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Assessing Determinants of Technical Efficiency in Livestock Production: A Case Study from Shaanxi, China

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ABSTRACT

The demand for livestock products is rising, and China is actively encouraging farmers to increase their livestock production to meet this growing demand. At Shaanxi Province's livestock industry's current production output and growth rate, it appears unfeasible to meet the government's production target for 2025. Inefficiencies within livestock production can significantly impede the development of this industry. Therefore, this research employs the Data Envelopment Analysis (DEA) technique, considering Constant Returns to Scale (CRS) and Variable Returns to Scale (VRS) assumptions, to assess the technical efficiency of the livestock industry in Shaanxi Province. The data utilised are secondary data from 2010 to 2019. The findings reveal that the Shaanxi livestock industry has an average technical efficiency of 0.84 (CRS) and 0.92 (VRS), suggesting that there is room for further production growth with the current inputs, breeding scales and technology. Although dairy cows, cattle and goats have achieved full technical efficiency. Technical and scale inefficiencies still exist in hog and layer farming practices, which can be improved to increase production. Notably, hog farming demonstrated the lowest technical efficiency, scoring 0.68. The results of factors affecting inefficiency suggest that increasing spending on disease prevention and raising the selling price can both improve technical efficiency. Additionally, reducing death loss has the potential to improve technical efficiency. Thus, the government is expected to promote farm consolidation and expansion while actively advocating for establishing livestock production cooperatives.

Keywords: Data Envelopment Analysis (DEA), inefficiency, livestock industry, technical efficiency, Tobit regression

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INTRODUCTION

The global demand and production of livestock products are increasing rapidly, especially in China, due to population growth, rising income, and changes in lifestyle and dietary habits (Food and Agriculture Organization, 2021). In 2022, the National Bureau of Statistics of China reported that China's livestock industry produced 52.959 million tons of pork, 6.975 million tons of beef, 5.141 million tons of mutton, 24.825 million tons of poultry, 34.088 million tons of eggs, and 36.827 million tons of milk (National Bureau of Statistics of China, 2023). China is a major producer of livestock products, ranking first in the world in producing pork, mutton, broiler and eggs and third in dairy production (Food and Agriculture Organization, 2022a). Despite the increasing annual production of livestock products, China remains the world's top importer of livestock products (Food and Agriculture Organization, 2022b). Empirical research shows that China's current pork, beef, and mutton production is inadequate to meet domestic demand (Shi et al., 2015). In 2020, the proportion of imported meat in China's total meat production reached 12.7%, equivalent to 9.91 million tons, indicating a significant increase over the previous five years (AskCI Consulting, 2022). Amid the COVID-19 pandemic, China intensified restrictions on imported food products after detecting the virus in frozen food (Cadell, 2020). It has caused challenges not only for food suppliers and supply chains but also for China's dependence on imported meat and dairy products. The China Government's 14th Five-Year Plan (2021–2025) includes a target to increase livestock production, with an expected growth of 15% in meat production (Patton, 2022; Shaanxi Provincial Department of Agriculture, 2022). If all producers operate at full technical efficiency, the production of the livestock industry would more easily align with the output targets expected by the government, consequently reducing the demand for imported products.

The livestock industry plays a significant role in Shaanxi. Because it contributes to 80% of China's goat milk production, and its egg production is crucial to meeting the demand of surrounding provinces (National Bureau of Statistics of China, 2021). Moreover, pork and milk provide the most protein for Shaanxi residents. However, this industry confronts obstacles such as outbreaks of diseases, including African swine fever for hog (Wang, Zhao, et al., 2021) and avian influenza for layer. All these obstacles may reduce the production enthusiasm of farmers and lead to a scaling down of farming operations.

As of 2021, Shaanxi's livestock industry ranked 20th out of 31 provinces in mainland China, contributing 21.3% of the agricultural production value. The province produced 1.274 million tons of meat, 634,000 tons of eggs, and 1.619 million tons of dairy products. The most recent "14th Five-Year Plan for Livestock and Veterinary Development in Shaanxi" (Shaanxi Provincial Department of Agriculture,

2022) anticipated a rise in production, with an expected production of 1.8 million tons of meat, 0.8 million tons of eggs and 3 million tons of dairy products by 2025. Maintaining the current breeding practices will make it challenging for the livestock industry to achieve this government objective in production.

