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Differences and Factors of Raw Milk Productivity between China and the United States

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Abstract: In order to explore the differences in the productivity level and influencing factors of raw milk between China and the United States, this study uses the stochastic frontier production function and is based on the input and output of factors of raw milk in China and the United States from 2005 to 2020 to measure the impact of factor inputs on raw milk output and the output differences. The results of the study found that: the inefficiency term of raw milk production technology in China is higher than that in the United States; feed costs and fuel power costs have a significant positive role in promoting the growth of raw milk output in China and the United States; health and epidemic prevention costs, as well as maintenance costs, have significant impacts on the output value of raw milk in China, but they have no significant impact on the output value of raw milk in the United States. In terms of the contribution of each input factor, the contribution share of feed costs to the output value of raw milk in China is 52.53% and 25.74%, respectively, compared to the value of raw milk in the United States; The contribution share of technological progress to the output value of raw milk in China is 34.92%, and 53.77%, respectively, compared to U.S. raw milk production value. In order to narrow the productivity gap with the United States dairy industry, China's dairy industry must pay attention to the moderate-scale breeding of dairy cows; develop an integrated production mode of planting and breeding; promote the development of grain to feed; accelerate the genetic improvement of dairy cattle populations; and learn from the pasture management experiences of foreign countries.

Keywords: raw milk; productivity level; input and output factors; technological progress; stochastic frontier production function; China and the United States

1. Introduction

China mainly imports whey from the United States. From 2005 to 2020, the United States was China's third largest source of dairy imports, according to trade data released by the United Nations Comtrade (UN Comtrade). China's imports of dairy products from the United States increased from 83,200 tons to 277,945 tons, of which whey imports from the United States increased from 76,900 tons to 246,255 tons, and the proportion of whey products imported from China by the United States fell from 40.97% to 39.34%; however, the United States was China's largest source of whey imports. This indicates that American whey has strong competitiveness in the Chinese dairy market [1–3].

The current condition of raw milk production shows that there is a huge gap between China and the United States in milk industry productivity. On the one hand, this gap is reflected in the level of growth in raw milk production in both countries [3]. Statistics from the United States Department of Agriculture (USDA) show that, in 2020, the production of raw milk in the United States was 101.252 million tons, the number of dairy cows was 9.388 million, and the yield per unit of dairy cows was 10,603 kg. Data collected from the China Dairy Yearbook show that the output of raw milk in China was 34.401 million tons, the number of dairy cows was 10.431 million, and the yield per unit was 8300 kg. Comparing the above data, it can be found that the number of dairy cows in China is higher than that of the United States, but there is a huge gap compared to both the production of raw milk and the level of dairy cattle per unit in the United States. The low level of dairy cow yield indicates that China's dairy industry lags behind in dairy cow breeding technology and pasture management [4]. On the other hand, the differences can also be elaborated on in terms of nutritional and hygienic standards for raw milk. China's raw milk nutritional hygiene standards are lower than those of the United States when comparing the relevant regulations of the Ministry of Agriculture and Rural Affairs of China and the United States; for example, the number of somatic cells per milliliter of raw milk in the United States is 750,000, while China has not established clear regulations on the number of somatic cells in raw milk. The United States also stipulates that the total number of colonies contained in each milliliter of raw milk should not exceed 100,000, while the total number of colonies per milliliter of raw milk in China should not exceed 2 million. The United States stipulates that the protein content of raw milk per 100 g should not be less than 3.4 g, while China stipulates that the protein content of raw milk should not be less than 2.8 g per 100 g. The United States stipulates that the fat content of raw milk should not be less than 4 g per 100 g, while China stipulates that the fat content of raw milk should not be less than 3.1 g per 100 g (U.S. and Chinese raw milk hygiene standards: https://www.aphis.usda.gov/animal_health/nahms/dairy/downloads/dairy_monitoring/btscc_2019infosheet.pdf (accessed on 21 June 2021). http://www.nhc.gov.cn/zwgkzt/zswdx/201306/1d5f7a29e2a14ae59aeee704fc11b2b0.shtml (accessed on 5 June 2013)). Through the comparison of data regarding raw milk nutrition and hygiene standards between China and the United States, it can be found that the nutritional hygiene standards of raw milk in China are lower than those in the United States. According to Italian Dairy Economic Consulting (U.S. and Chinese raw milk price: https://www.clal.it/en/index.php (accessed on 6 January 2021)), in 2020, the of price raw milk in the U.S. was 2.45 ￥/kg and in China it was 3.82 ￥/kg. In summary, the output of raw milk, the per unit yield of dairy cows, the price of raw milk, and the nutrient content of raw milk leads China to import a large number of dairy products from the United States [5]; this also evidences the objective fact that there is a large gap in the level of raw milk productivity between China and the U.S.

