Resilience of Agricultural Sector Financing: Examining the Impact of Domestic Macroeconomic Transmission and Global Commodity Prices in Indonesia

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Abstract

This study examines the resilience of agricultural sector financing in Indonesia to domestic macroeconomic transmission and global commodity prices using a Vector Error Correction Model (VECM) approach for January 2008 to December 2025. The analysis reveals that agricultural credit is cointegrated with agricultural output, interest rates, inflation, and the exchange rate. In the long run, agricultural credit shows a significant positive relationship with agricultural output but a significant negative relationship with the exchange rate. In the short run, global agricultural commodity and energy price dynamics significantly impact the provision of agricultural credit. Agricultural credit responds positively to shocks in agricultural output and inflation, but negatively to shocks in interest rates and the exchange rate, with agricultural output serving as the largest contributor to credit variation, aside from credit itself. These findings underscore the importance of maintaining interest rate and exchange rate stability to support sustainable agricultural financing. It is recommended that the government and monetary authorities design credit schemes that better adapt to global commodity price fluctuations, strengthen exchange rate risk-mitigation instruments, and foster increased agricultural productivity to sustainably bolster the resilience of financing in this sector.

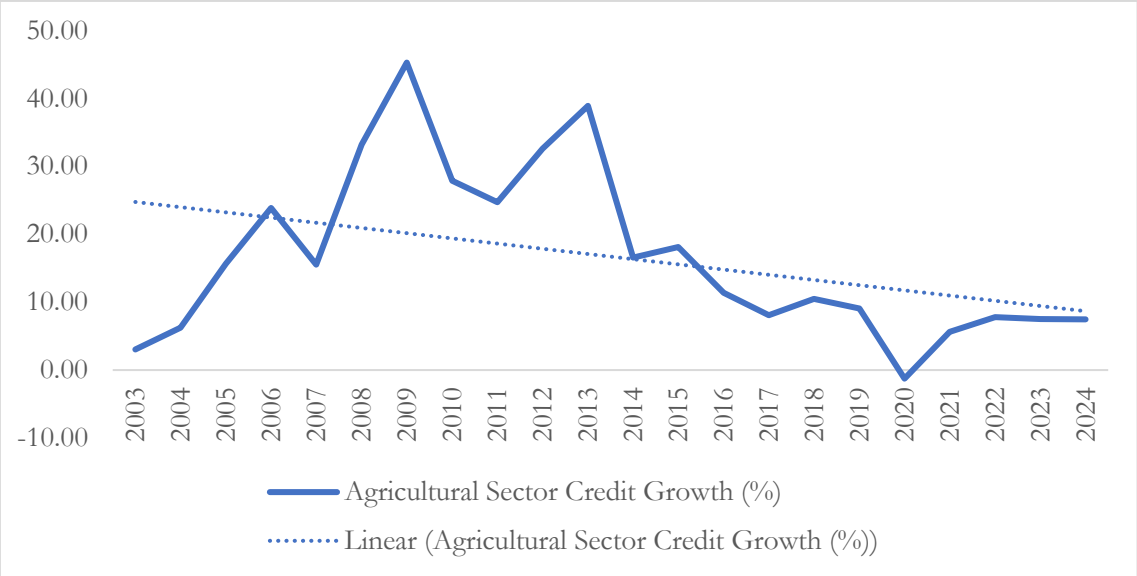
Keywords: agricultural credit; financing resilience; global commodity prices; macroeconomic transmission; VECM

I. INTRODUCTION

Agriculture remains a cornerstone of Indonesia's economy and of its food security. In 2025, the agriculture, forestry, and fisheries sector accounted for roughly 13% of gross domestic product (GDP) at current prices (Badan Pusat Statistik, 2026), and agriculture was among the sectors with the largest employment gains over the year to August 2025, adding 0.49 million workers (Badan Pusat Statistik, 2025). Farming is working-capital intensive and subject to long production cycles, so access to formal finance is a binding condition for purchasing inputs, expanding production, and absorbing shocks. Cross-country evidence shows that agricultural credit raises agricultural productivity, with a doubling of credit associated with a 4–5% increase, mainly through agricultural value added in developing countries (Seven & Tumen, 2020). Modern inputs such as fertilizers are likewise central to raising yields and supporting wider economic development (McArthur & McCord, 2017), and they must be financed before the harvest.

Agricultural credit disbursement in Indonesia is characterized by fluctuating growth in credit for agriculture and agricultural MSMEs, alongside a long-term downward trend in credit growth, as illustrated in Figure 1. Given that population growth drives rising food

demand, agricultural credit growth should ideally increase to keep pace with this demand, while also facilitating adaptation to climate change and supporting sustainable agriculture.



Source: Bank Indonesia (2025)

Figure 1. Agricultural Sector Credit Growth in Indonesia (%), 2003–2024.