The output of the livestock industry in Shaanxi increased annually, but the growth rate has shown a decreasing trend year on year (Figure 1). In comparison to the national average growth rate, Shaanxi exhibits a lower growth rate (National Bureau of Statistics of China, 2021). It is possibly due to technical inefficiencies, which consequently impact the production of Shaanxi's livestock industry (Terry et al., 2021). Thus, it is important to know whether inefficiency exists in the Shaanxi livestock industry and identify the factors affecting it. Such an understanding would enable producers in the livestock industry to take necessary steps to improve efficiency and enhance the overall performance of the livestock industry.

Many studies in the field of livestock do not distinguish between animal species or focus solely on specific animal species (Kuhn et al., 2020; Wang, Han, et al., 2021; Zhou et al., 2015), whereas this study adopts a more comprehensive approach. This study not only individually examines the primary livestock species within Shaanxi's livestock industry but also conducts a comparative analysis of technical efficiency across different scales of production. Moreover, a significant portion of research on factors affecting inefficiency focuses on emphasising the factors related to livestock farmers, such as farmers' gender or their experience in the livestock industry (Tian et al., 2015; Wang, Han, et al., 2021). In contrast, this paper extends the analysis to explore how medical and epidemic prevention, death loss, and selling prices affect inefficiency in the Shaanxi livestock industry.

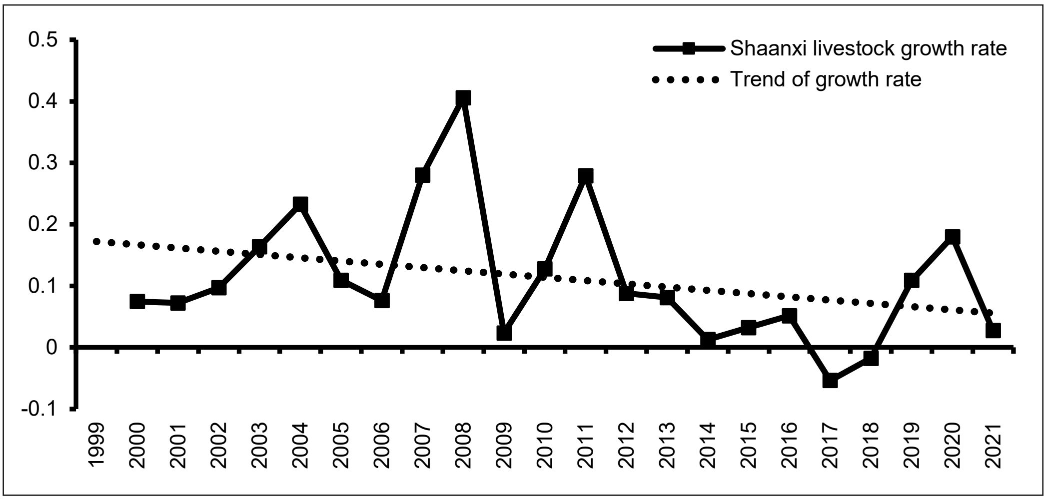

Figure 1. Shaanxi livestock growth rate
Source: National Bureau of Statistics of China (2021)

In light of the abovementioned considerations, this study seeks to accomplish two objectives: (1) to evaluate the level of technical efficiency and (2) to identify factors that affect technical inefficiency in the Shaanxi livestock industry. The findings of this study will provide valuable insights for policymakers on how to increase livestock production and modify relevant policies to promote sustainable development in the industry.

LITERATURE REVIEW

Production efficiency refers to a firm's ability to achieve the maximum output with a given set of inputs and contemporary technology (Farrell, 1957). However, efficiency cannot be directly observed. Therefore, appropriate methods are needed to measure it. There are two main techniques for measuring technical efficiency: non-parametric Data Envelopment Analysis (DEA) and parametric Stochastic Frontier Analysis (SFA). The choice of technique can influence the technical efficiency results, and there is no consensus on which technique is most appropriate for agricultural technical efficiency (Heshmati et al., 1995). DEA cannot require a specific functional form to be imposed on the data and can easily be adapted to multiple outputs. Additionally, DEA is deterministic and attributes all deviations from the frontier to inefficiency, making it sensitive to measurement errors and other statistical noise in the data. Unlike SFA, DEA is more inclusive of small samples (Zhu, 2009). SFA represents a parametric approach, also known as an econometric approach, which involves fitting an assumed structure of the observed data (Aigner et al., 1977; Meeusen & van Den Broeck, 1977). The main advantage of SFA is its ability to handle random noise. However, SFA requires a specific functional form to be imposed on the underlying technology and a distributional assumption to be imposed on the inefficiency term. Upon comparison, the DEA method has been selected as the preferred technique for measuring efficiency in this study.

