The impact of el niño southern oscillation and covid-19 on the rice price dynamics in Indonesia: the vector error correction model approach

P Hasudungan¹*, I Irham¹², A W Utami¹

¹ Department of Agricultural SocioEconomics, Universitas Gadjah Mada, Jl. Flora, 55281, Indonesia
² Center of Asia-Pacific Study (PSAP), Universitas Gadjah Mada, Jl. Teknika Utara, 55281, Indonesia

* E-mail: peterhasudungan@mail.ugm.ac.id

Abstract. Half of the world’s population makes rice a crop of focus because it has many opportunities in the future. However, there are disruptors for rice development in 2020, which are climate variability and COVID-19 Pandemics. El Nino-Southern Oscillation (ENSO) is a climate variability that can threaten the rice price dynamics. Besides that, COVID-19 also has implications for rice price dynamics. The objectives of this paper are: (1) to empirically study the impact of the El Nino-Southern Oscillation on rice price dynamics and (2) to analyze the effect of COVID-19 pandemics on rice price in Indonesia. The study utilized the vector error correction model (VECM) estimation method and the variables used were sea surface temperature (SST), COVID-19 daily cases, rice price, rice production, and rice price regulation. The result is that El Nino has a positive effect on rice prices, which can increase the price level. The opposite is true also for a La Nina shock. COVID-19 also has a positive impact on the daily cost of rice. The results of this study ought to be of interest to rice producers in Indonesia, as well as processors and intermediaries in the rice markets.

1. Introduction
Rice is a staple food in Asia and nearly half of the world’s population makes it a crop of focus because of a lot of opportunities in the future [1]. Rice production is predicted to increase towards 2020 with a growth of 0.76 percent per year [2]. Unfortunately, rice will suffer the most due climate variability and COVID-19 because they disrupt high water and labor requirements [3], [4]. Furthermore, the impacts will be discussed in this study.

The impact of climatic factors on production has become a concern of some Indonesian researchers, such as Dhamira & Irham and Mulyasari et al. [5], [6]. First, we talk about climate variability. El Niño-Southern Oscillation (ENSO) is a climate variability that fluctuates between a warm phase (El Niño) and a cold phase (La Niña) [7] and it has terrible implications for hydrology and productivity of crops [8]. The worst thing about ENSO is that it has a severe and negative impact on developing countries, especially Indonesia, which has a vast agricultural sector [9].

Rice requires a more significant amount of water than other cereal crops, but it will be optimal if the water availability is stable, especially rainfall [10]. Unfortunately, the ENSO phenomenon makes rainfall fluctuate due to the warm phase (decreasing rainfall) [11] and the cold phase (increasing rainfall) [12]. Furthermore, these fluctuations will reduce rice productivity [3], [13], [14].

The decline in rice productivity can fluctuate rice price dynamics because it cannot meet the increasing demand for rice [15]. Indonesian rice demand is relatively high with an average growth in
rice consumption of 0.9% per year [16]. Based on that facts, it can be concluded that rice prices are vulnerable to El Niño and La Niña through high increasing demand.

Several studies have revealed the relationship between ENSO and rice price dynamics. Falcon et al. stated that rice price dynamics are closely related to El Niño and La Niña events [17]. Brunner found that rice is a commodity that is more price affected by El Niño and La Niña events than other items [18]. Deng et al. indicated that El Niño had a significant effect on international rice prices [14]. In his research, the El Niño event contributed significantly to the increase in domestic rice prices in Indonesia and the Philippines. These studies underline the impact of ENSO on prices between the warm phase (El Nino) and the cold phase (La Nina). As a comparison with other commodities, several studies have found that prices increase during El Niño and decrease during La Niña [19]–[21].

Besides, rice has the most considerable price volatility than other cereal crops [22]. Rice prices also quickly increase from time to time due to the rice market's uncertainty [23]. With these characteristics, coupled with El Niño and La Nina's occurrence, rice prices' volatility will worsen and become the most significant contributor to inflation in a country. Therefore, the El Nino phenomenon is quite dangerous for a country's economy even though 20% of the movement of commodity price inflation is influenced by El Nino [18].

