Business Predictive Analytics of Smallholder Indonesian Maize using Vector Error Correction

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***Abstract*—Maize stands as a cornerstone of Indonesia's agricultural landscape, serving both as a vital food source and an essential fortifier. However, the marketing process of smallholder maize in Indonesia has yet to reach an optimal level of efficiency. This research endeavors to delve into the vertical integration of smallholder maize in the Indonesian agricultural sector.To conduct this analysis, we employ a forward-looking predictive model, applying the Vector Error Correction Model (VECM) to analyze time series data related to smallholder maize in Indonesia. Our findings yield critical insights that shed light on the intricate dynamics of smallholder maize markets in the archipelago.Notably, our research underscores the long-term integration between producer-level smallholder maize markets and consumer-level smallholder maize markets in Indonesia. This integration implies that changes in producer-level smallholder maize prices are intrinsically linked to shifts in consumer-level smallholder maize prices in the country. These findings provide a valuable foundation for collaborative efforts within the agricultural sector, guiding stakeholders toward more effective strategies for optimizing smallholder maize markets in Indonesia.**

***Index Terms*— Business Analytics, Predictive, Vector Error Correction, Maize, Corn**

1. Introduction

Both domestic production and imports can cover the national demand for food. Given that the population continues to grow and is spread across many islands, dependence on imported food has led to vulnerable food security, impacting various aspects of life, including social, economic, and even politics[1], [2]. In Indonesia, around 18 million farmers cultivate rice, contributing 66% to the gross domestic product (GDP) of food crops. In addition, rice farming has provided employment and income opportunities for more than 21 million households, with an income contribution of 25-35%. Hence, rice remains a strategic commodity in the national economy and food security, thus becoming the primary basis for future agricultural revitalization[3], [4].

Ensuring food availability at affordable prices is essential for strengthening economic and political stability in Indonesia. Growing demand for food in line with population growth and not being balanced by the amount of supply has driven price jumps in various food products. Meeting the shortage of needs through imports causes world prices also to affect domestic price spikes. World food commodity price data shows a very high price spike from 2007 to 2008; even in rice, the price spike reached 110.65 percent, obtained to IMF data in 2014. The world price trend from 2007 to 2013 shows that the commodity prices of rice and corn are still favorable. We can distinguish market integration into two based on the market relationship, which is spatial market integration and vertical market integration [5].

Indonesia has a broad sea area, making the entire distribution process more difficult. The location of food consumer markets far away from production areas and the uneven production and consumption have resulted in high trade costs and poor market integration of food commodities[6]–[9]. In integrated markets with good trade relations, implementing government intervention in reducing price fluctuations can be channeled to other needs. The implementation of price policies can be carried out at a lower cost so that in the event of price fluctuations in a region, effective action can be taken so that the price fluctuations do not spread and become national fluctuations.

A World Bank policy study on trade sector development in 2019 examined the spatial integration of soybean, corn, rice, sugar, and cooking oil commodities. It concluded that for items that receive a lot of intervention from the government, such as rice, the level of integration will be slightly higher. The story of spatial integration between provinces is quite significant, as shown by joint solid price movements, in the sugar commodity has 83% integrated provincial market pairs, rice 76% integrated pairs, cooking oil 30% integrated pairs, corn 28% integrated pairs, and soybean commodity 26% integrated provincial market pairs[2]–[4], [10], [11]. Some aspects of market integration that policymakers need to consider include the extent, speed, determinants, and geographic impact of price transmission[10], [12]–[14]. The degree of integration can also show whether the structure of trade flows in Indonesia

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has worked well or not. By understanding all aspects of market integration, policymakers can better formulate policies that benefit producers while protecting consumers. This study aims to analyze the degree of market integration of rice and unhusked maize in Indonesia.

