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Optimizing Sustainable Broiler Production Through Elasticity Analysis: Evidence from Partnership-Based Closed House Systems

Reynaldi Rizalianus Hutama[1], Dewi Masyithoh[1], Inggit Kentjonowaty[1], Arsalan Fadlan Aziz[2], Muhammad Helmi[2], Budi Hartono[2], Puji Akhiroh[2], Nanang Febrianto[2*]

[1] Faculty of Animal Husbandry, Universitas Islam Malang, Malang, Indonesia.
[2] Department of Socio Economic, Faculty of Animal Science and Technology, Universitas Brawijaya, Malang, Indonesia.

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Corresponding Author:
Nanang Febrianto
nanangfeb@ub.ac.id

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Abstract: The broiler industry plays a critical role in Indonesia's food supply chain, yet productivity challenges persist, particularly in partnership-based closed-house systems. This study examines the influence of production inputs on broiler output using data from 50 contract farmers in Malang Regency through multiple linear regression, LASSO regression, and elasticity analysis. Severe multicollinearity was detected among chicken population, feed quantity, and total cost (VIF > 100), addressed using LASSO regularization. The resulting adjusted R^2 of 0.9994 is unusually high for cross-sectional socio-economic data and should therefore be interpreted cautiously due to potential overfitting. Regression results indicate that number of employees, depletion rate, and performance index significantly contribute to production volume, while chicken population and feed quantity have negative and statistically non-significant coefficients. Elasticity analysis shows that significant input variables, except performance index, are inelastic (coefficients < 1), whereas performance index is elastic (1.899). The counterintuitive negative coefficients for population and feed, alongside the positive depletion coefficient, suggest residual multicollinearity and conceptual overlap between performance index and other inputs, which future work should address through model re-specification. These findings nonetheless highlight labor management, mortality control, and performance monitoring as priority areas for improving productivity in partnership-based closed-house broiler systems in Indonesia.

Keywords: Broiler production; Closed house system; Contract farming; Elasticity; LASSO regression; Productivity efficiency

Introduction

The livestock sector plays a strategic role in Indonesia's agricultural development, particularly in supporting national food security and meeting the increasing demand for animal-based protein. Among livestock commodities, broiler chickens are one of the most important sources of affordable animal protein due to their short production cycle, relatively high feed conversion efficiency, and strong market demand (Yasin, 2024). In recent years, Indonesia's broiler production has continued to increase, as indicated by the reported growth of more than 554.813 tons in national broiler output (Badan Pusat Statistik, 2025). However, the main challenge facing the broiler industry is not merely the ability to produce sufficient quantities, but rather the persistence of production inefficiency, high input costs, and fluctuating farm-gate prices. These conditions reduce the competitiveness of domestic broiler production and place considerable pressure on farmers, especially those operating under partnership-based production systems.

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One of the key constraints in broiler farming is the high-cost structure, with feed accounting for 60–70% of total production expenses (Wongnaa et al., 2023). In addition to feed costs, productivity is also influenced by the number of birds placed, labor management, harvest age, and depletion, which refers to the loss of birds due to mortality or culling. High depletion directly reduces the number of marketable birds, thereby lowering total output and farm profitability (Sambuo & Kasagama, 2025). Improving resource-use efficiency is essential not only for increasing farm-level productivity but also for supporting a more stable and sustainable broiler production system.

Closed-house systems have been increasingly adopted in Indonesia because they provide better environmental control, improved biosecurity, and more efficient production management than conventional open-house systems (Wahyuni et al., 2025). In principle, these systems can reduce heat stress, improve feed conversion efficiency, and lower mortality rates through controlled temperature, ventilation, and automated farm management. However, the potential efficiency gains of closed-house technology are not always fully realized at the partner-farmer level. In practice, variations in farmers' technical skills, labor allocation, equipment operation, feed quality, and flock management can lead to differences in production performance. This highlights an important research gap: although closed-house systems are designed to enhance production efficiency, the extent to which key production factors contribute to broiler output in partnership-based closed-house systems remains insufficiently understood.

Previous studies have examined the effects of individual production factors such as feed, labor, mortality, or farm management on broiler productivity. However, limited empirical evidence has evaluated the combined influence of physical and biological production factors on output elasticity within partnership-based closed-house systems. Production elasticity provides a useful analytical approach because it measures the responsiveness of broiler output to changes in specific input variables. This approach can help identify which production factors contribute most strongly to output and which resources may be overused or underutilized. Such evidence is important for improving input allocation, strengthening farm management decisions, and supporting sustainable intensification in the poultry sector.