The level of dairy productivity is restricted by several factors. First, the influence of natural factors. As northern hemisphere countries with similar latitudes, raw milk production in the U.S. and China share similar natural environments; for example, in terms of seasonal alternation, water and heat conditions, and pasture resources [6]. Second, based on input and output factors, the dairy industry's productivity level is still affected by production and processing capacity, health and epidemic prevention, mechanization levels, fuel fees, and technological investment. Lastly, productivity level is shown in the form of dairy product price and nutrient content [7]. The above descriptive analysis reflects the lack of advanced productivity in China's dairy industry, which is the fundamental reason for China's continued import of large quantities of dairy products from the United States.

To explore the differences and influencing factors of raw milk productivity between China and the United States, this study investigated the abovementioned input factors to study their impact on the output of raw milk in China and the United States. The contribution difference of each input factor to the output value of raw milk between China and the United States was also studied. Finally, based on the results, relevant suggestions on how to narrow the gap in raw milk productivity between China and the United States are put forward.

2. Literature Review

There are differences in factor endowment between China and the United States in dairy production. Heckscher-Ohiln Thery (H-O Thery) [8] argued that differences in factor endowments are a major cause of international trade, and accordingly proposed the factor endowment theory (H-O Thery, 1933): differences in geographical location, pasture resources, labor force proficiency, and stages of dairy development between China and the United States result in differences in the resource endowments of the dairy industry between the two countries [6], which, in turn, lead to the advantages of each country in terms of productivity levels in the dairy industry [9–14].

There has been a relatively large amount of research on the factors influencing raw milk productivity. Mishra (2001) believed that pasture size, pasture organization, education level, and participation in technical extension activities affected the operator's labor and management income of dairy farms in the United States [15]. Mwanga (2019) used logistic regression and factor analysis to study the influencing factors of dairy farming decision-making in sub-Saharan regions, and held that management practices such as dairy farming experience, water supply, feed supply, and neighbor influences were significantly correlated with raw milk production [16]. Using a multivariate regression model, Bórawski (2020) stated that market-price Gross Domestic Product (GDP) affects the supply of raw milk production, while final consumption expenditure has a negative impact on raw milk production, and population growth has a positive impact on EU raw milk production [17]. Shine (2018) used a multiple regression model to analyze the impact of electricity and water consumption on the production of raw milk on Irish dairy farms, and found that the consumption of electricity and water in dairy farms has seasonal characteristics, and the increase in the number of cows and raw milk production will increase water and power consumption [18]. According to the existing research literature, it can be concluded that the production efficiency of raw milk production is significantly different due to the different input levels of production factors, such as cow population structure, the abundance of forage resources, and the level of pasture management.

The measurement methods used in the study of factors affecting the productivity of raw milk are relatively concentrated. The total factor productivity theory gradually replaced the input factor accumulation theory in the mid-to-late 1990s. Factor productivity is able to make a larger contribution to economic growth [19] and it is applied in agricultural economics. The existing research on the productivity level of raw milk mainly measures total factor productivity and technical efficiency. Ahmed (1995) used a stochastic frontier production function to decompose the growth of raw milk output in Vermont into technological progress and technical efficiency. It was calculated that the state's raw milk output annually grew by 2.5%, of which 56% of the growth came from scale effects and 44% from the improvement of production efficiency. The contribution rate of technical efficiency to raw milk productivity was 6%, and the contribution rate of technological progress was 94% [20]. By constructing the Tornqvist index, Kompas (2004) analyzed the changes in input, output, total factor productivity, and in terms of trade of the dairy industry in Australia; it was believed that the average annual growth rate of total factor productivity of dairy products in Australia decreased from 1.8% in 1979–1989 to 0.9% in 1990–1999. Affected by extreme weather, Victoria, as Australia's most important dairy production area, had a total factor productivity of dairy products of almost zero. It was also determined that the growth in dairy production in Australia in the 1990s was mainly due to the increase in factor inputs [21]. With the help of a multi-output distance function, Newman (2006) used the Irish National Farm Survey data from 1984 to 2000 to measure the productivity of dairy farms and found that the total factor productivity of Irish dairy farms had the characteristics of periodic growth; the efficiency level of large-scale dairy farms was the highest [22].

