e-ISSN 2579-9479
p-ISSN 2828-4348
Accredited by a Directorate General of Higher Education, Research and Technology No. 79/E/KPT/2023

Jurnal Ilmu Peternakan Terapan
March 2026, 9 (2): 100-109
DOI: https://doi.org/10.25047/jipt.v9i2.6404
Available online at https://publikasi.polije.ac.id/index.php/jipt

Input–output cost dynamics in farmers' and agribusiness terms of trade, Indonesia livestock

Dinamika biaya input–output pada nilai tukar petani dan nilai tukar usaha pertanian di subsektor peternakan Indonesia

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ARTICLE INFO

Received:
29 August 2025
Accepted:
24 February 2026
Published:
30 March 2026

Keywords:
Agribusiness
Farmers
Input–output cost
Livestock,
VAR

ABSTRACT

The livestock subsector is vital to Indonesia's economy, supporting food security, employment, and rural livelihoods. Farmers' terms of trade and agricultural business terms of trade are key welfare indicators, yet their short-run dynamics in the livestock subsector remain underexplored. This study examines short-run interactions and forecasts the dynamics of livestock farmers' welfare and business conditions using a Vector Autoregressive (VAR) framework. Monthly data for 2019 to 2024, totaling 72 data were obtained from BPS (Badan Pusat Statistik)-Statistics. The analysis includes stationarity testing, lag selection, Granger causality, impulse response functions, variance decomposition, and one-year-ahead forecasting. The results indicate no long-run cointegration between the two indicators, implying the absence of a stable equilibrium relationship. However, strong short-run dynamics are observed: farmers' terms of trade respond persistently to their own past values, while changes in agricultural business terms of trade exert negative and significant effects. Causality tests confirm a unidirectional relationship from agricultural business conditions to farmers' welfare. Forecasts suggest modest improvements of about 2 to 3 percent in early 2025, which gradually taper later in the year. These findings suggest that stabilizing input costs is central to strengthening livestock farmers' resilience.

ABSTRAK

Subsektor peternakan berperan penting bagi perekonomian Indonesia melalui kontribusinya terhadap ketahanan pangan, penyerapan tenaga kerja, dan penghidupan masyarakat pedesaan. Nilai Tukar Petani (NTP) peternakan dan Nilai Tukar Usaha Pertanian (NTUP) merupakan indikator kesejahteraan yang relevan, namun dinamika jangka pendek keduanya pada subsektor peternakan masih relatif terbatas dikaji. Studi ini menganalisis interaksi jangka pendek serta memproyeksikan dinamika NTP peternakan dan NTUP menggunakan kerangka Vector Autoregressive (VAR). Data bulanan periode 2019 sampai 2024 berjumlah 72 data yang diperoleh dari Badan Pusat Statistik (BPS). Estimasi VAR mencakup uji stasioneritas, pemilihan panjang lag, uji kausalitas Granger, impulse response function, variance decomposition, dan peramalan satu tahun ke depan. Hasil penelitian menunjukkan tidak terdapat kointegrasi jangka panjang antara kedua indikator, yang mengindikasikan tidak adanya hubungan keseimbangan yang stabil. Namun, dinamika jangka pendek tetap kuat: NTP peternakan dipengaruhi secara persisten oleh nilai masa lalunya, sedangkan perubahan NTUP memberikan pengaruh negatif dan signifikan terhadap NTP. Uji kausalitas mengonfirmasi hubungan satu arah dari kondisi

Kata kunci:
Agribisnis
Biaya input–output
Petani
Peternakan
VAR

usaha pertanian menuju kesejahteraan petani, yang menegaskan peran tekanan biaya input. Peramalan memproyeksikan perbaikan moderat sekitar 2 sampai 3 persen pada awal 2025, tetapi cenderung melemah pada bulan berikutnya. Temuan ini menegaskan kerentanan peternak terhadap guncangan biaya dan fluktuasi pasar, sehingga kebijakan perlu memprioritaskan stabilisasi harga input serta penguatan rantai pasok dan akses pasar untuk mendorong kesejahteraan berkelanjutan.