Understanding these dynamics is crucial for improving input-output optimization, enhancing farm-level decision-making, and formulating data-driven policy recommendations. This study aims to identify and quantify the elasticity of key production factors in partnership-based closed-house broiler farming. The analysis focuses on physical and biological production variables, including poultry population, feed quantity, labor, depletion, and harvest age. Conceptually, total production cost is a derived monetary aggregate of input prices and quantities rather than a physical input; the performance index is an output-based efficiency indicator calculated after harvest from harvest weight, feed conversion ratio, viability, and harvest age, rather than an independent input; and incentive-based bonuses are better understood as managerial or motivational factors rather than direct biological inputs affecting broiler growth. By clearly distinguishing these variables at a conceptual level, this study lays the groundwork for a more conceptually consistent elasticity analysis and contributes to the development of more efficient, competitive, and sustainable broiler production systems in Indonesia.

Method

Research Location and Time

This study was conducted in Malang Regency, East Java Province. The selection of research location is based on the broiler industry is well-developed and contract farming with integrators is common in Malang Regency (Febrianto et al., 2024). The area is characterized by modern poultry production facilities, particularly the implementation of closed house systems that allow for better environmental control and production efficiency.

Sampling Procedure

The population of this study consisted of broiler farmers involved in partnership schemes with integrator companies operating closed-house broiler farming systems. A purposive sampling method was used to select 50 farmers who had participated in contract farming and operated closed houses for at least three consecutive production cycles. The selection ensured representation from different integrator companies, including PT. Super Unggas, PT. Bintang Tama Santosa, PT. Kedu Lintang Berbintang, and PT. Mitra Berlian Unggas.

Data Collection

The data collection method in this study involved both primary and secondary data sources to ensure comprehensive findings. Primary data were collected using structured questionnaires, direct interviews, and field observations. The questionnaires were designed to capture data on farm characteristics, socioeconomic variables, input and output quantities, cost structures, labor use, and partnership details. Direct interviews were conducted with both farmers and technical field officers to clarify questionnaire responses. Observational data included barn layout, management practices, and technical assistance provided by integrators. Secondary data were sourced from the Central Bureau of Statistics, Department of Agriculture, company records, and relevant scientific publications. All farmers involved in the study were informed about the objectives, and their consent was obtained before participation. The research was methodically structured, commencing with the determination of the number of respondents.

Data Analysis

This study employed a quantitative approach to examine the association between production inputs and broiler production volume. Prior to regression analysis, the validity and reliability of the questionnaire were assessed to ensure data quality. Classical assumption tests, including normality, multicollinearity, linearity, and heteroscedasticity, were performed before the regression analysis (Desmiarni et al., 2025). Multiple linear regression was used to examine the associations of population, feed quantity, depletion rate, total cost, harvest age, bonus/incentive, number of employees, and performance index with production volume. SPSS version 26 was used for descriptive analysis, validity and reliability testing, classical assumption tests, and multiple linear regression, while R-software was used for LASSO regression and variable selection to address multicollinearity.

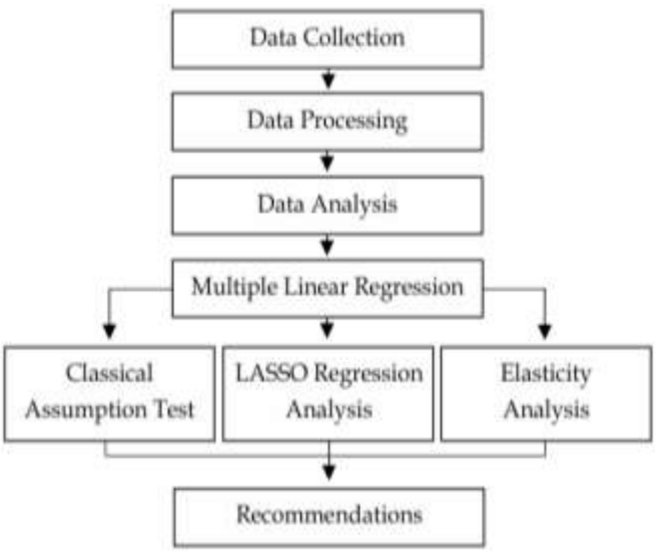

Figure 1. Analytical flowchart of this research

Data analyzed through regression were transformed into logarithmic form to estimate production elasticity. The transformation of regression data into logarithmic form is standard practice when calculating elasticity, as it linearizes multiplicative relationships between variables and allows regression coefficients to be interpreted directly as elasticities. In this log-linear (Cobb-Douglas-type) specification, each coefficient represents the percentage change in production output resulting from a one percent change in the corresponding input, holding other inputs constant. This is distinct from demand elasticity, which describes the responsiveness of quantity demanded to changes in price or income; the elasticities estimated in this study are production elasticities, describing input-output relationships rather than consumer demand behavior. The multiple linear regression equation is as follows:

$$\begin{aligned} \ln Y = \ln a + b1\ln X1 + b2\ln X2 + b3\ln X3 + b4\ln X4 \\ b5\ln X5 + b6\ln X6 + b7\ln X7 + b8\ln X8 + e \end{aligned} \quad (1)$$

