allow us to identify the strength and direction of the relationships between variables. However, this information is also helpful for developing hypotheses, exploring relationships between variables, and selecting variables for inclusion in regression models (Field,

2013).

**Table 4.2: Correlation Matrix**

	<b>LN BIO</b>	<b>LNCPO</b>	<b>LNCRD</b>	<b>LNCTL</b>	<b>LNGAS</b>	<b>LNMTN</b>	<b>LNPAD</b>
LN BIO	1.00	-	-	-	-	-	-
LNCPO	0.974634	1.00	-	-	-	-	-
LNCRD	0.769853	0.750600	1.00	-	-	-	-
LNCTL	0.382780	0.369112	0.591718	1.00	-	-	-
LNGAS	0.439570	0.354498	0.437380	0.552313	1.00	-	-
LNMTN	0.393496	0.368458	0.609756	0.989770	0.564169	1.00	-
LNPAD	0.932576	0.945186	0.806364	0.343272	0.290711	0.343504	1.00

*Source: Author's Computation*

Table 4.2 displays the correlation matrix of linear relationship strengths among the following variables LN BIO, LNCPO, LNCRD, LNCTL, LNGAS, and LNPAD. The table coefficient correlation range can be seen between -1 and 1, where coefficient 1 represents a perfect positive correlation, coefficient -1 represents a perfect negative correlation, and coefficient 0 means no correlation among the variables.

The correlation matrix shows pairwise correlation coefficients between each pair of variables. According to the correlation coefficients in the matrix, LN BIO appears to be moderate to significantly positively linked with all other variables. In addition, the LN BIO and LNPAD (0.932576), LN BIO and LNCPO (0.974634), and LN BIO and LNCRD (0.769853) had the strongest correlations. However, LN BIO and LNCTL have a slight positive link, as indicated by the low correlation coefficient between the two variables (0.382780). The association between LN BIO and LNGAS is positive (0.439570). However, it is not particularly strong. These findings collectively imply that LN BIO substantially correlates with each variable.

### **4.1.3 Stationarity Test**

In time series analysis, stationarity is a fundamental concept that refers to a process with constant statistical properties over time. In addition, stationary time series have statistical properties that remain constant over time, such as mean, variance, and autocorrelation. On the other hand, non-stationary time series exhibit changing trends, cycles, and different systematic patterns, making it challenging to model and predict their behavior (Gujarati, 2012). Before applying models and

analysis techniques, it is essential to perform stationarity tests on the data to ensure the validity of time series analysis results.

According to Box and Jenkins (1976, p. 37), before modeling a time series, it is important to determine whether the series is stationary or not. However, the Phillips-Perron and Augmented Dickey-Fuller (ADF) tests are well-known for checking stationarity. Both methods determine whether or not a unit root exists in time series data. Table 5 and 6 show the results of stationarity tests through the methods mentioned above (Phillips-Perron (PP) and Augmented Dickey-Fuller (ADF)) for time series variables of this study that includes LNBIO(Biodiesel), LNCPO (Crude Palm Oil), LNCRD (Crude Glycerin), LNCTL(Catalyst), LNGAS(Gasoil), LNMTN(Methanol), and LNPFD (Palm Fatty Acid Distillates).

**Table 4.3: Unit Root Test Results by Phillips-Perron (PP) Test**

		<b>At Level</b>						
		LNBIO	LNCPO	LNCRD	LNCTL	LNGAS	LNMTN	LNPFD
With Constant	t-Statistic	-1.7551	-1.9797	-1.7923	-2.2986	-0.8433	-2.3063	-1.7240
	<b>Prob.</b>	<b>0.4002</b>	<b>0.2952</b>	<b>0.3819</b>	<b>0.1749</b>	<b>0.8011</b>	<b>0.1724</b>	<b>0.4155</b>
With Constant & Trend	t-Statistic	n0	n0	n0	n0	n0	n0	n0
	<b>Prob.</b>	<b>0.4377</b>	<b>0.4724</b>	<b>0.8291</b>	<b>0.5920</b>	<b>0.7409</b>	<b>0.4853</b>	<b>0.6461</b>
Without Constant & Trend	t-Statistic	n0	n0	n0	n0	n0	n0	n0
	<b>Prob.</b>	<b>0.7681</b>	<b>0.5784</b>	<b>0.2573</b>	<b>0.3742</b>	<b>0.9495</b>	<b>0.3532</b>	<b>0.3989</b>
		n0	n0	n0	n0	n0	n0	n0
		<b>At First Difference</b>						
		d(LNBIO)	d(LNCPO)	d(LNCRD)	d(LNCTL)	d(LNGAS)	d(LNMTN)	d(LNPFD)
With Constant	t-Statistic	-8.1093	-7.7825	-5.4324	-6.6656	-6.4775	-9.0315	-6.3674
	<b>Prob.</b>	<b>0.0000</b>	<b>0.0000</b>	<b>0.0000</b>	<b>0.0000</b>	<b>0.0000</b>	<b>0.0000</b>	<b>0.0000</b>
		***	***	***	***	***	***	***
With Constant & Trend	t-Statistic	-8.0536	-7.7173	-5.4333	-6.6517	-6.4652	-9.0249	-6.3280
	<b>Prob.</b>	<b>0.0000</b>	<b>0.0000</b>	<b>0.0001</b>	<b>0.0000</b>	<b>0.0000</b>	<b>0.0000</b>	<b>0.0000</b>
		***	***	***	***	***	***	***
Without Constant & Trend	t-Statistic	-8.1080	-7.8205	-5.4697	-6.7001	-6.5065	-9.0638	-6.3917
	<b>Prob.</b>	<b>0.0000</b>	<b>0.0000</b>	<b>0.0000</b>	<b>0.0000</b>	<b>0.0000</b>	<b>0.0000</b>	<b>0.0000</b>
		***	***	***	***	***	***	***

**Notes:** (\*) Significant at 10%; (\*\*) Significant at 5%; (\*\*\*) Significant at 1% and (no) Not Significant.

\*MacKinnon (1996) one-sided p-values.

**Source:** Author's Computation.

**Table 4.4: Unit Root Test Results by Augmented Dickey-Fuller (ADF)**

		At Level						
		LN BIO	LN CPO	LN CRD	LN CTL	LN GAS	LN MTN	LN PFAD
With Constant	t-Statistic	-1.6204	-1.8443	-2.7917	-2.6734	-0.9154	-2.3063	-1.8473
	<b>Prob.</b>	<b>0.4677</b>	<b>0.3569</b>	<b>0.0641</b>	<b>0.0830</b>	<b>0.7787</b>	<b>0.1724</b>	<b>0.3554</b>
With Constant & Trend	t-Statistic	n0	n0	*	*	n0	n0	n0
	<b>Prob.</b>	<b>0.5085</b>	<b>0.5629</b>	<b>0.2715</b>	<b>0.2833</b>	<b>0.7371</b>	<b>0.4853</b>	<b>0.5073</b>
Without Constant & Trend	t-Statistic	n0	n0	n0	n0	n0	n0	n0
	<b>Prob.</b>	<b>0.7381</b>	<b>0.5844</b>	<b>-0.0024</b>	<b>0.2935</b>	<b>0.8784</b>	<b>0.3753</b>	<b>0.2609</b>
		n0	n0	n0	n0	n0	n0	n0

		At First Difference						
		d(LN BIO)	d(LN CPO)	d(LN CRD)	d(LN CTL)	d(LN GAS)	d(LN MTN)	d(LN PFAD)
With Constant	t-Statistic	-8.1610	-7.8441	-1.5266	-6.7898	-6.6086	-9.0187	-6.3674
	<b>Prob.</b>	<b>0.0000</b>	<b>0.0000</b>	<b>0.0050</b>	<b>0.0000</b>	<b>0.0000</b>	<b>0.0000</b>	<b>0.0000</b>
With Constant & Trend	t-Statistic	***	***	***	***	***	***	***
	<b>Prob.</b>	<b>0.0000</b>	<b>0.0000</b>	<b>0.0049</b>	<b>0.0000</b>	<b>0.0000</b>	<b>0.0000</b>	<b>0.0000</b>
Without Constant & Trend	t-Statistic	***	***	***	***	***	***	***
	<b>Prob.</b>	<b>0.0000</b>	<b>0.0000</b>	<b>0.0001</b>	<b>0.0000</b>	<b>0.0000</b>	<b>0.0000</b>	<b>0.0000</b>
		***	***	***	***	***	***	***

*Notes: (\*) Significant at 10%; (\*\*) Significant at 5%; (\*\*\*) Significant at 1% and (no) Not Significant.*

*\*MacKinnon (1996) one-sided p-values.*

*Source: Author's Computation.*

Tables 4.3 and 4.4 summarize the PP and ADF Test results to test the stationarity. In both tests, the null hypothesis is that the time series has a unit root; however, the alternative hypothesis is that it is stationary. The PP and ADF test results are presented for three different scenarios: with constant, with constant and trend, and without constant and trend. Therefore, when the test statistic is less than the critical value at the specified significance level in both tests, the null hypothesis of a unit root is rejected. However, the test statistic and its corresponding probability value are reported.

In addition, based on the results of the PP test presented in Table 4.3, we cannot reject the null hypothesis of a unit root at a 5 percent significance level when the series is in levels (without taking the first difference). The results indicate that these variables are not stationary at the level. However, the null hypothesis is rejected at the 1 percent significance level for all variables when the series is differentiated (i.e., in first differences). This suggests that the series becomes

stationary after taking the first difference of all variables.

According to the ADF test results, the unit root null hypothesis cannot be disproven at the 5 percent significance level for any of the variables since the series is leveled. The ADF test also shows that LNCRD and LNCTL are significant at a level of 10 percent. However, when the series is differentiated, the null hypothesis is rejected at the 1 percent significance level for all variables. This suggests the series becomes stationary for all variables after the first difference. Since our variables are integrated into order one, we might check if they are long-term (cointegrated). A Johansen Cointegration Test can be used to determine whether this is accurate. Johansen Cointegration Test can be seen in Table 9.

#### 4.1.4 VAR Lag Order Selection Criteria

The information about the VAR lag criteria for this study is presented in this section. The best number of lags in a VAR model can be found statistically using the VAR Lag Order Selection Criteria. Thus, the VAR Lag Criteria is essential for precise forecasting and reflecting the dynamic interactions between variables over time. However, the lag order can be chosen using several parameters, including AIC, BIC, and HQIC (Lütkepohl, 2006). Pfaff (2008) found that the context and research issue will influence the criterion selection of lag. The VAR lag order selection criteria can be seen in Table 4.5.

*Table 4.5: 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: LR: sequential modified LR test statistic (each test at 5% level), FPE: Final prediction error, AIC: Akaike information criterion, SC: Schwarz information criterion, HQ: Hannan-Quinn information criterion

*Source:* Author's Computation

Table 4.5 summarizes the findings from the Akaike information criterion

(AIC), the Schwarz information criterion (SC), and the Hannan-Quinn information criterion (HQ), all of which are considered for lag orders ranging from 0 to 7. Furthermore, it shows the final prediction error (FPE), sequential modified LR test statistic (LR), and log-likelihood (LogL).