With different calculation methods, the calculation results will be different. The current mainstream productivity measurement methods can be classified into parametric methods, represented by stochastic frontier production functions, and non-parametric methods, represented by data envelopment analysis methods. Based on the sample data of 165 dairy farms in Greece, Theodoridis and Psychoudakis (2008) compared estimation results of the stochastic frontier function and the data envelopment analysis function, and concluded that the stochastic frontier function has a higher level of technical efficiency. According to the analysis of the Spearman rank coefficient, the results obtained by the two methods were positively correlated and highly significant. The most significant are the stochastic frontier model and the variable returns to scale data envelopment analysis (VRS-DEA) model [23]. Moreira (2006) used the stochastic frontier production function to measure the technical efficiency of raw milk production in Argentina from 1997 to 2002, and believed that the average technical efficiency fluctuated between 67.2% and 88.4%; the technical progress of dairy farms was remarkable, with an average annual increase of 16.8–17.7% [24]. Jan (2009) used the Malmquist index to measure the total factor productivity of Swiss alpine dairy farms from 1999 to 2007, and held that total factor productivity increased by 1.4% per year, and that the size of dairy farms had a strong positive effect on raw milk productivity [25]. Armagan (2012) measured large-scale dairy farms in Turkey and believed that the management cost of large-scale dairy farms was the highest, and that the external optimal conditions greatly fluctuated, while the cost of small- and medium-scale dairy farms was obviously lower. The total factor productivity of large-scale dairy farms did not increase, but declined. The reason was the lack of utilization of labor resources, and technical efficiency was inversely proportional to the scale of the dairy farms [26]. Madau (2017) used Data Envelope Analysis (DEA) to analyze the efficiency of European dairy farms from 2004 to 2012, and believed that the productivity of the European dairy industry was in a downward trend, and its future technical efficiency improvement space was small [27]. Using the stochastic frontier production function, Čechura (2021) deemed that after the abolition of milk quotas in the Europe Union (EU), the total factor productivity of raw milk in most member states has shown an upward trend, and that the scale effect was the main driving force for the improvement of raw milk productivity [28].

According to existing research, it can be seen that the influencing factors of raw milk productivity mainly include forage input, fuel, sanitation and epidemic prevention, maintenance, and infrastructure investment [29,30]. The research method of raw milk production efficiency is mainly based on the stochastic frontier production function, and the research on raw milk production efficiency mainly includes the scale efficiency, technical efficiency, and total factor productivity of raw milk production [31,32]. The main purpose of this study is to determine the influence and difference of factor inputs on raw milk productivity between China and the United States. To achieve this, we use the unified input and output factors of raw milk, and use the stochastic frontier production function to empirically analyze the influencing factors and differences of raw milk productivity in China and the United States, as well as the contribution of factor inputs to the output values of raw milk. This study can fill gaps in the existing research that use non-uniform variables to empirically analyze the impact of factor inputs on raw milk productivity in a single country; non-uniform variables would make it impossible to accurately measure raw milk productivity in different countries from an empirical perspective. This study would also avoid the limitations of using descriptive methods to compare the current situation of raw milk production in multiple countries, so as to provide a reference for China on how to narrow the gap in terms of raw milk productivity level with the United States.