Where:
Y : Production volume/tonnage (dependent variable)
a : Constant
b : Regression Coefficient
X1 : Chicken livestock Population
X2 : Feed Quantity
X3 : Depletion
X4 : Total Cost
X5 : Harvest Age
X6 : Bonus/Incentive
X7 : Number of employees
X8 : Performance Index
e : Standard error

Correlation Analysis

The correlation test is conducted to determine the strength of the relationship between variables. The correlation coefficient value ranges between -1 < r < 1. A value of -1 indicates a perfect negative correlation, 0 indicates no correlation, and a value of 1 indicates a perfect positive correlation. The range of the correlation coefficient between -1, 0, and 1 can be interpreted as follows: the closer the value is to 1 or -1, the stronger the relationship, while the closer the value is to 0, the weaker the relationship. Based on Papageorgiou (2022) table classifying correlation values are as follows:

Table 1. Classifiying correlation

Correlation coefficient	Description
0.80 – 1.000	Very strong
0.60 – 0.799	Strong
0.40 – 0.599	Moderately strong
0.20 – 0.399	Weak
0.00 – 0.199	Very weak

Result and Discussion

Socioeconomic Characteristics

The socioeconomic characteristics provides a key basis for understanding production management, as these characteristics influence technology adoption, resource allocation, and overall farm performance. Socioeconomic characteristics observed in this study include age, family members, educational level, business experience, and additional occupations.

Table 2. Socioeconomic characteristics

Characteristic	Number of respondents	Percentage (%)
Age:		
<29 years old	4	7.7
30-39 years old	22	42.3
40-49 years old	18	34.7
>50 years old	8	15.3
Family person:		
3 persons	11	21.2
4 persons	24	46.1
5 persons	8	15.4
>6 persons	9	17.3
Educational Level:		
Elementary school	7	13.5
Junior high school	14	26.9
Senior high school	29	55.8
Bachelor	1	1.9
Master	1	1.9
Business experience:		
5-10 years	12	23.1
11-15 years	37	71.1
>16 years	3	5.8
Additional occupations:		
Employee	9	17.3
Fish farmer	17	32.7
Home industry	6	11.5
Trader	11	21.2
Lecturer	1	1.9
Farmer	8	15.3

The demographic profile of respondents in this study reveals several socioeconomic attributes relevant to broiler farming under partnership schemes. Based on (Table 2) in terms of age, most respondents were within the productive age group, specifically between 30–39 years (42.3%) and 40–49 years (34.7%). This age distribution shows that broiler chicken farms in the research area are mostly managed by individuals who have adequate physical abilities and experience, which supports effective farm management. Meanwhile, only 7.7% of respondents were under 29 years, and 15.3% were above 50, indicating minimal participation from both younger and older generations. This demographic pattern has implications for future succession planning and the necessity of intergenerational knowledge transfer.

Household size is another essential factor that may influence labor availability in farm operations. The data (Table 2) show that most respondents had three household members (46.1%), followed by those with five (17.3%) and four members (15.4%). A relatively small household size may limit the availability of family labor, particularly for labor-intensive, home-based enterprises. According to Fajarika et al. (2024) small and medium enterprises (SMEs) significantly contribute to employment generation and economic sustainability. However, smaller household sizes may reduce opportunities for intra-family collaboration, potentially affecting productivity in broiler farming.

Education level among respondent demonstrates encouraging potential for technology adoption. The majority had completed senior high school (55.8%), while 26.9% had only primary education. This indicates that many broiler farmers possess at least basic literacy necessary to understand and implement innovative practices. A medium level of education is beneficial for adopting technologies such as IoT-based automatic feeding systems, which have been shown to improve feeding efficiency and poultry health (Surahman et al., 2021).

Regarding farming experience, a significant portion of respondents (71.1%) had been in business for 5–10 years, suggesting relative stability and accumulated operational knowledge. Those with under five years of experience made up 23.1%, while only 5.8% had been operating for more than 11 years. Experience plays a vital role in shaping decision-making capacity, resource management, and the adoption of efficiency-enhancing innovations (Sudrajat et al., 2024).

Finally, employment diversification emerged as a strategic approach among respondents. As presented in (Table 2), 17.3% reported involvement in private sector jobs, while 15.4% engaged in fish farming. These findings demonstrate rural households' efforts to attain economic stability through multiple income sources. Broiler farming thus contributes not only to food security but also to enhancing rural livelihoods. Widianingrum & Septio (2023) emphasized the livestock sector’s critical role in supporting household economies and facilitating risk-reducing enterprise diversification.

