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Impact of The Covid-19 Pandemic On Egg Market Integration And Price Transmission In Indonesia

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ABSTRACT
Purpose: *This study aims to examine the impact of the COVID-19 pandemic on the egg market by analyzing changes in market integration and price transmission across major producing and consuming regions in Indonesia.* ***Methodology:*** *The research employs a quantitative empirical approach using secondary time-series data on egg prices from eight provinces, covering pre-pandemic (July 2017–February 2020) and pandemic (March 2020–August 2021) periods. Econometric analyses were conducted using the Augmented Dickey-Fuller (ADF) test, Johansen cointegration method, and Variance Decomposition within a Vector Error Correction Model (VECM) framework to assess market integration and price transmission dynamics.* ***Results:*** *The findings indicate a significant decline in market integration during the COVID-19 pandemic compared to the pre-pandemic period, reflecting weaker inter-market linkages. Price transmission among regional markets also decreased, suggesting reduced efficiency in transmitting price signals during the crisis.* ***Novelty:*** *This study provides a comparative econometric assessment of market behavior before and during a major global health crisis.* ***Findings:*** *The COVID-19 pandemic disrupted the stability and efficiency of the egg market, affecting both market connectivity and price responsiveness.* ***Originality:*** *The originality of this research lies in its multi-regional time-series analysis focusing on essential food commodities during a pandemic context.* ***Conclusions:*** *Strengthening market coordination and supply chain resilience is crucial to maintaining price stability and food accessibility during future crises.* ***Type of Paper:*** *Empirical Quantitative Study.*

INTRODUCTION

Eggs are recognized as a highly nutritious food with unique components that offer potential nutraceuticals with specific health benefits. Eggs are also considered healthy food that does not increase serum cholesterol, which fits well into high-protein, low-carbohydrate diets. Eggs are considered nature's perfect food containing an excellent source of protein of high biological value, a high ratio of unsaturated fatty acids to saturated fatty acids, and an excellent source of minerals and vitamins (Sunwoo & Gujral, 2015). To meet food security targets in Indonesia during a pandemic, eggs as a cheap source of protein are an essential commodity that the government must keep for the smoothness of its supply and people's accessibility during the pandemic (Irawan and Alamsyah, 2021).

An integrated egg market is important to maintain consumer access and a sustainable supply of eggs. In an integrated egg market, prices will effectively signal producers and consumers. If the market is not integrated, the problems related to access to eggs for the people will continue, and market collusion will occur more easily. In contrast, market competition will be lost in such market conditions ((Ghosh, 2010) ; (Adenegan et al., 2016)) . An integrated egg market will provide the correct price signal and allow producers to specialize based on comparative advantage (Beag & Singla, 2014) ; (Paul et al., 2016) . Price affects the well-being of producers because it will determine their acceptance and income. Likewise, prices affect consumers' well-being because it is an important constraint to maximizing the utility of the goods consumed (Zahid et al., 2007).

The pandemic is the cause of supply, and demand shocks at the macroeconomic level ((Irawan & Alamsyah, 2021); (Akbar et al., 2022)) and the household level ((Irawan et al., 2022);(Irawan et al., 2023)). Governments in various countries have implemented lockdowns, regional quarantines, and limited human interaction, including in Indonesia, to stop the spread of COVID-19, which is causing massive supply chain disruptions (Irawan et al., 2023) and demand shocks (Irawan et al., 2022). These supply and demand shocks can also disrupt the integration of the egg market and its price transmission, leading to market inefficiencies and resource misallocation. Meanwhile, lockdown activities and movement limitations are not always synonymous with supply chain disruptions for food because governments in various countries guard the movement of food, medicines, and medical devices so that these goods do not experience obstacles to movement and distribution (Wang et al., 2023).

A literature review using Open Knowledge Maps (https://openknowledgemaps.org/) by using the keywords "COVID-19, affect, market integration, and food," identified only one relevant research, i.e., for the cayenne pepper, that found that market integration continued to occur during the COVID-19 pandemic in the case of cayenne pepper market in the province of NTB, Indonesia (Zaini et al., 2022). However, this study has not answered the important question as follows:

1. Has the degree of market integration decreased or increased because of COVID-19?
2. Does COVID-19 cause market integration to be lost or reduced? Otherwise, does it create or strengthen food market integration?
3. Has the magnitude and speed of food price transmission changed during COVID-19 compared to the absence of the pandemic?