Additionally, these criteria are intended to aid in selecting the lag order that offers the ideal compromise between model fit and parsimony. In general, the best lag order is the one that minimizes the values of the criterion (Gujrati, 2011). However, different criteria may yield other best lag orders. The table above indicates each criterion's optimal lag order with an asterisk (\*). The findings demonstrate that the choice of criterion affects the ideal lag order. For instance, the SC criterion suggests a lag order of 0, the HQ test statistic suggests a lag order of 1, the LR and FPE choose a lag order of 2, and the HQ chooses a lag order of 7. Therefore, the specific objective and the trade-off between model complexity and accuracy may impact the choice of lag order. After considering several factors, this study chose to abide by 2 lags, as suggested by LR and FPE, for the VAR model estimation.

#### **4.1.5 Cointegration Test**

The co-integration results and interpretation of the equations are presented in this section. Cointegration is a statistical term that describes the long-run equilibrium relationship between two or more non-stationary time series (Gujrati, 2011). Therefore, the Johansen approach is one of the most often used cointegration procedures based on the trace and eigenvalue tests. In addition, the Johansen procedure was first developed by Sren Johansen in his essential publication "Statistical Analysis of Cointegration Vectors" (1991). Similarly, the Engle-Granger test is another widely used cointegration test based on the residual-based approach. Robert Engle and Clive Granger (1987) established the Engle-Granger test in their publication "Co-Integration and Error Correction: Representation, Estimation, and Testing." Since then, it has been frequently applied in empirical investigations.

The results of a cointegration test performed on a set of variables are shown

in Table 8. Based on the trace statistic, the test determines how many cointegrating equations (CE) are necessary to describe the relationship between the variables.

**Table 4.6: 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

*Note: Trace test indicates 6 cointegrating eqn(s) at the 0.05 level, \* denotes rejection of the hypothesis at the 0.05 level*

*\*\*MacKinnon-Haug-Michelis (1999) p-values*

*Source: Author's Computation.*

Table 4.6 shows the test results for various CE number hypotheses. In the Johansen cointegration test, the null hypothesis of no cointegration claims that variables are not connected; in other words, there is no relationship between the variables. Moreover, there are several economic consequences if there is no cointegration pattern, such as lack of long-term stability, inaccurate forecasting, risk of spurious regression, inefficiencies in policy formulation, and increased volatility. The hypothesized cointegration equation (CE) numbers are shown in the first column. However, the hypothesis of no more than one cointegrating equation is represented by the second row, no more than six cointegrating equations by the third row, and so on.

In addition, the table also shows the trace statistic and eigenvalue for each hypothesis. The trace statistic is the sum of the eigenvalues for all cointegrating equations up to a given rank, whereas the eigenvalues represent the strength of the cointegrating relationship (Gujrati, 2011). The table also shows the likelihood of rejecting the null hypothesis for each hypothesis and the critical value of 0.05. Nevertheless, the likelihood of rejecting the null hypothesis in this situation is zero for all hypotheses, which strongly supports the cointegration of the variables.

#### 4.1.6 Granger Causality Test

The causal connection between the variables is covered in this section. To determine if one variable caused another or whether both had cause over the other, we employed the Granger Causality test. The Granger causality test is a statistical technique to examine if one time series is helpful in predicting another. Therefore, it is crucial in this study to establish causal relationships between variables and identify the direction of causality (Ding et al., 2006; Kim et al., 2018; Gujarati, 2006). In this case, the Granger Causality test was applied for all variables that include biodiesel (LNBIO), crude palm oil (LNCPO), methanol (LNMTN), crude glycerin (LNCRD), catalyst (LNCTL), palm fatty acid distillate (LNPFAD), and gasoil/gasoline (LNGAS). Table 4.7 presents the result of the Granger Causality Test.

*Table 4.7: Granger Causality Test Result*

<b>Null Hypothesis</b>	<b>Obs.</b>	<b>F-Statistic</b>	<b>Prob.</b>
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 4.7 summarizes the Granger causality test results that show whether one variable causes another. Although, the null hypothesis says that one variable does not cause the other variable through Granger causation. The null hypothesis is used to test whether one thing causes the other.

Consequently, when we look at the results (Table 4.7), we can observe that certain variables are connected in ways that explain why they have their specific values. For example, LNCPO Granger causes LNBIO with an F-statistic of 3.27457

and a p-value of 0.0432. This means that CPO is a strong predictor of biodiesel. Also, LNCTL Granger causes LNBIO with an F-statistic of 4.17369 and a p-value of 0.0190. This means that the catalyst is also a strong predictor of biodiesel. According to the results, there are no clear links between some factors (variables). We can see in Table 5 that shows LNGAS does not Granger cause LNBIO because the p-value is not significant. This means that gasoil is not a strong indicator of biodiesel in Indonesia. Similarly, LNCRD with (0.5888) and LNMTN (1.38664) value does not Granger cause LNBIO because the p-value is higher than 0.05. This means that crude glycerin is not a strong indicator of biodiesel.

#### **4.1.7 VAR Estimation**

This section presents the VAR estimation results to fulfill the objectives of this study. VAR (Vector Autoregressive) is a statistical tool for modelling the dynamic relationship between various time series variables. In this case, the VAR model is used to understand the dynamic interactions among prices of all variables of this study that, includes Biodiesel (DLNBIO) price, crude palm oil (DLNCPO) price, methanol (DLNMTN) price, catalyst (DLNCTL) price, glycerin (DLNCRD) price, palm fatty acid distillate (DLNPFAD) price, and gasoil/gasoline (DLNGOIL) price. However, we have taken the first difference of prices of all variables; thus, “D” represents the first difference, and “LN” indicates the log of variables. Table 5 presents the result of VAR Estimation.

*Table 4.8: VAR Estimation Results*

	<b>DLNBIO</b>	<b>DLNCPO</b>	<b>DLNCRD</b>	<b>DLNCTL</b>	<b>DLNGAS</b>	<b>DLNMTN</b>	<b>DLNPFAD</b>
DLNBIO (-1)	0.013095 (0.17320) [ 0.07561]	0.216668 (0.21267) [ 1.01880]	0.017437 (0.44134) [ 0.03951]	0.115577 (0.13039) [ 0.88642]	-0.138053 (0.34621) [-0.39875]	0.127632 (0.30436) [ 0.41935]	0.019920 (0.34702) [ 0.05740]
DLNBIO (-2)	-0.372286 (0.14711) [-2.53063] *	0.010256 (0.18064) [ 0.05678]	-0.115603 (0.37487) [-0.30838]	-0.065196 (0.11075) [-0.58869]	0.485766 (0.29407) [ 1.65189]	-0.381497 (0.25852) [-1.47571]	0.002835 (0.29475) [ 0.00962]
DLNCPO (-1)	-0.029290 (0.14204) [-0.20620]	-0.226624 (0.17441) [-1.29934]	-0.185941 (0.36195) [-0.51372]	-0.092280 (0.10693) [-0.86298]	-0.054378 (0.28393) [-0.19152]	-0.134754 (0.24961) [-0.53986]	0.543746 (0.28460) [ 1.91059]
DLNCPO (-2)	0.134658 (0.12578) [ 1.07060]	-0.289542 (0.15444) [-1.87475]	0.378527 (0.32050) [ 1.18104]	-0.059118 (0.09469) [-0.62435]	-0.655419 (0.25142) [-2.60685]	0.085619 (0.22103) [ 0.38737]	-0.038129 (0.25201) [-0.15130]
DLNCRD (-1)	-0.008467 (0.04997) [-0.16945]	-0.051615 (0.06135) [-0.84127]	0.611915 (0.12732) [ 4.80600] *	-0.030331 (0.03762) [-0.80636]	-0.252489 (0.09988) [-2.52794] *	0.037035 (0.08781) [ 0.42179]	-0.072080 (0.10011) [-0.71999]
DLNCRD (-2)	-0.095080 (0.05448) [-1.74526]	-0.086445 (0.06689) [-1.29226]	-0.395777 (0.13882) [-2.85097]	0.017295 (0.04101) [ 0.42171]	0.133080 (0.10890) [ 1.22204]	9.05E-05 (0.09573) [ 0.00095]	-0.006083 (0.10915) [-0.05573]
DLNCTL (-1)	1.227436 (0.43650) [ 2.81200]	0.731592 (0.53598) [ 1.36497]	2.058664 (1.11227) [ 1.85086]	0.375350 (0.32860) [ 1.14226]	0.489617 (0.87253) [ 0.56114]	2.537994 (0.76705) [ 3.30877] *	-0.225245 (0.87457) [-0.25755]
DLNCTL (-2)	0.654017	0.310032	1.734533	-0.179590	-0.138956	0.560524	-0.228324

	(0.41735)	(0.51246)	(1.06348)	(0.31419)	(0.83425)	(0.73340)	(0.83620)
	[ 1.56707]	[ 0.60499]	[ 1.63100]	[-0.57160]	[-0.16656]	[ 0.76428]	[-0.27305]
DLNGAS (-1)	-0.162131	0.003956	-0.043194	-0.048525	0.215852	-0.121792	-0.026925
	(0.06088)	(0.07475)	(0.15513)	(0.04583)	(0.12169)	(0.10698)	(0.12198)
	[-2.66318] *	[ 0.05293]	[-0.27844]	[-1.05879]	[ 1.77375]	[-1.13845]	[-0.22074]
DLNGAS (-2)	0.106919	0.061175	0.096401	-0.004329	-0.052891	-0.036286	-0.106757
	(0.05993)	(0.07359)	(0.15271)	(0.04512)	(0.11980)	(0.10531)	(0.12008)
	[ 1.78405]	[ 0.83131]	[ 0.63126]	[-0.09594]	[-0.44151]	[-0.34455]	[-0.88908]
DLNMTN (-1)	-0.472347	-0.291863	-0.980042	-0.079182	0.152603	-1.018557	0.126824
	(0.18262)	(0.22424)	(0.46535)	(0.13748)	(0.36505)	(0.32092)	(0.36590)
	[-2.58650] *	[-1.30157]	[-2.10604] *	[-0.57596]	[ 0.41804]	[-3.17392] *	[ 0.34661]
DLNMTN (-2)	-0.156238	-0.054119	-0.741147	0.082860	0.189973	-0.133437	-0.039038
	(0.17142)	(0.21049)	(0.43682)	(0.12905)	(0.34266)	(0.30124)	(0.34346)
	[-0.91141]	[-0.25711]	[-1.69670]	[ 0.64208]	[ 0.55440]	[-0.44296]	[-0.11366]
DLNPFAD (-1)	0.583422	0.796951	0.027847	0.112455	0.357517	0.211117	0.284466
	(0.07312)	(0.08978)	(0.18632)	(0.05505)	(0.14616)	(0.12849)	(0.14650)
	[ 7.97894] *	[ 8.87631] *	[ 0.14946]	[ 2.04294] *	[ 2.44602] *	[ 1.64303]	[ 1.94171]
DLNPFAD (-2)	-0.054945	-0.084033	0.141446	0.030451	0.144398	0.041911	-0.268651
	(0.09385)	(0.11524)	(0.23915)	(0.07065)	(0.18760)	(0.16492)	(0.18804)
	[-0.58545]	[-0.72920]	[ 0.59145]	[ 0.43099]	[ 0.76970]	[ 0.25413]	[-1.42869]
C	0.004688	0.000934	0.002751	0.001455	0.007185	0.005139	0.004357
	(0.00525)	(0.00644)	(0.01337)	(0.00395)	(0.01049)	(0.00922)	(0.01051)
	[ 0.89350]	[ 0.14494]	[ 0.20575]	[ 0.36845]	[ 0.68505]	[ 0.55741]	[ 0.41443]

Source: Author's computation; Note: The Asterisk (\*) sign shows the significant Variables.