DEA is a non-parametric technique to measure the efficiency of firms by comparing their production set with a production frontier. Based on the fundamentals of efficiency, DEA was developed into two assumptions: CCR (Charnes, Cooper and Rhodes) and BCC (Banker, Charnes and Cooper). The CCR assumption is also known as the CRS (constant returns to scale) assumption. Assuming that the Decision-Making Units (DMUs) are operating using the given inputs and technology, the results generated by DEA would indicate the technical efficiency (TE) score. When the score equals 1, the DMUs function efficiently and operate at optimal production levels. Conversely, a score lower than 1 suggests that the DMUs are inefficient (Zhang et al., 2017). Banker et al. (1984) introduced the BBC assumption (also known as VRS, variable returns to scale) as an improvement over the CRS assumption, which envelops the data points more tightly than the CRS assumption. Technical efficiency (TE) is the result of CRS DEA, while pure technical efficiency (PTE) is the result of VRS DEA. The difference between these two is the scale efficiency (SE), which represents the ratio of the actual output of a DMU to its optimal output at the efficient scale of operation. If there is a difference between the TE and PTE scores, it indicates that the firm is operating at a suboptimal size. Scale efficiency equals one only when the scores of TE and PTE are equal (Färe & Lovell, 1978).

Efficiency is widely used in the livestock industry, with DEA commonly employed. Such studies have identified inefficiencies in several countries in the dairy industry, including Australia (Fraser & Cordina, 1999), Sweden (Hansson & Öhlmér, 2008), and Estonia (Luik-Lindsaar et al., 2019). Some studies have utilised both CRS DEA and VRS DEA for efficiency analysis. Notably, the VRS efficiency scores are relatively higher than the CRS efficiency scores, as VRS can capture the efficiency from scale benefits. For example, previous studies have found that in Hawaii's pig farming industry, the VRS efficiency score was 0.726, whereas the CRS score was 0.644 (Sharma et al., 1997). Similarly, Lansink and Reinhard (2004) reported a VRS score of 0.90 and a CRS score of 0.89 in the Netherlands. Mugera and Featherstone (2008) found VRS and CRS scores of 0.41 and 0.33 in the Philippines. Besides, Galluzzo (2019) investigated dairy farms in Iceland and reported a CRS score of 0.881 and a VRS score of 0.946. İlkikat et al. (2020) studied hair goat farms in Turkey and found a CRS score of 0.67 and a VRS score of 0.76. These findings suggest that the DEA technique can be applied to various livestock categories, regardless of geographic location. Also, scale inefficiency is prevalent in most livestock farming, making it important to analyse CRS and VRS to enhance farming scale.

Most previous studies on efficiency in the livestock industry in China have mostly concentrated on the hog industry (Kuhn et al., 2020; Somwaru et al., 2003; Tian et al., 2015; Wang, Zhao, et al., 2021; Yang et al., 2008; Zhou et al., 2015). For instance, Yang et al. (2008) surveyed 39 hog farmers to assess their technical efficiency in Taiwan between 2003 and 2004. The results demonstrated that farms could increase their output by an average of 52.8% while maintaining the same input levels. In an earlier study, Somwaru et al. (2003), who used a non-parametric technique, discovered that Shaanxi experienced technical inefficiency in the livestock industry with technical efficiency scores of 0.75, higher than the national average of 0.24 in 1996. Similarly, several studies, such as Tian et al. (2015), Zhou et al. (2015), and Wang, Zhao, et al. (2021) used parametric methods to examine the efficiency of the hog industry in China and found it to be inefficient. Moreover, these studies revealed that the technical efficiency of the northern provinces, including Shaanxi, is lower than that of other provinces.

The variance in technical efficiency among farms can be utilised to discover the factors that affect inefficiency. The standard approach entails conducting a regression analysis of efficiency scores against a series of explanatory variables (Lansink & Reinhard, 2004). In economics, determining the impact of exogenous factors on production involves converting the technical efficiency score into technical inefficiency, which is obtained by subtracting the technical efficiency score from 1 (Coelli et al., 2005; Farrell, 1957). Then, factors affecting inefficiency can be identified through Tobit regression analysis applied to truncated data (Dogan et al., 2018; Liu et al., 2021; Zhang et al., 2017). Several studies examining efficiency in the hog farming industry across different countries, including China (Tian et al., 2015), the Philippines (Mugera & Featherstone, 2008), and Turkey (İkikat et al., 2020), found that a higher level of education among farmers leads to increased efficiency in hog farming, likely due to improved knowledge of scientific breeding techniques. Similarly, Wang, Han, et al. (2021) conducted a survey involving 449 herders within the Inner Mongolia grassland area of China in 2017. Their findings revealed that the existing policies have facilitated the expansion of livestock farming scales, leading to the departure of inefficient farmers from the industry. Additionally, Jo et al. (2021) surveyed farms in Heilongjiang Province, determining that a reduction in death losses contributes to enhanced technical efficiency within the livestock industry.