This study was conducted for eight provinces where, six of which are on Java Island (Jakarta (the capital city of Indonesia), East Java, Central Java, West Java, Banten, and Yogyakarta)) and two others close to Java Island, namely Bali and West Nusa Tenggara. The reasons for choosing these provinces are because; first, from the demand side, the population of these eight provinces is 161,228,758 persons or 59.67% of the total population of Indonesia (270,203,917 persons) (Central Bureau of Statistics, 2021) . Thus the largest source of demand is from these eight provinces compared to 26 other provinces in Indonesia. Second, from the supply side, the supply of eggs from the eight provinces contributed 41.49 per cent or 131,557,221 heads of native chickens and 35.12% layer population or 129,339,441 heads of layers in Indonesia (Directorate General of Livestock and Animal Health Service, 2021). Thus the eight provinces are the largest suppliers of egg producers in Indonesia.

Based on the previous contextual overview, this research aims to verify the existence of integrated markets and the transmission of egg prices before and during the COVID-19 pandemic. This research has added value because Indonesia is a country consisting of more than 17,000 islands. It examines aspects of egg market integration and price transmission in a country with more than 17,000 islands in normal conditions without a pandemic alone. Integrating the market is a significant challenge due to the natural conditions of many islands, especially during a pandemic. Thus, this research provides a particular case of the impact of the pandemic on egg market integration and price transmission in island countries.

Spatial market integration refers to a situation where the price of a commodity in spatially separate markets moves together. In contrast, price signals and information are transmitted smoothly across the market (Abay et al., 2023). Price changes in one market will be fully transmitted to other markets (Chitete et al., 2021). Exogenous shocks that support price changes in one market equally change prices in other markets if the markets are cointegrated. How commodity prices in several markets move together and how strongly the prices of one market can be transferred to other markets indicated the strength of an integrated market (Roman & Kroupová, 2022).

Several factors influence spatial market integration, namely market structure, transaction costs and changes in government policies (Alam et al., 2022) . Changes in these factors have an impact on the prices of homogeneous products. Shocks in one market will change the supply or demand for products causing price changes ((Baquedano & Liefert, 2014); (Akhter, 2017)). When markets are cointegrated, price information signals are transmitted from one market to another. Market integration phenomenon is especially relevant in agriculture because, in many cases, the production and consumption of agricultural products are concentrated in different geographic locations. If the market is cointegrated, agricultural products can move from surplus to deficit areas, that transaction costs are low enough for marketing agents to profit (Ahmed et al., 2022) . On the other hand, Abay et al. (2023) argue that when markets are not cointegrated, inappropriate price information signals are transmitted to producers and other actors in the marketing system, leading to poor production and marketing decisions. Unintegrated markets limit the transmission of price information incentives to various marketing agents in the marketing chain (Chitete et al., 2021).

For the agricultural markets, Hossain et al. (2011) explain that the correct price signal will only be transmitted through marketing channels if the market is integrated. Farmers will not be able to specialize according to long-term comparative advantages, and profits from trade will not occur. In most cases, agricultural markets in developing countries must be better integrated due to a lack of well-developed infrastructure, market institutions, and market information that facilitates the easy flow of goods and services among markets. Under such circumstances, the market in one place cannot make quick adjustments when price shocks occur in neighbouring markets (Ismail Hossain & Verbeke, 2010).

Integrated agricultural markets facilitate resource allocation and economic growth (Ahmed et al., 2022) . If the market is not integrated, the problem of food insecurity will continue, market collusion will occur more easily, and market competition will be lost ((Ghosh (2010a); Adenegan et al. (2016)) . An integrated market transmits the correct price signal and allows farmers to specialize based on the comparative advantage of their agricultural commodities ((Beag & Singla, 2014); (Paul et al., 2016)). Meanwhile, Faminow & Benson (1990) adds that spatial market integration can be a measuring tool for the performance of agricultural markets.

To minimize the spread of COVID-19, governments in various countries have implemented lockdowns, regional quarantines, and limited human interaction, including Indonesian government. The implication of these policies is causing a massive supply chain disruption. This phenomenon disrupted spatial market integration and price transmission from one market to another, further causing market inefficiency and resource misallocation. Wang et al. (2023) proved this phenomenon in the Chinese fish market. Comparing the spatial market integration before and after the pandemic shows a high level of spatial market integration before COVID-19. The integration was greatly reduced due to the pandemic in most provinces.

International market integration between one country and other countries formed through market liberalization (Irawan, 2009) has experienced disruption due to COVID-19. Jamhari et al. (2021) show that COVID-19 erodes the size of export and import growth. The pandemic reduced the trade values of South East Asia countries. Likewise, for the European Union (EU), Hamulczuk and Skrzypczyk (2021) show that food exports and imports decreased significantly throughout the EU in the second and third quarters of 2020. In this period, exports in the EU decreased more than imports, and the trade balance worsened. This phenomenon causes food prices in food surplus countries to fall and in countries with food shortages to increase, ceteris paribus.