Second, we talk about COVID-19 impact on rice prices. As the number of positive cases continues to rise, agricultural especially rice markets, face disruptions because of labor shortages created by restrictions on movements of people and shifts and income losses [24]. Research has been conducted to study rice prices in China and resulted that no significant impact on rice price [25]. However, it may be different from Indonesia cases until November 2020 because Indonesian COVID-19 cases have increased more than 444,000 cases, while China's growth has decreased sharply and significantly [26].

Therefore, this study was conducted to clarify further the impact of El Nino-Saharan Oscillation and COVID-19 on rice prices so that price volatility can be reduced. Because if food prices are stable, poor farmers and consumers will not fall into the poverty trap [27]. This study's objectives are: (1) to empirically study the impact of the El Nino-Southern Oscillation on rice price dynamics and (2) to analyze the effect of COVID-19 pandemics on rice price in Indonesia.

2. Review of Literature

2.1. The Impact of El Nino-Southern Oscillation on Rice Price Dynamics

El Niño has the meaning of 'The Little Boy 'or' Christ child 'in Spanish. It was recognized as the appearance of warm water in the Pacific Ocean [28]. Hot ocean temperatures in the Equatorial Pacific are evidence of El Niño's existence. Meanwhile, the opposite of El Niño is called La Niña, which is characterized by freezing ocean temperatures in the Equatorial Pacific. El Niño and La Niña are the opposite phases of the El Niño-Southern Oscillation (ENSO) cycle, a scientific term that describes the fluctuations in temperature between the ocean and atmosphere in the east-central equatorial Pacific [7].

There is a consistent wind called trade winds, blowing from east to west under the normal condition in Tropical Pacific. These winds push warm water near the surface and slowly accumulated on the western side of the ocean (near Asia and Australasia). The warmer water near South and Central America gets pushed away from the coast and replaced by cold water from the deep sea. This process is called upwelling. The upwelling process creates a temperature difference across the tropical Pacific, with warmer water accumulates in the west (Asia and Australasia) and cooler water in the east (South and Central America). Warmer water adds extra heat to the air which causes the air to rise rapidly and this rising air creates a scenario of more unsettled weather with more clouds and rainfall. The rising air in the west sets up an atmospheric circulation across this part of the world with warm moisture rising on the western Pacific Ocean and cooler dry air descending on the other side. This circulation reinforces the easterly winds so that this part of the world sits in a self-perpetuating state until the El Niño event begins [29].

There has been no research that directly addresses the impact of El Niño and La Niña on rice prices in Indonesia. Previous research only focuses on its effect on rice production [3]. However, if El Niño is associated with drought, Jati has proven that the phenomena cause increase rice prices [30].
However, if we look at the broader context than rice, El Niño and La Niña also affect the price of other commodities. For example, Credit Suisse's recent report highlights the spikes in palm oil prices, mostly in the El Niño period (Figure 1). Additionally, several studies have found that El Niño causes an increase in prices, while La Niña causes a decrease in prices [19], [20], [31], [32].

![Figure 1. CPO Prices (Line) Soaring During El Niño (Marked in Blue)](image)

Prices also react differently between El Nino and La Nina. Ubilava and Holt stated that prices are more responsive to El Niño shocks than La Nina shocks [19]. This statement means that the response of rice prices is more volatile to the El Nino shock than the La Nina shock. Meanwhile, prices are more sensitive to La Niña shocks than to El Nino shocks. Sensitive means that the La Nina shock variance contribute more to the price of rice than El Nino.

In Indonesia, the price of rice is regulated by state policies, namely Harga Pembelian Pemerintah (HPP) and HET (Harga Eceran Tertinggi). The HPP policy protects the price of grain or rice at the farm level and the HET policy protects the purchasing power of consumers for rice products as a staple food [33], [34]. Rachman et al. stated that the implementation of HET increases the selling price at the farmer level and increases rice farming profitability [35]. HPP implementation's impact is that the purchase price of rice increases at the farm level so that the rice farmer surplus increases [36].

2.2. The Impact of COVID-19 Pandemics on Rice Price

The coronavirus disease 2019 (COVID-19) is an infectious disease caused by the novel coronavirus. Before it has been a global pandemic, the first case was first founded in Wuhan city of China. Almost all the countries in the world have been suffering due to its transmission [37]. Figure 2 shows that how are the changes in COVID-19 cases in Indonesian which shows positive trends.