The environment in which agricultural lenders and borrowers operate has also become more volatile. Since 2008, the sector has faced a succession of external shocks, from the global financial crisis and commodity price swings to the COVID-19 pandemic and the Russia–Ukraine war, which sharply raised food, fuel, and fertilizer prices in 2022 (Arndt et al., 2023) . Energy prices affect agriculture directly through fuel, machinery, and transport, and indirectly through fertilizer, whose cost follows natural gas and crude oil prices (Aye & Odhiambo, 2021; Bor & Sakarya, 2026; Wongpiyabovorn & Hart, 2024). Because many inputs are priced internationally, exchange-rate movements add a further source of cost uncertainty (Bor & Dagistan, 2024). These cost and price shocks can erode farm margins and repayment capacity, and banks may respond by tightening credit. Evidence from developing countries shows that commodity price movements are transmitted to bank lending, particularly through banks with weaker deposit bases and poorer asset quality (Agarwal et al., 2020) and that uncertainty in agricultural commodity prices raises the cost of credit for commodity-dependent firms (Bermpei et al., 2023).

Global shocks reach agricultural borrowers through domestic macroeconomic conditions. In Indonesia, monetary policy transmission to lending rates is incomplete and asymmetric: since the 2016 change in the benchmark policy rate, lending rates have become more rigid upward (Handayani & Kacaribu, 2021), and pass-through varies with the business cycle (Triwibowo et al., 2022). The bank lending channel itself depends on funding liquidity and on the volume of undisbursed loans (Soedarmono et al., 2023). Evidence from Türkiye suggests that exchange-rate depreciation can discourage banks from directing funds toward agriculture (Keskin & Gün, 2026), while recent Indonesian evidence on aggregate bank credit points to lagged exchange-rate and inflation effects and a stronger role for short-run fluctuations than for long-run relationships (Indraswari et al., 2026). Whether comparable mechanisms govern credit to the agricultural sector specifically remains unclear.

Despite these strands of research, the literature leaves an empirical and conceptual gap. First, studies of agricultural credit in Indonesia have largely examined farm-level access, uptake, and income effects (e.g., Susriani et al., 2022), whereas macro-level studies of Indonesian bank credit (Handayani & Kacaribu, 2021; Indraswari et al., 2026; Soedarmono

et al., 2023) treat lending in aggregate and do not isolate agriculture, whose risk profile and exposure to input and output prices differ from those of other borrowers. Second, work linking global commodity prices to bank lending relies on broad samples of developing countries and all-sector lending (Agarwal et al., 2020; Bermpei et al., 2023), while energy–agriculture studies focus on price transmission rather than financing (Bor & Sakarya, 2026); the financing consequences of global energy price dynamics for agriculture therefore remain largely unexamined. Third, existing evidence rarely separates long-run equilibrium relationships from short-run adjustment, a distinction that matters for judging resilience: a financing system is resilient not only if credit is anchored by economic fundamentals in the long run but also if it absorbs shocks without prolonged disruption. Cointegration-based frameworks such as the vector error correction model (VECM) are well suited to this task and have been used to trace how external price shocks propagate to agricultural output through exchange-rate and nominal channels (Aliaga-Miranda et al., 2026). However, to date, this method has been applied to agricultural credit in Indonesia only to examine domestic macroeconomic variables and global commodity prices within an integrated system.

Addressing this gap is timely for three reasons. First, the period from 2008 to 2025 spans repeated global shocks, which makes it possible to assess resilience across different regimes rather than in a single episode. Second, credit schemes remain a key policy instrument for supporting farmers (Susriani et al., 2022); designing them without knowing how credit responds to interest rates, inflation, the exchange rate, and energy prices risks misdirecting support. Third, if agricultural credit is sensitive to macroeconomic instability and imported cost shocks, financing may contract precisely when producers need liquidity most, weakening productivity growth and food security. Evidence on which variables anchor agricultural credit, and which shocks matter most, therefore has direct implications for monetary authorities and agricultural policy makers.

This study examines the resilience of agricultural sector financing in Indonesia, understood as the extent to which agricultural credit remains anchored by domestic macroeconomic fundamentals and adjusts to global commodity price shocks. Using data from January 2008 to December 2025 and a VECM, it pursues four objectives: (1) to test whether agricultural credit shares a long-run equilibrium with agricultural output, interest rates, inflation, and the exchange rate; (2) to estimate the direction and size of these long-run relationships; (3) to assess the short-run effects of global commodity prices, particularly agricultural commodities, energy, and fertilizer prices, on agricultural credit; and (4) to quantify, through impulse response and forecast error variance decomposition analysis, how credit responds to shocks in each variable and which variable explains most of its variation.