INTRODUCTION

The livestock subsector plays a multifaceted and pivotal role in Indonesia's economy, contributing significantly to agricultural gross domestic product (agricultural GDP) through the production of meat, milk, and eggs, and of on-farm and off-farm employment (BPS, 2025). It is essential to meet the growing demand for animal protein, driven by rising incomes and rapid urbanization. Within this subsector, poultry is the dominant component and supplies around 65% of Indonesia's animal-protein intake. Haryana (2025), but ruminant (beef and buffalo), small-ruminant (goat and sheep), and dairy industries also contribute substantially to total livestock output and rural incomes. This broad contribution is crucial as Indonesia undergoes dietary transitions marked by rising consumption of livestock products, especially poultry meat, as well as beef and other red meats, linked to both population growth and lifestyle changes (Soedjana et al., 2017). Furthermore, the livestock subsector's integration with other agricultural activities enhances productivity and strengthens regional economic structures (Said, 2022).

Beyond economic value, the livestock subsector is vital for food security. It provides diverse products, including beef, poultry, milk, and eggs, that are central to improving dietary quality and ensuring access to essential nutrients (Man et al., 2023). This diversification supports both nutritional needs and rural agricultural practices, helping maintain a stable food supply under environmental pressures, including climate change, that can disrupt livestock production and downstream supply-chain activities (Godde et al., 2021). Moreover, the subsector serves as a major source of employment, engaging around 12 million people across production, processing, and distribution activities (Haryana et al., 2025). This employment extends into ancillary industries such as feed production, veterinary services, and logistics, thereby amplifying its economic significance (Hermaliza et al., 2022). Livestock products also carry cultural value, with regional consumption patterns such as in Aceh, reflecting their role not only as food but also as sources of income and household investment (Hermaliza et al., 2023).

Within this context, Farmers' Terms of Trade (NTP) and Agricultural Business Terms of Trade (NTUP) serve as key indicators of farmers' welfare and the broader performance of the agricultural sector. NTP measures the relative prices farmers receive for their outputs compared to the prices they pay for inputs, thereby reflecting their purchasing power and economic well-being (Wibowo, 2019). A rising NTP signals improved welfare, whereas a decline indicates economic vulnerability that can reduce purchasing power and constrain farm investment and production decisions (Nose et al., 2016). Similarly, NTUP reflects the balance between agricultural business revenues and operational costs, providing insights into the sustainability of agribusinesses and their contribution to rural development (Untari et al., 2022). In Indonesia, it is still dominated by descriptive and static assessments, while the short-run transmission mechanism between these indicators using monthly data in the livestock subsector remains insufficiently examined. Limited studies quantify how changes in agribusiness conditions captured by NTUP translate into changes in farmers' welfare captured by NTP over time, how persistent these effects are, and what they imply for short-horizon forecasting. Current methods for measuring NTP and NTUP values in Indonesia are limited to identifying the Farmer Welfare Index as an indicator for assessing strengths and weaknesses using limited time series data from the previous year. However, this method has limitations in determining weights and integrating dimensions (Setiawan et al., 2019).

Accordingly, this study aims to analyze the dynamics of NTP and NTUP in Indonesia's livestock subsector using a Vector Autoregressive (VAR) model and to generate one-year-ahead forecasts. Monthly NTP and NTUP index total 72 data for the livestock subsector, covering January 2019 to December 2024, were obtained from BPS-Statistics Indonesia through its official statistical releases and online database. This study examines whether NTP and NTUP share a long-run equilibrium relationship, as indicated by cointegration; how short-run shocks in NTUP affect NTP and how persistent these effects are; whether Granger-type causality exists between the two indicators; and what the one-year-ahead forecast trajectories of NTP and NTUP imply based on the estimated VAR model.

MATERIALS AND METHODS

This study applies a quantitative approach, which involves the collection of numerical data and its statistical analysis to identify patterns, relationships, and trends within the observed phenomena. The research procedure follows the stages illustrated in.