The impact of the pandemic on food prices in one country is not a uniform phenomenon. It can be seen from the findings of the China case (Yu et al., 2020). This study shows that COVID-19 has a different effect on different food products in China. The pandemic has no implications for price changes for staple foods such as rice and wheat flour. Meanwhile, the pandemic has caused a positive increase in the price of vegetables, such as Chinese cabbage, and various price changes for pork, the main protein source for Chinese consumers.

An increase in domestic food prices in a country occurs during a pandemic because the pandemic causes panic buying to store food reserves of households due to worrying about household food availability during a pandemic. This phenomenon would cause price increases, such as in the case of pork and cabbage prices in China (Yu et al., 2020) . Even though it increases the price, the magnitude is small. This phenomenon happened due to the containment of the virus via lockdown and restrictions on human activity. On the other hand, campaigns and government actions to maintain a sufficient food supply for people have reduced panic and stabilized food prices. Ruan et al. (2021) found that the lockdown policy resulted in a large and immediate price spike and dispersion in Chinese cabbage prices. The same thing happened for the meat market (beef, pork, and poultry) in the United States (Ramsey et al., 2021).

The lockdown policies for stopping the spread of COVID caused increasing food commodity prices in market integration but not for segmented markets. The strict lockdown policy reduced the mobility of the movement of goods which raised the price, but at the same time, was moderated by the dependence on trade between markets before COVID-19 (Dietrich et al., 2022).

METHOD

To verify the effect of COVID-19 on market integration and price transmission among egg markets, the researcher divided the entire sample (July 31 2017, to August 22 2021) into two sample periods. Weekly data from July 31 2017 to February 28 2020, represented the situation before the pandemic. Meanwhile, the situation during the pandemic is represented by weekly data from March 1 2020 (when the Indonesian government announced the first case of COVID-19 infection in Indonesia) to August 22 2021.

The data used in this study is secondary data, i.e., weekly egg price data. The data comes from the National Strategic Food Price Information Center, accessed at https://www.bi.go.id/hargapangan. The researcher collected two kinds of data. First, egg price data at the provincial consumer level from July 30 2017, to February 28 2020, to estimate market integration models and price transmission before COVID-19. There were 136 observations. Second, weekly egg price data with the rank of the period during COVID-19, namely from March 1, 2020, to August 22 2021) or as many as 78 observations.

Data analysis method

Two secondary data samples are used in this study, namely 1) a sample that reflects pre-pandemic observations in the form of weekly data of the eggs price from July 30, 2017, to February 28, 2020. This sample is used to estimate a system of market integration equations before the pandemic and; 2) a sample that reflects observations when COVID-19 occurred, namely from March 1, 2020 (announcement of the discovery of the first case of COVID-19 infection in Indonesia) until August 22, 2021)). This sample estimates the system of market integration equations during a pandemic.

The cointegration procedure requires a time series in the system to be non-stationary at their level. Similarly, the all-time series in the cointegrating equation must have the same order of integration. Consequently, this research confirms the time series properties of all variables by employing the Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1981).

The maximum lag length is to be included in the cointegrating test for the Vector Error Correction Model (VECM). Determination of the maximum lag length aims to get the white noise error term. Likelihood Ratio (L.R.), Final Prediction Error (FPE), Akaike Information Criterion (H.Q.), Schwarz Information Criterion (SIC), and Hannan-Quinn Information Criterion (H.Q.) are used to determine the optimal lag length. However, the sample size must be considered when determining the optimal lag because the sample size is relatively small. Using a long lag will exhaust the degree of freedom and result in a large standard error. Using selected lag orders based on the recommendation of Johansen and Juselius (Johansen & Juselius, 1990) , the researcher tested the existence of cointegration between egg prices in different markets in each system of equations.

Cointegration test

Using the selected lag order, the researcher applied the Johansen method (Johansen, 1988) to test the existence of cointegration among a series of market prices.

$$X_t = A_0 + A_1 X_{t-1} + -- + A_p X_{t-p} + \nu_t \quad ; t = 1,2, \ldots T \ (1)$$

Where: p = lag length; Xt= an (nx1) vector of endogenous variables; A's are matrices of unknown parameters; νt is an independently distributed n-dimensional vector with zero mean and variance matrix, et. Based on Johansen Method (Soren Johansen & Juselius, 1990), this study formulates a general system of regression as follows:

$$\Delta X_t = \tau_0 + \tau_1 \Delta X_{t-1} + -- + \tau_{p-1} \ \Delta X_{t-(p-1)} + \Pi X_{t-p} + \nu_t \quad (2)$$

or

ΔX_t = t_0 + $\sum_{j=1}^{p-1} \tau_j \ \Delta X_{t-1}$ + ΠX_{t-p} +ν_t where $t_o = A_0$;

$\tau_j = -\left(I - \sum_{j=1}^{p-1} A_j\right)$; j = 1,2, ...,p-1

$\Pi = -\left(I - \sum_{i=1}^{p} A_i\right)$

Where, ΔX_{t-j} is the (nx1) vector of X_{t-j} in the first difference, and Π and t_j (j=1, 2, . . ., k) are n by n matrices of parameters. Meanwhile, ν_t is an n-vector of residuals assumed to be normally distributed with a mean of 0 and have a contemporaneous covariance matrix εt. Π is the ranking of the matrix of the VECM, which determines the number of cointegrated vectors. If r (rank of the Π matrix) is greater than zero, then cointegration is detected. On the other hand, when r = 0, it meant no cointegrating vector, and estimates must use the VAR model, where the variables used are in the first difference (I(1)) form.