Data Feasibility Testing

Classical Assumption Testing

The correlation analysis reveals that Feed Quantity (X2), Total Cost (X4), and Chicken Livestock Population (X1) have the strongest and most significant positive correlations with Tonnage (Y), with correlation coefficients of 0.995, 0.992, and 0.953 respectively ($p < 0.05$). Additionally, Number of Employees (X7) also shows a strong and significant correlation ($r = 0.722$, $p < 0.05$). Depletion (X3) demonstrates a moderately strong yet significant correlation ($r = 0.404$, $p = 0.004$). On the other hand, Harvest Age (X5) and Bonus/Incentives (X6) show no significant relationship with Production ($p > 0.05$). Performance Index (X8) presents a low but statistically significant correlation ($r = 0.248$, $p = 0.083$) at the 10% level. Overall, the results highlight that feed, cost, livestock population, and Number of Employees are the most influential factors in determining production tonnage.

Increases in livestock population, feed quantity, and efficient cost management will have a significant impact on production levels. Makkar (2016) explains that the efficient utilization of feed resources and the implementation of appropriate feeding strategies are crucial for improving production and strengthening environmental, social, and economic sustainability.

Additionally, the number of employees (X7) also shows a strong and significant relationship, indicating that adequate and effective labor can support production optimization. Depletion (X3), which refers to the mortality or loss of chickens during the rearing period, has a significant relationship with broiler production. High depletion rates can reduce the number of chickens ready for harvest, thereby decreasing total production. Sehabudin et al. (2022) demonstrated that each 1% increase in depletion rates could reduce broiler production by up to 5%.

Increasing the harvest age from 35 to 42 days only raised production by 2%, which is considered insignificant in the context of production elasticity (TarjiJunaedi et al., 2025). A study by Iskamto et al. (2024) found that while financial incentives improved job satisfaction, there was no strong correlation between incentives and broiler production increases.

Performance index, which includes factors such as feed conversion and daily growth, is theoretically related to production. However, research by Ferreira et al. (2024) found that variations in performance index did not significantly impact total production in closed house systems, likely due to more stable environmental control. Therefore, the primary focus for improving chicken production should be directed at livestock population, feed quantity, cost efficiency, and employees, while other variables can be considered as additional factors as needed.

Table 3. Multicollinearity test

Coefficients[a]		
Model	Collinearity statistics	
	Tolerance	VIF
(Constant)		
Chicken livestock Population (X1)	0.009	116.038
Feed (X2)	0.003	386.445
Depletion (X3)	0.382	2.619
Total cost (X4)	0.002	424.395
Harvest age (X5)	0.115	8.668
Bonus/incentive (X6)	0.739	1.353
Number of employees (X7)	0.262	3.812
Performance index (X8)	0.338	2.956

a. Dependent variable: production/tonnage (Y)

The multicollinearity test (Table 3) is used to detect whether there is a strong linear relationship among the independent variables in a regression model. If the independent variables are highly correlated with one another, multicollinearity may occur, which can interfere with the regression analysis results. According to Kyriazos & Poga (2023) data is considered free from multicollinearity if the Variance Inflation Factor (VIF) value is < 10 and the Tolerance value is > 0.1. If the VIF value exceeds 10, it indicates a multicollinearity problem. However, Chicken Livestock Population (VIF = 116.038), Feed (VIF = 386.445), and Total Cost (VIF = 424.395) far exceed this threshold, with correspondingly low tolerance values, indicating severe multicollinearity among these three variables. The remaining variables (Depletion, Harvest Age, Bonus/Incentive, Number of Employees, Performance Index) satisfy the VIF < 10 and Tolerance > 0.1 criteria. This severe multicollinearity among population, feed, and total cost is the reason LASSO regression is applied in the following section.

LASSO Regression Analysis

In the multicollinearity test, multicollinearity was identified among the variables Livestock Population (X1), Feed Quantity (X2), and Total Cost (X4). This issue can be resolved using the LASSO Regression method. This study utilized RStudio software and the LARS package to perform LASSO regression (Table 4). The process employed a numerical approach with the LARS algorithm. Before applying the LARS algorithm, the dependent variables in the model needed to be normalized to follow a N (0,1) distribution.

Based on (Table 4) reports an adjusted R^2 of 0.9994 for the LASSO model. While a value this close to 1 could be read as evidence that the model explains nearly all of the variability in production volume, such a high R^2 in cross-sectional socio-economic data from only 50 farmers is unusually high and should be interpreted with caution rather than presented as a straightforward strength. It is more plausibly explained by residual multicollinearity among the retained predictors and by overfitting given the small sample size. This aligns with findings in the literature emphasizing the importance of high R^2 in regression assessments, as it signals a robust model where independent variables play a significant explanatory role.

Based on Gao (2024) provides insight into the critical role of R^2 in understanding variability in outcomes as attributable to selected predictors. The article discusses misinterpretations of R^2, highlighting the need for accuracy in reporting, which underscores its relevance in evaluating the explanatory power of regression models. However, it primarily cautions against overestimating the effects based on inflated R^2 values rather than affirming robust relationships.