Table 4.8 summarizes the results of VAR estimation. In the table, each variable is regressed on its lags (up to two lags) as well as the lags of the other variables. The coefficients of the lagged variables represent the impact of past values of each variable on its current value. Therefore, the VAR results display the coefficients of the lagged variables, which represent the dynamic relationship between the prices of inputs (DLNCPO, DLNMTN, DLNPFAD, etc.) and the price of output (biodiesel (DLNBIO)) in the conversion process. These coefficients reveal the short-term relationships between variables.

Moreover, positive coefficients indicate a positive relationship, whereas negative coefficients indicate a negative relationship between the variables. In the table above, a matrix format is used to present the coefficient estimates. The columns show the lagged values of the variables, and the rows show the dependent variables. However, the estimated coefficients are represented in the matrix by the numbers. Their standard errors can be seen in parentheses “(),” and the corresponding t-statistics are in square brackets “[].” According to results from VAR estimates, we can see the values with an asterisk (\*) sign are significant in this research. However, the values without an asterisk are insignificant even though they fluctuate over time.

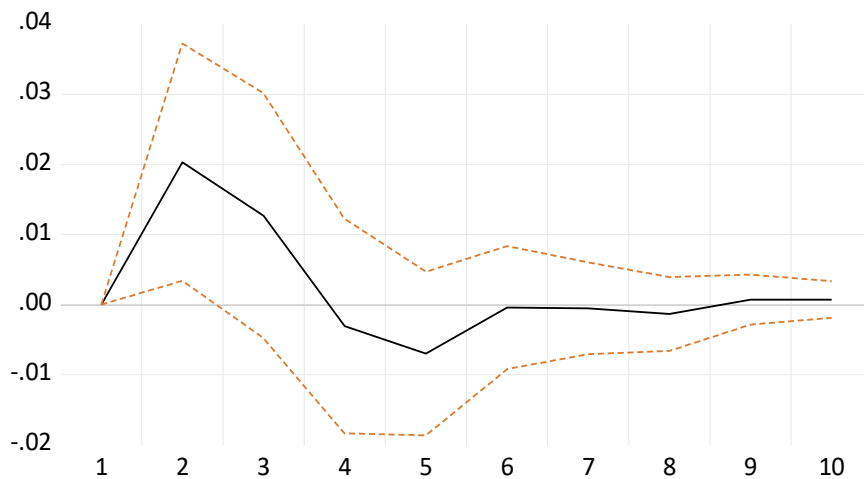
#### **4.1.8 Impulse Response Function (IRF)**

This section analyses the impulse response of biodiesel to CPO, catalyst, methanol, gasoil, glycerin, and PFAD. However, the Impulse response function (IRF) is a statistical method for examining a system's dynamic interactions between variables. The inclusion of the Impulse Response Function (IRF) subsection in this research is intuitively justified from both an economic and a statistical standpoint. Economically, understanding the dynamic effect of shocks and policy interventions is critical for assessing their impact on the variables. The IRF provides a systematic framework for analyzing how a single exogenous variable affects the entire system over time. Regarding statistics, the IRF enables the identification and quantification of causal relationships, which aids in interpreting the estimated model. However, the economic consequences would be less clear without the IRF because we would be unable to fully comprehend the transmission mechanisms and potential

outcomes resulting from changes in the variables under study.

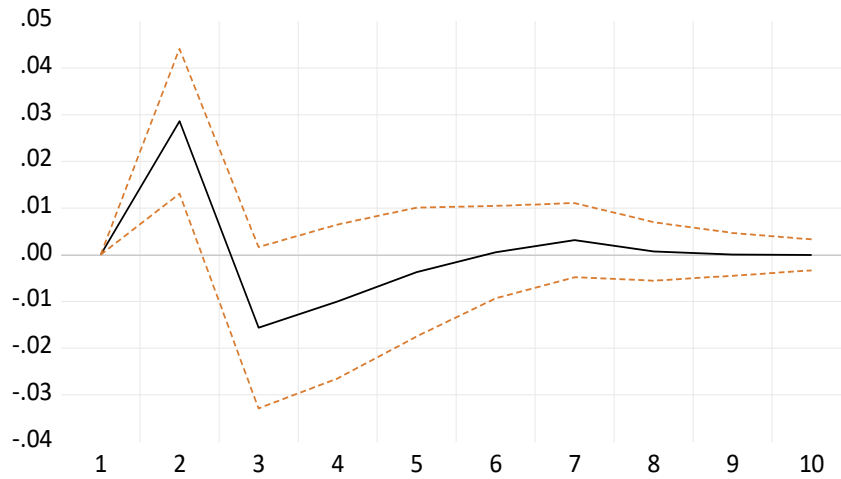
Therefore, it is essential to see the dynamic interaction to accomplish the study goals and test the hypothesis. In addition, it shows how they respond to a sudden change in a variable. Furthermore, the impulse response function shows how the variable will affect itself and other factors in the future while keeping all other variables constant (Enders, 2015). The response of biodiesel to shock/innovation in crude palm oil (CPO) is shown in Figure 4.1.

*Figure 4.1: Response of Biodiesel to CPO/Biodiesel Shock to CPO*



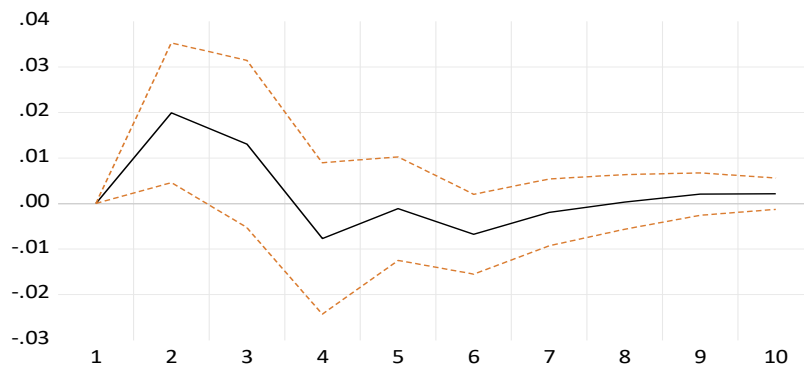
The above impulse response functions show how biodiesel price changes in reaction to a change in the CPO price by one unit. The figure above shows that biodiesel prices increase when there is a shock/innovation in CPO prices. In the first period, there was no response of biodiesel to changes in the CPO price. However, after the first period, 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 until it reached zero or no response in the fourth period, and then it constantly decreased and stopped in the fifth period. Afterward, it slightly increased positively and again touched zero at period six, then faded away. From the above figure, we could figure out that the CPO price has a good effect on biodiesel price. The response of biodiesel to shock/innovation in crude glycerin is shown in Figure 4.2.

**Figure 4.2:** Response of Biodiesel to Crude Glycerin Shock



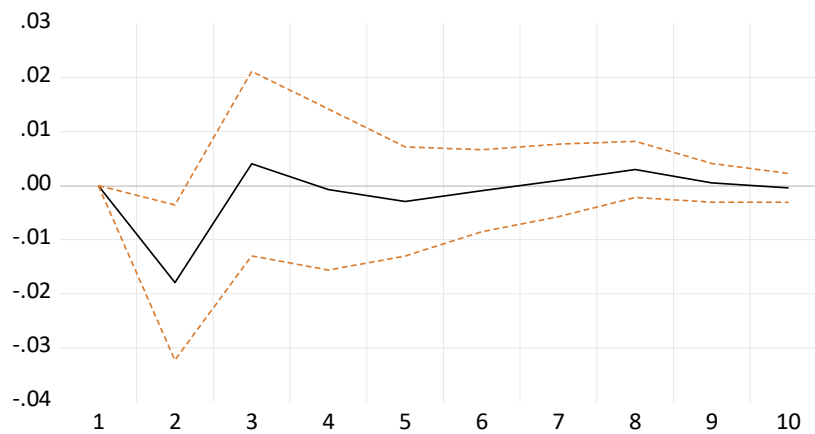
The graph above shows how the price of biodiesel changes when the price of crude glycerin goes up or down. The graph of the impulse response function shows that the price of biodiesel doesn't change immediately during the first period after the glycerin price shock. However, in the next period, biodiesel was found to respond positively to shock in the price of crude glycerin until it peaked and then stopped. Furthermore, in the third period, the biodiesel price was found to decline to zero or no response; it continued and stayed at a minimum response to biodiesel. After that, the price of biodiesel slowly increases in reaction to the shock in the price of glycerin. It stabilizes in the ninth period and stays faded after that. We can conclude from the figure above that crude glycerin has a positive impact on the price of biodiesel. The response of biodiesel to shock/innovation in the catalyst price is shown in Figure 4.3.

**Figure 4.3:** Response of Biodiesel to Catalyst/Biodiesel Shock to Catalyst



The above impulse response function shows the response of biodiesel to shock/innovation in the price of the catalyst. The figure above shows how biodiesel prices react when the price of catalyst fluctuates or goes up and down in time. It shows the price of biodiesel doesn't change in the first period after that due to shock in the catalyst. Eventually, biodiesel seemed to respond positively to shock in the price of catalyst in the second period; it moved up and stopped at a peak in the second period. Although, the figure shows that shock occurs again in the price of catalyst, and the price of biodiesel declined slightly negatively to zero or no response or negative response and stopped at the third period. Again, the positive shock occurred, and biodiesel prices moved up, but still, they didn't touch the x-axis and again declined slightly in the sixth period. Afterward, the biodiesel prices increased positively and went away. According to the impulse response function above, we can say that catalysts positively influence the price of biodiesel in Indonesia. The response of biodiesel to shock in the price of gasoil is shown in Figure 4.4.