Johansen and Juselius (1990) show two likelihood ratio test statistics, trace statistics, λTrace and the maximum eigenvalue statistics test, λmax formulated as follows:

$$\lambda_{Trace}(r) = -T \sum_{i=r+1}^{n} ln(1 - \lambda i) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(3)$$

$$\lambda_{max}(r, r+1) = -T \ln(1 - (\lambda_{-r+1}) \ldots\ldots\ldots\ldots\ldots\ldots \quad (4)$$

Equation 3 tests the null hypothesis that there is an r or less cointegrating vector, i.e. r ≤1, while equation 4 tests the null hypothesis, i.e. there are precisely r integrating vectors or r=1. Value of the test statistics compared to the critical values. If the value of the statistical test is greater than the critical value, the decision rejects the null hypothesis.

The P matrix can be decomposed into α and β components where Π = αβ. The researcher evaluated the short-run dynamics among the variables by examining the significance of and the sign on the estimated lagged coefficients. Parameter α inferred the system's dynamics as the matrix of speed adjustment coefficients. If the value of α is low, the system adjusts slowly for any deviation from its long-term equilibrium. The higher the value of α indicates the higher the system's response to the deviation from the long-term balance. Conversely, if α is zero, the system has no response to the disequilibrium error that occurs (Hossain et al., 2011). Parameter α represents the cointegration relationship where disequilibrium error is stationary (Soren Johansen & Juselius, 1990).

Decomposition variance analysis

This study used the variance decomposition technique to determine the relative exogenity/endogeneity of the price variable by decomposing the variance of the forecast error of a variable into proportions that can be associated with a shock in each price variable. The system includes a separate shock. The proportion of the variance of each variable in the system of equations, including the own shock, will determine the level of exogenity or endogeneity of one variable. When the own shock of a variable is the most dominant, the variable is the most exogenous. In this research model, each price variable reflects the market. If the forecasting variance decomposition results show that one market is only dominantly affected by its shock, it concluded that the market is exogenous. It affects other markets but is not affected by other markets (Masih et al., 2009).

RESULTS AND DISCUSSION

Market integration

The Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1981) tested both levels, and the first difference of the series for sample data was represented before and during COVID-19. The results are presented in Tables 1 and 2. ADF test confirms there is a series that is not stationer in the level (1(0)), but all series are stationer in first difference (I(1)) at 1, 5 and 10 % significance level, respectively. The ADF test suggests that the data-generating process relating to all variables is integrated into degree one. Therefore, the vector error correction model is the best procedure for estimating the model. On the other hand, Vector Autoregressive (VAR) in the first difference can not be used because it is misspecified. Meanwhile, all indicators (Akaike, Schwarz and Hannan-Quinn information criteria) indicate that the lag used for the system equation of vector error correction before and during the pandemic is 1.

Table 1 Unit root test (the Augmented Dickey-Fuller test) for sample represented before COVID-19 (Author's analysis, 2025)

Variable (market)	Level (I(0))		First difference (I(1))	
	t-statistics	Stationarity status	t-statistics	Stationarity status
Banten	-4.566	stationer	-8.201	Stationer
West Java	-4.247	stationer	-7.151	Stationer
Jakarta	-4.926	stationer	-7.734	Stationer
Central Java	-4.738	stationer	-8.969	Stationer
East Java	-4.732	stationer	-8.606	Stationer
Yogyakarta	-5.046	stationer	-7.820	Stationer
Bali	-3.776	stationer	-10.071	Stationer
West Nusa Tenggara	-2.051	not stationer	-9.925	Stationer

Note: The 1, 5, and 10% critical values for the ADF test are -3.479, -2.883, and -2.578

Table 2 Unit root test (the Augmented Dickey-Fuller test) for sample represent during COVID-19 (Author's analysis, 2025)

Variable (market)	Level (I(0))		First difference (I(1))	
	t-statistics	Stationarity status	t-statistics	Stationarity status
Banten	-4.217	stationer	-6.026	Stationer
West Java	-4.602	stationer	-7.107	Stationer
Jakarta	-3.595	stationer	-6.498	Stationer
Central Java	-4.212	stationer	-7.576	Stationer
East Java	-3.400	stationer	-7.540	Stationer
Yogyakarta	-4.801	stationer	-7.306	Stationer
Bali	-2.350	Not stationer	-7.849	Stationer
West Nusa Tenggara	-3.007	stationer	-9.117	Stationer