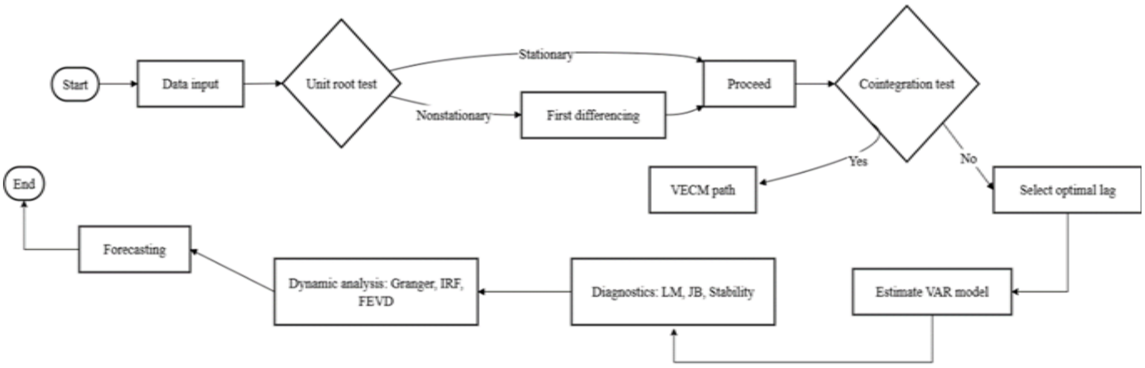

Figure 1. Research Stages and Flowchart Using the VAR Method

Data

This study uses monthly time series data for the livestock subsector in Indonesia, covering January 2019 to December 2024. The variables are Farmers' Terms of Trade for livestock (NTP) and Agricultural Business Terms of Trade for livestock (NTUP). Both series are index numbers published by the BPS-Statistics Indonesia through official statistical releases and its online database. To support the interpretation of the NTP–NTUP dynamics, the study also refers to livestock output price indicators, specifically monthly retail prices for key livestock products such as eggs, chickens, and beef, obtained from PIHPS Nasional. These supporting price indicators are used for descriptive context only and are not treated as endogenous variables in the VAR model. To stabilize variance and interpret changes in proportional terms, the series are transformed into natural logarithms, denoted as ln(NTPt) and ln(NTUPt).

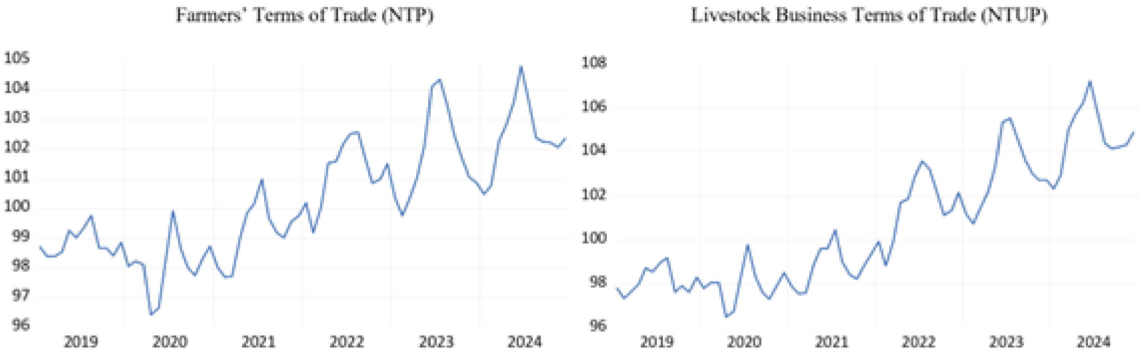

Figure 2. Indonesia monthly trends in NTP and NTUP, 2019–2024 (index, 2018 = 100).

Vector Autoregressive (VAR)

Short run dynamics between Farmers' Terms of Trade and Agricultural Business Terms of Trade are modeled using a bivariate VAR (p) framework. Let the endogenous vector be defined as:

$$Y_t = \begin{bmatrix} LNTP_t \\ LNTUP_t \end{bmatrix}$$

where $LNTP_t = \ln(NTP_t)$ and $LNTUP_t = \ln(NTUP_t)$.

Because the log-level series are non-stationary and there is no evidence of cointegration, the VAR is estimated in first differences. Define:

$$\Delta Y_t = Y_t - Y_{t-i} = \begin{bmatrix} \Delta LNTP_t \\ \Delta LNTUP_t \end{bmatrix},$$

$$\Delta LNTP_t = LNTP_t - LNTP_{t-i},$$

$$\Delta LNTUP_t = LNTUP_t - LNTUP_{t-i}.$$

Thus, the estimated VAR(p) is written as:

$$\Delta Y_t = \boldsymbol{c} + \sum_{i=1}^{p} A_i \Delta Y_{t-i} + \varepsilon_t.$$

where ccc is a 2×1 intercept vector, A_i are 2×2 coefficient matrices, and ε_t is a white-noise innovation vector. The lag length p is selected using information criteria and residual diagnostic tests. Based on the estimated VAR, Granger causality tests are used to examine directional predictability. In contrast, impulse response functions and forecast error variance decompositions are used to assess the dynamic responses and the relative contribution of shocks. One-year-ahead forecasts are generated from the fitted model.