Table 4. The LASSO regression coefficients at each step of the LARS algorithm

Step	In (X1)	In (X2)	In (X3)	In (X4)	In (X5)	In (X6)	In (X7)	In (X8)
0	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
1	0.0000	0.8384	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2	0.0000	0.8400	0.0000	0.0016	0.0000	0.0000	0.0000	0.0000
3	0.0007	0.8416	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
4	0.0342	0.8751	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
5	0.2216	0.7586	0.0000	0.0000	0.0000	0.0000	0.0000	0.0958
6	0.2591	0.7217	0.0000	0.0000	0.0107	0.0000	0.0000	0.0997
7	0.3344	0.6479	0.0000	0.0000	0.0323	0.0007	0.0000	0.1074
8	0.4148	0.5710	-0.0032	0.0000	0.0552	0.0015	0.0000	0.1140
9	0.4675	0.5284	-0.0050	0.0000	0.0667	0.0037	-0.0094	0.1168
10	0.4795	0.5677	-0.0034	-0.0503	0.0667	0.0037	-0.0111	0.1172
R-Square : 0.9994749								

Chicco et al. (2021) emphasizes that the coefficient of determination, or R^2, is informative regarding the proportion of explained variability and is preferable to other metrics like mean absolute error (MAE) and root mean square error (RMSE) in evaluating model adequacy. This is because R^2 correlates directly with how well the regression predictions align with actual data, offering clearer interpretations of model performance, particularly within complex data frameworks.

LASSO regression, a method designed to address the issue of multicollinearity in regression analyses, engages in shrinkage by minimizing the absolute values of the regression coefficients, producing coefficients that can be exactly zero (Figure 1). This characteristic is particularly useful in datasets with numerous predictors, allowing for a more interpretable model consisting solely of relevant variables (McEligot et al., 2020). The transition of estimated regression coefficients during LASSO, as executed by the Least Angle Regression (LARS) algorithm, illustrates how coefficients move from zero to align with Ordinary Least Squares (OLS) estimates as the regularization parameter approaches 1. This behavior exemplifies LASSO's effectiveness in managing multicollinearity and enhancing predictability in various applications (Sun et al., 2023; Nur et al., 2024).

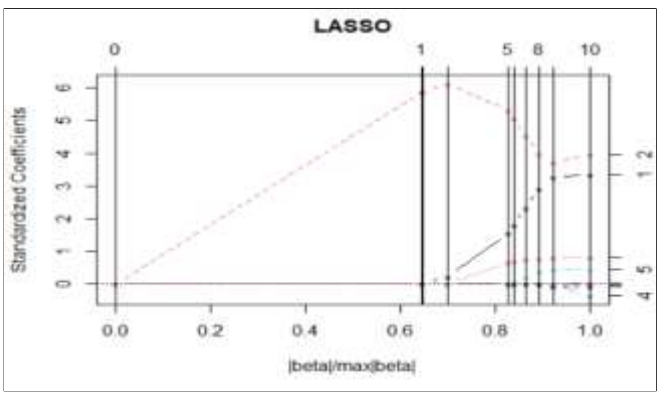

Figure 1. LASSO regression

Research has shown that the continuous shrinking operation inherent in LASSO significantly reduces the risk of overfitting, thus maintaining the model's robustness and generalizability (Sun et al., 2023). For example, studies have efficiently applied the LASSO regression approach to select features in medical datasets, where collinearity among potential predictors is common (Shen et al., 2024; Mao et al., 2023). In these contexts, variables with non-zero coefficients derived from the LASSO model play a crucial role in constructing robust predictive frameworks, such as nomograms that can accurately assess patient outcomes across various settings and diseases.

Based on (Figure 1) illustrates the relationship between the value of β / max(|β|) on the x-axis and the standardized coefficient values on the y-axis. At the beginning of the graph, the standardized coefficient values tend to remain close to zero (Obuchi & Kabashima, 2016), indicating that the independent variables have not yet entered the model. As the value of β / max(|β|) increases, the standardized coefficients begin to deviate from zero, reflecting the gradual inclusion of independent variables into the model and their increasing influence on the dependent variable.

Several "breakpoints" in the graph signify the progressive inclusion of independent variables into the model. Toward the end of the graph, only a few independent variables exhibit significant standardized coefficient values, while others approach zero. Overall, this graph provides insights into the variable selection process in the LASSO regression model, where the most relevant variables show larger coefficient values.

The next step is to determine at which step of the LARS algorithm the best LASSO regression model is achieved. This can be identified by the optimal value of ss, which is obtained using cross-validation criteria. The smallest cross-validation value indicates the most optimal. The output from the cross-validation analysis is presented below (Figure 2).