3. Materials and Methods

3.1. Stochastic Frontier Production Function

To estimate the level of raw milk production in two countries, this paper applies a stochastic frontier production function to estimate the production efficiency of raw milk and its influencing factors. The Frontier production function is a parametric analysis method used to estimate production efficiency, usually based on the Cobb-Douglas (C-D) or the superlogarithmic form. It was first proposed by scholars such as Aligner, Loveall and Schmidt, Meeusen, and Van Den Broeck [33,34]. In subsequent studies, scholars have improved and perfected the model on this basis. Its basic form is as follows:

$$y_{it} = \beta X_{it} + (V_{it} - U_{it}) \tag{1}$$

Formula (1) is the benchmark model used, where y_{it} refers to the output; X represents the matrix of various inputs; β represents a set of parameters to be estimated. The error term in this model consists of two independent parts. The first part is the classical random error term V_{it}, which is customarily assumed to obey the normal distribution N(0, $\sigma_v{}^2$). In the second part, U_{it} is a non-negative random term that denotes the technical efficiency loss of production unit i in period t, and it is usually assumed that U_{it} obeys a half-normal distribution N(m_{it}, $\sigma_v{}^2$). In this formula, m_{it} is equal to z_{it} multiplied by d, denoting the index of lost production efficiency; where z_{it} represents the p variables affecting the technical efficiency of production, unit i and d represent its corresponding parameters to be estimated. These parameters reflect the degree of influence of the variable on technical efficiency. If the parameter is negative, it indicates that the variable has a positive impact on technical efficiency; conversely, if the parameter is positive, it indicates that the variable has a negative impact on technical efficiency.

As to the estimation method of the parameters, the maximum likelihood method is chosen because the error term of the function differs from the classical assumption [35]. It is assumed that $\sigma^2 = \sigma_v{}^2 + \sigma_u{}^2$ and $\gamma = \sigma u^2/(\sigma v^2 + \sigma_u{}^2)$; γ denotes the proportion of the random disturbance term that is technically invalid and it takes values between 0 and 1. In this way, an initial value of γ can be obtained by searching for the optimal solution within the interval; then, using non-linear estimation techniques, the maximum likelihood estimates of all parameters are obtained. A statistical test of the estimated value of γ reflects whether the variation in the technical efficiency of the production unit is statistically significant. When γ tends to 1, the error in the frontier production function is mainly due to the random variable U_{it}. This indicates that the difference between the actual output of the production unit and the maximum possible output is mainly due to the difference in the effectiveness of the use of the technology (i.e., the ineffectiveness of the technology). When γ tends to zero, the difference between the actual output and the maximum possible output is mainly due to the random error v, and there is no significant difference in technical efficiency at this point. The estimated value of γ can be used as a basis for comparing the degree of inefficiency terms of different units and testing the reasonableness of the model set.

In constructing the empirical model, it is necessary to rely on the C-D production function and the superlogarithmic production function to calculate the input-output efficiency. Compared with the C-D production function, the factor output elasticity of the superlogarithmic production function reflects the substitution effects and interactions between input factors, as well as time-varying effects. It thus reflects the differences in the technical progress of different inputs and also relaxes the strict assumption of technological neutrality [36], which can reveal more characteristics of the economic system. In addition, its form is more flexible [37], which can effectively avoid the deviation caused by the misconfiguration of the function.

Therefore, combined with the data characteristics of this paper, this study will use the superlogarithmic stochastic frontier production function to analyze the input-output efficiency of raw milk production in China and the United States. The specific model expression is as follows:

$$LnY_{it} = \beta_0 + \beta_1 LnX_{1t} + \beta_2 LnX_{2t} + \beta_3 LnX_{3t} + \beta_4 LnX_{4t} + (V_{it} - U_{it}) \tag{2}$$

In Formula (2), Y_{it} represents the output of i production unit in t period. X_{1t} represents the fodder investment in the sample interval; X_{2t} represents the sanitation and epidemic prevention costs in the sample interval; X_{3t} represents the fuel and impetus expenses in the sample interval; X_{4t} represents the repair and safeguard expenses. In order to distinguish the input-output variables of raw milk between China and the United States, in terms of output, the output value of raw milk in China is recorded as Y_c, and the output value of raw milk in the United States is recorded as Y_u. In terms of input of production factors, the expense of feed required for raw milk production in China is recorded as X_{1c}; the expense of feed in the United States is recorded as X_{1u}. In terms of sanitation and epidemic prevention, the expense of sanitation and epidemic prevention required for raw milk production in China is recorded as X_{2c}, and the expense of sanitation and epidemic prevention in the United States is recorded as X_{2u}. In terms of fuel and impetus expenses, China is recorded as X_{3c}, and the United States is recorded as X_{3u}. In terms of maintenance expenses, Chinese raw materials maintenance costs invested in milk production are denoted as X_{4c}, and raw materials maintenance costs in the United States as X_{4u}.