This study's selection of factors affecting inefficiency draws upon theoretical frameworks and previous empirical investigations. Within the Keynesian theory, governmental financial aid to farmers for epidemic prevention is perceived to safeguard their operations and stimulate heightened production. It aligns with the objectives outlined in the 10th to the 14th Shaanxi Five-Year Development Plans (spanning from 2001 to 2025) within the livestock industry, which accentuate the importance of bolstering epidemic control measures to enable farmers to achieve enhanced incomes (Crop Farming Management Office of Shaanxi Province, 2022; Shaanxi Government, 2008, 2022; Shaanxi Provincial Department of Agriculture, 2018; Shaanxi Statistics Bureau, 2015). Moreover, according to risk management theory, death loss has adverse impacts on production outcomes by introducing uncertainty and potential disruptions to agricultural operations, thereby diminishing efficiency. The law of supply implies that as prices of agricultural products escalate, farmers exhibit a heightened inclination to expand production and augment supply to the market. Conversely, lower prices might lead to diminished production or market exit, resulting in reduced quantities supplied.

METHODOLOGY

Variable Selection and Description

To obtain precise results of technical efficiency, the number of input variables should be neither too few nor too many (Reinhard et al., 1999). Based on livestock features and plenty of readings, such as Sharma et al. (1997), Fraser and Cordina (1999), Galluzzo (2019) and Soh et al. (2021), this study selected one output variable, three input variables and three factors that are likely to have an impact on inefficiency. The description of the variables is as follows:

(1) Output: The output value measurement is based on each animal's farm price. In the case of hogs, cattle, and goats, the primary output is determined by the live weight price of each animal at the time of sale. In the case of layer, the output value is the farm price of total eggs from 100 layers.

(2) Labour: In livestock production, labour input is quantified as the number of employees' working days required per animal. However, when evaluating layers specifically, the measurement unit employed is the working days required for the management of 100 layers. These working days are calculated based on 8 hours per day. For instance, if one goat needs six workdays of labour, an employee would spend 48 hours on one goat.

(3) Young: This variable is measured as the average purchase price of each young animal. The expenses of young animals vary across different livestock categories. The expenses for cattle, hogs, and goats consist of the acquisition cost of each young animal. While the layer is small livestock, the expenses are the purchase price of 100 chicks.

(4) Feed: The weight of feed is the total weight of grains, beans, fodder and additives consumed by each animal or 100 layers.

(5) MEP: Medical and epidemic prevention (MEP) expenses include immunising livestock, preventing epidemics, testing, quarantine, eradicating infectious diseases and government-enforced controlling measures. MEP measures the individual expenditures for each animal, while for layers, it quantifies the expenses of 100 layers. As it protects farmers' output, this variable is expected to have a negative impact on technical inefficiency.

(6) DL: Livestock death loss (DL) occurs when livestock dies due to various causes, such as disease, disaster, nutritional deficiencies and inadequate management. Calculating the death loss per animal involves dividing the number of animal deaths by the initial number of animals and multiplying the result by the farm price per animal. The loss of livestock can lead to reduced production, increased costs and decreased profitability for farmers.

(7) SP: The selling price (SP) represents the average selling price at which 50 kg of livestock products are sold in the Shaanxi agricultural wholesale market. This factor is expected to have a negative effect on technical inefficiency since high selling prices can encourage farmers to increase their breeding activities.

Data

A two-stage analysis was used in this study to examine the technical efficiency of the ten categories of animals in the Shaanxi livestock industry (Liu et al., 2021). In the first stage, Data Envelopment Analysis (DEA) is employed to calculate the technical efficiency score of each category in the Shaanxi livestock industry. In the second stage, Tobit regression is used to estimate the factors that affect inefficiency in each category. Variables such as inputs (including labour, young animals and feed), output, and factors affecting inefficiency (medical and epidemic prevention, death loss and selling price) are selected. The data utilised in this study constitute secondary data sourced from the China Agricultural Product Cost–Benefit Compilation (Price Department of the National Development and Reform Commission & Price Cost Research Centre of the National Development and Reform Commission, 2020). This dataset, characterised as panel data, encompasses ten categories of animals within the Shaanxi livestock industry from 2010 to 2019. A linear interpolation method was applied to generate missing data points to minimise the impact of missing data. This study's price data is anchored to 2010, with adjustments made using the Shaanxi Livestock Consumer Price Index (CPI) or the Shaanxi Young Animal CPI. The CPI data are sourced from the Shaanxi Statistical Yearbook. The data source also classifies livestock into four categories based on their breeding scale: backyard, small-, medium- and large-scale. Backyard farming refers to a practice that involves individual households or small farmers raising livestock in a small pen or backyard. This study utilises ten categories of DMUs: backyard and medium-scale dairy cows, backyard, small-, medium-, and large-scale hogs, small- and medium-scale layers, and backyard goats and cattle. The classification standard of the breeding scales for each category is shown in Table 1.