The study contributes in three ways. First, it provides sector-level evidence that links agricultural credit to both domestic macroeconomic transmission and global commodity prices within one framework, extending macro-level studies of Indonesian bank credit that do not isolate agriculture. Second, by separating long-run and short-run effects, it offers a more complete test of financing resilience than single-horizon estimates. Third, it draws policy implications for interest-rate and exchange-rate stability, for credit schemes that adapt to commodity price fluctuations, and for measures that raise agricultural productivity. The remainder of the paper is organized as follows. Section 2 describes the data and empirical strategy, Section 3 presents the results and discusses the findings and their policy implications, and Section 4 concludes.

II. METHOD

3.1 Research Design, Data, and Variables

This study uses a quantitative time-series design to examine how domestic macroeconomic variables and global energy prices relate to credit supply to Indonesia's

agricultural sector. The sample covers January 2008 to December 2025 (T = 216 monthly observations). The sample begins with the global financial crisis and ends with the COVID-19 pandemic and the Russia–Ukraine war, so the analysis spans several distinct macroeconomic regimes.

Five variables are treated as endogenous: agricultural credit, agricultural output, the interest rate, inflation, and the exchange rate. Global agricultural, energy, and fertilizer prices are treated as exogenous variables that enter the short-run dynamics, because Indonesia is small relative to global energy markets and takes world prices as given. Credit, output, the exchange rate, and the agricultural, energy, and fertilizer price index are expressed in natural logarithms so that long-run coefficients can be read as elasticities. In contrast, the interest rate and inflation are kept in percent. Variable definitions, measurements, and data sources are presented in Table 1.

Table 1. Variables, measurement, and data sources

Variable	Symbol	Definition and unit	Transformation	Source
Agricultural credit	AGCR	Outstanding bank credit to the agriculture, forestry, and fisheries sector (IDR billions)	Natural log	Bank Indonesia
Agricultural output	AGOUTPUT	Real gross domestic product of agriculture, forestry, and fisheries (constant prices, 2010 = 100), interpolated from quarterly to monthly	Natural log	BPS
Interest rate	PIR	Bank Indonesia policy rate (% per annum)	Level	Bank Indonesia
Inflation	INF	Year-on-year change in the consumer price index (%)	Level	BPS
Exchange rate	EXR	Rupiah per US dollar (higher value = depreciation)	Natural log	Bank Indonesia
Global agricultural price (exogenous)	GAP	Global agricultural price index comprising food, beverages, and raw materials. (US dollars, nominal, 2010 = 100)	Natural log	World Bank
Global energy price (exogenous)	GEP	A composite energy price index, which includes crude oil, natural gas, and coal. (US dollars, nominal, 2010 = 100)	Natural log	World Bank
Global fertilizer price (exogenous)	GFERP	A composite fertilizer price index, which includes natural phosphate rock, phosphate, potassium, and nitrogenous. (US dollars, nominal, 2010 = 100)	Natural log	World Bank

3.2 Empirical Strategy

The empirical strategy follows this sequence. After establishing the order of integration of each series, the lag length is selected, and the Johansen procedure is used to test for cointegration among the endogenous variables. The long-run relationship and the short-run dynamics are then estimated in a vector error correction model (VECM), which separates the equilibrium relationship from the adjustment process (Engle & Granger, 1987; Johansen,

1988). Residual diagnostics assess the model, and impulse response functions (IRFs) and forecast error variance decomposition (FEVD) describe how credit reacts to shocks and which shocks explain its variation. This approach matches the research objectives and aligns with using VECMs to trace external price shocks to agricultural output (Aliaga-Miranda et al., 2026) and error-correction models to study monetary transmission in Indonesia (Handayani & Kacaribu, 2021; Triwibowo et al., 2022).

3.3 Unit Root Tests

Johansen cointegration analysis requires the variables to be integrated of the same order, usually I(1) (Engle & Granger, 1987; Johansen, 1988). The order of integration is therefore established first with the augmented Dickey–Fuller (ADF) test (Dickey & Fuller, 1979) and the Phillips–Perron (PP) test (Phillips & Perron, 1988). The ADF regression is

$$\Delta y_t = a + \delta t + \gamma y_{t-1} + \Sigma_{i=1,\dots,k} \varphi_i \Delta y_{t-i} + u_t \quad (1)$$

where y_t is the series, t is a time trend, k is the number of lagged differences chosen by the Schwarz criterion, and u_t is the error term. The null hypothesis of a unit root is $\gamma = 0$. The PP test applies a nonparametric correction for serial correlation and heteroskedasticity to the same regression and is therefore robust to unspecified error dependence (Phillips & Perron, 1988). A variable is classified as I(1) when the unit-root null is not rejected in levels but is rejected in first differences. Constant and trend terms are included for the trending series (LAGCR, LAGOUTPUT, ER, EP) and a constant only for PIR and INF.