Something that requires a special explanation here is that the input-output efficiency model of raw milk production in China and the United States discards labor costs, land costs, and depreciation costs of fixed assets. There are three main reasons for this. Firstly, because of the statistical caliber problem in China and the United States, China only counted the number of days of domestic labor required for raw milk production, with the unit of days, while the United States counted the labor costs, with the unit of dollars per hundredweight. Secondly, China did not count the land cost for raw milk production, while the United States did. Thirdly, China has created statistics on the depreciation of fixed assets, while the United States has created statistics pertaining to the capital recovery of machinery and equipment. After consulting the accounting professor, it is believed that the depreciation of fixed assets in China cannot be equivalent to that in the United States, so fixed assets depreciation expenses are abandoned.

3.2. Data Source

This paper uses the panel data of the input and output of raw milk in China and the United States from 2005 to 2020, of which the input and output data of China's raw milk comes from the National Agricultural Product Cost and Benefit Data Compilation (https://data.cnki.net/yearbook/Single/N2021120200 (accessed on 1 July 2022)) (2006–2021), and the input and output data of the United States's raw milk comes from the USDA website (https://www.ers.usda.gov/data-products/milk-cost-of-production-estimates.aspx (accessed on 3 October 2022). In terms of data processing, the input and output units of raw milk in China and the United States are denominated in RMB and U.S. dollars; thus, this study uses the annual Consumer Price Index (CPI) of China and the United States, respectively, to make a flat reduction in the input expense and output value of raw milk to eliminate the impact of inflation. In this paper, the production efficiency of raw milk in China and the United States is measured using Frontier 4.1 software (The Centre for Efficiency and Productivity Analysis (CEPA), Brisbane, Australia,).

4. Results

The maximum likelihood method was used to estimate the model parameters, and the specific estimation results are shown in Table 1. From the overall regression results, most of the parameter estimation results passed the 1% significance level test, which proved that the input-output technical efficiency model of raw milk production in China and the United States was effective.

In the Stochastic Frontier Analysis (SFA) model, γ in Table 1 represented the technical invalid item, which was the proportion of the variance of the technical inefficiency to the coincident variance. The technical inefficiency term of raw milk production in China was γ = 0.1214, which passed the T-test and was significant at the 1% significance level, which indicated that the impact of technical inefficiency on the production of raw milk in China was 12.14%. The technical inefficiency term of raw milk production in the United States was γ = 0.0109, which also passed the T-Test and was significant at the 1% significance level; that is, the impact of technical inefficiency on the production of raw milk in the United

States was 1.09%. The horizontal comparison showed that the technical efficiency loss of raw milk production in China was much greater than that in the United States.

Table 1. Estimation results of the stochastic frontier production function.

	Variable	Coefficient	S. E	T-Value
China raw milk production	Constant term	4.9396 ***	0.2371	20.8318
	Feed expense	0.4843 ***	0.0268	18.0884
	Health and epidemic prevention expense	0.0632 ***	0.0174	3.6361
	Fuel and impetus expense	0.0869 ***	0.0150	5.7811
	Maintenance expense	0.0215 **	0.0100	−2.1476
	δ^2	0.0205 ***	0.0020	10.3941
	γ	0.1214 ***	0.0432	2.8095
U.S. raw milk production	Constant term	2.3596 ***	0.1413	16.7012
	Feed expense	0.2895 ***	0.0507	5.7159
	Health and epidemic prevention expense	0.0094	0.0521	0.1799
	Fuel and impetus expense	0.1924 ***	0.0529	3.6336
	Maintenance expense	−0.0467	0.0626	−0.7463
	δ^2	0.0170 ***	0.0020	8.5881
	γ	0.0109 ***	0.0041	2.6769

Note: ** and *** represent passing the significance test at the levels of 5% and 1%. S·E represents Standard Error; T represents T-Value.