Estimation procedure

The analysis follows these steps. First, unit root tests are conducted to determine the order of integration of each series. Second, cointegration is tested to assess whether a long run equilibrium relationship exists. If cointegration is detected, a Vector Error Correction Model is appropriate; otherwise, a VAR in stationary form is estimated. Third, the optimal lag length p is selected using standard information criteria. Fourth, dynamic interactions are evaluated using Granger causality tests, impulse response functions (IRF), and forecast error variance decomposition (FEVD). Finally, diagnostic tests are performed with software E-views 13 for windows, including stability checks and residual diagnostics such as autocorrelation and heteroskedasticity tests. One year ahead forecasts are generated based on the estimated model.

RESULTS AND DISCUSSION

Stationarity Test

The Augmented Dickey–Fuller (ADF) test results (Table 1) indicate that both LNTP and LNTUP are nonstationary in levels but become stationary after first differencing, implying that the series are integrated of order one, I (1). In practical terms, I (1) behavior means that shocks to the level of LNTP or LNTUP can be persistent and may have long-lasting effects, so the series do not automatically return to a fixed mean. Therefore, the dynamic analysis is conducted using first differences, which removes stochastic trends and allows valid inference on short run movements. Because the series are I (1), the analysis is conducted in first differences to ensure stationarity and avoid spurious inference. Long-run equilibrium interpretation requires cointegration; otherwise, inference should focus on short-run dynamics using a VAR in differences rather than a VECM (Kilian et al., 2017).

Table 1. Results of augmented dickey–fuller (ADF) unit root tests

Variable	Level	First difference	Order of integration
LNTP	–2.307 (0.1728)	–6.525	I (1)
LNTUP	–1.088 (0.7161)	–6.459	I (1)

Note: Entries are ADF t-statistics with MacKinnon p-values in parentheses. Critical values at the 1%, 5%, and 10% levels are –3.528, –2.904, and –2.589, respectively.

Determination of Optimal Lag Length

As presented in Table 2, the optimal lag length was evaluated using LogL, FPE, AIC, SC, and HQ criteria. The AIC and FPE criteria reached their minimum at lag 11, whereas the SC and HQ criteria favored a shorter lag length of 2. Given the monthly sample size and the risk of over-parameterization in higher-order VAR models, this study adopts VAR (2) as the baseline specification to balance model fit and parsimony. This choice is also supported by residual diagnostics, since higher lag orders do not improve model adequacy (Enders, 2015). Accordingly, the estimated model is a bivariate VAR in first differences with endogenous variables ΔLNTP and ΔLNTUP, including an intercept term. Each equation includes two lags of ΔLNTP and two lags of ΔLNTUP.

Table 2. VAR lag order selection criteria

Lag	LogL	FPE	AIC	SC	HQ
0	3.623.504	2.08E-08	-120.117	-119.419	-119.844
1	4.968.113	2.69E-10	-163.604	-161.509	-162.785
2	5.107.018	1.94E-10	-166.901	-16.341*	-16.553*
3	5.143.407	1.96E-10	-16.678	-161.893	-164.869
4	5.161.807	2.11E-10	-16.606	-159.777	-163.603
5	5.242.254	1.85E-10	-167.409	-159.729	-164.405
6	5.251.008	2.07E-10	-166.367	-157.292	-162.817
7	5.276.006	2.19E-10	-165.867	-155.395	-161.771
8	5.300.223	2.33E-10	-165.341	-153.473	-160.699
9	5.343.213	2.34E-10	-16.544	-152.176	-160.252
10	5.392.654	2.31E-10	-165.755	-151.095	-160.021
11	552.307	1.74E-10*	-16.877*	-152.712	-162.488
12	5.529.404	2.00E-10	-167.647	-150.194	-16.082

Note: An asterisk indicates the minimum value for each information criterion. In this study, we select lag order 2, because it is chosen by the Schwarz criterion (SC) and the Hannan Quinn criterion (HQ) (Souisa et al., 2025), and it provides well-behaved residuals without serial correlation.