3.4 Lag Length Selection

Let $Y_t = (AGCR_t, AGOUTPUT_t, PIR_t, INF_t, EXR_t)'$ denote the K = 5 vector of endogenous variables. The lag order p of the VAR in levels is chosen with the Akaike (H. Akaike, 1974), Schwarz (Schwarz, 1978), and Hannan–Quinn (Hannan & Quinn, 1979) information criteria, complemented by sequential likelihood-ratio and final prediction error tests. When the criteria disagree, the smallest lag that yields serially uncorrelated residuals is selected, because residual autocorrelation can distort the cointegration tests.

3.5 Johansen Cointegration Test

Cointegration among the endogenous variables is tested with the Johansen maximum likelihood procedure (Johansen, 1988, 1991, 1995). The VAR(p) in levels is reparameterized as the VECM

$$\Delta Y_t = \Pi Y_{t-1} + \Sigma_{i=1,\dots,p-1} \Gamma_{1i} \Delta Y_{t-i} + \Sigma_{j=0,\dots,q} \Lambda_j \Gamma_{2i} \Delta G_{t-j} + \mu + \varepsilon_t \quad (2)$$

where Π is the long-run impact matrix, Γ_i are the short-run coefficient matrices, Λ_j captures the short-run effects of global prices (agricultural commodities, energy, and fertilizers), μ is a vector of constants, and ε_t is a vector of white-noise errors with covariance matrix Σ. If the rank of Π is r with $0 < r < K$, then $\Pi = \alpha\beta'$, where β contains the r cointegrating vectors, and α contains the speed-of-adjustment coefficients (Johansen, 1988). The rank is determined with the trace and maximum eigenvalue statistics. Critical values are taken from MacKinnon et al. (1999). The null hypothesis of at most r cointegrating vectors is tested sequentially from r = 0, and the first rank that is not rejected is selected. The deterministic specification (restricted constant or restricted trend in the cointegrating space) is chosen based on the data plots and information criteria. With r = 1, the cointegrating vector is normalized on agricultural credit, giving the long-run relationship

$$AGCR_t = \beta_0 + \beta_1 AGOUTPUT_t + \beta_2 PIR_t + \beta_3 INF_t + \beta_4 EXR_t + ect_t \quad (3)$$

where ect_t is the equilibrium error; the coefficients are interpreted as elasticities for the log-transformed variables and as semi-elasticities for PIR and INF. Weak exogeneity of each variable with respect to the long-run parameters is tested with likelihood-ratio restrictions on the corresponding element of α (Johansen, 1995), and the significance of the speed-of-adjustment coefficient in the AGCR equation shows whether credit corrects toward equilibrium.

3.6 VECM Estimation and Short-Run Effects

Given the cointegrating rank, the VECM in Eq. (2) is estimated with $\Pi = \alpha\beta'$. Global agricultural, energy, and fertilizer prices are included in differenced form, contemporaneously and with q lags, as exogenous I(1) regressors that do not enter the long-run relationship, following the treatment of exogenous variables in vector error correction models proposed by Pesaran et al. (2000). The equation for agricultural credit is

$$\Delta AGCR_t = a_{AC}\, ect_{t-1} + \Sigma_{i=1,\dots,p-1}\, \gamma_{AC,i}'\Delta Y_{t-i} + \Sigma_{j=0,\dots,q}\, \lambda_{1j}\Delta GAP_{t-j} + \Sigma_{j=0,\dots,q}\, \lambda_{2j}\Delta GEP_{t-j} + \Sigma_{j=0,\dots,q}\, \lambda_{3j}\Delta GFERP_{t-j} + \mu_{AC} + \varepsilon_{AC,t} \quad (4)$$

A negative and significant α_{AC} indicates that credit adjusts back toward its long-run path after a deviation.

3.7 Impulse Response Functions

Impulse response functions trace the dynamic response of agricultural credit to a one-standard-deviation shock in each endogenous variable (Sims, 1980). The VECM is first inverted to its moving-average representation. Because the innovations are contemporaneously correlated, shocks are identified with a Cholesky decomposition of the covariance matrix. In a cointegrated system, shocks to the common stochastic trends can have permanent effects on the variables' levels, so the interpretation of persistence accounts for the cointegrating restrictions.

3.8 Forecast Error Variance Decomposition

Forecast error variance decomposition measures the share of each variable's h-step-ahead forecast error variance attributable to shocks in each endogenous variable (Lütkepohl, 2005). The decomposition is reported at horizons of 1, 12, 24, and 36 periods and is recomputed with generalized shocks, normalized so that each row sums to one (Pesaran & Shin, 1998). Through variance decomposition, it can be demonstrated which variables, following the credit shock itself, contribute the largest share of the forecast error variance for agricultural credit.