From the impact of various input factors on raw milk output, the input of feed expenses and health and epidemic prevention expenses all had a significant positive role in promoting the growth of raw milk output value in China and the United States, and the input of fuel and impetus expenses had a significant positive impact on the growth of raw milk output value in China. For China, it can be seen from Table 1 that at the 1% significance level, every 1% increase in feed input in China's raw milk production process will drive China's raw milk output value to increase by 0.48%. At the 1% significance level, every 1% increase in health and epidemic prevention costs will drive the output value of each cow to increase by 0.06%. Additionally, at the 1% significance level, every 1% increase in fuel and impetus expenses will drive the output value of raw milk to increase by 0.09%. Maintenance expenses had a positive and negative influence on the growth of China's raw milk output. At the 5% significance level, every 1% increase in maintenance expenses will lead to a 0.02% decrease in China's raw milk output. For the United States, the input of feed expense and fuel impetus expense in the United States has a significant positive effect on the growth of its raw milk output value. At the 1% significance level, every 1% increase in feed expenses will drive a 0.29% increase in the output value of raw milk in the United States, and every 1% increase in fuel expenses will drive a 0.19% increase in its raw milk output value. However, the impact of health and epidemic prevention expenses and investment of maintenance expenses on the value of raw milk production in the United States was not significant.

According to each factor's input-output elasticity coefficient and average annual growth rate, the contribution rate and contribution share of each input factor were calculated. The specific results are shown in Table 2. It can be seen from the table that the development of raw milk production in China is dominated by the increase in the number of factor inputs, while that in the United States has been primarily driven by technology.

For China, among the input factors of raw milk production in China, the average annual growth rate of feed expenses, fuel and impetus expenses, and health and epidemic prevention expenses are relatively high, and their contribution growth rates are 5.23%, 0.64%, and 0.42%, respectively; important driving factors for the growth of China's raw milk output value. Maintenance expenses have a negative effect on the growth of raw milk output value. The contribution share of scientific and technological progress rate to the growth of China's raw milk output value is 34.92%, and the growth rate of scientific and technological contribution is much lower than that of feed costs, which indirectly shows that the current production of raw milk in China is still dominated by the increase in the number of input factors, and there is still huge room for development in the transformation of raw milk production to a technological growth mode. For the United States, the input of feed, fuel, and impetus expenses contributed 1.49% and 1.21% to the output value of raw milk in the United States, and their corresponding contribution shares were 25.74% and 20.77%, respectively. The contribution share of technological progress to the growth of raw milk production value in the United States was 53.77%, that is because the current growth of raw milk production value in the United States is dominated by scientific and technological progress, which is mainly reflected in the continuous promotion of dairy cattle breeding technology, feeding technology, disease control technology, and ranch management.

Table 2. Contribution of input factors to the growth of raw milk output value.

Variable		Elasticity Coefficient	Average Annual Growth Rate	Contribution Growth Rate	Contribution Share
China	Feed expense	0.4843	10.7993%	5.2305%	52.5255%
	Health and epidemic prevention expenses	0.0632	6.5809%	0.4159%	4.1764%
	Fuel and impetus expenses	0.0869	7.3197%	0.6364%	6.3912%
	Maintenance expense	−0.0215	6.0326%	−0.1299%	1.3045%
	Raw milk production value	/	9.9580%	/	/
	Technological progress rate	/	/	3.4769%	34.9159%
U.S.	Feed cost	0.2895	5.1597%	1.4939%	25.7375%
	Health and epidemic prevention expenses	0.0094	1.9842%	0.0186%	0.3201%
	Fuel and impetus expenses	0.1924	6.2658%	1.2054%	20.7676%
	Maintenance expense	−0.0467	3.7817%	−0.1767%	3.0446%
	Raw milk production value	/	5.8043%	/	/
	Technological progress rate	/	/	3.1212%	53.7732%

From the above empirical results, it can be found that there is still a big gap between the production of raw milk between China and the United States in terms of technological progress. Comparing the contribution of various input factors to the output value of raw milk in China and the United States, it is believed that although the contribution growth rate of technological progress in raw milk production in China to the output value of raw milk is higher than that of the United States and the growth potential is relatively large, its contribution share to the growth of raw milk output value was much lower than that of the United States, with a gap of about 18.85%. Therefore, relying solely on the growth of factor input quantity is not conducive to the sustainable development of China's raw milk production, and the transformation of China's raw milk production to technological growth has a long way to go.