In the introduction, the study conducted by Yu et al. of the COVID-19's impact on rice prices in China was mentioned [25]. There are no enough empirical studies to prove the existence of COVID-19 impact on rice price dynamics. On the contrary, several studies have supported how the COVID-19 pandemic impacted the food agro system to illustrate how the effects on the agricultural sector [24], [38]. In addition, a phenomenon of food crisis could be mirrored by increasing food prices, which are caused by the working limit of low labor [39], [40].
3. Data and Methods

3.1. Data

We estimate a Vector Error Correction Model (VECM) model with macroeconomic variables, namely $y_t \equiv [sst_t; prod_t; rpr_t, reg_t]$ and $y_t \equiv [rprd_t, covd_t]$ where $sst_t$ denotes Sea Surface Temperature (SST) anomalies in the Nino 3.4 region", $prod_t$ is the rice production, $rpr_t$ is the rice price in Indonesia, and $reg_t$ is the representative of government regulation, which it dried harvested rice price.

Variables are sampled monthly and cover January 2000 until December 2018, for a total of 228 observations. For the COVID-19 model, $rprd_t$ is the daily rice price in Indonesia and $covd_t$ is the new positive cases reported daily. The variables are sampled daily and cover the period March 15, 2020 (WFH regulation legalized) until November 9, 2020, for a total of 240 observations.

Figure 3 shows that the real price of rice is highly volatile. This practical aspect is coherent with a low price elasticity of supply and low price and income elasticities of demand, whose interaction tends to magnify the price impact of actual and expected supply shortages. Figure 2, the number of positive cases COVID-19, shows higher price volatility than rice even though it shows an increasing trend.

3.2. Identification of the Vector Error Correction Model.

Our VECM model can be written as:

$$RPR_t = \sum_{j=1}^{n} RPR_{t-j} + \sum_{j=1}^{n} SST_{t-j} + \sum_{j=1}^{n} PROD_{t-j} + \sum_{j=1}^{n} REG_{t-j}$$

$$RPRd_t = \sum_{j=1}^{n} RPRd_{t-j} + \sum_{j=1}^{n} Covd_{t-j}$$

The first model is an ENSO model. The following model is a COVID-19 model. Also, an "ENSO shock" is defined as an unpredictable change of the SST index. Positive ENSO shocks identify unexpected El Nino events, while the SST index's unpredictable negative changes represent La Nina episodes. To correctly specify the VECM model, this research followed the standard procedure of time series analyses by following these procedures: (1) Pairwise Granger Causality Test, (2) Impulse Response Function, and (3) Forecast Error Variance Decomposition.

Figure 3. The Real Price of Rice in Indonesia for 2000-2018
4. Results and Discussion

The present empirical analysis starts with checking the time series variables' stationarity as that is the prime requirement for the cointegration and causality test. We found that all the variables do not appear to be stationary in variable levels, which means the variables are non-stationary in their level data and suggest that stationarity be checked at a higher order of differencing (first difference). Following that, the three series are integrated of order one, the cointegration relationship between them is established using Johansen's maximum likelihood (ML) test. The results indicate that the time series variables (rice price, SST, production, GKP, COVID-19 cases) are cointegrated. It gave us Pairwise Granger Causality to testing specific hypothesized causality.

4.1. The Relationship ENSO, COVID-19, and Rice Price Dynamics with Pairwise Granger Causality

Granger causality test is employed to observe whether a causality relationship between each of the variables. In other words, every variable has causality to another variable and can become the exogenous variable and endogenous variable. This research uses $\alpha = 5\%$ as the indicator.

4.1.1. The causality relationship on ENSO Model and COVID-19 Model

The result of the causality test for the ENSO model is shown in Table 1 below. This result also finds between rice price and production, even between rice production and regulation. It shows that climate does not have bidirectional causality, it can be concluded only climatic factor that can affect economic factors, not vice versa [18].

| Dependent | RPR | SST | REG | PROD | Inferences |
|-----------|-----|-----|-----|------|------------|
| RPR       | -   | -   | 0.0023* | 0.0136* | RPR $\nmid$ REG, RPR $\nmid$ PROD |
| SST       | -   | -   | -    | -    | RPR, REG, PROD can not affect SST (climate) |
| REG       | 0.0106* | -  | -   | 0.0121* | REG $\nmid$ RPR, REG $\nmid$ PROD |
| PROD      | 0.0332* | -  | 0.0004* | -    | PROD $\nmid$ RPR, PROD $\nmid$ REG |

