Total Factor Productivity in Dairy Buffalo Milk Production in Nueva Ecija, Philippines

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ABSTRACT

This study analyzed the total factor productivity in dairy buffalo milk production in Nueva Ecija, Philippines. Specifically, it aimed to identify the factors that affect dairy buffalo milk production and analyze technical efficiency, scale efficiency, and technological change as sources of TFP growth. Panel data was established by gathering data from randomly selected dairy buffalo milk producers in Nueva Ecija for the years 2017 and 2020. The stochastic frontier analysis was applied to a Cobb-Douglas production function with an inefficiency effects model. It was found that the statistically significant factors of milk production were cows, forage areas, and dairy feeds. Cleaning frequency was the sole predictor that explained the variability among the respondents' technical inefficiency. For the years covered, the computed TEC was zero, while scale efficiency change and technological progress were at (-0.52%) and 48.60%, respectively, making the total TFP change equal to 48.08%.

Keywords: *dairy farm productivity, technical efficiency, waste management, sustainable farming*

Introduction

An analysis of the performance of Philippine agriculture using data from the Philippine Statistics Authority (PSA) showed that livestock's dairy subsector contributed to around 0.04% of the total value of agricultural production from 2016 to 2019 at constant 2000 prices. The volume of milk production declined from 0.05% annual average growth rate between 2002 and 2015 to 0.03% between 2018 and 2019. The latest comprehensive Dairy Industry Performance Report in 2016 posted a milk production of 20.39 million liters in liquid milk equivalent (LME), 34.93% of which was contributed by the water buffalo species *(Bubalus bubalis)*. Buffalo's milk volume increased by 3.83%, with 6.86 million liters in 2014 jumping to 7.12 million liters in 2015. The report further provided that only 1.12% of the total milk demand was supplied locally, underscoring the extremely low per capita supply per year of 16.20 liters in 2015. Approximately 99% of imported products are made using technologies (e.g., "powderization" and ultra-high temperature (UHT)) that are too advanced for our local processors (PSA 2016). The report basically described the Philippines as an import-dependent country with low productivity growth over the years.

The same report also provided the breakdown of cattle, buffalo, and goat inventory as of January 2016, revealing that dairy animals comprise of only less than 1% of their respective total headcounts, with dairy buffalos at 17,802 out of 2.9 million heads (0.62%). Based on the 2018 Carabao

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Situation Report (PSA, 2019), there are 2.87 million heads in inventory as of January 1, 2019 – 99% of which were tended on a backyard scale. The regions with the most number of buffalos are the Bicol Region, Western Visayas, and Central Luzon, accounting for nearly 30% of the total. These figures point to low number of cows as a driver of productivity growth. Meanwhile, based on secondary data from the Philippine Carabao Center (PCC), Nueva Ecija is the top dairy province with 3,139 purebred riverine female buffaloes and with approximately 3:1 female-to-male ratio. Of the females, 42% are cows, while 52% are heifers – the future cows. The province produced 1.5 million liters of milk in 2019, which accounted for 18% of the total buffalo milk production in that year.

With the efforts of the government, the National Dairy Authority (NDA) was created in 2015 by virtue of Republic Act (RA) No. 7884 and was placed under the Department of Agriculture (DA). It is mandated to ensure the accelerated development of the Philippine dairy industry through policy direction and program implementation. Before NDA, the PCC, a national agency attached to the DA, was created through RA No. 7307 in 1992 to conserve, propagate, and promote carabaos as sources of milk, meat, draft power, and hide to benefit the rural farmers. Aside from research programs, they have an operational presence in most regions, providing various support on production, market, extension, education, and training. However, despite the establishment of PCC and NDA, dairy production performance still suffered a continuous decline from the observed peak in 1990 to the trough in 1998. It took two decades for the subsector to produce again at 19 million liters capacity, implying that growth acceleration is not yet achieved.

One of the components of the PCC's Carabao Development Program is the Genetic Improvement Program (GIP). Its main strategy is to upgrade the local swamp-type genetic stock by infusion of the dairy-proficient riverine-type genes through crossbreeding via artificial insemination (Pablico 2006). In 1982, quality frozen semen from India and Pakistan was imported as input to this cause. Subsequently, live animals with superior dairy genetics were also imported from America (1994), Bulgaria (1995-1996), Brazil (2009), and Italy (2013-2014) partly for progeny testing by PCC to harness the dairy production capacity and partly for loaning out to qualified farmers (Del Barrio 2016). However, gaps in the performance of imported buffaloes were observed. For instance, imported buffalos tended by Nueva Ecija dairy farms produce a daily average of 4.77 liters per cow as compared to 8.22 liters per cow in Italy (Borghese 2013), 6.38 liters per cow in Brazil (Hurtado-Lugo et al. 2011), and 6.7 liters per cow in Bulgaria (Borghese and Mazzi 2004).