II. MARKET INTEGRATION WITH PREDITIVE BUSINESS ANALYTICS

This study uses monthly time series data on the price of smallholder maize at the producer level in Indonesia and data on the cost of smallholder maize at the consumer level for 2013-2022. We analyze business predictive analysis and market integration using the Vector Error Correction Model (VECM) [15], [16]. Most of the time, series of price data are non-stationary. With that being said, non-stationary data will result in a spurious regression parameter estimation. When this spurious regression is interpreted, it will result in a wrong analysis, resulting in a false decision [17]–[21]. The stationarity of data is a necessary condition in analyzing time series data because it can minimize model errors[22]–[28]. The stationarity test in this study uses the Augmented Dickey-Fuller (ADF) unit root test. The ADF test formulation for smallholder maize is shown in equation 1.

$$\Delta_{maizeprod_t} = \alpha_0 + \alpha_1 T + \beta_1 \Sigma^m \Delta_{maizeprod_{t-1}} + \gamma_{1_{maizze\ t-1}} + \epsilon_t \quad (1)$$

Equation 1 explains that $\Delta_{maizeprod_t}$ the variable price of small maize in Indonesia in the current period (t) (IDR/kg). $\Delta_{maizeprod_{t-1}}$ the price of maize in Indonesia for the previous period (t-1) (IDR/kg), m represents as the lag time series, intercept is explained by α, and $\alpha 1$, $\beta 1$, $\gamma 1$ as the Parameter Coefficient, lastly, ε_t shows our error model. We then construct a second model to look at the price level at the consumer level.

$$\Delta_{cons_t} = \alpha_0 + \alpha_1 T + \beta_1 \Sigma^m \Delta_{const_{t-1}} + \gamma_{1_{const\ t-1}} + \epsilon_t \quad (2)$$

Similar to the preceding part, Δ_{cons_t} describes the variable of the consumer-level price of smallholder maize in Indonesia in the current period (t) (Rp/kg) while $\Delta_{cons_{t-1}}$ = the variable of the difference between the consumer-level price of smallholder maize in Indonesia in the current period (t) and the consumer-level price of smallholder maize in Indonesia in the previous period (t-1) (Rp/Kg).

It is necessary to have an optimal lag length to see the effect of each variable on other variables in the Vector Autoregressive (VAR) model [29]–[31]. The value of the lag of a variable can affect other variables because it takes time for a variable to respond to the movement of other variables. The determination of the optimal lag length can use several criteria, namely: Akaike Information Criteria (AIC), Schwartz Information Criteria (SIC), Hannan- Quinn Criteria (HQ), Likelihood Ratio (LR), and Final Prediction Error (FPE). Determination of the optimal lag length in this study uses Akaike Information Criteria (AIC).A cointegration test is conducted if the price variables studied are not integrated at the level / I (0). This test is conducted to determine whether there is integration in the long term or not. The cointegration test in this study uses the Johansen cointegration test, which can be used to see the amount of cointegration (rank cointegration) between variables. The trace statistic or maximum eigenvalue test can be used to test this hypothesis. The presence or absence of cointegration is based on the likelihood ratio (LR) test. If we can find the LR value greater than the critical value, we accept the cointegration of some variables and vice versa; if the LR value is smaller than the critical value, there is no cointegration [32], [33].

VECM is used when variables are not stationary at the level but stationary at the same level of differentiation and cointegrated. The VECM measures how to price deviations can return to equilibrium[31], [34]–[36]. The VAR/VECM model used in this study is as follows: VECM analysis describes the dynamic short-run and long-run equilibrium relationships in a system of equations. While there is a long-term equilibrium between markets, there is a deviation from the short-term equilibrium relationship. Therefore, the cointegration equation represents the long-term equilibrium relationship between markets, while the short-term equilibrium relationship may vary significantly. Furthermore, VECM combines short-term and long-term relationships between price variables from different needs[37].