Cointegration Test

The Johansen cointegration test was applied to LNTP and LNTUP using two lags in first differences and a restricted intercept specification. As shown in Table 3, both the Trace test and the Maximum Eigenvalue test fail to reject the null hypothesis of no cointegration at the 5% significance level. These results indicate that LNTP and LNTUP are not cointegrated, so there is no evidence of a long-run equilibrium relationship between farmers' terms of trade and livestock business terms of trade.

Consequently, the analysis proceeds with a VAR model in first differences to capture short run dynamics. The absence of cointegration suggests that the two indicators adjust largely

Table 3. Johansen cointegration test results for LNTP and LNTUP

Trace Test				
Hypothesized No. of CE(s)	Eigenvalue	TS	0.05 Critical value	Prob.
None (r = 0)	0.1309	12.383	20.261	0.415
At most 1 (r - 1)	0.0355	2.464	9.164	0.685
Maximum Eigenvalue Test				
Hypothesized No. of CE(s)	Eigenvalue	MES	0.05 Critical value	Prob.
None (r = 0)	0.1309	9.918	15.892	0.342
At most 1 (r - 1)	0.0355	2.464	9.164	0.685

Note: TS= Trace Statistic; MES= Max-Eigen Statistic.

independently over time, which is consistent with a livestock subsector that is exposed to recurrent supply shocks, policy interventions, and market imperfections, rather than a single stable long-term path. More broadly, evidence from livestock-related economic studies suggests that recurring shocks and policy disruptions can weaken long-run integration among sectoral indicators. (Abdi et al., 2024).

Estimation of the VAR Model

The VAR model was estimated with ΔLNTP and ΔLNTUP as endogenous variables and two lags in first differences. The estimation results in Table 4 describe the short-run interactions between the two indicators. The positive and significant own-lag coefficients (1.5266 for ΔLNTP and 1.6458 for ΔLNTUP) indicate strong short-run persistence in both farmers' terms of trade and livestock business terms of trade. By contrast, past shocks to ΔLNTUP have a negative and statistically significant effect on ΔLNTP, while the reverse effect is smaller in magnitude, which suggests that increases in livestock production costs (higher NTUP) tend to erode farmers' welfare (lower NTP) more than improvements in NTP feed back into business conditions. This asymmetry is consistent with evidence that rising input prices can quickly reduce livestock farmers' purchasing power (Hermaliza et al., 2023).

Table 4. Selected coefficients from the VAR (2) model

Variable	ΔlnTP (Coefficient [t-stat])	ΔlnTUP (Coefficient [t-stat])
ΔLNTP	1.5266 [2.40] **	1.6458 [2.41] **
ΔLNTUP	-1.8241 [-3.09] **	-1.9359 [-3.05] **
Constant	0.0027 [2.04] **	0.0031 [2.17] **
R^2	0.6300	0.6160
Adj. R^2	0.4100	0.3880
AIC	-6.9540	-6.8110
SC	-6.1510	-6.0080

Note: ** indicates significance at 5%.

Diagnostic Tests

Residual diagnostic tests were conducted to evaluate the adequacy of the estimated VAR model. As shown in Table 5, the LM statistics for most lag orders have p-values above the

Table 5. VAR residual serial correlation LM tests

Lag	LM statistic	Prob.	Rao F statistic	Prob.
1	42.283	0.3760	10.743	0.376
2	4.019	0.4034	10.196	0.403
3	32.249	0.5209	0.813	0.521
4	18.665	0.7603	0.466	0.760
5	13.642	0.8504	0.339	0.850
6	4.745	0.3145	12.102	0.314
7	130.516	0.0110**	35.398	0.011**
8	20.704	0.7228	0.517	0.722
9	17.394	0.7836	0.434	0.784
10	13.323	0.8559	0.331	0.856
11	97.253	0.0453**	25.732	0.045**
12	42.736	0.3702	10.862	0.370

Note: The LM test reports the multivariate Lagrange multiplier (LM) statistic and the corresponding Rao F statistic for residual serial correlation at lag h. "Prob." denotes the p value for each statistic. The null hypothesis is no residual serial correlation. Values marked with ** indicate significance at the 5% level.

5 percent level, so the null hypothesis of no residual serial correlation cannot be rejected, indicating that the model is broadly well specified. (Enders, 2015; Kilian et al., 2017). Although significant LM statistics appear at lags 7 and 11, these do not persist across adjacent lags. Because occasional rejections may occur in finite samples, model adequacy is assessed based on the overall pattern of the LM results together with stability diagnostics and other specification checks (Boswijk et al., 2015).