Models

Essentially, the DEA technique is built on the technical assumptions of Constant Returns to Scale (CRS), which assumes that the DMUs are operating at an optimal scale. Banker et al. (1984) extended this method to incorporate technologies with Variable Returns to Scale (VRS), which would envelop the data points more tightly than the CRS assumption. Prior to computing technical efficiency, it is essential to select the orientation of minimising the inputs or maximising the outputs based on the variable (input or output) that the manager needs to control the most. Substantively,

Table 1
Standard classification of breeding scale based on quantity

Livestock	Backyard	Small-scale	Medium-scale	Large-scale
Dairy Cow	Q≤30	-	50<Q≤500	-
Hog	Q≤30	30<Q≤100	100<Q≤1000	Q>1000
Layer	-	300<Q≤1000	1000<Q≤10000	
Goat	Q≤100	-	-	-
Cattle	Q≤50	-	-	-

Notes. Q = Quantity, signifying the number of animals bred on the farms
Source: Price Department of the National Development and Reform Commission (2019)

the Shaanxi Provincial Government has been encouraging the enhancement of livestock production. Thus, this study adopts an output-oriented approach. Following Coelli et al. (2005), the output-oriented VRS assumption in Equation 1 and the CRS assumption in Equation 2 for measuring technical efficiency are given:

$$max_{\phi,\lambda}\ \phi,$$

subject to

$$\begin{aligned} -\phi q_i + Q\lambda &\geq 0, \\ x_i - X\lambda &\geq 0, \\ I'_{I\times 1}\lambda &= 1 \\ \lambda &\geq 0, \end{aligned} \tag{1}$$

$$max_{\phi,\lambda}\ \phi,$$

subject to

$$\begin{aligned} -\phi q_i + Q\lambda &\geq 0, \\ x_i - X\lambda &\geq 0, \\ \lambda &\geq 0, \end{aligned} \tag{2}$$

where λ represents a $I \times 1$ vector of constants (weights). The parameter ϕ signifies the ratio between the distance from the optimum point to the origin of the coordinate axes and the distance from the observed point to the origin of the coordinate axes. This ratio is equivalent to calculating the inverse of technical efficiency, subject to the constraint that $1 \leq \phi \leq \infty$. The vectors X and Q are the observed inputs and outputs, respectively. The value of $\frac{1}{\phi}$ refers to the level of technical efficiency (TE) ranging from 0 to 1 of the i-th decision-making unit, with a value of 1 indicating that the farm is technically efficient and on the production frontier (Farrell, 1957). The VRS DEA assumption involves three constraints. In the first constraint, the observed output (q_i) of the i-th farm is multiplied by ϕ and compared to the maximum output vector of the theoretically efficient farm ($\phi\lambda$). With the same quantity of inputs, the constraint indicates that the theoretically efficient farm produces more or the same volume output than the actual output produced by the i-th farm. The second constraint illustrates that the observed input (x_i) in the i-th farm is more than or equal to the input ($X\lambda$) of the theoretically efficient farm. The third constraint of $I'_{I\times 1}\lambda = 1$ signifies the inefficiency of a farm evaluated against other farms of similar size. Such constraint enables the evaluation of farm efficiency in terms of technical and scale efficiencies (Mohd Idris et al., 2013).

If the technical efficiency score turns out to be $\frac{1}{\phi} = 1$, this farm is technically efficient. Then, the output of this farm is as much as the production of the technically efficient farm using the same volume of inputs. If the efficiency score turns out to be $\frac{1}{\phi} < 1$, the farm is technically inefficient. It means that the farm's output can be increased to the level of $\phi\lambda$. Notably, the linear programming problem needs to be solved I times to obtain a value for each sample farm. Hence, a value of ϕ is calculated for each farm. As shown in Equation 2, the VRS DEA assumption can be transformed into the CRS DEA assumption by removing the constraint of $I'_{I\times 1}\lambda = 1$ (Siafakas et al., 2019).