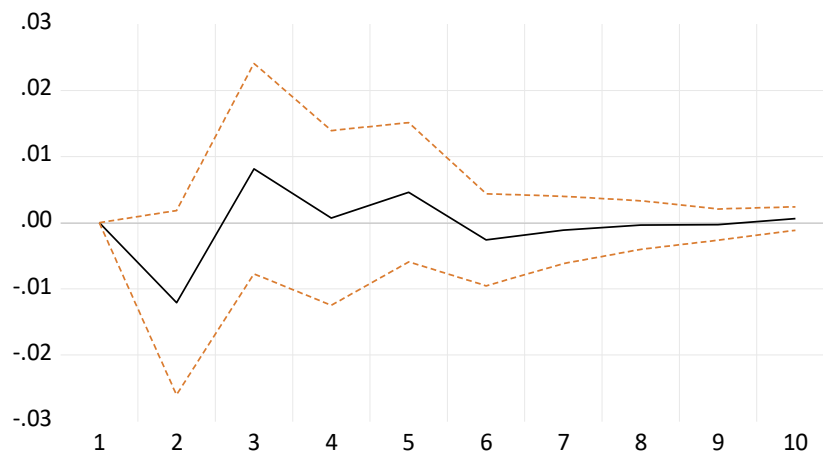
**Figure 4.4:** Response of Biodiesel to Gasoil/Biodiesel Shock to Gasoil



The impulse response function above shows the impact/response of biodiesel to gasoil when there is a unit shock or innovation in the price of gasoil. The graph above shows that biodiesel responds negatively to the gasoil price shock. Initially, there was no response of biodiesel to shock in gasoil price in the first period. Still, after the first period, biodiesel was found to respond negatively in a decreasing manner until it reached a minimum response in the second period. Afterward, it began to increase quickly due to the shock in gasoil price. However,

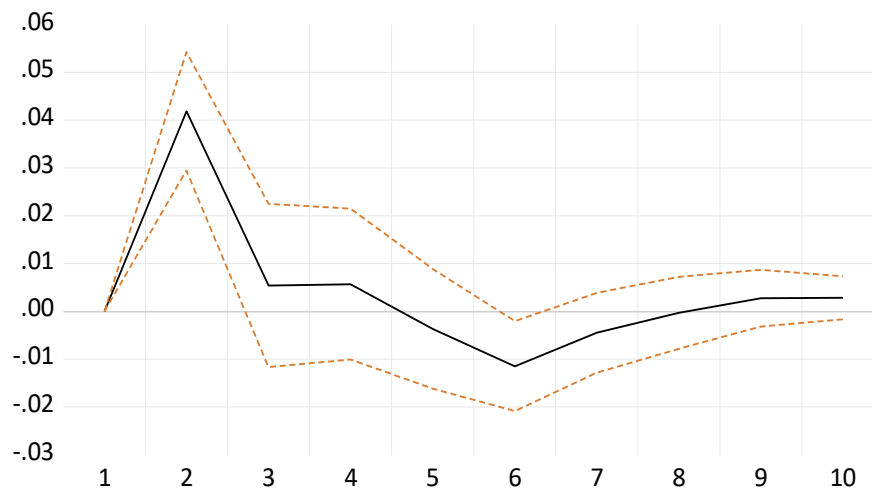
it crossed the x-axis and stopped between 0 to 1. After reaching the positive side, it moves slightly again to the negative side and stops at the fifth period, and it reacts the same in other periods but with slight changes in fluctuation. According to the above impulse response function, we can say that gasoil has a negative impact on the price of biodiesel in Indonesia.

**Figure 4.5:** *Response of Biodiesel to Methanol/Biodiesel Shock to Methanol*



The figure above shows how biodiesel responds to a unit shock/innovation in the price of methanol. The impulse response function above shows that methanol has a negative impact on the price of biodiesel. Initially, there was no response from the biodiesel to the shock in the methanol in the first period. Afterward, biodiesel seemed hostile, decreasing until it reached the minimum response to methanol and stayed at the second period. But, after the second period, biodiesel was found to respond positively to shock in methanol in an increasing manner until it reached a peak on the positive side in the third period. 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. In short, the fluctuation seems onward after the fifth period of shock, and we can summarize from the above impulse response function that methanol negatively impacts biodiesel prices in Indonesia. Figure 4.6 presents the response of biodiesel to shock or innovation in the PFAD (Palm Fatty Acid Distillate).

**Figure 4.6:** *Response of Biodiesel to PFAD (Palm Fatty Acid Distillate)/Biodiesel Shock to PFAD*



The impulse response function above tells the response or impact of biodiesel to unit shock/innovation in the price of PFAD. From the figure above, biodiesel responds positively to a shock in the PFAD. Initially, there was no response of biodiesel to unit shock in the PFAD in the first period. Still, after the first period, PFAD responded positively quickly until it reached its maximum response in the second period. After that, biodiesel was found to decline to no response or zero response in the third period and stayed constant until the fourth period, even though there was a unit shock in the price of PFAD. Afterward, biodiesel seemed to decline again slightly and reached no response in the sixth period, but due to another shock in the PFAD, it started moving upward to the positive side. According to the above impulse response function, we could deduce that PFAD positively impacts the price of biodiesel in Indonesia.

#### 4.1.9 Variance Decomposition

Variance decomposition is discussed in this section to demonstrate how forecasting variance error can be influenced by shocks to both the forecasted variable and another variable in the system. In addition, this statistical approach has been used to streamline analysis when dealing with many variables in the study. However, the variance decomposition method divides the dataset's variability into parts connected to particular variables or elements. It provides us with the percentage of variation in a time series of attributed variables at the specific time horizon. Therefore, it indicates which variables have a short-term or long-term

impact on a variable. In macroeconomic research, the relationships between variables provided by vector autoregressive (VAR) models are evaluated utilizing a specific type of variance decomposition known as "forecast error variance decomposition" (Anderson, 2003). The results of variance decomposition for variables over five periods are shown in Table 4.9.

**Table 4.9: Shows the Variance Decomposition of All Variables**

<b>Variance Decomposition of DLNBIO</b>								
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
<b>Variance Decomposition of DLNCPO</b>								
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
<b>Variance Decomposition of DLNCRD</b>								
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
<b>Variance Decomposition of DLNCTL</b>								
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
<b>Variance Decomposition of DLNGAS</b>								
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
<b>Variance Decomposition of DLNMTN</b>								
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
<b>Variance Decomposition of DLNPFAD</b>								
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*

Table 4.9 shows the output breakdown of a specific variable, with the seven columns (DLNBIO, DLNCPO, DLNCRD, DLNCTL, DLNGAS, DLNMTN, and DLNPFAD) representing the variable's various sources of variance. However, with the first row displaying the variance contribution in the first period and so on, the rows reflect the various periods (in this case, five periods). The estimate's standard error for each period is shown in the standard error (S.E.) column.

We take the first table for the variable DLNBIO (Biodiesel). It shows when DLNBIO is responsible for 100 percent of the variance in forecast error in the first period, and we can say it fully explain the variance. But at the second time horizon, 35.5 percent of the error variance in forecasting biodiesel price comes from a shock that happened in the past. The other 64.5 percent variance comes from the other variables. Similarly, DLNBIO contributes 32.4 percent, 31.4 percent, and 31.0 percent in the third, fourth, and fifth periods, respectively. We could infer from our result that CPO, crude glycerin, catalyst, gasoil, methanol, and PFAD impact biodiesel price in Indonesia.

Additionally, we took a similar look at the second table for the variable DLNCPO (Crude Palm Oil). It indicates that CPO forecasted up 52.9 percent of the error variance decomposition in the first period, and biodiesel forecasted up the remaining 47.1 percent. Nevertheless, CPO contributes 21.8 percent of the total for the second period, with the remaining 78.2 percent coming from the other variables. Similarly, DLNCPO contributes 20.1 percent, 19.6 percent, and 19.5 percent in the third, fourth, and fifth quarters, respectively. For the variable DLNCRD (Crude

Glycerin), we can see that DLNCRD accounts for 98 percent of the forecast error variance in the first period. The other factors account for the additional 2 percent in the third table. In the second period, we can also see that DLNMTN (Methanol) makes up 3.6 percent, DLNCRD makes up 93.6 percent, and the other variables contribute the remaining 2.8 percent. In the same way, DLNCRD contributes 91.2 percent, 87.0 percent, and 84.7 percent, respectively, in the third, fourth, and fifth quarters.

In the fourth table for the variable DLNCTL, we can see that it accounts for 97.3 percent of the forecast error variance in the first period and that the other variables account for the remaining 2.7 percent. DLNCTL, on the other hand, predicted up to 90.1 percent error variance in the second period, with the remaining 9.9 percent coming from other variables. Similarly, in the third, fourth, and fifth quarters, DLNCTL contributed 85.8 percent, 84.6 percent, and 84.2 percent, respectively. Finally, in the fifth table, the variable DLNGAS (Gasoil) accounts for 93.0 percent of the forecast error variance in the first period, with the other variable accounting for the remaining 7.0 percent. However, DLNGAS accounts for 73.1 percent of the total in the second period, with the remaining 26.9 percent coming from variables. Similarly, in the third, fourth, and fifth periods, DLNGAS contributes 63.3 percent, 58.6 percent, and 53.2 percent, respectively.

## **4.2 Discussions of Findings**

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. However, the impulse response function for biodiesel itself shows that it has a significant negative impact on the price of biodiesel. This indicates that the biodiesel market has a mechanism for rectifying itself. This means that any change or shock in the price of biodiesel will result in a negative response that will fade with time. This result suggests that biodiesel prices will tend to stabilize in the long run. This means that the market has reached a certain level of balance (Harahap et al., 2019).

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 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 (Sahirman et al., 2018). We found that the hypothesis that the price of CPO influences the price of biodiesel has been accepted.

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 (Purba et al., 2018).

Furthermore, the response of biodiesel to shock in the price of crude glycerin is also positive, and it is another byproduct generated in the biodiesel production process. This shows that the price of crude glycerin influences the biodiesel market. This could mean that crude glycerin and biodiesel compete as biofuel feedstock sources. The impulse response function suggests that an increase/shock in the price of crude glycerin results in a rise in the price of biodiesel in Indonesia (Soebroto et al., 2021). The positive correlation between crude glycerin and biodiesel prices in Indonesia is caused by the dependence on crude glycerin as a feedstock, increased production costs, supply-demand dynamics, market competition, and market expectations.

The impulse response trend shows that PFAD (Palm Fatty Acid Distillate) significantly impacts the price of biodiesel in Indonesia. PFAD is a byproduct that is usually made when biodiesel is produced from CPO. So, when the price of PFAD changes, the price of biodiesel also changes; we can say that it directly impacts

biodiesel prices. 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 material used in biodiesel production. As a result, biodiesel prices increase to maintain profitability and cover the additional expenses.

On the other hand, the negative response of biodiesel prices to methanol price fluctuations can be explained by the cost of dynamics of the biodiesel production process. Methanol is a crucial ingredient in biodiesel synthesis and is frequently utilized as a reactant or solvent in that process. 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 to acquire this essential input. In order to maintain profitability, biodiesel producers frequently pass on these increased expenses to consumers in the form of higher biodiesel prices (Habibie et al., 2019). However, these results contradict the actuality of methanol; there are several reasons why methanol has a negative effect on the price of biodiesel.

According to the results, the impulse response function demonstrates a negative relationship; when there is a shock in methanol, the biodiesel prices decrease. 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 that influence 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. It is due to methanol's role in the production process; one might anticipate this increase to 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 (Suhariyanto et al., 2017).

Furthermore, the negative impulse response of biodiesel prices to shock in gasoil prices 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 decreased 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 (Mundi et al., 2008).

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.

Additionally, the variance decomposition analysis helps us to learn more about the things that affect the price of biodiesel in Indonesia. The results show that biodiesel explains a big part of the price variation. Still, other input factors such as CPO, crude glycerin, catalysts, gasoil, and methanol also play a crucial role in the price variation (Khatiwada, 2018). Based on these results, it seems that 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, it seems that the prices of CPO, methanol, catalysts, PFAD crude glycerin, and gasoil significantly impact the price of biodiesel. Understanding these factors is essential for policymakers and industry players who want to ensure Indonesia's biodiesel industry is stable and will last. Furthermore,

the findings highlight the need to consider how different input prices interact and change over time to develop successful government policies and market interventions.

# **CHAPTER 5**

## **CONCLUSION AND RECOMMENDATIONS**

In this last chapter, we summarized the essential findings and insights from the entire investigation and offered policy suggestions based on the results. We review the primary objectives and research questions discussed in earlier sections and summarize the study findings. We also discussed the problems during the study process and pointed out where more research is needed. Even though our study gives valuable information, it is essential to know its limitations and possible ways to improve it. Lastly, we talk about future directions for study, pointing out ways to help us learn more about the topic and make essential contributions to the field. By the end of this chapter, you will fully understand the study's implications, policy suggestions, study limitations, and possible future research areas.