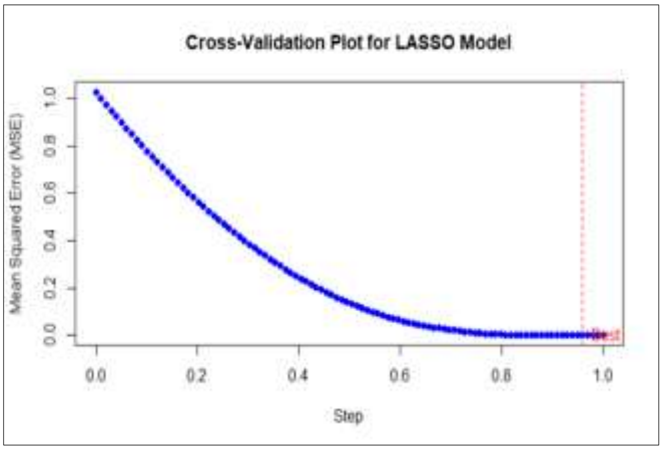

Figure 2. Cross-validation values using fraction mode

This (Figure 2) displays the cross-validation plot for the LASSO model, a regression method used to address multicollinearity issues in regression analysis. In this plot, the x-axis represents the steps in the variable selection process, while the y-axis shows the mean squared error (MSE) obtained through cross-validation. The graph indicates that as the number of steps (on the x-axis) increases, the error value decreases. This suggests that adding more variables to the model improves its predictive performance. However, the graph also reveals that after reaching a certain point, adding more variables does not significantly enhance the model's performance. This point is referred to as the "best" and identifies the optimal number of variables to include in the LASSO model. The general form of the Lasso regression model equation is as follows:

$$\begin{aligned} \ln(Y) = {} & \beta_0 + \beta_1 \ln(X1) + \beta_2 \ln(X2) + \beta_3 \ln(X3) \\ & + \beta_4 \ln(X4) + \beta_5 \ln(X5) + \beta_6 \ln(X6) \\ & + \beta_7 \ln(X7) + \beta_8 \ln(X8) + e_i \end{aligned} \tag{2}$$

$$\begin{aligned} \ln(\text{Production}) = {} & 4.211 + 0.479 \ln(\text{Chicken Livestock Population}) + 0.568 \ln(\text{Feed}) - 0.003 \ln(\text{Depletion}) \\ & -0.050 \ln(\text{Total Cost}) + 0.067 \ln(\text{Hasrvest Age}) + 0.004 \ln(\text{Bonus/Incentive}) \\ & -0.011 \ln(\text{Number of Employees}) + 0.117 \ln(\text{Performance Index}) + e_i \end{aligned}$$

The regression model reveals key factors influencing tonnage (Y) in poultry production. Chicken Livestock Population (X1) and Feed Quantity (X2) are the most influential positive contributors, with coefficients of 0.479 and 0.568 respectively, indicating that efficient increases in both significantly boost production. Harvest Age (X5), Bonus/Incentive (X6), and Performance Index (X8) also positively impact tonase, though to a lesser extent. On the other hand, Depletion (X3), Total Cost (X4), and Number of employee's (X7) show negative coefficients, meaning increases in these variables lead to reductions in tonnage. Notably, Total Cost (-0.050) and Number of employee's (-0.011) have the most pronounced negative effects. The model underscores the importance of optimizing poultry population, feed, and harvest age while managing operational costs and workforce efficiency to enhance overall production tonnage. Each variable's direction and magnitude provide strategic insights for decision-making in poultry farm management.

Key variables such as Chicken Population (X1), Feed Amount (X2), Harvest Age (X5), Bonuses/Incentives (X6), and Performance Index (X8) have a significant and positive influence on production tonnage (Y). Enhancing these variables directly increases output, making them strategic levers in production optimization. For instance, proper feed allocation ensures optimal chicken growth and nutrition (Tanjung et al., 2025), while timely harvesting prevents unnecessary costs and supports ideal harvest weights (Nursita & Putra, 2024). Bonuses and incentives were also shown to elevate labor motivation and productivity (Liu & Liu, 2022), making them an effective tool to drive performance improvement.

On the other hand, Depletion (X3), Total Cost (X4), and number of employees (X7) exhibit negative regression coefficients, indicating that their increase significantly reduces tonnage (Y). Excessive mortality or loss due to disease, for example, hampers production efficiency (Vecerek et al., 2016). Therefore, effective health management and biosecurity are crucial to minimize depletion. Additionally, unproductive cost increases can diminish output, requiring vigilant financial oversight and technical and economic efficiency in maximizing productivity. An oversized labor force can also lead to operational inefficiencies; thus, workforce optimization is essential. In summary, improving tonnage requires enhancing positively impactful variables while minimizing the detrimental effects of cost, mortality, and labor inefficiency to support evidence-based production decisions.

Elasticity Analysis

Elasticity analysis in the context of regression is used to measure the responsiveness or sensitivity of the dependent variable (Y) to changes in the independent variable (X). Conversely, if the coefficient is less than 1, the impact of changes in the independent variable on the dependent variable is relatively small. If the coefficient equals 1, it means that changes in the independent variable cause proportional changes in the dependent variable. Research by Febrianto & Putritamara (2017) in Malang Raya found that the price elasticity of demand for commercial chicken eggs was elastic, with a value of -2.301, indicating that a 1% increase in egg price would reduce consumer demand by more than proportionate amount. In contrast, the income elasticity of egg demand was inelastic at 0.285, meaning that eggs are categorized as a normal good whose demand grows only marginally with rising household income. This suggests that consumer purchasing behavior toward eggs is far more sensitive to price fluctuations than to changes in income level.