Scale efficiency refers to the extent to which a DMU is operating at the most productive scale size. If a DMU is operating below its optimal scale size, it may be able to increase its efficiency by adjusting its practice scale. Dividing the CRS efficiency score by the VRS efficiency score allows the capture of the impact of the scale effect. Scale efficiency can be expressed as:

$$SE = \frac{TE_{CRS}}{TE_{VRS}} \tag{3}$$

After obtaining the technical efficiency scores through DEA in the first stage, the efficiency scores are converted into inefficiency scores. Subsequently, a regression analysis is conducted to examine the relationship between inefficiency scores and other exogenous variables in the second stage. The technical inefficiency scores are derived by subtracting the TE_{CRS} or TE_{VRS} scores obtained from the first stage from 1 (Coelli et al., 2005; Farrell, 1957). The Tobit regression handles the truncated inefficiency estimates at 0 and 1 (Greene, 1994). The explanatory variables in the regression model, such as medical and epidemic prevention, death loss and selling price, reflect the factors that affect inefficiency (the explained variable). The following equation expresses the Tobit regression:

$$Ineff_{i,t} = \beta_0 + \beta_1 MEP_{i,t} + \beta_2 DL_{i,t} + \beta_3 SP_{i,t} + \varepsilon_{i,t} \tag{4}$$

Where $Ineff_{i,t}$ refers to the technical inefficiency score of each category of livestock (i-th) ranging between 0 and 1 for t periods. It is obtained from the reciprocal of results of the CRS or VRS DEA assumption subtracted by one; β_0 is the intercept; β_1 to β_3 are coefficients estimated for individual independent variables; $MEP_{i,t}$ denotes medical and epidemic prevention expenses; $DL_{i,t}$ indicates livestock death loss during farming; $SP_{i,t}$ is the average selling price in Shaanxi wholesale markets; and $\varepsilon_{i,t}$ refers to the error term.

RESULTS AND DISCUSSION

Technical Efficiency

Figure 2 indicates that there have been fluctuations and downward trends in the technical efficiency scores of the Shaanxi livestock industry in recent years. The average technical efficiency scores over the decade reached 0.84 (CRS) and 0.92 (VRS); the scale efficiency score was 0.91. The technical efficiency scores under the VRS assumption, which range from 0.70 to 1, are higher than those under the CRS assumption (0.54–1). Additional details regarding these findings are presented in Table 2. Geometric means are calculated for each category to compare the technical efficiencies across various categories between 2010 and 2019. Dairy cow, goat, and cattle farms are operating at full technical efficiency (1.00) during the study period. However, inefficiencies are mainly observed in hog and layer farming practices, indicating that enhancing the performance of these two species could lead to an overall improvement in the technical efficiency of the livestock industry in Shaanxi.

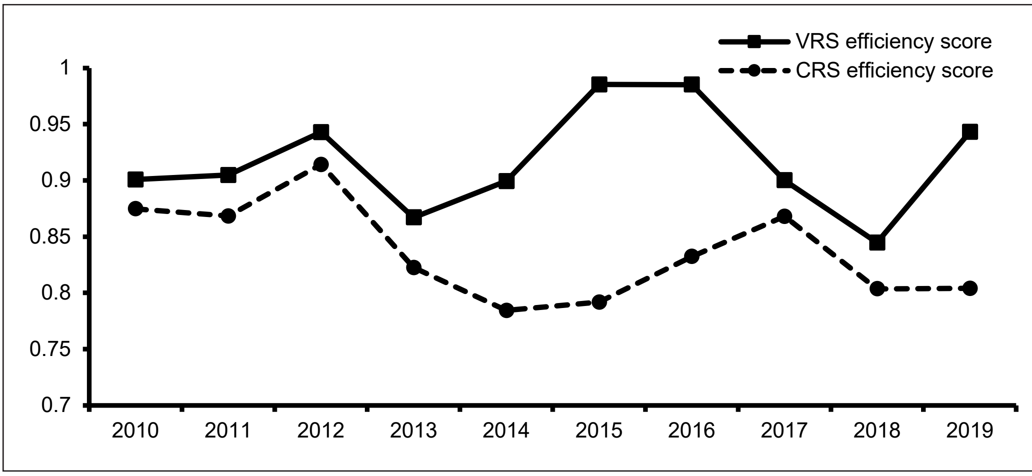

Figure 2. Technical efficiency score in the Shaanxi livestock industry
Source: Authors' work

Table 2
Technical efficiency and inefficiency in the Shaanxi livestock industry from 2010 to 2019