III. DATASET

Impulse response analysis can explore the response of the dependent variable in the VAR model to disturbances in each variable. In each variable of each different equation, a disturbance is applied to its error term (ε1t) to show the impact on the VAR model over time. Suppose there are g variables in the model; then there will be g2 impulse responses that will be generated. This technique is used in VAR models called Vector Moving Average (VMA). If the model stabilizes, the disturbance will gradually disappear [38].Impulse response analysis is necessary for VAR/VECM estimation because the individual coefficients in the VAR/VECM model are difficult to interpret. The function of the impulse response is to track the response of endogenous variables in the VAR/VECM system due to disturbances or changes in the disturbance variables. Using impulse response can help researchers track shocks for several periods into the future [39].

IV. DATA ANALYSIS AND FINDINGS

Following the DF and ADF tests, it was found that both the producer and consumer maize price data are stationary at the first level of differentiation (I(1)) at the 5% confidence level where the critical value > the ADF statistic and the probability value is below 0.05. The ADF test results are shown in **Table I**. Results of the Data Stationarity Test Using the ADF Test on Producer-level and Consumer-level Data of Groundnuts in 2013-2022. (Influenced by Trend and Intercept). The optimal lag test results with the AIC criterion show that lag 6 is the optimal lag. Using lag six as the optimal lag in the model means that from an economic perspective, all variables in the model affect each other not only in the current period but the price variables that are interrelated in the previous period. The results of the optimum lag test are shown in **Table II.** The method of determining lag length using AIC (Akaike Information Criteria) Subsequently, the optimal lag test was conducted to determine the optimal lag length used to analyze the long-term relationship between the variables tested and significant using $\alpha = 5\%$.

TABLE I
STATIONARITY TEST

Level	Equation Test (Trend and Intercep)	ADF Stat	*Critical Value*		Prob.
Producer	Level	-4.5486	1 %	-4.03766	0.0020
			5 %	-3.44834	
			10 %	-3.14932	
	First Differentiation	-9.3776	1 %	-4.03766	0.0000
			5 %	-3.44834	
			10%	-3.14932	
Consumer	Level	-2.9106	1 %	-4.03698	0.1630
			5 %	-3.44802	
			10 %	-3.14913	
	First Differentiation	10.9830	1 %	-4.03766	0.0000
			5 %	-3.44834	
			10%	-3.14932	

TABLE II
LAG OPTIMUM

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1263.5	NA	2740018	22.801	22.850*	22.8216*
1	-1258.6	9.4707	2697620	22.786	22.932	22.8456
2	-1256.4	4.1880	2787173	22.818	22.062	22.9177
3	-1254.1	4.2821	2875245	22.849	23.191	22.9882
4	-1251.8	4.2755	2964390	22.879	23.319	23.0580
5	-1248.2	6.4080	2989945	22.887	23.424	23.1056
6	-1236.0	21.5603*	25810030*	22.739*	23.3745	22.99733
7	-1233.6	4.11486	26606067	22.769	23.5013	23.06615
8	-1230.6	5.20963	27094240	22.785	23.6156	23.12241

Before moving on to further stages of analysis, the estimation results of the VAR equation system that has been formed need to be tested for stability through the VAR stability condition check in the form of roots of the characteristic polynomials for all variables used multiplied by the number of lags of each VAR. VAR stability needs to be tested since if the VAR stability estimation result is unstable, the IRF and FEVD analysis will be invalid. Based on the test findings, a VAR system is stable if all of its roots have a modulus smaller than one. In this study, using the VAR stability test shown in **Table III**, it can be concluded that the estimated VAR stability used for IRF and FEVD analysis is stable given the range of modulus < 1.