Considering these gaps, this study attempted to answer the following research questions, "Does the dairy buffalo subsector have the potential to increase its productivity, and if so, what could drive its productivity growth?" Accordingly, this study analyzed the total factor productivity of dairy buffalo milk production given the case of Nueva Ecija, Philippines. Specifically, it aimed to determine the factors that affect dairy buffalo milk production; analyze technical efficiency (TE), scale efficiency, and technological change; and provide recommendations to increase productivity.

Theoretical and Conceptual Framework

Theoretical Framework

This study is premised on the theory of production. Production refers to the transformation of inputs into outputs or products consistent with the producer's goals. The basic tenet in this theory is the production function which refers to the technical or physical relationship between inputs of resources and outputs of goods per unit of time and therefore is the best representation of the current state of technology (Debertin 2012). A general way to write a production function is:

$$y = f(x) \quad (1)$$

where y is the quantity of output and x is a vector of n inputs. This function gives the maximum producible output given a farmer's TE and the current state of technology.

Measuring production functions is integral in analyzing productivity. A firm's productivity is basically the ratio of the outputs produced to the inputs used. If the firm produces only one output and uses a single input, computation of productivity is easy. However, this is often not the case, particularly in agriculture, where multiple inputs are necessary to produce at least one output. For such, a method for aggregating inputs into a single index is necessary to measure productivity. When this happens, it becomes total factor productivity (TFP).

Theoretically, TFP analysis postulates that output can increase not just by increasing the current input levels. One way to increase the maximum output is through a shift in technology or technological progress. Assuming technical inefficiency exists among farmers, productivity can also grow by enhancing TE. Another source of TFP is the ability to operate toward the optimal scale of operation, thereby reflecting scale efficiency.

Conceptual Framework

The problem at hand is whether there is a potential to increase the productivity of dairy buffalo milk production and identify the sources of this growth potential towards formulating effective policy and program interventions. As such, TFP in dairy buffalo milk production is analyzed by looking at its components – TE, scale effects, and technological progress. The milk production flow includes the use of inputs to wit, capital, labor, cows, forage area, and dairy feeds. These inputs are transformed through the dairy production process to produce milk.

An important concept necessary in determining the sources of TFP is the production frontier. The production frontier, representing the maximum output attainable at given input levels and technology available, will be the basis for estimating farmers' TE and scale efficiency, while the shift in this frontier will reveal technological change. Referring to Figure 1 based on Quilloy (2019), the sources of output growth through TFP change were possible first by movement towards the frontier from a to b (i.e. improvement in TE (output increasing from q_1 to q_2)), and then from b to c due to the shift in technology from PF_1 to PF_2, thereby setting a higher maximum attainable output for any given input level (i.e. technological progress (output increasing from q_2 to q_3)).

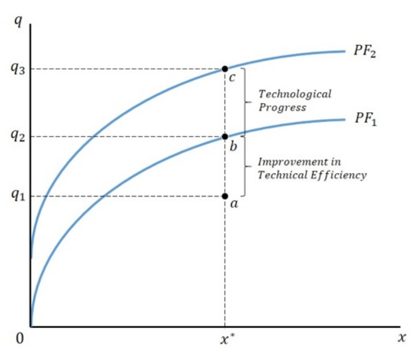

Figure 1. Improvement in technical efficiency and technological progress as sources of TFP change

When time is factored in, a source of productivity change called technological change is possible involving technological advances such as product and process innovations. This technical change is represented by the upward shift of the frontier from PF_1 to PF_2, as shown in Figure 1. Upward frontier shifts connote higher attainable output using the same input level. Technological progress may be neutral, that which is not associated with any of the factors of production, or biased, that which is embodied in at least one of the factors of production or a combination of both.