### **5.1 Summary and Conclusion**

Indonesia is the world's largest producer of biodiesel, attracting the focus of the government and biodiesel producers despite price fluctuations and instability. Thus, it is crucial to know what factors impact the price of biodiesel so we can stabilize the market and help Indonesia's biodiesel industry's sustainability and rapid growth. Therefore, the study's main objective was to examine the relationship between the price of biodiesel and input factors such as crude palm oil (CPO), crude glycerin, catalyst, gasoil, methanol, and palm fatty acid distillate (PFAD). The VAR model analysis showed that changes in the price of inputs, including CPO, crude glycerin, catalyst, gasoil, methanol, and PFAD, significantly impact biodiesel prices in Indonesia.

These findings show how important it is to consider several factors when determining the price of biodiesel since changes in the prices of these input factors can have a significant effect on the final price of biodiesel. By understanding how these factors influence biodiesel prices, policymakers and other industry stakeholders can make wise choices to stabilize the market and ensure the biodiesel industry grows sustainably. Furthermore, the impulse response functions show that

the VAR model analysis provided beneficial information about how the prices of biodiesel change in response to changes in the prices of the input factors and substitutes. Biodiesel prices increase when CPO, crude glycerin, catalyst, and PFAD prices increase. This suggests that rising prices for these inputs cause rising biodiesel prices. Accordingly, the study's main hypothesis is accepted—that increasing prices for the primary raw materials used to produce biodiesel in Indonesia—CPO, methanol, and catalyst—have a significant effect on biodiesel prices. The result demonstrates that biodiesel prices and profitability depend on tracking and regulating the prices of these inputs.

In contrast, biodiesel prices decrease when gasoil and methanol prices increase, indicating that higher gasoil and methanol prices cause biodiesel prices to decrease. This finding suggests that the price of biodiesel is affected by how competitive biodiesel is compared to regular gasoline. As gasoline and methanol prices rise, biodiesel prices fall because they become less competitive on the market. Therefore, policies and businesspeople in Indonesia involved in the biodiesel industry should note this study's results. For policymakers to help stabilize biodiesel prices, reduce the amount of price volatility, and boost the biodiesel industry, they should learn what drives changes in biodiesel prices over time. This way, Indonesia will become less dependent on fossil fuels and move toward a greener, more environmentally friendly energy sector.

In conclusion, this thesis has filled a critical research gap by investigating the dynamics of biodiesel pricing and numerous potential determinants in the Indonesian biodiesel market. The intricate correlations between biodiesel prices and components such as CPO, crude glycerin, catalyst, gasoil, methanol, and PFAD have been investigated using the Vector Autoregressive (VAR) model.

This analysis' findings shed light on the profound interdependence of these variables, giving valuable insights into governmental decision-making and industry practices. According to the study, the pricing of CPO, crude glycerin, catalyst, and PFAD favorably influences biodiesel pricing, underlining their importance in promoting price stability and stimulating the biodiesel sector's expansion. On the other hand, price shocks in gasoil and methanol have a negative impact, underlining

the need to address the volatility of these elements to provide a more stable pricing environment. The study emphasizes the need for a multi-factor approach when developing pricing strategies for the Indonesian biodiesel market. By considering the interconnections between various components, policymakers and industry stakeholders can cooperate to improve price stability, promote renewable energy adoption, and accelerate Indonesia's transition to sustainable energy sources.

Furthermore, the study emphasizes the environmental benefits of biodiesel, such as lower CO<sub>2</sub> emissions and improved air quality. Biodiesel is essential in guaranteeing energy supply reliability and contributing to national sovereignty by reducing dependency on imported fossil fuels and boosting the use of renewable energy. As a whole, the findings of this thesis contribute to a better understanding of the Indonesian biodiesel market and lay the groundwork for influencing governmental decisions and business practices. The research findings can be a significant resource for policymakers and stakeholders working to ensure price stability, expand the biodiesel industry, and help Indonesia move toward a more sustainable energy future.

## **5.2 Policy Recommendations**

Based on the findings of this study on the determinants of biodiesel prices in Indonesia, the following policy recommendations are proposed to stabilize biodiesel prices, promote the growth of the biodiesel industry, and contribute to the development of sustainable energy sources:

1. **Price Stabilization Mechanisms:** To mitigate excessive fluctuations in biodiesel prices, policymakers should contemplate implementing price stabilization mechanisms. This may involve establishing price categories or limits within which the cost of biodiesel can fluctuate. These mechanisms can provide biodiesel producers and consumers with stability and predictability, thereby reducing market volatility.
2. **Strategic Reserves:** Strategic reserves of essential input materials such as crude palm oil (CPO), crude glycerin, catalyst, and palm fatty acid distillate (PFAD) can mitigate the effects of supply disruptions and price spikes.

Maintaining a sufficient inventory can assure a stable supply of inputs for biodiesel production, thereby reducing price volatility.

3. Policymakers must routinely monitor the costs of critical inputs, such as CPO, crude glycerin, catalyst, gasoil, methanol, and PFAD. Timely data on input price fluctuations can facilitate proactive decision-making and prompt interventions in response to any significant price fluctuations that may affect biodiesel prices.
4. **Subsidies and Incentives:** During periods of input price volatility, policymakers may consider offering targeted subsidies or incentives to support the biodiesel industry. Subsidies can help mitigate increased production costs caused by higher input costs, making biodiesel more affordable for consumers. Incentives can also encourage investment in R&D, innovation, and infrastructure, thereby fostering the expansion of the biodiesel industry.
5. **Market Competitiveness:** Policymakers should enhance biodiesel's market competitiveness relative to conventional gasoil. This can include promoting research and development to increase the efficacy of biodiesel production processes, supporting technological advances, and providing incentives for adopting cleaner and more sustainable energy sources.

Policymakers and industry stakeholders can work together to stabilize biodiesel prices, support the biodiesel industry's growth, and contribute to Indonesia's sustainable energy development by implementing these policy recommendations. These measures can facilitate biodiesel production, reduce reliance on fossil fuels, mitigate the effects of climate change, and promote a greener and more sustainable energy sector.

### **5.3 Study Limitation and Future Research**

Even though this study tells us a lot about what affects the price of biodiesel in Indonesia, it is essential to note that it has some limits. The study used monthly data from the MEMR from 2016 to 2022. The accuracy of the research may depend on the availability and quality of the data. Also, the study focused on specific input factors and did not look at other things that could affect biodiesel costs, like

government policies or competition in the market. Using a VAR model made it possible to look at the relationships between variables, but it didn't prove cause and effect, and endogeneity could make it hard to figure out the way to cause and effect. Also, the results only apply to the Indonesian biofuel market during the studied period. They may not apply to other countries or other times. Future research should try to fix these problems by looking at a broader range of factors, using different econometric methods, considering market dynamics, and doing comparative studies in other places and times.

There are several prospective avenues for future research and development based on the results of this study on the factors influencing biodiesel prices in Indonesia. These directions can contribute to the sustainable development of the biodiesel industry by enhancing our understanding of biodiesel pricing dynamics. The study's findings suggest the following prospective rules: A VAR model was used to evaluate biodiesel pricing and input parameters. Structural VAR or time series econometric models can capture dynamic interactions among components and enhance biodiesel price estimations in future investigations. Macroeconomic variables, policy changes, and global energy market dynamics may be included in these models to improve prediction. Biodiesel demand and supply price elasticity show market participants' price sensitivity. Indonesia's biodiesel price elasticity can be studied using consumer preferences, government policies, and alternative fuel availability. Biodiesel's price elasticity shows the industry's ability to adjust output to market conditions.

The study found policy action stabilizes biodiesel prices. Price stabilization and subsidies can be tested to grow and stabilize biodiesel prices. This study can assist policymakers in designing successful market stability, industry viability, and environmental sustainability rules. Renewable energy development demands sustainable biodiesel production and consumption. Indonesian biodiesel production can be examined for environmental and social sustainability. Land use, greenhouse gas emissions, and water consumption can be reviewed for biodiesel production. Social implications on local communities and labor conditions can affect biodiesel production's viability. Biodiesel production technological advances lower costs,

increase efficiency and boost competitiveness. Indonesian companies can study advanced feedstock conversion, enzymatic biodiesel synthesis, and process intensification. These technologies' economic viability, environmental impact, and scalability can help stakeholders and policymakers support sustainable and efficient biodiesel production.

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## APPENDIX

### Descriptive Summary of Statistics

	LN BIO	LNCPO	LNCRD	LNCTL	LNGAS	LNMTN	LNP FAD
Mean	9.090554	6.438681	5.815781	6.677438	8.721734	5.843731	6.470253
Median	9.041022	6.422585	5.705446	6.689164	8.727880	5.878078	6.417956
Maximum	9.652394	7.057456	6.930495	6.843217	9.623655	6.199494	7.430707
Minimum	8.759512	6.002837	5.129899	6.478509	7.937875	5.327876	5.769882
Std. Dev.	0.205856	0.234628	0.505291	0.091631	0.357127	0.209341	0.355713
Skewness	0.922440	0.628080	0.655978	-0.241278	0.452686	-0.345797	0.580391
Kurtosis	3.270332	3.190289	2.393844	2.110315	3.070984	2.200435	2.989208
Jarque-Bera	12.16833	5.649526	7.310283	3.585402	2.886580	3.911619	4.716365
Probability	0.002279	0.059323	0.025858	0.166510	0.236150	0.141450	0.094592
Sum	763.6066	540.8492	488.5256	560.9048	732.6256	490.8734	543.5012
Sum Sq. Dev.	3.517272	4.569181	21.19152	0.696886	10.58582	3.637374	10.50211
Observations	84	84	84	84	84	84	84

### Correlation Matrix

	LN BIO	LNCPO	LNCRD	LNCTL	LNGAS	LNMTN	LNP FAD
LN BIO	1.000000	0.974635	0.769854	0.382780	0.439570	0.393496	0.932577
LNCPO	0.974635	1.000000	0.750600	0.369112	0.354498	0.368459	0.945186
LNCRD	0.769854	0.750600	1.000000	0.591718	0.437381	0.609756	0.806365
LNCTL	0.382780	0.369112	0.591718	1.000000	0.552313	0.989771	0.343272
LNGAS	0.439570	0.354498	0.437381	0.552313	1.000000	0.564170	0.290712
LNMTN	0.393496	0.368459	0.609756	0.989771	0.564170	1.000000	0.343505
LNP FAD	0.932577	0.945186	0.806365	0.343272	0.290712	0.343505	1.000000

### Phillips-Perron (PP) Test Results

#### UNIT ROOT TEST RESULTS TABLE (PP)

Null Hypothesis: the variable has a unit root

		<u>At Level</u>						
		LN BIO	LNCPO	LNCRD	LNCTL	LNGAS	LNMTN	LNP FAD
With Constant	t-Statistic	-1.7551	-1.9797	-1.7923	-2.2986	-0.8433	-2.3063	-1.7240
	<i>Prob.</i>	<b>0.4002</b>	<b>0.2952</b>	<b>0.3819</b>	<b>0.1749</b>	<b>0.8011</b>	<b>0.1724</b>	<b>0.4155</b>
		n0	n0	n0	n0	n0	n0	n0
With Constant & Trend	t-Statistic	-2.2838	-2.2196	-1.4792	-2.0010	-1.7040	-2.1960	-1.8990
	<i>Prob.</i>	<b>0.4377</b>	<b>0.4724</b>	<b>0.8291</b>	<b>0.5920</b>	<b>0.7409</b>	<b>0.4853</b>	<b>0.6461</b>
		n0	n0	n0	n0	n0	n0	n0
Without Constant & Trend	t-Statistic	0.7681	0.5784	0.2573	0.3742	0.9495	0.3532	0.3989
	<i>Prob.</i>	<b>0.8777</b>	<b>0.8393</b>	<b>0.7584</b>	<b>0.7901</b>	<b>0.9079</b>	<b>0.7846</b>	<b>0.7965</b>
		n0	n0	n0	n0	n0	n0	n0