The analysis results (Table 5) indicate that most variables influencing production are inelastic (coefficients below 1 in absolute value), including chicken population (–0.044), feed quantity (–0.057), total cost (–0.279), harvesting age (0.028), and bonus/incentives (–0.017), implying that their effects on production tonnage are relatively minor even where statistically significant. Depletion (0.210) and the number of employees (0.565) are statistically significant and positive, but their coefficients also remain below 1 and are therefore inelastic as well, indicating a less-than-proportional response of production to changes in these inputs. The assessment and management of livestock production efficiency are critical, particularly given its connection to overall production output. The performance index coefficient of 1.899 is the only elastic estimate in the model (exceeding 1), meaning production responds more than proportionally to changes in the performance index in this fitted specification.

Table 5. Elasticity analysis

Model	Coefficients[a] Unstandardized coefficients B	Std. Error	Standardized coefficient Beta	t	Sig.
(Constant)	.154	2.768		.056	.956
Chicken livestock population	-.044	.025	-.144	-1.757	.086
Feed	-.057	.178	-.027	-.322	.749
Depletion	.210	.077	.290	2.709	.010
Total cost	-.279	.215	-.115	-1.302	.200
Harvesting age	.028	.272	.010	.102	.919
Bonus/Incentive	-.017	.008	-.197	-2.218	.032
Number of Employees	.565	.091	.585	6.235	.000
Performance Index	1.899	.419	.471	4.536	.000

a. Dependent Variable: Production

This relationship underscores the necessity for optimized production practices, especially in feed management, which typically accounts for approximately 60-70% of total production costs in poultry (Azizah et al., 2024). Effective feeding strategies impact the cost-effectiveness of livestock systems and are crucial for ensuring optimal health and productivity of the animals (Kumar et al., 2024). Additionally, efficient labor utilization plays a vital role in improving production efficiency. Research indicates that farm management practices, combined with educational initiatives like training on local feed preparation, can lead to increased productivity among livestock farmers (Azizah et al., 2024).

The performance index variable exhibits the strongest influence on production tonnage. This index, which includes feed efficiency, growth rate, and feed conversion, plays a pivotal role in enhancing production output in broiler farming. Zampiga et al. (2021) reported that improvements in feed conversion rates are directly proportional to increased broiler weights, subsequently elevating production tonnage. Additionally, farm assistants (labor) contribute significantly and positively. Ilham et al. (2025) emphasized that worker motivation and welfare positively affect overall farm performance, which in turn increases production tonnage. While depletion also contributes positively, its impact remains modest. Conversely, total cost, chicken population, and bonuses/incentives exhibit negative effects, suggesting that managers should emphasize cost control, livestock population management, and incentive optimization to avoid diminishing productivity. Moreover, feed quantity and harvesting age have minimal influence on production tonnage, thus making them less critical factors in production management.

Supporting these findings Gabdo et al. (2017) analyzed 296 broiler farms in Malaysia and discovered that production inputs such as day-old chicks (DOC), medications, and utilities exhibited highly elastic coefficients of 6.29, 5.99, and 3.76, respectively, while feed costs demonstrated relatively low elasticity. This supports the present study's finding that while feed constitutes a major production cost, increasing feed input does not necessarily lead to proportional output gains, likely due to diminishing marginal returns in feed efficiency. Similar conclusions were drawn by Nwadiolu et al. (2023) in their study of broiler production in Nigeria, where farm size (0.42) and labor (0.13) showed higher elasticities compared to feed (0.17), further emphasizing that labor management and scale optimization contribute more significantly to broiler production than feed quantity alone.

Furthermore, Sa'ad et al. (2025) observed that variations in feed formulation with different nutrient compositions did not significantly affect final broiler weights in closed house systems, highlighting the dominant role of environmental management and animal health in determining production outcomes. Purnomo et al., (2024) also found that variations in harvesting age between 30 and 35 days had no significant effect on production tonnage. Therefore, optimization of harvesting age should consider economic returns and market demand rather than focusing solely on maximizing production volume.

Within the context of production elasticity analysis in broiler farming under closed house partnership systems, feed quantity and harvesting age may not serve as the primary determinants of production tonnage. Instead, production improvement efforts should prioritize system performance optimization, effective labor management, farm scale efficiency, and the strategic management of inputs such as DOC and veterinary care, as supported by empirical findings from multiple international studies.