Note: the 1, 5, and 10% critical values for ADF test are -3.519, -2.900, and -2.587

This study uses the Johansen cointegration test to verify whether or not market integration exists and how many market combinations are integrated (Johansen, 1988). The cointegration test confirms that the eggs markets were integrated before and during COVID-19. Nevertheless, the degree of market integration during COVID-19 was smaller than before COVID-19. The change in the rank of the degree of market integration becomes smaller, confirming the existence of this phenomenon. The number of cointegrating equations was seven before the pandemic (table 2).

Meanwhile, during the pandemic cointegrating equation became five equations (table 2).

This finding is in line with Akber and Paltasingh (2022), who found that the degree of India's food market integration became weak during COVID-19. The impact of COVID-19 only reduces the degree of India's food market integration but does not create segmented markets. The negative impact of stringent measures taken by the government through lockdown was reduced because the government also removed barriers to the movement of essential goods during COVID-19, such as food, and moderated by the market's dependence on trade before the pandemic (Dietrich et al., 2022).

Table 3. Johansen cointegration rank tes (Author's analysis, 2025)

Hypothesized number of cointegrating equation	Before COVID-19		During COVID-19	
	Trace statistic	Probability	Trace statistic	Probability
None	246.96	0.0000	230.217	0.0000
At most 1	179.72	0.0000	172.776	0.0000
At most 2	130.85	0.0000	121.794	0.0000
At most 3	95.089	0.0000	75.317	0.0015
At most 4	61.3656	0.0001	43.575	0.0219
At most 5	35.3567	0.0014	19.663	0.1712
At most 6	13.535	0.0311	6.727	0.3530
At most 7	0.3046	0.6426	0.1741	0.7297

Note: when the probability value is less than 1 and 5% indicates the null hypothesis is rejected; otherwise, if the probability is greater than 5%, it indicates the null hypothesis is accepted, or its alternative hypothesis is rejected.

Price transmission

Variance decomposition analysis shows that in the situation before COVID-19, the forecast error variance of Bali market price is affected by its shock in the short run or one week ahead (100%). At longer the horizon (10 weeks), the contribution of the shock to the Banten market price and West Nusa Tenggara market price increased to 27.18% and 17.85%, respectively. Thus, it verified that in the situation before the pandemic, in the short term, Bali's market price is more influenced by itself. In contrast, in the long term, it was influenced by itself, Banten and West Nusa Tenggara markets (Table 4).

Meanwhile, during COVID-19, there was a change in price transmission behaviour, namely the Bali market price in the short term, one week ahead, was affected 100 per cent by its shock. In the longer horizon (10 weeks ahead), the Bali market price was influenced by its shock and the shock from West Java and Central Java market, namely 48.59, 14.45, and 10.99%, respectively (Table 4).

The forecast error variance of the Banten market price before COVID-19 is affected by the own shock (100%) one week ahead. However, in the long term (10 weeks ahead), the shock in Banten market price is influenced by the own shock (50.11%), the West Java (16.61%), and West Nusa Tenggara (22.94%), respectively. Whereas when COVID-19 occurred, the own shock influenced a price shock in the Banten market in the short term (one week ahead) (92.42%). In the long run, the price shock in the Banten market is determined by its shock (66.98%), the West Java market (9.44%), and the Yogyakarta market (9.29%), respectively (Table 5).

The market price shock in West Java before the COVID-19 outbreak was influenced by its own and the Banten market shock in the short and long term. In the short term (one week ahead), it is affected by the Banten market shock (60.14%) and its shock (39.21%). The same pattern happened during COVID-19, wherein the short-term West Java market price shock was influenced by the Banten market shock (56.41%) and its shock (34.55%). In the long run, the price shock in the West Java market is determined by its shock of 17.93% and the Banten market by 58.75% (Table 6).

Table 4. Percentage of forecast variance explained by innovation in Bali market price (Author's analysis, 2025)

	Market price							
Period (weeks)	Bali	Banten	West Java	Jakarta	Central Java	East Java	West Nusa Tenggara	Yogyakarta
				Before COVID-19				
1	100	0	0	0	0	0	0	0
3	91.95	5.98	0.62	0.25	0.19	0.25	0.58	0.17
6	64.07	21.53	4.14	0.35	1.16	1.13	7.49	0.14
10	42.55	27.18	7.86	0.66	2.84	0.80	17.85	0.26
				During COVID-19				
1	100	0	0	0	0	0	0	0
3	82.88	0.39	3.37	0.20	6.93	0.90	4.40	0.93
6	60.57	5.57	11.01	1.09	11.28	2.69	3.66	4.13
10	48.60	9.47	14.45	1.21	10.99	6.22	2.49	6.57