TABLE III
VAR STABILITY

ROOT	MODULUS
0.480004	0.480004
-0.045866 – 0.329524 i	0.332701
-0.045866 + 0.329542 i	0.332701
-0.259051	0.259051

We conducted the Johansen cointegration test to determine the long-term relationship that occurs at the marketing level. The results of the Johansen cointegration test are shown in **Table IV**. The trace statistic and the max eigenvalue of the Johansen cointegration test results for producer and consumer prices show cointegration. The trace statistic between producer and consumer prices of smallholder maize indicates one cointegration at rank = 0 (none) and at most 1. This is seen from the trace statistic value, greater than the critical value of 5%, and the probability value, less than 5%. Based on these results, there is a long-term relationship or equilibrium in these markets, but there may be an imbalance in the short term.

TABLE IV
JOHANSEN COINTEGRATION TEST RESULTS RELATIONSHIP BETWEEN PRODUCER AND CONSUMER

Number of Cointegration	Trace Stat	0,05 Critical Value	Prob	Max-Eigen Stat	0,05 Critical Value	Prob
None	78.036	15.4947	0.000	47.772	14.264	0.00
At most 1	30.263	3.84146	0.000	30.263	3.8414	0.00

However, the Granger Causality test is employed to examine the effect of each variable on the other variables individually. Our Granger Causality results are shown in **Table V**. These results show that the F statistical value and the probability at the producer and consumer levels are one-way causalities, i.e., the price at the producer level is influenced by the price at the consumer level ($\alpha < 0.05$). The Granger Causality test results show that the F statistical value and probability at the level of producers and consumers of maize are one-way causality, i.e. the price at the consumer level of maize is influenced by the price at the producer level of maize ($\alpha < 0.05$).

TABLE V
GRANGER CAUSALITY TEST

Hypothesis	Obs	F-Stat	Prob
H0:Maize Consumer Price does not granger cause Maize Producer Price	118	2.63891	0.0758
H1: Maize Producer Price does not granger cause Maize Consumer Price	118	6.29573	00026

The VECM equation is considered valid if the retraction results show over-identified with the LR test criteria having a p-value of more than 5%. The results of the VECM model estimation are shown in **Table VI**. The error correction terms on the producer and consumer prices of smallholder corn are significant at the 5% absolute level and have a negative effect and a positive effect of -0.640536 and 4.036121, respectively. This indicates the importance of a long-term cointegration relationship in the price formation process in each market.

The ECT coefficient value indicates that price adjustment at the consumer level is faster than at the producer level because the ECT value at the consumer level is greater than that at the producer level. **Table VI** also explains that the long-term relationship between producers and consumers influences producer price changes. In the short term, changes in producer prices are only affected by their own changes in the previous month and two months earlier, without influencing consumer prices.

On the other hand, changes in consumer prices are influenced by the long-term relationship between producers and consumers. In the short term, changes in consumer prices are only affected by their own changes in the previous two months and are not influenced by changes in producer prices. This indicates that the producer and consumer markets are not integrated in the short term.On the whole, from the results of the VAR and VECM analysis of the smallholder corn market in Indonesia, it can be said that in the long run, there is long-term integration between producer and consumer markets. In the short term, changes in producer prices and consumer prices do not affect each other, which indicates that in the short time, there is no integration between the two markets.

The absence of market integration between producer and consumer markets in the short term indicates that the market at the producer level leads to imperfectly competitive markets; the results of this study are similar to research with the results of research on vertical corn market integration in East Java firmly integrated into the long term [40].

TABLE VI
ESTIMATION RESULTS OF THE VECM MODEL

Error Correction	D(Smallholder) Coefficient	T-Statistics	D(Consumer) Coefficient	T-Statistics
ECT1	-0.64053	[-5.2868]	4.036121	[5.20909]
D(Smallholder (-1)	-0.07659	[-0.65446]	-2.441548	[-3.26216]
D(Smallholder (-2)	0.009915	[1.05144]	-1.123461	[-1.8628]
D(Smallholder (-1)	-0.05563	[-3.0308]	-0.225032	[-1.9170]
D(Smallholder (-2)	-0.01067	[-0.7424]	-0.119770	[-1.3030]
C	-0.01166	[-0.0039]	1.410338	[0.0754]
R-Squared	0.394007		0.467858	