These results are different from the research Rahayu et al. (2023) namely the VAR model which does not fulfill the assumptions of multivariate white noise and multivariate normality causes the model diversity of each partial equation so that there are other variables outside the model which have more influence in the research period. The, it was regarded as approximately free of serial correlation, and the VAR specification used to model the dynamics between LNTP and LNTUP can be considered stable and reliable, in line with good practice in applied VAR analysis (Martignone et al., 2022).

Residual Normality Test

The residual normality test results are reported in Table 6. Residual normality was assessed using Jarque–Bera skewness–kurtosis tests for each equation and a joint multivariate test, which are commonly reported diagnostics in applied VAR and VECM studies (Gupta et al., 2016; Arestis et al., 2020). While the skewness components are broadly acceptable, one component displays excess kurtosis, and the joint test rejects the null hypothesis of multivariate normality at the 5 percent level. In practice, however, VAR inference is usually robust to moderate departures from normality, particularly when the model also satisfies homoskedasticity and dynamic stability conditions, as in this case (Enders, 2015). Therefore, the mild non-normality detected in the residuals is not considered severe enough to undermine the reliability of the estimated impulse responses and other VAR-based inferences.

On the other hand, DLNTUP responds positively to its own shocks with the strongest

Table 6. VAR residual normality tests

Component	Skewness	Kurtosis	Jarque–Bera
1	4.147 (0.0417)	5.573 (0.0182)	9.720 (0.0078)
2	0.018 (0.8935)	0.508 (0.4759)	0.526 (0.7687)
Joint	4.165 (0.1246)	6.081 (0.0478)	10.246 (0.0365)

*Note: Entries are test statistics with p-values in parentheses. Under the χ^2 distribution, the null hypothesis is that residuals are normally distributed.

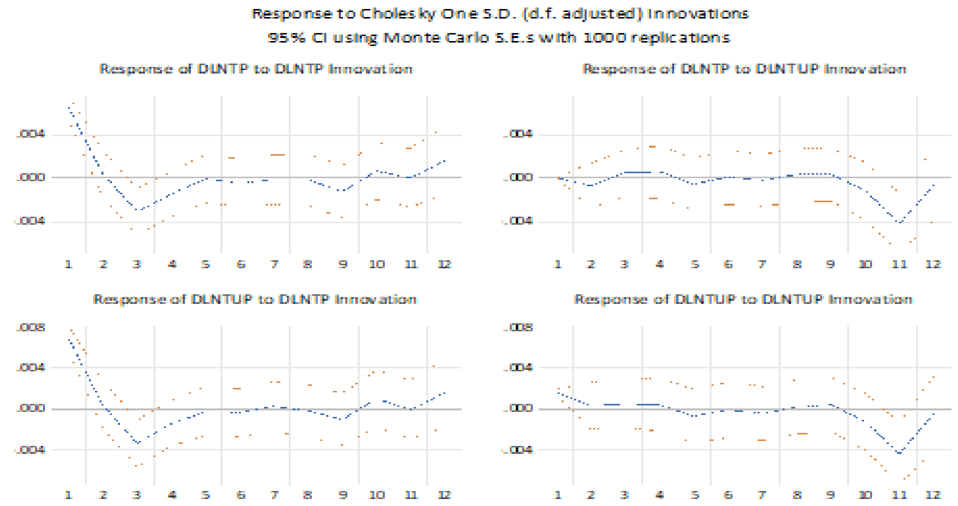

Figure 3. Impulse Response Functions (IRFs) of DLNTP and DLNTUP

impact in the first two months, followed by a gradual decline toward neutrality. When DLNTP shocks DLNTUP, the effect is initially positive but weak and becomes statistically insignificant after about four months.

Overall, the results indicate that both variables exhibit short-term dynamic interactions. However, the effects are not persistent and tend to vanish after five to six months, suggesting a limited long-run influence of shocks between NTP and NTUP. This highlights the fragility of farmer welfare to agribusiness shocks, a pattern consistent with evidence that smallholders respond to adverse shocks by cutting household expenditures and, in some cases, liquidating livestock or other assets as short-term coping measures. (Touch et al., 2024)