Agribusiness Partnership Model

The agribusiness partnership model in broiler production under a closed house system comprises three interrelated subsystems: upstream, midstream, and downstream. This model highlights the integration of various actors within the poultry value chain, where integrator companies are responsible for input provision, technical guidance, and marketing, while contract farmers manage operational production processes. In this study, 50 contract farmers partnered with four main integrators: PT. Super Unggas, PT. Bintang Tama Santosa, PT. Kedu Lintang Berbintang, and PT. Mitra Berlian Unggas.

Upstream Subsystem

This subsystem involves the provision of essential inputs such as day-old chicks (DOC), feed, vaccines, and veterinary drugs. These components are critical for achieving high productivity and maintaining biosecurity standards in closed housing systems. Day-Old Chicks (DOC): DOCs were sourced from PT. Dinamika Megatama Citra (DMC) and PT. Charoen Pokphand Indonesia (CPI), using strains such as Cobb, Hubbard, and Lohmann, known for their performance and adaptability to local conditions. Hatchery protocols included pre-vaccination and sanitary handling to maintain chick quality (Bhuiyan et al., 2021).

Before chick placement, farmers prepared the houses by disinfecting the facilities, setting up internal curtains, preheating the brooding area to 31–33°C, and arranging feeders, drinkers, and lighting (20 lux intensity). Viability indicators such as active chirping, bright eyes, and alertness were observed to assess DOC quality (Saeed et al., 2019). This initial preparation process is illustrated in (Figure 3), which outlines the operational flow of brooding and early-stage chick management in a closed house system.

Figure 3. Closed house preparation before chick placement

Despite fluctuations in DOC market, contract farmers were shielded from risk through fixed input pricing stipulated in contractual agreements. This mechanism promoted financial certainty and protected against input market volatility (Putri & Rondhi, 2020). The organizational flow and actor roles involved in DOC and feed input distribution describe the sequence of processes and the interactions among key stakeholders, including producers, integrator companies, distributors, intermediaries, and farmers, in ensuring the timely and efficient supply of DOC and feed to poultry production systems.

Midstream Subsystem

This subsystem centers on farm-level broiler production managed by contract farmers. On average, each farmer raised 12.000 broilers per cycle, with total feed consumption reaching 17.500 kg. Integrators supplied all inputs and provided technical support throughout the production period. Farmers oversaw daily routines including brooding management, feed distribution, and environmental control implemented using automatic ventilation and digital temperature monitoring, which are standard features of closed house systems.

Each production cycle lasted 30–34 days. Performance benchmarks required by integrators included a feed conversion ratio (FCR) of less than 1.6, a mortality rate below 5%, and a performance index (IP) exceeding 400. Integrator supervisors conducted periodic visits to monitor farm conditions, provide consultation, and enforce compliance with partnership obligations. Although integrators bore market risks and input procurement, farmers assumed biological and operational risks. Underperformance in achieving productivity targets could result in the withholding of incentive payments, reinforcing a system of accountability between parties.

Downstream Subsystem

The downstream subsystem includes harvesting, slaughtering, processing, and product distribution, all managed by the integrators. Farmers were exempt from post-harvest activities and marketing tasks, which allowed them to focus solely on production performance. This arrangement also reduced the operational burden on farmers and enabled them to allocate greater attention to flock management, biosecurity, and production efficiency. Bonus payments were awarded when farmers met or exceeded set standards, especially when achieving an IP greater than 400. Bonus distribution was executed based on transparent and standardized performance assessments. This contractual arrangement reflects findings from Kamruzzaman et al. (2021) who emphasized that well-regulated partnerships increase trust, reduce marketing uncertainty, and improve overall satisfaction among farmers.

Conclusion

This study identifies that in the fitted model, number of employees, depletion rate, and performance index are the variables significantly associated with broiler productivity, while chicken population and feed quantity. Despite their theoretical importance as production inputs show negative and statistically non-significant coefficients. This result is consistent with the severe multicollinearity among population, feed, and total cost and should be re-examined using alternative model specifications, particularly by treating performance index as an outcome rather than an input. The positive coefficient on depletion is counterintuitive relative to production theory and may reflect confounding with farm scale rather than a genuine causal effect; this discrepancy warrants further investigation with additional data before drawing firm conclusions. From a practical perspective, strengthening labor management and farm performance monitoring are the recommendations best supported by the present results; recommendations regarding cost efficiency are not made here, since the total cost variable was affected by severe multicollinearity and its estimated coefficient is unreliable in the current model. These findings are based on 50 contract farmers in Malang Regency operating partnership-based closed-house systems and should be interpreted within that scope; further studies across other regions and partnership systems are needed before generalizing to the broader Indonesian broiler industry.

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Author Contributions
Developing ideas, methodology, overseeing data collection, conceptualization, and reviewing, D.M. and N.F.; data collection, writing, editing, visualization, and draft preparation, R.R.H. and I.K.; analyzing data development, data curation, and writing, A.F.A., P.A., and M.H.; conceptualization, data curation, reviewing scripts and validation, B.H. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest
The authors confirm that there are no conflicts of interest related to this study.

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