		<u>At First Difference</u>				d(LNGA S)	d(LNMT N)	d(LNPFAD D)
With Constant	t-Statistic	-8.1093	-7.7825	-5.4324	-6.6656	-6.4775	-9.0315	-6.3674
	<i>Prob.</i>	<b>0.0000</b> ***	<b>0.0000</b> ***	<b>0.0000</b> ***	<b>0.0000</b> ***	<b>0.0000</b> ***	<b>0.0000</b> ***	<b>0.0000</b> ***
With Constant & Trend	t-Statistic	-8.0536	-7.7173	-5.4333	-6.6517	-6.4652	-9.0249	-6.3280
	<i>Prob.</i>	<b>0.0000</b> ***	<b>0.0000</b> ***	<b>0.0001</b> ***	<b>0.0000</b> ***	<b>0.0000</b> ***	<b>0.0000</b> ***	<b>0.0000</b> ***
Without Constant & Trend	t-Statistic	-8.1080	-7.8205	-5.4697	-6.7001	-6.5065	-9.0638	-6.3917
	<i>Prob.</i>	<b>0.0000</b> ***	<b>0.0000</b> ***	<b>0.0000</b> ***	<b>0.0000</b> ***	<b>0.0000</b> ***	<b>0.0000</b> ***	<b>0.0000</b> ***

**Notes:**

a: (\*)Significant at the 10%; (\*\*)Significant at the 5%; (\*\*\*) Significant at the 1% and (no) Not Significant

b: Lag Length based on SIC

c: Probability based on MacKinnon (1996) one-sided p-values.

**This Result is The Out-Put of Program Has Developed By:**

**Dr. Imadeddin AlMosabbeh**

**College of Business and Economics**

**Qassim University-KSA**

### Augmented Dickey-Fuller (ADF) test Results

**UNIT ROOT TEST RESULTS TABLE (ADF)**

Null Hypothesis: the variable has a unit root

		<u>At Level</u>						
With Constant	t-Statistic	-1.6204	-1.8443	-2.7917	-2.6734	-0.9154	-2.3063	-1.8473
	<i>Prob.</i>	<b>0.4677</b> n0	<b>0.3569</b> n0	<b>0.0641</b> *	<b>0.0830</b> *	<b>0.7787</b> n0	<b>0.1724</b> n0	<b>0.3554</b> n0
With Constant & Trend	t-Statistic	-2.1537	-2.0546	-2.6234	-2.5960	-1.7120	-2.1960	-2.1557
	<i>Prob.</i>	<b>0.5085</b> n0	<b>0.5629</b> n0	<b>0.2715</b> n0	<b>0.2833</b> n0	<b>0.7371</b> n0	<b>0.4853</b> n0	<b>0.5073</b> n0
Without Constant & Trend	t-Statistic	0.7381	0.5844	-0.0024	0.2935	0.8784	0.3753	0.2609
	<i>Prob.</i>	<b>0.8721</b> n0	<b>0.8407</b> n0	<b>0.6789</b> n0	<b>0.7685</b> n0	<b>0.8967</b> n0	<b>0.7904</b> n0	<b>0.7594</b> n0
		<u>At First Difference</u>						
With Constant	t-Statistic	-8.1610	-7.8441	-1.5266	-6.7898	-6.6086	-9.0187	-6.3674
	<i>Prob.</i>	<b>0.0000</b> ***	<b>0.0000</b> ***	<b>0.5150</b> n0	<b>0.0000</b> ***	<b>0.0000</b> ***	<b>0.0000</b> ***	<b>0.0000</b> ***
With Constant & Trend	t-Statistic	-8.1106	-7.7882	-1.5980	-6.7825	-6.6318	-9.0122	-6.3280

	<i>Prob.</i>	<b>0.0000</b> ***	<b>0.0000</b> ***	<b>0.7849</b> n0	<b>0.0000</b> ***	<b>0.0000</b> ***	<b>0.0000</b> ***	<b>0.0000</b> ***
Without Constant & Trend	t-Statistic	-8.1596	-7.8755	-4.1325	-6.8196	-6.5518	-9.0525	-6.3917
	<i>Prob.</i>	<b>0.0000</b> ***	<b>0.0000</b> ***	<b>0.0001</b> ***	<b>0.0000</b> ***	<b>0.0000</b> ***	<b>0.0000</b> ***	<b>0.0000</b> ***

**Notes:**

a: (\*)Significant at the 10%; (\*\*)Significant at the 5%; (\*\*\*) Significant at the 1% and (no) Not Significant

b: Lag Length based on SIC

c: Probability based on MacKinnon (1996) one-sided p-values.

**This Result is The Out-Put of Program Has Developed By:**

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**Qassim University-KSA**

**Granger Causality Test Result**

Pairwise Granger Causality Tests

Date: 04/30/23 Time: 15:50

Sample: 1 84

Lags: 3

Null Hypothesis:	Obs	F-Statistic	Prob.
DLNCPO does not Granger Cause DLNBIO	80	3.23318	0.0271
DLNBIO does not Granger Cause DLNCPO		0.19207	0.9015
DLNCRD does not Granger Cause DLNBIO	80	5.85237	0.0012
DLNBIO does not Granger Cause DLNCRD		1.68067	0.1786
DLNCTL does not Granger Cause DLNBIO	80	2.89112	0.0411
DLNBIO does not Granger Cause DLNCTL		0.43354	0.7296
DLNGAS does not Granger Cause DLNBIO	80	0.66127	0.5785
DLNBIO does not Granger Cause DLNGAS		0.56720	0.6384
DLNMTN does not Granger Cause DLNBIO	80	1.37065	0.2585
DLNBIO does not Granger Cause DLNMTN		0.33485	0.8002
DLNPFAD does not Granger Cause DLNBIO	80	36.1250	2.E-14
DLNBIO does not Granger Cause DLNPFAD		2.37507	0.0770
DLNCRD does not Granger Cause DLNCPO	80	5.06992	0.0030

DLNCPO does not Granger Cause DLNCRD		2.29231	0.0852
DLNCTL does not Granger Cause DLNCPO	80	2.86559	0.0424
DLNCPO does not Granger Cause DLNCTL		0.38359	0.7651
DLNGAS does not Granger Cause DLNCPO	80	0.36721	0.7769
DLNCPO does not Granger Cause DLNGAS		0.36286	0.7800
DLNMTN does not Granger Cause DLNCPO	80	1.70777	0.1729
DLNCPO does not Granger Cause DLNMTN		0.50872	0.6775
DLNPFAD does not Granger Cause DLNCPO	80	35.6037	3.E-14
DLNCPO does not Granger Cause DLNPFAD		3.87248	0.0125
DLNCTL does not Granger Cause DLNCRD	80	2.09628	0.1081
DLNCRD does not Granger Cause DLNCTL		0.22135	0.8813
DLNGAS does not Granger Cause DLNCRD	80	0.44685	0.7203
DLNCRD does not Granger Cause DLNGAS		0.97874	0.4076
DLNMTN does not Granger Cause DLNCRD	80	2.87351	0.0420
DLNCRD does not Granger Cause DLNMTN		1.32441	0.2730
DLNPFAD does not Granger Cause DLNCRD	80	3.24051	0.0269
DLNCRD does not Granger Cause DLNPFAD		0.18320	0.9075
DLNGAS does not Granger Cause DLNCTL	80	1.02342	0.3873
DLNCTL does not Granger Cause DLNGAS		5.20994	0.0026
DLNMTN does not Granger Cause DLNCTL	80	0.73024	0.5373
DLNCTL does not Granger Cause DLNMTN		5.35479	0.0022
DLNPFAD does not Granger Cause DLNCTL	80	1.78704	0.1572
DLNCTL does not Granger Cause DLNPFAD		0.43826	0.7263
DLNMTN does not Granger Cause DLNGAS	80	3.90828	0.0120
DLNGAS does not Granger Cause DLNMTN		0.83108	0.4811
DLNPFAD does not Granger Cause DLNGAS	80	2.79856	0.0460
DLNGAS does not Granger Cause DLNPFAD		0.46479	0.7077

DLNPFAD does not Granger Cause DLNMTN	80	2.62968	0.0565
DLNMTN does not Granger Cause DLNPFAD		0.69258	0.5595

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## Cointegration Test Result

Date: 04/30/23 Time: 13:43

Sample (adjusted): 5 84

Included observations: 80 after adjustments

Trend assumption: Linear deterministic trend

Series: DLNBIO DLNCPO DLNCRD DLNCTL DLNGAS DLNMTN DLNPFAD

Lags interval (in first differences): 1 to 2

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### Unrestricted Cointegration Rank Test (Trace)

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

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Trace test indicates 7 cointegrating eqn(s) at the 0.05 level

\* denotes rejection of the hypothesis at the 0.05 level

\*\*MacKinnon-Haug-Michelis (1999) p-values

### Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.697235	95.58386	46.23142	0.0000
At most 1 *	0.477816	51.97889	40.07757	0.0015
At most 2 *	0.418306	43.34485	33.87687	0.0028
At most 3 *	0.387914	39.27062	27.58434	0.0010
At most 4 *	0.331866	32.26133	21.13162	0.0009
At most 5 *	0.207839	18.63926	14.26460	0.0095
At most 6 *	0.159696	13.91936	3.841465	0.0002

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Max-eigenvalue test indicates 7 cointegrating eqn(s) at the 0.05 level

\* denotes rejection of the hypothesis at the 0.05 level

\*\*MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegrating Coefficients (normalized by  $b^*S11*b=I$ ):

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DLNBIO	DLNCPO	DLNCRD	DLNCTL	DLNGAS	DLNMTN	DLNPFAD
62.75157	-61.05994	1.265068	50.59058	1.191501	-23.50432	5.408293
-7.864093	2.360415	2.886658	-211.9588	1.720722	93.39313	-2.999595
26.53946	14.97277	2.594577	-53.06905	7.039107	15.92945	-24.02418
-9.008135	10.82087	9.101678	54.62137	-1.741057	-35.18256	-12.05012
-4.552449	-9.026434	-1.753322	6.276632	14.87182	-13.52880	9.447823
5.648300	-6.268558	3.540680	-43.01850	3.150875	7.125391	16.02179
10.10126	-9.005036	-9.082432	-45.71052	-5.977301	6.868278	10.05544

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Unrestricted Adjustment Coefficients (alpha):