5. Discussion

Similarities and Differcences within the Existing Research

Many scholars have discussed the scale of dairy farming in China. The scale of dairy farming in China has continuously improved, and the investment in dairy farm construction has rapidly increased, but the maintenance cost has had a significant negative impact on the output value of China's raw milk. From 2005 to 2020, the proportion of large-scale dairy farms with more than 100 cows in China increased from 11.2% to 67.2% [38,39]. The demand for advanced equipment becomes more and more obvious with the increase in the number of dairy scale dairy farms, which promote the purchase of new equipment such as mechanized milking and Total Mixed Ration (TMR) feeding, scraping plates for defecation, automatic estrus identification, automatic milk volume measurement, and electronic earmarks [5,40]; all of which would result in additional capital investment. The expansion of the breeding scale has had a diminishing effect on gains in dairy cattle breeding, especially the depreciation of fixed assets and maintenance costs. These have had a negative impact on China's raw milk output values, which have had a negative impact on overall breeding efficiency [39,41].

Previous studies have shown that the technology of dairy cattle breeding in China is slowly improving. The scale efficiency and allocation efficiency of China's dairy farms are high, and the overall level of technical efficiency and cost efficiency is low [7,41]. For dairy farms, technological progress is the key driving factor for the growth of dairy cow total factor productivity, but the truth is that, except for large-scale dairy farms, technological progress changes are obviously insufficient in promoting China's free-range, medium- and small-scale dairy farms [41–43]. From 2010 to 2018, on large-scale dairy farms, the total factor productivity of raw milk in China decreased by 4.26%, and technological progress only increased by 0.88% [42]. However, the ratio of concentrate to crude feed has had a significant positive impact on the technical efficiency and scale efficiency of dairy cattle breeding and has increased rapidly [40]; therefore, the growth of raw milk value in China is oriented by feed input. Conversely, the growth of raw milk output value in the United States mainly depends on scientific and technological progress. From 2000 to 2016, the total factor productivity of large-scale raw milk in the United States increased by 2.85% and technological progress increased by 3.46% [44]; which means the growth of raw milk value in the U.S. is affected by technological progress. The backwardness of cow breeding technology and pasture management experience leads to the slow progress of raw milk production technology in China. According to the Council on Dairy Cattle Breeding (CDCB), the Holstein is recognized as a high-quality cow breed. It was first introduced to the United States in 1795, and in 1914 the USDA began to carry out Dairy Herd Improvement (DHI). In 1960, the United States Dairy Artificial Fertilization Center, DHI, and Holstein Friesian Association formulated a unified selection standard and comprehensive selection index for dairy cattle, selected excellent bulls for genetic improvement in dairy farms and sold breeding cattle, cold winter semen, and embryos to the world. Holstein cattle were bred and improved in the United States, and accounted for 90% of the total number of American cows. In 2020, the average annual yield of Holstein cattle registered in the United States will reach 12,733 kg, the milk fat rate will be 3.84%, and the milk protein rate will be 3.1%. Artificial insemination has a positive impact on farm profits and a negative impact on milk production costs. While advanced breeding technology has a positive impact on the milk yield of each cow [45], the generic [46] adoption of management practices, such as complementary bovine somatotropin [47] and increased milk frequency (Stelwagen, 2001), have all contributed to increase in the productivity of U.S. daily cows [48]. American dairy farms widely apply TMR, wireless cow identification devices, biotechnology, fecal waste treatment technology, etc., to provide technical support for the sustainable development of pastures [49]. While the USDA, Ranch Management Consultants, and other institutions provide technical support, financial support, and other services for American cows. Compared with the United States, the basic work of cow breeding in China is weak, the independent cultivation ability of cow core provenance is not strong, the accuracy of genetic evaluation of genetic organization selection needs to be improved, the technical efficiency of improved cow breeding is low, and the quality supervision of cow frozen semen products is not ideal. In 2008, the Ministry of Agriculture and Rural Affairs of China began to implement the DHI project. In 2012, China independently developed and established a technology platform for cow genome selection, and built a reference group for Chinese Holstein cattle genome selection [50]. China's experience in ranching management is usually borrowed from European and American countries and improved according to its own situation [5]. The late start in terms of breeding technology, lagging dairy cattle breeding technology, and lack of management experience are the main reasons for the weak level of dairy cattle breeding technology in China, which ultimately leads to a lower level of raw milk productivity in China than in the United States.