In the short term, ideal price integration between farm-level and consumer-level markets remains elusive, signaling inefficiencies within the marketing system. However, notable exceptions exist, such as the integration observed between organic grain and organic rice prices. Here, adjustments in organic rice prices at the consumer level prompt corresponding changes in grain prices by producers, revealing a degree of integration. Notably, the value of price transmission elasticity (et) surpasses unity (et > 1), indicating that a 1 percent shift in consumer-level prices leads to changes greater than 1 percent at the producer level. This elastic response underscores the market's inefficiencies, which can be attributed, in part, to the influence of a limited number of dominant marketing institutions that render the market imperfectly competitive. A study by Nuraeni et al. (2015) supports these observations, noting long-term integration between producer and retail markets, with short-term integration remaining elusive.

The Impulse Response Functions (IRF) analysis, unlike its short-term focus, provides insights that extend into the future. In Figure 1, the IRF analysis showcases the response of smallholder maize producer prices to shocks within the same variable. This response displays a positive trend from the first to the tenth period, with the IRF line consistently positioned above the horizontal line. The initial period exhibits a substantial response of 31.46%, while the fourth period witnesses a more modest response of 6.85%.

Furthermore, Figure 1 illustrates the response of producer prices for smallholder maize when subjected to consumer price shocks, again revealing a positive trend from the first to the tenth period. The Impulse Response Functions (IRF) lines consistently hover above the horizontal line, with the first period registering a robust response of 12.97% and the initial period recording no discernible response (0.00%).

Similar patterns emerge in the demand response of consumer prices for shelled corn following producer price shocks. The trend remains positive from the first to the tenth period, as indicated by the IRF line's position above the horizontal line. The fourth period showcases a substantial response of 77.39%, while the first period records a more modest response of 3.47%.

In a parallel scenario, consumer price responses to consumer price shocks for smallholder corn exhibit a consistent positive trend from the first to the tenth period, characterized by the IRF line's position above the horizontal line. The first period demonstrates a substantial response of 201.2%, while the initial period records a more moderate response of 23.44%.

Table VII provides a comprehensive overview of the output variance decomposition for maize producer prices. In the first period, producer maize prices are significantly influenced by maize producer price shocks (100%), with consumer-level price shocks remaining negligible during this period. As we progress from the second to the tenth period, the contribution of maize producer price shocks to the overall producer maize price progressively diminishes, accounting for 65.98%. In contrast, consumer price shocks begin to exert a more pronounced influence, culminating in a contribution of 34.01% by the tenth period.

This analysis delves into the intricate dynamics of price integration in the Indonesian smallholder maize market, offering valuable insights for stakeholders and researchers seeking to enhance market efficiency and optimize price integration within the agricultural sector.

TABLE VII
VARIANCE DECOMPOSITION TOWARDS SMALLHOLDER AND CONSUMER

Variance Decomposition of D (Smallholder Price):			
Period	S.E.	D(Smallholder Price)	D(Consumer Price)
1	31.46647	100.0000	0.000000
2	34.19192	91.73142	8.268576
3	38.11028	81.75634	18.24366
4	40.12952	76.65660	23.34340
5	42.44016	74.13714	25.86286
6	44.60229	72.05658	27.94342
7	46.76519	70.27457	29.72543
8	48.78384	68.59397	31.40603
9	50.72520	67.18198	32.81802
10	52.58257	65.98370	34.01630
Variance Decomposition of D (Consumer Price):			
Period	S.E.	D(Smallholder Price)	D(Consumer Price)
1	201.2351	0.029866	99.97013
2	208.8147	5.895184	94.10482
3	221.4489	13.13075	86.86925
4	243.3762	20.98423	79.01577
5	256.9134	23.73368	76.26632
6	270.8825	26.14575	73.85425
7	283.7866	28.13122	71.86878
8	296.1711	29.99771	70.00229
9	308.1655	31.55901	68.44099
10	319.7345	32.88699	67.11301