III. RESULTS AND DISCUSSIONS

A. Result

1. Prerequisite test

This study conducts unit root tests using the Augmented Dickey–Fuller (ADF), Phillips–Perron (PP), and DF-GLS tests. The null hypothesis of a unit root cannot be rejected in levels for any of the endogenous variables (LAGCR, LAGOUTPUT, PIR, INF, and LEXR) or the exogenous variables (LGAP, LGEP, and LGFERP). In contrast, it is rejected for all variables in first differences. The DF-GLS test, which applies GLS detrending to increase power relative to the ADF test (Elliott et al., 1996), yields the same conclusion as the ADF and PP tests. All variables are therefore integrated of order one, I(1), which satisfies the precondition for Johansen cointegration analysis.

The VAR in levels is estimated for the sample 2008M04–2025M12, yielding 213 observations after adjustments, with lags 1 to 2 in first differences selected using lag-selection criteria and a linear deterministic trend assumption. The three global price variables enter as exogenous series. Table 2 presents the Johansen trace and maximum eigenvalue tests.

Table 2. Johansen unrestricted cointegration rank tests

No. of CE(s) under H_0	Eigenvalue	Trace statistic	5% critical value	p-value	Max-eigen statistic	5% critical value	p-value
None *	0.4078	193.4872	69.8189	0.0000	111.5773	33.8769	0.0000
At most 1 *	0.1673	81.9099	47.8561	0.0000	39.0052	27.5843	0.0011
At most 2 *	0.1084	42.9048	29.7971	0.0009	24.4465	21.1316	0.0164
At most 3 *	0.0679	18.4583	15.4947	0.0174	14.9809	14.2646	0.0385
At most 4	0.0162	3.4773	3.8415	0.0622	3.4773	3.8415	0.0622

Note. * denotes rejection of the null hypothesis at the 5% level. p-values are from MacKinnon et al. (1999). The first p-value column belongs to the trace test and the second to the maximum eigenvalue test.

Source: Authors' calculation

Both tests reject the null hypotheses of no cointegration ($r = 0$), at most one, at most two, and at most three cointegrating equations at the 5% level, while the null of at most four is not rejected ($p = 0.062$). The trace and maximum eigenvalue statistics, therefore, both indicate four cointegrating equations. The fourth relationship is only marginally accepted ($p = 0.017$ for the trace test and 0.039 for the maximum eigenvalue test), and the first eigenvalue (0.408) is much larger than the second (0.167), which points to one dominant long-run relationship. The result supports the hypothesis that agricultural credit shares a long-run equilibrium with agricultural output, the policy rate, inflation, and the exchange rate (Johansen, 1988, 1995).

2. Long-Run Relationship

Table 3 reports the normalized cointegrating vector. EViews presents the cointegrating equation as $LAGCR - 6.384 \cdot LAGOUTPUT - 0.018 \cdot PIR - 0.041 \cdot INF + 1.949 \cdot LEXR + 42.973 = 0$, so the coefficients must be sign-reversed to obtain the long-run effect on credit. Solving for credit gives

$$LAGCR = -42.973 + 6.384\ LAGOUTPUT + 0.018\ PIR + 0.041\ INF - 1.949\ LEXR$$

Table 3. Normalized cointegrating vector (dependent variable: LAGCR)

Variable	Coefficient	Std. error	t-statistic	Long-run effect on LAGCR	t-statistic (effect)	Significance
LAGOUTPUT	−6.3841	0.5120	−12.470	+6.3841	+12.470	1%
PIR	−0.0182	0.0524	−0.347	+0.0182	+0.347	n.s.
INF	−0.0406	0.0353	−1.150	+0.0406	+1.150	n.s.
LEXR	+1.9486	0.4924	+3.958	−1.9486	−3.958	1%
Constant	42.9735			−42.9735		

Note. n.s. = not significant at the 10% level. The sign of the coefficient reported by EViews is the opposite of its effect on LAGCR because the equation is normalized with LAGCR on the left-hand side and all terms moved to one side. Log-likelihood = 1348.850.