Products	**Technical Inefficiency**		**SE**	**Technical Efficiency**	
	VRS	**CRS**		**VRS**	**CRS**
Dairy Cow					1
Backyard	0	0	1	1	1
Medium-scale	0	0	1	1	1
Hog					0.68
Backyard	0.30	0.46	0.77	0.70	0.54
Small-scale	0.17	0.41	0.71	0.83	0.59
Medium-scale	0.13	0.32	0.78	0.87	0.68
Large-scale	0	0.04	0.96	1	0.96
Layer					0.89
Small-scale	0.17	0.21	0.96	0.83	0.79
Medium-scale	0	0	1	1	1
Goat	0	0	1	1	1
Cattle	0	0	1	1	1
Mean for all livestock	0.08	0.16	0.91	0.92	0.84

Notes. CRS: Constant Returns to Scale, SE: Scale Efficiency, VRS: Variable Returns to Scale
Source: Authors' work

From Table 2, it is evident that within the Shaanxi livestock industry, hog farms demonstrate the lowest efficiency scores (0.68), lower than those of cows (1.00), goats (1.00), and layers (0.89). Moreover, across all scales of hog farming and small-scale layer farming, the technical efficiency score obtained via VRS analysis is consistently higher than that obtained through CRS analysis, indicating the potential for efficiency improvement through optimal scale management. Additionally, the results of the CRS and VRS assumptions provide evidence that the technical efficiency score increases with an expansion in the breeding scale.

In the case of layer, small-scale breeding demonstrates a technical efficiency score of 0.79, indicating a potential 21% increase in output. Meanwhile, medium-scale breeding operates at full technical efficiency. The findings are consistent with Zhong et al. (2021) and confirm the suitability of the government's five-year plan for livestock, which promotes farmers' increasing breeding scales in the layer sector.

The technical efficiency score of a hog (0.68) in Shaanxi is higher than the 0.58 reported by Tian et al. (2015) in Shaanxi and 11 other provinces but lower than the 0.75 measured by Somwaru et al. (2003) and 0.84 measured by Zhou et al. (2015). These findings are inconsistent with prior research and possibly attributable to divergent data sources where backyard farming is relatively more prominent in the surveyed data.

In Shaanxi, there has been a significant decrease in the proportion of households involved in backyard hog farming, which declined from 89% in 2010 to 43% in 2020 (National Bureau of Statistics of China, 2010, 2021). This shift has resulted in a corresponding increase in concentrated hog farming, encompassing small-, medium-, and large-scale farms, which has risen from 11% to 57% over the span of a decade (National Bureau of Statistics of China, 2010, 2021). The results indicate that hog farming across different scales does not demonstrate optimal technical efficiency. Yet, larger-scale operations tend to exhibit higher levels of technical efficiency. Backyard hog farms typically remain small-scale, with many still employing traditional labour-intensive feeding methods, such as using crop straw and swill for feed (Xiao et al., 2012). These practices contribute to low levels of technical proficiency and production efficiency. Due to the recent sharp rise in feed prices, backyard farmers have been compelled to reduce feed quantity, leading to an increased reliance on swill feeding. Regrettably, this tendency is anticipated to have adverse effects on hog health, including elevated mortality rates as well as lower farming efficiency (Xiao et al., 2012). Therefore, it is recommended that larger-scale breeding operations be adopted in the hog farming industry.

Factors Affecting Technical Inefficiency

The results of the Tobit regression analysis used to identify the factors affecting inefficiency in the Shaanxi livestock industry of each category are presented in Table 3. The expenses of medical and epidemic prevention have a negative impact on the overall technical inefficiency score, which implies that increasing prevention expenses might lead to a decrease in the inefficiency score, subsequently increasing the technical efficiency of Shaanxi's livestock industry. As discovered by Yan et al. (2023), compared to backyard farmers, large-scale hog farmers are more proactive in terms of biosecurity construction, aiming

Table 3
Results of the Tobit regression model on factors that affect technical inefficiency

Factors	Estimate		Std. Error		Prob.	
	VRS	CRS	VRS	CRS	VRS	CRS
Intercept	0.3678	0.8534	0.1857	0.1636	0.0477**	0.0000***
MEP	-0.0090	-0.0102	0.0021	0.0018	0.0000***	0.0000***
DL	0.0181	0.0136	0.0064	0.0054	0.0044***	0.0111**
SP	-0.0006	-0.0009	0.0002	0.0002	0.0068***	0.0000***