This study explored the influencing factors and differences in raw milk productivity levels between China and the United States from an empirical perspective, analyzed the impact of factor inputs on raw milk output value, and discussed the differences in raw milk production efficiency and production technology. Although this study was committed to being rigorous and scientific, there were still limitations in that this study did not include land costs and labor costs, due to the differences in statistical caliber between China and the United States. In future research, we will use unified methods and data to calculate the total factor productivity and its decomposition index of raw milk production in China and the United States, and determine the gap between raw milk production in China and the United States in terms of technological progress, technical efficiency, and scale efficiency.

6. Conclusions and Recommendation

6.1. Conclusions

In order to explore the difference between China and the United States in terms of raw milk productivity, based on the input-output data of raw milk production in China and the United States from 2005 to 2020, this paper used the stochastic frontier production function to compare and analyze the differences in the influence degree and contribution of each input factor on the output value of raw milk in China and the United States, and analyzed the reasons for these differences; establishing the following conclusions:

Firstly, China's raw milk production technology is inefficient and higher than that of the United States. Production technology inefficiency in terms of animal husbandry production is an objective problem, and China's raw milk production technology invalidity rate is 0.1214, while it is 0.0109 in the United States. The current Chinese raw milk production efficiency loss is significantly higher than that in the United States, resulting in high input and low output in raw milk production in China. This also shows that there is still much room for improvement in China's technological levels in raw milk production.

Secondly, feed costs and fuel power costs have a significant and positive role in promoting the growth of raw milk output value in China and the United States. Health and epidemic prevention costs and maintenance costs significantly affect the output value of China's raw milk, but the impact on the output value of raw milk in the United States is not significant. The positive impact of feed costs on China's raw milk output value is greater than that in the United States. One of the reasons is that the price of forage for Chinese dairy cattle is generally higher than that of the United States, and the other is that the inventory of Chinese dairy cattle is 3.24 times that of the United States. The per-unit yield level of dairy cows in the United States is 1.49 times that of China. China's raw milk production needs to consume more forage, which would comprehensively lead to an impact on China's forage input in terms of the output value of raw milk and make it higher than that of the United States. The positive impact of fuel costs on the output value of raw milk in the United States is greater than that in China. The first reason being that the production scale of raw milk in the United States is greater than that of China, and the second reason is that the degree of dairy farms in the United States that combine dairy cattle breeding and forage planting is higher than that in China; thus, U.S. ranches need to consume more fuel in forage planting, feed processing, raw milk storage, and transportation. Therefore, the impact of fuel costs on the output value of raw milk in the United States is greater than that in China.

Thirdly, the growth of China's raw milk output value is mainly based on the increase in the number of factor inputs, while that in the United States is mainly based on technological progress. Comparing the contribution of various input factors to the growth of raw milk output value in China and the United States, it is found that the contribution growth rate and contribution share of feed expenses to China's raw milk production value are greater than the contribution growth rate to the United States. The contribution of technological progress to China's raw milk production is smaller than that to the United States, which indicates that the current growth of China's raw milk output value mainly comes from the increase in the number of factor inputs; thus, the contribution of technological progress to China's raw milk production is far lower than that of the United States. Therefore, a production model that relies solely on the quantitative increase of factor inputs is unsustainable, and the transformation of China's raw milk production to the technology-based model has a long way to go.

6.2. Policy Recommendation

(1) China should steadily promote the moderate-scale breeding of dairy cows and try to avoid the inefficiency rate of raw milk production technology caused by the diseconomies of scale. At the same time, moderate-scale breeding is conducive to reducing the cost of equipment maintenance and is conducive to the sanitation and epidemic prevention of pasture. (2) Developing the integrated production mode of planting and breeding, as well as promoting the development of grain into feed, will help reduce the problem of high feed cost in China's raw milk production. At the same time, cow dung could be returned to the field after green treatment to reduce environmental pressure. (3) Accelerate the genetic improvement of the dairy cattle population, strengthen the innovation of molecular breeding technology for dairy cattle genome selection, carry out research on independent breeding of high-quality bulls, establish a national dairy cattle big data breeding platform, speed up the promotion of improved dairy cattle varieties, and essentially improve the productivity of raw milk in China. (4) Learn from the pasture management experience of European and American countries, carry out technical training for dairy farmers and low-interest loan activities.

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