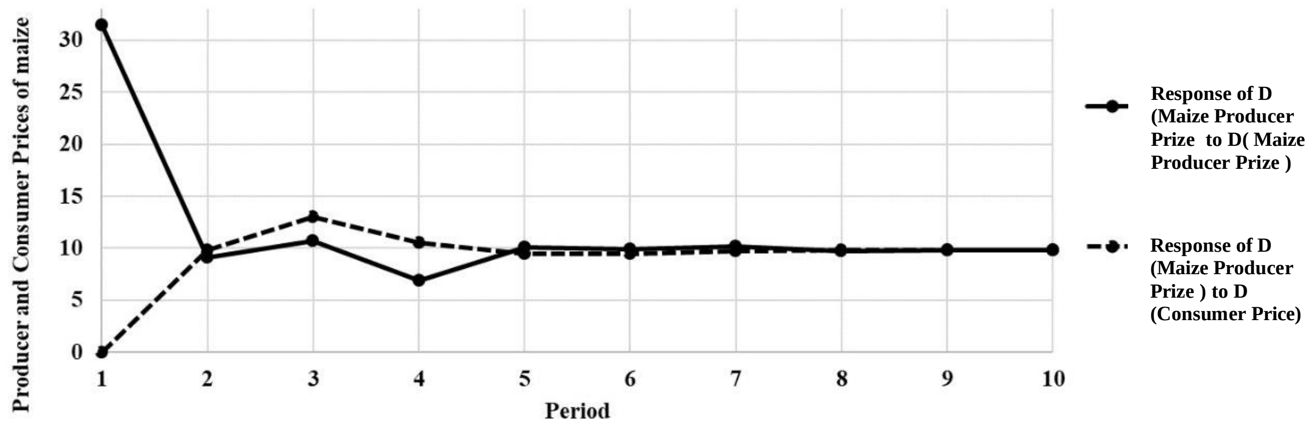
Variance decomposition, a vital statistical technique within time series analysis, plays a pivotal role in unraveling the complexities of price dynamics in the Indonesian smallholder maize and consumer markets. Its application allows for a detailed breakdown of the sources of price variation, shedding light on the fundamental factors that influence pricing mechanisms. The variance decomposition in this study dissects the variance in maize producer prices into two primary components: producer price shocks and consumer price shocks. By understanding the relative contributions of these components, the analysis offers crucial insights into the dynamics of these markets. A higher proportion of variance explained by producer price shocks suggests that changes in smallholder maize prices are predominantly shaped by factors intrinsic to the producer market itself. This implies that producers have a significant degree of control over their pricing, influenced by aspects such as supply and demand within the producer market and production costs.

Conversely, a substantial proportion of variance attributed to consumer price shocks signifies the influential role of factors originating from the consumer market. Consumer demand, pricing strategies at the consumer level, and other variables impacting consumer market dynamics become key drivers of changes in producer maize prices. This indicates a strong price transmission mechanism from the consumer market to the producer market, reflecting either market efficiency or a high level of producer responsiveness to consumer dynamics. The implications of this variance decomposition are manifold. They offer valuable insights into the market dynamics and the interplay between smallholder maize producers and consumers in Indonesia. These insights can guide policymakers in developing targeted interventions that aim to enhance market efficiency, ensure fair pricing mechanisms, and ultimately benefit both smallholder farmers and consumers. Furthermore, this analysis contributes to the ongoing discourse about the temporal aspects of market integration. It highlights whether observed integration is a result of short-term or long-term factors, which is crucial information for designing policies and strategies that aim to foster more efficient and equitable agricultural markets.