Meanwhile, TE refers to the ability of the farmer to produce the maximum output given his or her input level selection and technology. In Coelli *et al.* (2005), efficiency was distinguished from productivity by first introducing the production frontier, the locus of production sets representing maximum output at a given indexed level of inputs, as depicted in Figure 1. Line PF_1 is the initial production frontier and is reflective of the state of technology at that time. Thus, a firm operating at the frontier (point b) is considered fully technically efficient, while a firm located beneath the frontier (point a) carries a certain degree of technical inefficiency. Technical efficiency change (TEC)is a measure of the rate at which a farm's output moves toward or away from the frontier.

Finally, scale efficiency refers to the farms' degree of scale optimization. Figure 2 illustrates the distinction between TE and productivity (Coelli *et al.* 2005) by using a ray through the origin to measure productivity at a particular data point with slope y/x, representing productivity. The greater the slope of the ray – depicting movement from A to B-- implies improved productivity. However, moving to point C, the ray from the origin is at a tangent to the production frontier and thus, defines the point of maximum possible productivity. This latter movement exploits scale economies with point C as the technically optimal scale, and therefore any other point on the production frontier indicates lower productivity.

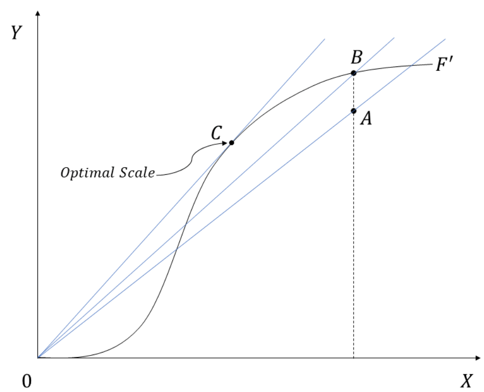

Figure 2. Production frontier with optimal scale depiction

Methodology

Sources of Data and Methods of Data Collection

Since the presence of technological progress between identified time periods was assumed, panel data was necessary to analyze the total factor productivity of dairy buffalo milk production. Secondary data coming from PCC's Intensified Research-based Enterprise Build-up (iREB) online database were used for the farmers' 2017 production data. Interviews guided by the survey instrument developed by PCC's Business Development and Commercialization Unit (BDCU) were conducted to gather data about the respondents, their farm, and their milk production output and input for a given year. The iREB online database[1] initiative was started in 2016 in lieu of PCC's 2015 to 2020 medium-term strategy focusing on measuring client-level incomes. Following random selection, 2017 was selected as the baseline year in establishing the panel data vis-à-vis the year 2020. The 2017 data were collected by PCC personnel under the carabao-based enterprise development (CBED) program.

For the production year 2020, primary data were gathered through trained enumerators using the same survey instrument in 2017. A separate survey instrument was developed to gather primary data on respondents' 2017 and 2020 waste management practices. These were gathered simultaneously with the 2020 dairy production data via a combination of face-to-face and phone call interviews, considering the travel constraints due to COVID-19 protocols at that time.

Sampling Procedure

Study area was selected based on the following criteria: (1) buffalo milk production volume; (2) population of dairy buffalo animals; (3) value chain development in terms of the number of milk producers, organized groups, processors, and marketing outlets; and (4) presence of the PCC, which ensures the flow of appropriate technologies and practices and provision of various technical assistance.

A review of the data coming from PCC's CBED program vis-à-vis the criteria provided revealed Nueva Ecija as the most viable study area. Aside from farm-level data availability and quality, Nueva Ecija was selected because, province-wise, it has the highest population of riverine-type water buffaloes, milk production, and a number of organized groups and processing plants in the country. This is also where the National Headquarters of PCC, which operates with a pool of scientists and researchers as well as technical extension officers and veterinarians, is located.

Meanwhile, selection of respondents in 2017 was guided by the following criteria: (1) the herd is composed only of purebred riverine-type buffalos; (2) the farmer employs individual animal and herd level production and financial recordkeeping; (3) the farmer tends at least two adult females ready for breeding; and (4) the farmer has been actively selling his/her milk harvest in any type of market as evidenced by his/her sales records.

According to the iREB database for the reference year 2017, there are 116 farmers in Nueva Ecija. Initially excluded from the final sample were 21 farms for having incomplete production data and one medium-scale farm tending 25 lactating cows making the smaller population composed of 94 backyard/small-scale farms. Considering budget and mobility limitations due to the COVID-19 pandemic, 60 farmers were randomly selected from these 94 farms in 2017 to initially serve as the respondents for 2020. Creating balanced panel data, the same 60 randomly selected farms were collected with primary data for 2020. However, after gathering their 2020 production data, not all 60 farmers satisfied the criterion that all their animals must be the riverine type. To further homogenize the population, the farms which employed swamp-type or crossbred buffalos were all excluded making the final sample consisting of 44 dairy buffalo farms.