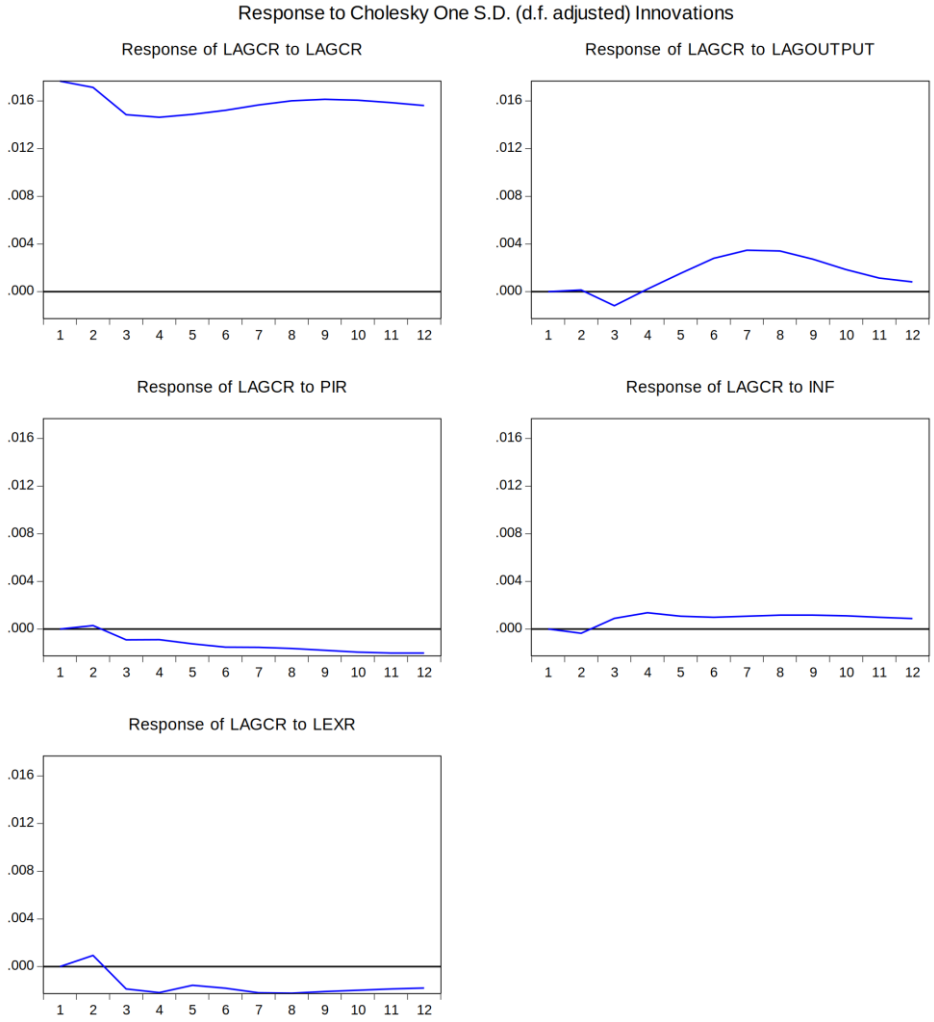
Source: Authors' estimation

Two long-run coefficients are statistically significant. The elasticity of agricultural credit with respect to agricultural output is positive and large (coefficient = 6.38; t = 12.47). The elasticity with respect to the exchange rate is negative (coefficient = −1.95; t = −3.96), so a 1% depreciation of the rupiah against the US dollar is associated with a 1.95% lower level of agricultural credit in the long run. The long-run coefficients of the policy rate (coefficient = 0.018; t = 0.35) and inflation (coefficient = 0.041; t = 1.15) are small and statistically insignificant. In the long run, therefore, the equilibrium level of agricultural credit is anchored by agricultural output and the exchange rate rather than by the policy rate or inflation. The output elasticity far above one implies that credit grew much faster than real agricultural output over 2008–2025, so it should be interpreted as a long-run association between two trending series and not as a structural elasticity.

Based on error correction and short-run dynamics, deviations from the long-run relationship are corrected mainly through agricultural output, and credit behaves as weakly exogenous with respect to the long-run parameters (Johansen, 1995). In the short run, the exchange rate lagged two months has a significant negative effect on credit growth (coefficient = −0.096; t = −2.08), consistent with the negative long-run exchange-rate effect, and output lagged two months has a weaker negative effect that is significant at the 5% level. Lagged changes in the policy rate, inflation are not significant, meanwhile, two months lagged credit growth itself is significant at the 10% level. Among the exogenous global variables, global energy prices have a significant effect on credit (coefficient = 0.0143; t = 2.13): because the equation is in log differences, a 5% higher level of the energy price index is associated with about 0.014 percentage points higher monthly credit growth. Meanwhile, global agricultural commodity prices have a significant effect on credit (coefficient = -0.0233; t = 1.50) at the 10% level. Global fertilizer prices are not significant. Global energy prices also have a significant positive effect on the change in the policy rate (coefficient = 0.2165; t = 3.75), which suggests an indirect channel from energy prices to financing conditions.

3. Impulse Response Functions

Figure 2 shows agricultural credit's response to one-standard-deviation Cholesky innovations over 12 months. A shock to credit itself has a large, highly persistent effect: the response starts at about 0.018, equal to the standard error of the credit equation, and remains around 0.015–0.016 after 12 months. Responses to the other variables are much smaller. A shock to agricultural output has almost no effect in the first two months, a slightly negative effect in the third month, and a positive effect from the fourth month that peaks at about 0.0035 in months 7–8 before fading to about 0.001 at month 12. A shock to the policy rate produces a small negative response from the third month onward, reaching about −0.002 by the end of the horizon. A shock to inflation produces a small positive response of about 0.001 from the third month onward. A shock to the exchange rate (a depreciation) produces a small positive response in month 2 followed by a small negative response that persists.