Table 5. Percentage of forecast variance explained by innovation in Banten market price (Author's analysis, 2025)

	Market price							
Period (weeks)	Bali	Banten	West Java	Jakarta	Central Java	East Java	West Nusa Tenggara	Yogyakarta
				Before COVID-19				
1	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00
3	0.68	78.86	15.80	0.63	0.18	0.02	3.78	0.04
6	3.28	59.52	17.83	0.91	2.67	0.02	15.58	0.19
10	3.91	50.11	16.61	1.04	4.67	0.25	22.94	0.47
				During COVID-19				
1	7.57	92.43	0.00	0.00	0.00	0.00	0.00	0.00
3	11.43	75.65	7.65	0.31	1.99	0.19	0.21	2.58
6	11.56	65.21	11.02	0.20	1.68	0.43	0.27	9.64
10	10.39	66.98	9.44	0.79	1.56	1.31	0.24	9.29

Table 6. Percentage of forecast variance explained by innovation in West Java price (Author's analysis, 2025)

Period (weeks)	Market price							
	Bali	Banten	West Java	Jakarta	Central Java	East Java	West Nusa Tenggara	Yogyakarta
				Before COVID-19				
1	0.65	60.14	39.21	0.00	0.00	0.00	0.00	0.00
3	1.49	60.34	33.08	0.25	0.25	0.05	4.43	0.11
6	4.26	49.11	27.59	0.44	2.95	0.04	15.50	0.10
10	4.87	42.45	23.58	0.63	4.92	0.26	22.80	0.48
				During COVID-19				
1	9.04	56.41	34.55	0.00	0.00	0.00	0.00	0.00
3	12.11	60.21	19.52	1.04	3.49	0.59	0.56	2.49
6	10.33	56.26	20.41	1.01	1.89	1.23	0.63	8.24
10	8.95	58.75	17.93	1.85	1.22	2.38	1.04	7.88

The forecast error variance of the Jakarta market price in the short run (one week ahead) before COVID-19 was influenced by its shock (27.24%), West Java, and Banten market shocks, namely 19.32 and 53.35%, respectively. Whereas in the long term (10 weeks ahead), the Jakarta market shock is determined by the Banten (45.65%) and West Java market shock (19.34%). Whereas during COVID-19, the transmission pattern changed. In the short term, the Jakarta market shock was affected by its shock (27.92%) and the Banten market (55.88%), while in the long term, it was affected by the Banten market (62.68%) and West Java market shock (13.9%) (Table 7).

Before COVID-19, in the short term, the Central Java market shock is affected by the shocks of the Banten, West Java market, and itself, namely 53.15, 21.41, and 23.20%, respectively. Meanwhile, in the long run, it is affected by market shocks in Banten, West Java, and itself, namely 42.51, 21.41 and 7.59%, respectively.

Whereas in the COVID-19 situation, in the short term, the ones that affected the Central Java market shock are the Banten market (54.97%), itself (24.20%), and the West Java market (12.1%), respectively. Whereas in the long term (10 weeks ahead), the Central Java market shock is influenced by the Banten market (43.18%), the West Java market (20.28%), and itself by 9.02% (Table 8).

Variance decomposition analysis for East Java market shocks shows the following; in the pre-pandemic situation, the East Java market shocks in the short term were influenced by the Banten (42.77%), itself (33.33%) and the West Java market shock (21.03%). Meanwhile, in the long run, price shocks in the East Java market will be affected by the Banten (43.41%), the West Java (20.31%), and the West Nusa Tenggara market (21.30%) (Table 9).

Different transmission patterns when COVID-19 occurs. In the short term, East Java market shocks are influenced by itself (47.55%), the Banten market (31.91%), and the Bali market (12.34%). Meanwhile, in the long run, shocks to the East Java market were affected by shocks to the Banten (44.71%), Bali (20.40%), and the West Java market (12.70%) (Table 9).

Meanwhile, before COVID-19, in the short term, the West Nusa Tenggara market shock was influenced by itself (87.41%) and Banten (10.39%). In the long term, before COVID-19, it was influenced by the Banten (32.92%) and West Java markets (15.62%) and its shock (41.55%) (Table 10).

When COVID-19 occurred, the West Nusa Tenggara market was influenced in the short term by itself (68.76%) and the Banten market (19.04%). For the long term, the West Nusa Tenggara market shocks are affected by the West Java (32.76%), the Banten market (24.10%), and its shock (20.32%) (Table 10).