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D(DLNBIO)	-0.007086	-0.001255	-0.028016	0.004755	0.009106	-0.007949	-0.004307
D(DLNCPO)	0.029843	0.009836	-0.025340	-0.000166	0.017274	-0.008886	0.001567
D(DLNCRD)	-0.018315	-0.028441	-0.004777	-0.037289	0.007650	-0.022943	0.027774
D(DLNCTL)	-0.003424	0.001058	-0.003164	0.013224	0.002809	0.003782	0.010204
D(DLNGAS)	0.012678	0.005464	-0.019974	-0.003120	-0.044725	0.011901	0.004330
D(DLNMTN)	-0.009471	-0.019780	-0.008422	0.038553	0.007117	0.008480	0.018364
D(DLNPFAD)	0.002141	0.003991	0.008484	0.019428	-0.003451	-0.032281	0.019691

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1 Cointegrating Equation(s):                      Log likelihood                      846.4052

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Normalized cointegrating coefficients (standard error in parentheses)

DLNBIO	DLNCPO	DLNCRD	DLNCTL	DLNGAS	DLNMTN	DLNPFAD
1.000000	-0.973042	0.020160	0.806204	0.018988	-0.374561	0.086186
	(0.05253)	(0.01845)	(0.31140)	(0.02345)	(0.13582)	(0.04562)

Adjustment coefficients (standard error in parentheses)

D(DLNBIO)	-0.444641
	(0.40225)
D(DLNCPO)	1.872665
	(0.45863)
D(DLNCRD)	-1.149302
	(0.89492)
D(DLNCTL)	-0.214850
	(0.27474)
D(DLNGAS)	0.795591
	(0.69884)
D(DLNMTN)	-0.594300
	(0.67792)
D(DLNPFAD)	0.134382
	(0.72987)

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2 Cointegrating Equation(s):                      Log likelihood                      872.3946

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Normalized cointegrating coefficients (standard error in parentheses)

DLNBIO	DLNCPO	DLNCRD	DLNCTL	DLNGAS	DLNMTN	DLNPFAD
1.000000	0.000000	-0.539796 (0.32902)	38.61569 (5.62616)	-0.324879 (0.42891)	-17.00619 (2.46301)	0.513126 (0.49818)
0.000000	1.000000	-0.575469 (0.33909)	38.85698 (5.79832)	-0.353393 (0.44204)	-17.09240 (2.53838)	0.438768 (0.51342)

Adjustment coefficients (standard error in parentheses)

D(DLNBIO)	-0.434773 (0.40528)	0.429692 (0.39158)
D(DLNCPO)	1.795315 (0.45563)	-1.798965 (0.44024)
D(DLNCRD)	-0.925642 (0.87345)	1.051188 (0.84394)
D(DLNCTL)	-0.223171 (0.27676)	0.211556 (0.26741)
D(DLNGAS)	0.752624 (0.70298)	-0.761247 (0.67922)
D(DLNMTN)	-0.438751 (0.66509)	0.531591 (0.64261)
D(DLNPFAD)	0.102994 (0.73490)	-0.121339 (0.71007)

3 Cointegrating Equation(s):            Log likelihood            894.0671

Normalized cointegrating coefficients (standard error in parentheses)

DLNBIO	DLNCPO	DLNCRD	DLNCTL	DLNGAS	DLNMTN	DLNPFAD
1.000000	0.000000	0.000000	3.532955 (0.97203)	0.118013 (0.07289)	-1.719553 (0.42517)	-0.421421 (0.07564)
0.000000	1.000000	0.000000	1.455747 (0.93129)	0.118768 (0.06983)	-0.795521 (0.40735)	-0.557539 (0.07247)
0.000000	0.000000	1.000000	-64.99262 (9.32440)	0.820481 (0.69918)	28.31931 (4.07849)	-1.731297 (0.72561)

Adjustment coefficients (standard error in parentheses)

D(DLNBIO)	-1.178305 (0.36808)	0.010214 (0.33764)	-0.085276 (0.02191)
D(DLNCPO)	1.122812 (0.44381)	-2.178371 (0.40711)	0.000400 (0.02642)
D(DLNCRD)	-1.052413 (0.94636)	0.979668 (0.86809)	-0.117662 (0.05633)
D(DLNCTL)	-0.307138 (0.29891)	0.164184 (0.27419)	-0.009486 (0.01779)
D(DLNGAS)	0.222532 (0.74289)	-1.060309 (0.68145)	-0.020013 (0.04422)
D(DLNMTN)	-0.662263 (0.71765)	0.405493 (0.65830)	-0.090929 (0.04272)
D(DLNPFAD)	0.328142 (0.79366)	0.005683 (0.72802)	0.036242 (0.04724)

4 Cointegrating Equation(s):            Log likelihood            913.7024

Normalized cointegrating coefficients (standard error in parentheses)

DLNBIO	DLNCPO	DLNCRD	DLNCTL	DLNGAS	DLNMTN	DLNPFAD
1.000000	0.000000	0.000000	0.000000	0.168326 (0.06314)	-0.120060 (0.08705)	-0.453134 (0.06587)
0.000000	1.000000	0.000000	0.000000	0.139500 (0.06560)	-0.136454 (0.09044)	-0.570607 (0.06844)
0.000000	0.000000	1.000000	0.000000	-0.105079 (0.27646)	-1.105129 (0.38113)	-1.147903 (0.28842)
0.000000	0.000000	0.000000	1.000000	-0.014241 (0.01044)	-0.452735 (0.01439)	0.008976 (0.01089)

Adjustment coefficients (standard error in parentheses)

D(DLNBIO)	-1.221136 (0.36896)	0.061664 (0.34049)	-0.042000 (0.05321)	1.653994 (1.23124)
D(DLNCPO)	1.124310 (0.44762)	-2.180171 (0.41308)	-0.001114 (0.06455)	0.760630 (1.49372)
D(DLNCRD)	-0.716508 (0.89838)	0.576168 (0.82906)	-0.457055 (0.12955)	3.318388 (2.99791)
D(DLNCTL)	-0.426260 (0.27895)	0.307278 (0.25743)	0.110874 (0.04023)	0.492724 (0.93087)
D(DLNGAS)	0.250637 (0.74878)	-1.094071 (0.69101)	-0.048410 (0.10798)	0.372918 (2.49870)
D(DLNMTN)	-1.009554 (0.64248)	0.822671 (0.59291)	0.259968 (0.09265)	6.266109 (2.14398)
D(DLNPFAD)	0.153129 (0.78265)	0.215915 (0.72226)	0.213072 (0.11286)	-0.126671 (2.61173)

5 Cointegrating Equation(s):            Log likelihood            929.8330

Normalized cointegrating coefficients (standard error in parentheses)

DLNBIO	DLNCPO	DLNCRD	DLNCTL	DLNGAS	DLNMTN	DLNPFAD
1.000000	0.000000	0.000000	0.000000	0.000000	0.024229 (0.08425)	-0.454791 (0.06657)
0.000000	1.000000	0.000000	0.000000	0.000000	-0.016874 (0.08490)	-0.571980 (0.06709)
0.000000	0.000000	1.000000	0.000000	0.000000	-1.195203 (0.36605)	-1.146868 (0.28925)
0.000000	0.000000	0.000000	1.000000	0.000000	-0.464942 (0.01423)	0.009117 (0.01124)
0.000000	0.000000	0.000000	0.000000	1.000000	-0.857200 (0.24954)	0.009845 (0.19718)

Adjustment coefficients (standard error in parentheses)

D(DLNBIO)	-1.262592 (0.36124)	-0.020532 (0.33596)	-0.057966 (0.05278)	1.711150 (1.20332)	-0.080663 (0.08690)
D(DLNCPO)	1.045672 (0.42288)	-2.336093 (0.39328)	-0.031401 (0.06178)	0.869052 (1.40862)	0.131298 (0.10173)
D(DLNCRD)	-0.751332 (0.89788)	0.507120 (0.83503)	-0.470467 (0.13118)	3.366402 (2.99088)	0.074301 (0.21600)
D(DLNCTL)	-0.439047	0.281925	0.105949	0.510354	-0.005781

	(0.27849)	(0.25900)	(0.04069)	(0.92768)	(0.06700)
D(DLNGAS)	0.454244	-0.690366	0.030007	0.092198	-0.775796
	(0.64257)	(0.59760)	(0.09388)	(2.14044)	(0.15458)
D(DLNMTN)	-1.041954	0.758429	0.247490	6.310780	-0.065882
	(0.64091)	(0.59605)	(0.09364)	(2.13491)	(0.15418)
D(DLNPFAD)	0.168841	0.247068	0.219124	-0.148334	-0.016018
	(0.78377)	(0.72892)	(0.11451)	(2.61080)	(0.18855)

6 Cointegrating Equation(s):            Log likelihood            939.1527

Normalized cointegrating coefficients (standard error in parentheses)

DLNBIO	DLNCPO	DLNCRD	DLNCTL	DLNGAS	DLNMTN	DLNPFAD
1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	-0.378696 (0.06303)
0.000000	1.000000	0.000000	0.000000	0.000000	0.000000	-0.624977 (0.05973)
0.000000	0.000000	1.000000	0.000000	0.000000	0.000000	-4.900604 (0.87837)
0.000000	0.000000	0.000000	1.000000	0.000000	0.000000	-1.451114 (0.30490)
0.000000	0.000000	0.000000	0.000000	1.000000	0.000000	-2.682335 (0.61180)
0.000000	0.000000	0.000000	0.000000	0.000000	1.000000	-3.140669 (0.65631)

Adjustment coefficients (standard error in parentheses)

D(DLNBIO)	-1.307491	0.029298	-0.086112	2.053113	-0.105710	-0.744047
	(0.35579)	(0.33135)	(0.05488)	(1.20156)	(0.08682)	(0.53650)
D(DLNCPO)	0.995480	-2.280389	-0.062864	1.251321	0.103299	-0.477639
	(0.41718)	(0.38853)	(0.06435)	(1.40890)	(0.10180)	(0.62908)
D(DLNCRD)	-0.880921	0.650939	-0.551701	4.353375	0.002011	-1.256810
	(0.87849)	(0.81815)	(0.13551)	(2.96682)	(0.21437)	(1.32469)
D(DLNCTL)	-0.417686	0.258218	0.119339	0.347665	0.006135	-0.347408
	(0.27748)	(0.25842)	(0.04280)	(0.93709)	(0.06771)	(0.41841)
D(DLNGAS)	0.521467	-0.764971	0.072146	-0.419785	-0.738296	0.693739
	(0.63634)	(0.59263)	(0.09816)	(2.14903)	(0.15528)	(0.95955)
D(DLNMTN)	-0.994055	0.705270	0.277516	5.945970	-0.039161	-3.151094
	(0.63879)	(0.59491)	(0.09854)	(2.15731)	(0.15588)	(0.96325)
D(DLNPFAD)	-0.013492	0.449424	0.104827	1.240349	-0.117732	-0.409293
	(0.73458)	(0.68412)	(0.11332)	(2.48081)	(0.17925)	(1.10769)

## Lag Order Criteria

VAR Lag Order Selection Criteria

Endogenous variables: DLNBIO DLNCPO DLNCRD DLNCTL DLNGAS DLNMTN  
DLNPFAD

Exogenous variables: C

Date: 04/12/23 Time: 13:13

Sample: 1 84

Included observations: 76

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

\* indicates lag order selected by the criterion

LR: sequential modified LR test statistic (each test at 5% level)

FPE: Final prediction error

AIC: Akaike information criterion

SC: Schwarz information criterion

HQ: Hannan-Quinn information criterion

### ***VAR Estimation Results***

Vector Autoregression Estimates

Date: 04/12/23 Time: 20:28

Sample (adjusted): 4 84

Included observations: 81 after adjustments

Standard errors in ( ) & t-statistics in [ ]