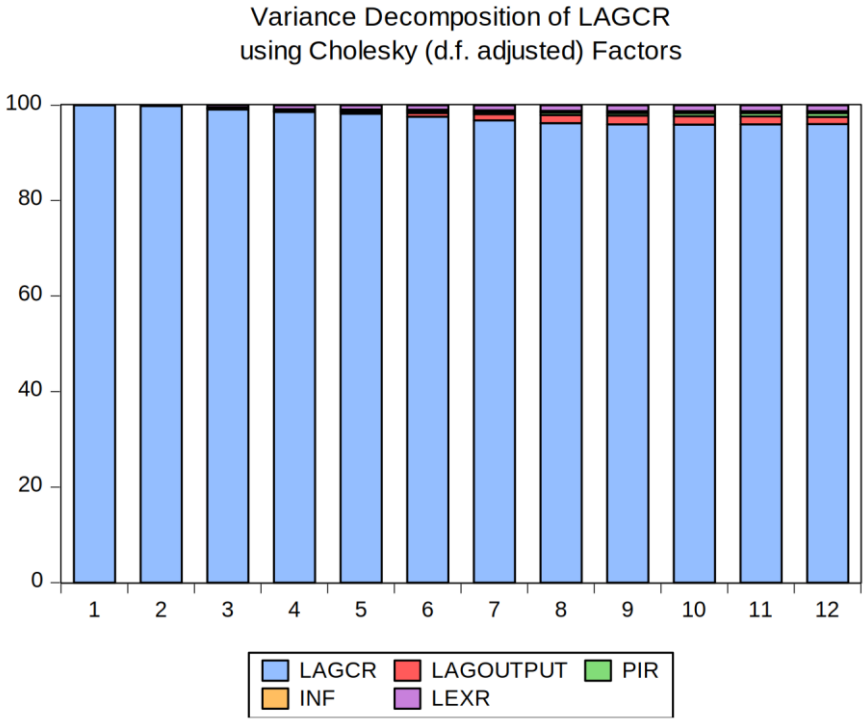


Note. Source: authors' estimation using EViews (Cholesky, degrees-of-freedom adjusted). Horizon: 12 months.

Figure 2. Impulse responses of LAGCR to Cholesky one-standard-deviation innovations

4. Forecast Error Variance Decomposition

Figure 3 presents the variance decomposition of agricultural credit. By construction, innovations to credit account for all forecast error variance in the first month, and their share declines slowly to about 96% after 12 months. The remaining 4% or so is split among the other variables. Agricultural output is the largest contributor, rising from the sixth month and stabilizing at roughly 1–3% after eight months, followed by the exchange rate at roughly 1%. The policy rate and inflation contribute less than 1%. Agricultural output is therefore the largest contributor to credit variation apart from credit itself.



Note. Source: authors' estimation using EViews (Cholesky, degrees-of-freedom adjusted).

Figure 3. Variance decomposition of LAGCR

B. Discussion

1. Long-Run Determinants of Agricultural Credit

The long-run results show that agricultural credit in Indonesia is tied to two fundamentals: agricultural output and the exchange rate. The positive output effect is consistent with the demand and risk arguments, in which higher output raises financing needs and improves repayment capacity. It is also consistent with cross-country evidence that agricultural credit and agricultural value-added move together (Seven & Tumen, 2020). The error correction results, however, add an important qualification. Because the adjustment coefficient is significant in the output equation but not in the credit equation, the long-run relationship is restored through output rather than through credit. This pattern is closer to the view that credit leads output than to the view that output drives credit, and it agrees with Seven & Tumen (2020), who find an effect of credit on agricultural productivity and no evidence of reverse causality. The positive long-run association between output and credit should therefore not be read as evidence that credit passively follows output.

The negative exchange-rate effect agrees with evidence from Türkiye that a higher exchange rate lowers credit orientation toward agriculture (Keskin & Gün, 2026). A plausible mechanism is the cost channel: a depreciation raises the rupiah cost of imported and internationally priced inputs (Bor & Dagistan, 2024), compresses farm margins, and raises credit risk, which can make banks less willing to lend. The finding that the exchange rate affects credit growth with a two-month lag parallels Indonesian evidence on aggregate bank credit, where exchange-rate effects appear with lags (Indraswari et al., 2026).