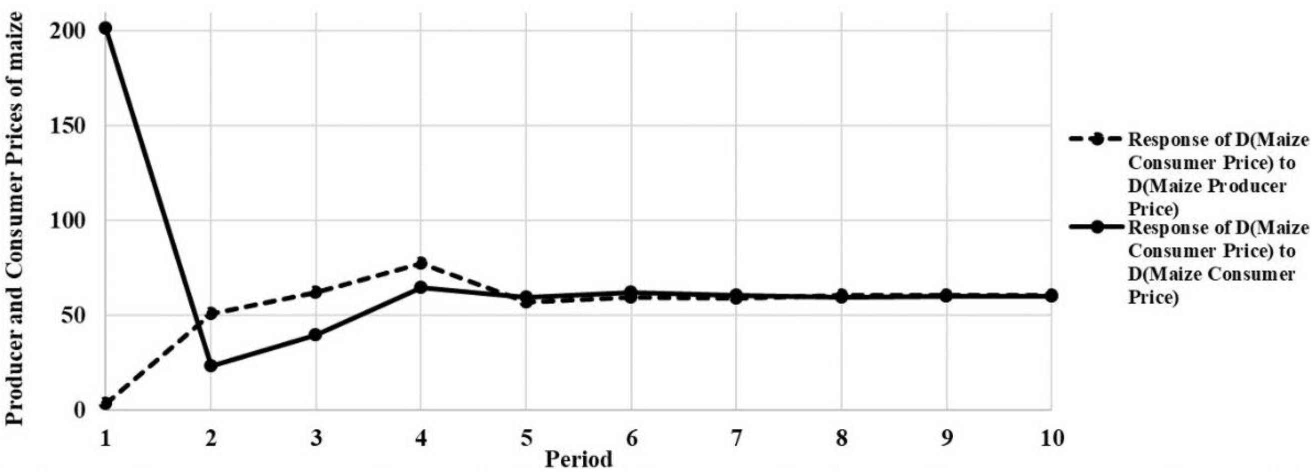
V. CONCLUSION

Producer-level and consumer-level smallholder maize markets in Indonesia are integrated into the long term, which means that changes in producer-level smallholder maize prices are affected by changes in consumer-level smallholder maize prices in Indonesia and are not incorporated in the short time. In the first period, the consumer price of smallholder maize is affected by the shock to the consumer price of smallholder maize (99.97%). In comparison, in that period, the shock to the consumer price of smallholder maize affects the producer price of smallholder maize (0.02%). Moving on, from the second to the tenth period, the proportion of the rice consumer price shock to the rice consumer price itself tends to decrease by 67.11%. Furthermore, a producer price shock for unhusked corn has an increasing contribution throughout the period. Starting from the 10th period, the producer price shock has contributed 32.88% to the consumer price of smallholder maize. Apparently, the size of the consumer price shock has a more significant influence on the consumer price of smallholder maize than the producer price shock.

In this study, we have developed a business model for analyzing the demand and prices of maize, which yields significant benefits.



(A)



(B)

Fig. 1. Impulse Response Functions (IRF) of Producer price (A) and Consumer Price (B)

Firstly, it enables better planning in maize-related business activities. The business model helps accurately identify the specific needs of maize supply in terms of quantity, quality, and specific types. This information facilitates more efficient production, procurement, and distribution planning. Moreover, the business model also aids in managing risks associated with maize price fluctuations, particularly in Indonesia. By analyzing historical data on maize prices, including trends and patterns, we can predict future price fluctuations. This knowledge allows for more informed decision-making regarding raw material procurement, pricing of final products, and risk management through financial instruments such as futures contracts.

Additionally, the business model provides a clear framework for analyzing data and information related to maize demand and prices. With a better understanding of the factors influencing maize demand and supply, we can make more informed decisions. For instance, we can adjust production strategies, expand into new markets, or establish partnerships with maize suppliers. In an era characterized by increasingly complex business environments and intense competition, having a business model for analyzing maize demand and prices is crucial. It enhances decision-making, reduces risks, and improves operational efficiency. Therefore, investing time and resources into developing a robust business model yields long-term benefits for sustainable business continuity and success.

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