Note. *** and ** denote significance at the 1 per cent and 5 per cent levels, respectively
Source: Author's work

to reduce losses and enhance production efficiency. Medium- and large-scale farms exhibit enhanced financial capabilities, providing farmers with greater capital to invest in improved disease-preventive measures. In turn, it facilitates increased specialisation and reduces the susceptibility to disease outbreaks. However, increasing investment in disease prevention necessitates transitioning farms into medium- and large-scale operations. Therefore, policies that support the farm consolidation of backyard and small-scale farms into larger ones and facilitate the growth of medium-scale farms are necessary to increase production and technical efficiency (Crop Farming Management Office of Shaanxi Province, 2022). Consolidating and expanding farms would allow larger farms to allocate more resources to preventing outbreaks like avian influenza (Wang, Zhou, et al., 2021).

Additionally, it is observed that death loss positively correlates with technical inefficiency, consistent with findings by Jo et al. (2021). Death loss results in a decrease in inefficiency scores, subsequently enhancing the technical efficiency of the livestock industry in Shaanxi, particularly in hog and layer farming. The breeding environment for hogs and layers is typically less sanitary, which can more easily result in death loss. An elevated death loss is associated with a decline in technical efficiency, resulting in decreased output production and diminished farmer income. This trend prompts the departure of numerous backyard and small-scale farmers from the livestock industry (Wang, Han, et al., 2021).

On the other hand, the average selling price of livestock products shows a negative impact on technical inefficiency in the Shaanxi livestock industry, suggesting that a higher selling price might lead to a decrease in the inefficiency score and improve the technical efficiency of Shaanxi's livestock industry. The market selling price and revenue of livestock products are key factors determining the duration of livestock feeding days. Farmers can adjust the length of feeding days to manage their production costs and maintain their income during price fluctuations. When farmers face an increase in the prices of livestock products, they may choose to shorten the duration of feeding days. Farmers may increase feeding days when food prices fall to maintain their income. It illustrates the relationship between higher prices and increased efficiency, as well as the inverse association between lower prices and declining efficiency due to prolonged feeding periods. It is not a healthy practice for farmers and consumers. Therefore, it is imperative for the government to implement measures to stabilise prices, enabling farmers to maintain a sustainable livestock feeding base.

CONCLUSION

This study employs Data Envelopment Analysis (DEA) to investigate technical efficiency. It utilises Tobit regression to examine the factors affecting inefficiency across various scales and species of farming operations in the Shaanxi livestock industry from 2010 to 2019.

The main findings of this study are as follows. Firstly, the livestock industry in Shaanxi exhibits inefficiencies in current farming practices. Goat, dairy cow and beef farming exhibit full technical efficiency. However, both hog and layer farming practices show the presence of technological inefficiency and scale inefficiency. Notably, the results indicate that the technical efficiency scores of hog and layer farming increase as the breeding scale increases. This study also employed the Tobit regression to explore the potential effect between technical inefficiency and three influencing factors. The findings indicated that increasing medical and epidemic prevention expenses, reducing death loss and raising selling prices are crucial improvements that can enhance industry performance.

From a policy perspective, the findings of this study provide valuable insights for policymakers. Firstly, the breeding of dairy cows, goats and cattle in Shaanxi has reached full technical efficiency, suggesting that the government should motivate more farmers to participate in these farming activities. Secondly, the technical efficiency of hog and layer farming increases with the expansion of the production scale. Therefore, the Shaanxi government could actively promote the establishment of livestock production cooperatives and incentivise farmers to participate by combining adjacent breeding facilities. This approach would enable farms to accumulate funds to enhance epidemic prevention measures. Additionally, reducing death losses could enhance technical efficiency within the livestock industry. Hence, the Shaanxi provincial authority could implement subsidies and encourage farmers to reduce stocking density. Lastly, raising the selling price of livestock products can enhance the technical efficiency of the industry and stimulate farmers to increase livestock numbers and achieve higher profits. However, it is important to note that this higher selling price is not beneficial to consumers. Therefore, it is advisable for the Shaanxi Provincial Government to establish market regulatory mechanisms, such as price support and reserve systems, to mitigate the effects of price volatility. Implementing these measures can help achieve the government's goal of boosting Shaanxi's livestock production.

However, this study's limitation is its oversight of the livestock industry's environmental and sustainability impact. Pursuing higher output through excessive resource exploitation may adversely affect Shaanxi's ecosystems and natural resources. Therefore, it is recommended that future studies focus on examining the environmental efficiency of Shaanxi's livestock industry. By quantifying the relationship between resource utilisation and environmental impacts, measures can be formulated to promote the sustainable development of Shaanxi's livestock industry.

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