The insignificant long-run effect of the policy rate is consistent with the evidence that monetary policy transmission to lending rates in Indonesia is slow, asymmetric, and dependent on the business cycle (Handayani & Kacaribu, 2021; Triwibowo et al., 2022), and

that the bank lending channel depends on banks' funding liquidity and undisbursed loans (Soedarmono et al., 2023). This also aligns with the finding that the interest rate is not retained in a model of aggregate Indonesian bank credit (Indraswari et al., 2026). The policy rate may therefore influence agricultural credit mainly through short-run dynamics, as the negative impulse response suggests, rather than through the equilibrium level of credit. The small positive response of credit to inflation differs from the negative lagged effect found for aggregate bank credit (Indraswari et al., 2026). This difference is consistent with a cost-push mechanism specific to agriculture, in which higher input prices raise the nominal amount that farmers need to borrow. Still, the evidence here is weak because the long-run inflation coefficient is not significant.

2. Adjustment Speed and the Resilience of Agricultural Financing

The results give a nuanced picture of resilience. On one hand, agricultural credit is very persistent: the response to its own shock stays near its initial level after 12 months, and the model explains little of the month-to-month variation in credit growth. This persistence indicates that agricultural credit is not easily disrupted by changes in the policy rate, inflation, or the exchange rate within a one-year horizon. In contrast, adjustment toward the long-run relationship is extremely slow (error-correction term: -0.0040) and statistically significant with p-value < 0.10, so credit does not quickly realign with output and the exchange rate after a disturbance. Resilience in the sense of stability is therefore accompanied by inertia: shocks that depress credit, such as a sustained depreciation, may have long-lasting effects on financing conditions in the sector. However, this conclusion should be treated with caution, because the credit series is nominal and aggregate, and the model does not separate demand from supply.

3. Global Energy Prices and the Transmission of Global Commodity Shocks

Among the global variables, agricultural commodity and energy prices significantly affect agricultural credit in the short run, with negative and positive effects, respectively. The positive sign suggests that the cost channel dominates the risk and balance-sheet channels. Energy affects agriculture directly through fuel and transport and indirectly through fertilizer (Bor & Sakarya, 2026; Wongpiyabovorn & Hart, 2024), and rising costs increase the working capital that farmers must finance. By contrast, evidence from other developing economies shows that commodity price movements and uncertainty can reduce bank lending or raise its cost (Agarwal et al., 2020; Bermpei et al., 2023); this restrictive effect is not visible in the Indonesian agricultural credit data. The surge in food, fuel, and fertilizer prices after 2022 (Arndt et al., 2023) falls within the sample, so the result is not driven by a tranquil period. The significant positive effect of energy prices on the policy rate points to an additional, indirect route in which energy price shocks affect financing conditions through monetary policy.

The insignificance of global fertilizer prices is notable. One possible explanation is that administered prices and subsidies partly insulate domestic fertilizer and farm-gate prices from world prices.

4. Dynamic Responses and Variance Decomposition

The impulse responses indicate that output, the policy rate, inflation, and the exchange rate have small effects on credit compared with the response to own shocks, and the variance decomposition confirms that credit shocks explain about 96% of its own forecast error variance after 12 months. Output is the largest contributor among the other variables, which agrees with its role in the long-run relationship and with the finding that output adjusts to restore equilibrium. The dominance of own shocks should be interpreted with care, because

the Cholesky decomposition in Figures 2 and 3 places credit first in the ordering, so credit does not react contemporaneously to any other variable, and all variance at the first horizon is attributed to own shocks. Results that depend on the ordering are a known limitation of the Cholesky approach (Sims, 1980).

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IV. CONCLUSION

Agricultural output has a significant positive long-run elasticity, and the exchange rate has a significant negative elasticity, so a weaker rupiah is associated with lower agricultural credit. The long-run effects of the policy rate and inflation are not statistically significant. The short-run and dynamic results add three further findings. First, among the global variables, agricultural commodity and energy prices have significant short-run effects on agricultural credit, and the effects are negative and positive, respectively. In contrast, fertilizer prices are not significant. Second, agricultural credit adjusts to its long-run relationship very slowly and significantly, while agricultural output adjusts significantly, so equilibrium is restored mainly through output. Third, the impulse responses and variance decomposition show that credit is highly persistent: its own shocks explain about 96% of its forecast error variance after 12 months, and output is the largest contributor among the other variables. Agricultural financing is therefore stable within a one-year horizon, but it is slow to realign with its fundamentals after a disturbance. These findings have three policy implications. Maintaining exchange-rate stability and strengthening instruments to hedge exchange-rate risk would help protect agricultural financing. Credit schemes that adapt to global energy price fluctuations, for example, through flexible working-capital limits or repayment schedules when input costs rise, would support farmers during energy price shocks. Policies that raise agricultural productivity would reinforce the output fundamental that anchors credit. Because the policy rate has little long-run effect on agricultural credit, monetary policy alone is unlikely to expand financing to the sector, and sector-specific measures are needed alongside it.

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