Source: Data Processed

4.1.2. The causality relationship between COVID-19 and Rice Price Dynamics

The result of the causality test is shown in Table 2 below. The result found the existence of bidirectional causality between daily rice prices and COVID cases. The costs can be affected by the COVID pandemic because of its disruption on high labor requirements due to the working restrictions [24]. COVID pandemic can also be affected by rice prices due to demand and consumption during a pandemic [41].
Table 2. Result Pairwise Granger Causality Test on COVID-19 Model

| Dependent | RPRd  | COVd  | Probability |
|-----------|-------|-------|-------------|
| RPRd      | -     | 0.0316** | RPRd ⇛ COVd |
| COVd      | 0.0000*** | -     | COVd ⇝ RPRd, has bidirectional causality |

Source: Data Processed

4.2. Impulse Response Function of ENSO model and COVID-19 Model

Impulse Response's function is to track the response of variable overtime after a shock to the VAR system. Kilian & Lüttkepohl explains the role of the IRF expectation k-period ahead and the error prediction variable caused by innovations of other variables [42]. Thus, the shock effect duration of one variable to another variable up to the point when the effect of shock disappears or returns to equilibrium can be seen and known.

4.2.1. Impulse Response Function of El Nino-Southern Oscillation Model

The result showed that the positive shocks of ENSO would increase and stabilize in positive areas of rice price dynamics. For La Nina's shock, rice prices tend to response negatively. It supports the statement of Bastianin et al. and Ubilava & Holt, which state that El Nino increases prices (positive response) and La Nina decreases costs (negative response) due to the fluctuating demand and supply of rice during El Nino and La Nina [19], [20]. The graph below shows the result of the analysis of impulse response, as follows in Figure 4.

4.2.2. Impulse Response Function of COVID-19 Model

The rice price response shows a high increase from the fifth period until the sixth period. However, the rice price response from the shock of COVID-19 in the last period is highest than in other periods. It can be implied that the more COVID-19 transmitted to other people, the more the price will be increased. Working restrictions caused it for rice farmers and rice supply decreased. The scarcity of rice will increase the price (Figure 5).

Figure 4. The response of Rice Price to Cholesky One S.D. (d.f. adjusted) Innovations of El Nino (left) and La Nina (right).
4.2.3. Variance Decomposition Test of El Nino-Southern Oscillation Model and COVID-19 Model

For the ENSO model, the results of the FEVD indicate that the rice price variance is explained more by itself shock than the ENSO, production, and regulator price shocks (Figure 7). The enormous contribution of rice prices to itself can mean that there is speculative behavior from rice market players considering that several studies have found that market speculators are vulnerable to rice price volatility [22], [23].

Unfortunately, the La Niña (SST negative) shock indicator explains less of the variance of prices. Only the El Nino (SST positive) indicator can explain price variances well. It indicates that prices are more sensitive to El Nino than La Nina, at the same time contradicting what was found by Ublava & Holt, who found that sensitivity tends to favor La Nina [19]. In Indonesia, drought has a more significant impact on rice prices rather than floods [17].

This figure has the same result as the COVID-19 model (Figure 6). The results of the FEVD indicate that the rice price variance is explained more by itself shock than the COVID-19 model. COVID-19 has started to contribute from the second period until the last period. It can be concluded that COVID-19 has a contribution to rice price fluctuations of 1-16%.

5. Conclusion

This study has examined and modeled a system of rice (price, production, and price-regulation), COVID-19, and the ENSO equation. This study aims to clarify the impact of the El Nino-Southern
Oscillation on rice price dynamics. Consistent with the previous literature [18], [43], evidence supports the hypothesis in the ENSO equation and the system of rice price equations. This study revealed a few features of interest, which can be summarized as follows: a positive ENSO shock—El Nino—has a positive effect on rice price, increasing the cost. The La Nina shock is actual. The second aim of this study is to clarify the impact of COVID-19 on rice prices. Using Granger causality, IRF, and VECD test, this study has concluded the following evidence that COVID-19 has a positive effect on rice prices. This study is the opposite of Yu et al. [25] in China that resulted that no significant impact on rice prices. Because China continues to report a lower number of new COVID-19 cases, it differs from Indonesia, which exposes a higher number every day. We hope this analysis is deemed vital for rice producers in Indonesia and processors and intermediaries in the rice markets.

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