Forecasting and Model Accuracy Evaluation

The estimated VAR model was used to generate dynamic forecasts for Farmers' Terms of Trade (NTP) and Agricultural Business Terms of Trade (NTUP) over a 12-month horizon for 2025. Figure 4 presents the forecast paths for the monthly first differences of the logarithmic indices, where M1–M12 denote forecast months from January to December 2025. These forecasts were first obtained in ΔLNTP and ΔLNTUP and then cumulated and transformed back into index levels to facilitate interpretation, following standard VAR forecasting procedures (Enders, 2015). Forecast accuracy was evaluated by comparing one-step-ahead forecasts in a 2024 hold-out sample with the realized values using conventional error measures such as the root mean squared error (RMSE) and mean absolute error (MAE), which are widely recommended for assessing the out-of-sample performance of time-series models (Diebold, 2015; Hyndman et al., 2018)

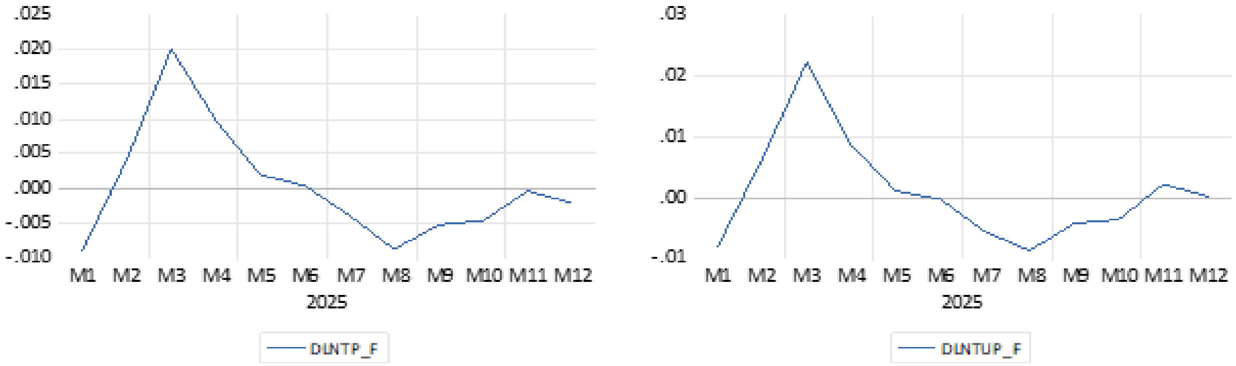

Figure 4. Forecasts of NTP and NTUP for 2025. M1–M12 denote forecast months from January (M1) to December (M12) 2025.

For NTP, the forecast indicates a sharp increase during the early months of 2025, peaking around March (M3), followed by a gradual decline through mid-year. A mild recovery is projected towards the final quarter, stabilizing around the baseline level by December (M12). Similarly, NTUP demonstrates a comparable pattern, with early gains reaching their maximum in March before tapering off in the second half of the year. The out-of-sample forecasts for 2025 were generated using the estimated VAR model. The results indicate that the forecast average NTP in 2025 is slightly higher than its 2024 level, while the forecast average NTUP shows a more modest increase. These projections suggest that both indicators may remain relatively stable over the forecast horizon, with only limited improvements.

This suggests that while livestock farmers may experience temporary improvements in trade terms in early 2025, these gains are unlikely to persist without stabilizing interventions. Policies aimed at controlling input costs and improving market access will therefore be critical to sustaining farmer welfare and agribusiness viability. This pattern reflects seasonal and structural instability, echoing concerns by Yang et al. (2017) that sustained improvements in agricultural welfare require structural policy interventions rather than temporary market gains. Without targeted measures to control input costs and strengthen market access, livestock farmers' welfare gains in early 2025 are unlikely to persist.

Table 7. Forecast summary table (Comparison of 2024 and 2025)

Variable	2024	2025	Change (%)
NTP	100.8	103.2	2.380952
NTUP	101.5	104.1	2.561576

Note: 2024 is the average actual, 2025 is the average of the forecast

CONCLUSIONS

This study applies a VAR model to examine the dynamics between Farmers' Terms of Trade for livestock (NTP) and Agricultural Business Terms of Trade for livestock (NTUP) in Indonesia. The results indicate no long-run equilibrium between the two indices, but clear short-run transmission, with NTUP shocks exerting a stronger influence on NTP, implying vulnerability to input cost pressure. One-year-ahead forecasts for 2025 suggest only modest improvements of around 2 to 3 percent early in the year, with gains tapering later. Policy should prioritize stabilizing key inputs, improving price transmission, and strengthening logistics and market access.

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