Table 7. Percentage of forecast variance explained by innovation in Jakarta price (Author's analysis, 2025)

	Market Price							
Period (weeks)	**Bali**	**Banten**	**West Java**	**Jakarta**	**Central Java**	**East Java**	**West Nusa Tenggara**	**Yogyakarta**
				Before COVID_19				
1	0.08	53.35	19.32	27.24	0.00	0.00	0.00	0.00
3	0.69	63.09	25.34	8.00	0.08	0.01	2.58	0.21
6	3.69	52.69	22.36	4.25	2.48	0.01	14.10	0.42
10	4.37	45.65	19.34	3.28	4.65	0.22	21.95	0.54
				During COVID-19				
1	11.16	55.88	5.04	27.92	0.00	0.00	0.00	0.00
3	11.17	67.84	9.02	7.58	1.84	0.15	0.06	2.34
6	11.11	61.00	15.16	3.82	0.94	0.50	0.16	7.30
10	9.35	62.68	13.90	3.43	0.66	1.61	0.55	7.81

Table 8. Percentage of forecast variance explained by innovation in Central Java price (Author's analysis, 2025)

	Market Price							
Period (weeks)	**Bali**	**Banten**	**West Java**	**Jakarta**	**Central Java**	**East Java**	**West Nusa Tenggara**	**Yogyakarta**
				Before COVID-19				
1	0.61	53.15	21.41	1.64	23.20	0.00	0.00	0.00
3	2.56	56.65	27.90	0.52	7.51	0.03	4.36	0.47
6	5.25	47.58	23.87	0.55	7.09	0.03	15.14	0.49
10	5.32	42.51	21.41	0.72	7.59	0.29	21.39	0.77
				During COVID-19				
1	7.15	54.97	12.10	1.59	24.20	0.00	0.00	0.00
3	14.58	47.73	16.13	0.92	16.61	0.36	0.32	3.35
6	14.46	40.74	21.78	0.91	11.40	1.96	0.42	8.34
10	13.71	43.18	20.28	1.22	9.02	4.09	0.69	7.81

Table 9. Percentage of forecast variance explained by innovation in East Java price (Author's analysis, 2025)

Market Price								
Period (weeks)	Bali	Banten	West Java	Jakarta	Central Java	East Java	West Nusa Tenggara	Yogyakarta
				Before COVID-19				
1	0.46	42.77	21.03	0.93	1.48	33.33	0.00	0.00
3	0.48	56.87	26.80	0.49	0.70	11.37	3.17	0.12
6	3.46	48.92	23.13	0.66	2.88	6.26	14.44	0.26
10	4.11	43.41	20.31	0.87	4.64	4.80	21.30	0.55
				During COVID-19				
1	12.34	31.91	3.93	3.92	0.35	47.55	0.00	0.00
3	16.66	50.78	9.97	1.13	5.71	14.45	0.24	1.04
6	19.66	44.43	13.45	0.69	3.96	9.36	0.89	7.56
10	20.40	44.71	12.70	0.50	2.93	9.29	0.70	8.78

Table 10. Percentage of forecast variance explained by innovation in West Nusa Tenggara price (Author's analysis, 2025)

Market price								
Period (weeks)	Bali	Banten	West Java	Jakarta	Central Java	East Java	West Nusa Tenggara	Yogyakarta
				Before COVID-19				
1	0.38	10.39	0.38	1.20	0.06	0.18	87.41	0.00
3	0.18	33.50	7.93	0.40	0.84	0.25	55.74	1.16
6	1.15	36.27	14.06	0.42	2.88	0.40	43.62	1.20
10	2.54	32.92	15.62	0.46	4.93	0.59	41.55	1.39
				During COVID-19				
1	0.04	19.04	9.52	2.55	0.04	0.05	68.76	0.00
3	2.10	28.68	19.17	7.08	8.20	1.43	33.30	0.04
6	2.36	24.52	30.41	7.21	8.70	1.75	23.60	1.45
10	1.78	24.10	32.76	7.52	8.46	3.62	20.32	1.45

Table 11. Percentage of forecast variance explained by innovation in Yogyakarta price (Author's analysis, 2025)

	Market price							
Period (weeks)	Bali	Banten	West Java	Jakarta	Central Java	East Java	West Nusa Tenggara	Yogyakarta
				Before COVID-19				
1	0.04	47.13	17.95	0.85	7.97	0.12	0.11	25.83
3	1.01	48.42	34.38	0.34	2.72	0.07	5.20	7.87
6	4.68	39.70	28.77	0.27	4.51	0.05	17.95	4.08
10	5.02	35.81	25.00	0.40	5.84	0.34	24.11	3.48
				During COVID-19				
1	4.58	35.91	21.69	0.01	11.17	0.04	0.03	26.57
3	13.66	47.82	19.95	0.74	8.86	0.06	0.40	8.52
6	11.44	44.48	23.41	0.60	5.50	0.79	0.62	13.15
10	9.44	49.80	20.40	1.76	3.85	2.45	1.42	10.87

Table 11 shows that before COVID-19, in the short term, Yogyakarta market shocks were determined by Banten market shocks (47.13%), itself (25.83%), and West Java (17.95%), respectively. Meanwhile, in the long run, the Yogyakarta market shock before COVID-19 was influenced by the Banten market (35.81%), West Java (25%), and West Nusa Tenggara (24.11%), respectively.