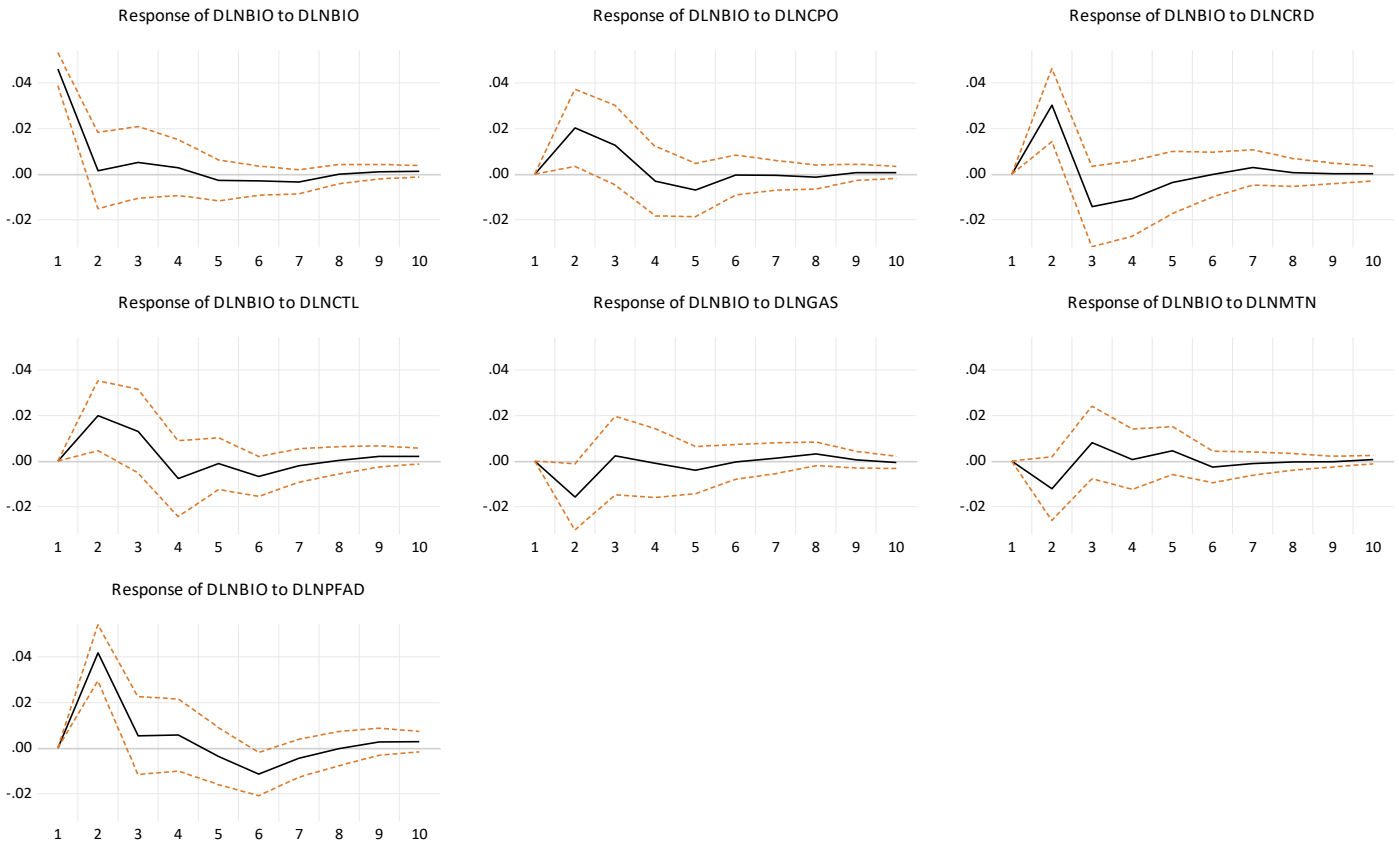
	DLNBIO	DLNCPO	DLNCRD	DLNCTL	DLNGAS	DLNMTN	DLNPFAD
DLNBIO(-1)	0.013095 (0.17320) [ 0.07561]	0.216668 (0.21267) [ 1.01880]	0.017437 (0.44134) [ 0.03951]	0.115577 (0.13039) [ 0.88642]	-0.138053 (0.34621) [-0.39875]	0.127632 (0.30436) [ 0.41935]	0.019920 (0.34702) [ 0.05740]
DLNBIO(-2)	-0.372286 (0.14711) [-2.53063]	0.010256 (0.18064) [ 0.05678]	-0.115603 (0.37487) [-0.30838]	-0.065196 (0.11075) [-0.58869]	0.485766 (0.29407) [ 1.65189]	-0.381497 (0.25852) [-1.47571]	0.002835 (0.29475) [ 0.00962]
DLNCPO(-1)	-0.029290 (0.14204) [-0.20620]	-0.226624 (0.17441) [-1.29934]	-0.185941 (0.36195) [-0.51372]	-0.092280 (0.10693) [-0.86298]	-0.054378 (0.28393) [-0.19152]	-0.134754 (0.24961) [-0.53986]	0.543746 (0.28460) [ 1.91059]
DLNCPO(-2)	0.134658 (0.12578) [ 1.07060]	-0.289542 (0.15444) [-1.87475]	0.378527 (0.32050) [ 1.18104]	-0.059118 (0.09469) [-0.62435]	-0.655419 (0.25142) [-2.60685]	0.085619 (0.22103) [ 0.38737]	-0.038129 (0.25201) [-0.15130]
DLNCRD(-1)	-0.008467 (0.04997) [-0.16945]	-0.051615 (0.06135) [-0.84127]	0.611915 (0.12732) [ 4.80600]	-0.030331 (0.03762) [-0.80636]	-0.252489 (0.09988) [-2.52794]	0.037035 (0.08781) [ 0.42179]	-0.072080 (0.10011) [-0.71999]

DLNCRD(-2)	-0.095080 (0.05448) [-1.74526]	-0.086445 (0.06689) [-1.29226]	-0.395777 (0.13882) [-2.85097]	0.017295 (0.04101) [ 0.42171]	0.133080 (0.10890) [ 1.22204]	9.05E-05 (0.09573) [ 0.00095]	-0.006083 (0.10915) [-0.05573]
DLNCTL(-1)	1.227436 (0.43650) [ 2.81200]	0.731592 (0.53598) [ 1.36497]	2.058664 (1.11227) [ 1.85086]	0.375350 (0.32860) [ 1.14226]	0.489617 (0.87253) [ 0.56114]	2.537994 (0.76705) [ 3.30877]	-0.225245 (0.87457) [-0.25755]
DLNCTL(-2)	0.654017 (0.41735) [ 1.56707]	0.310032 (0.51246) [ 0.60499]	1.734533 (1.06348) [ 1.63100]	-0.179590 (0.31419) [-0.57160]	-0.138956 (0.83425) [-0.16656]	0.560524 (0.73340) [ 0.76428]	-0.228324 (0.83620) [-0.27305]
DLNGAS(-1)	-0.162131 (0.06088) [-2.66318]	0.003956 (0.07475) [ 0.05293]	-0.043194 (0.15513) [-0.27844]	-0.048525 (0.04583) [-1.05879]	0.215852 (0.12169) [ 1.77375]	-0.121792 (0.10698) [-1.13845]	-0.026925 (0.12198) [-0.22074]
DLNGAS(-2)	0.106919 (0.05993) [ 1.78405]	0.061175 (0.07359) [ 0.83131]	0.096401 (0.15271) [ 0.63126]	-0.004329 (0.04512) [-0.09594]	-0.052891 (0.11980) [-0.44151]	-0.036286 (0.10531) [-0.34455]	-0.106757 (0.12008) [-0.88908]
DLNMTN(-1)	-0.472347 (0.18262) [-2.58650]	-0.291863 (0.22424) [-1.30157]	-0.980042 (0.46535) [-2.10604]	-0.079182 (0.13748) [-0.57596]	0.152603 (0.36505) [ 0.41804]	-1.018557 (0.32092) [-3.17392]	0.126824 (0.36590) [ 0.34661]
DLNMTN(-2)	-0.156238 (0.17142) [-0.91141]	-0.054119 (0.21049) [-0.25711]	-0.741147 (0.43682) [-1.69670]	0.082860 (0.12905) [ 0.64208]	0.189973 (0.34266) [ 0.55440]	-0.133437 (0.30124) [-0.44296]	-0.039038 (0.34346) [-0.11366]
DLNPFAD(-1)	0.583422 (0.07312) [ 7.97894]	0.796951 (0.08978) [ 8.87631]	0.027847 (0.18632) [ 0.14946]	0.112455 (0.05505) [ 2.04294]	0.357517 (0.14616) [ 2.44602]	0.211117 (0.12849) [ 1.64303]	0.284466 (0.14650) [ 1.94171]
DLNPFAD(-2)	-0.054945 (0.09385) [-0.58545]	-0.084033 (0.11524) [-0.72920]	0.141446 (0.23915) [ 0.59145]	0.030451 (0.07065) [ 0.43099]	0.144398 (0.18760) [ 0.76970]	0.041911 (0.16492) [ 0.25413]	-0.268651 (0.18804) [-1.42869]
C	0.004688 (0.00525) [ 0.89350]	0.000934 (0.00644) [ 0.14494]	0.002751 (0.01337) [ 0.20575]	0.001455 (0.00395) [ 0.36845]	0.007185 (0.01049) [ 0.68505]	0.005139 (0.00922) [ 0.55741]	0.004357 (0.01051) [ 0.41443]
R-squared	0.713626	0.673515	0.423747	0.225855	0.411476	0.326698	0.277710
Adj. R-squared	0.652880	0.604260	0.301511	0.061642	0.286638	0.183876	0.124497
Sum sq. resids	0.140567	0.211936	0.912723	0.079663	0.561666	0.434074	0.564289
S.E. equation	0.046150	0.056667	0.117597	0.034742	0.092250	0.081098	0.092465
F-statistic	11.74771	9.725219	3.466639	1.375378	3.296070	2.287455	1.812577
Log likelihood	142.5051	125.8757	66.73976	165.5043	86.40349	96.84001	86.21481
Akaike AIC	-3.148273	-2.737671	-1.277525	-3.716155	-1.763049	-2.020741	-1.758390
Schwarz SC	-2.704857	-2.294254	-0.834108	-3.272738	-1.319633	-1.577325	-1.314974
Mean dependent	0.005539	0.003828	0.003909	0.001607	0.012112	0.003966	0.004001
S.D. dependent	0.078330	0.090079	0.140708	0.035865	0.109223	0.089770	0.098821
Determinant resid covariance (dof adj.)		1.82E-18					
Determinant resid covariance		4.34E-19					

Log likelihood 907.8903  
 Akaike information criterion -19.82445  
 Schwarz criterion -16.72054  
 Number of coefficients 105

### Impulse Response Function (IRF)

Response to Cholesky One S.D. (d.f. adjusted) Innovations  $\pm 2$  S.E.



### Variance Decomposition

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
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Variance  
Decompositio  
n 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  
Decompositio  
n 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  
Decompositio  
n 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  
Decompositio  
n 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

Cholesky Ordering: DLNBIO DLNCPO DLNCRD DLNCTL DLNGAS DLNMTN DLNPFAD