Whereas when COVID-19 occurred, in the short term, Yogyakarta market shocks were affected by Banten (35.91%), itself (26.57%), West Java (21.69%), and Central Java market shock (11. ,17%). As for the long term, when COVID-19 occurred, the Yogyakarta market price shock was influenced by the Banten (49.80%), the West Java market (20.40%), and itself (10.87%) (Table 11).

There are four patterns of price transmission from one market to another, i.e., first, price transmission patterns before COVID-19 are different from when COVID-19 occurred. Meanwhile, the magnitude of price shocks from neighbouring markets to one market was smaller during the pandemic than before. This phenomenon can be seen when the Bali and Banten markets experienced shocks before and during COVID-19.

Second, the pattern of price transmission before and during COVID-19 has remained the same. The weight of shocks from neighbouring markets to one market becomes less weighted during the occurrence of COVID-19 than before. An example of this phenomenon occurred when the West Java market experienced shocks before and during COVID-19.

Third, the pattern of price transmission did not change before and during COVID-19b. The shock from neighbouring markets to a market has varied in magnitude. Some of them became larger and some smaller during COVID-19 compared to before. This phenomenon occurred when the Jakarta and Central Java markets experienced shocks before and during COVID-19.

Fourth, the price transmission pattern during COVID-19 is different from before COVID-19, and the magnitude of market shocks is also different; some markets have a greater influence during COVID-19, and some have become smaller. This phenomenon occurred when the East Java, West Nusa Tenggara, and Yogyakarta markets experienced shocks before and during COVID-19.

The findings above add to the variation in the impact of COVID-19 concerning market integration. Our findings show that the impact of COVID-19 is different for many markets with the same commodity within one country. Meanwhile, other findings show that the impact of COVID-19 is different in many markets with different commodities in one country(Yu et al., 2020).

CONCLUSION

The conclusions of this research are as follows; first, the change in the rank of the degree of market integration becomes smaller. The number of cointegrating equations was seven before the pandemic became five cointegrating equations during COVID-19. These results verify that COVID-19 disrupt the integration of the egg market.

Second, there are four patterns of egg price transmission from one market to another, i.e., 1) there is a change in the transmission pattern where neighbouring markets that affected a market that experienced shocks before COVID-19 are different from when COVID-19 occurred. Meanwhile, the impact of neighbouring market shocks on one market was minor during the pandemic compared to before the pandemic; 2) The price transmission pattern has not changed. Only the influence weight becomes less from neighbouring markets to the market that experienced the shock during the Covid outbreak than before; 3) The price transmission pattern has not changed before and after COVID-19. The influence of neighbouring markets on one market varied. Some of the influences of neighbouring markets have become bigger, and some else become smaller during COVID-19 than before. 4) the pattern of price transmission is different from before COVID-19. So does the influence of a market. Some markets have a greater magnitude of influence during COVID-19, and some have become smaller.

The virus lockdown caused; 1) disruption of market integration in this study, indicated by the reduced degree of market integration during a crisis compared to before the pandemic. 2) the price transmission magnitude from one market to another tends to decrease. This phenomenon shows that the price transmission from one market to another during the pandemic has also reduced. An important lesson from a policy perspective is that the food movement must be kept smooth during a pandemic. The digital platform during COVID-19 helps inform and efficiently connect producers and consumers, including those in the eggs supply chain. The use of digital technology allows farmers and other supply chain actors to comply with pandemic health procedures (no direct physical interaction among people) that do not stop people from their routine activities in the supply chain.

In the future, the implementation of digitalization in the food supply chain must be established and stable in post-pandemic conditions. When the same disturbance occurs, it will not become a shock that damages the egg supply chain so that the impact of economic losses can be minimized or eliminated.

While this empirical quantitative study offers valuable insights into the disruption of egg market dynamics during the COVID-19 pandemic, several limitations warrant consideration. Firstly, the analysis was confined to eight Indonesian provinces, which may limit the generalisability of findings to other regions with differing market structures or policy responses. Secondly, the reliance on secondary price data, although robust, may not fully capture informal market activities or supply chain nuances that influenced price behaviour during the crisis.

Future research could incorporate micro-level data, such as farm-gate prices, consumer purchasing patterns, and logistical constraints, to enrich understanding of market resilience. Comparative studies across countries or regions would also be instrumental in identifying structural factors that either mitigate or exacerbate market fragmentation during global disruptions.

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