Analytical Procedures

The milk production output and inputs, farmer characteristics, and waste management variables were first described using applicable descriptive statistics such as frequency count, percentage, mean, maximum, and minimum using Microsoft Excel 2016 software. Paired sample t-test was used to describe how selected variables changed between the two time periods and to confirm whether there was TEC among farmers between 2017 and 2020.

[1] This online database is accessible through the web address: http://ireb.pcc.gov.ph.

In analyzing and fully decomposing total factor productivity, the stochastic frontier analysis, a parametric approach initially and independently proposed by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977), was applied. It relaxes the assumption that all farmers are technically efficient. As a methodological approach, the parametric method of stochastic production frontier estimation uses a composite error term whereby one represents pure random error while the other represents technical inefficiency. Moreover, assuming panel data is available, the estimation of a stochastic production frontier with a time variable leads to the determination of technological change between specified time periods.

The Stochastic Production Frontier (SPF) can be represented by the following equation according to Battese and Coelli (1995):

$$y_{it} = \exp\left(x_{it}\beta + v_{it} - u_{it}\right) \tag{2}$$

where y_{it} denotes output for the *i*th farm in the *t*th time period; x_{it} is a vector of inputs and other explanatory variables for the *i*th farm in the *t*th time period; β is a vector of unknown parameters to be estimated; v_{it} is a normally distributed random error with zero mean and constant variance; and u_{it} is a nonnegative unobservable random error capturing the technical inefficiency of the i^{th} farm in period t such that the inefficiency effects can be expressed as:

$$u_{it} = z_{it}\delta + w_{it} \tag{3}$$

where w_{it} is a random variable defined by the truncation of the normal distribution with zero mean and variance σ^2, z_{it} is a vector of variables tested for exhibiting influence in farm's efficiency and, in this study's case, include farmer's age and education and dummy variables representing his/her waste management practices, and δ represents the vector of parameters to be estimated. Accordingly, this study followed the estimation and analytical procedures of Quilloy (2019) using the Stata v.14 software package whereby, in the panel data setup, technological progress, and scale efficiency change were estimated while the TE was analyzed by estimating separate frontier production functions for the years 2017 and 2020.

Econometric Model

The stochastic production function for the panel data case was expressed in Cobb-Douglas form with a time dummy to capture technological change as follows:

$$lnY_{it} = \beta_0 + \sum_{k=1}^{5} \beta_k lnX_{kit} + \theta T + v_{it} - u_{it}. \tag{4}$$

where the subscripts *k,i,* and *t* refer to the k^{th} input, the i^{th} farm, and the t^{th} time period, respectively; *T* is a time dummy variable representing technological change having a value of 0 for 2017 data and 1 for 2020 data; β and θ are the parameters estimated and v_{it} and u_{it} are as previously discussed. Equation 3 was followed as the technical inefficiency model with the farmer's age, education, and adoption of three waste management practices (i.e. vermicomposting, waste segregation, and cleaning frequency) as independent variables. Since the leading causes of low production at the farm level are mastitis and hardware diseases (Sarabia *et al.* 2015), waste management practices were tested as explanatory variables of technical inefficiency because it is believed as the root cause of such health problems among animals. The non-negative error term was also assumed to follow an exponential distribution. The study's variables, together with the description, are enumerated in Table 1 and Table 2.

Table 1. List of stochastic production function variables and their expected parameter signs according to literature

Dependent Variable	Description, Type, Unit	Expected Sign, Hypotheses
Milk	The Total Volume Of Milk Produced, Continuous, In Liters	
Explanatory Variables		
1. Capital	Farmer estimation of all assets employed as of the period end of each year excluding the value of the cows, continuous, in PHP	(+/-) – Sarabia *et al.*, (2009) (No Effect) – Al-Sharafat (2013)
2. Labor	The number of man-days devoted to the dairy farm by the owner and other people such as family member/s and hired workers, discrete, in man-days.	(+) – Lawson *et al.* (2004a), Lawson Et Al. (2004b), Al-Shafarat (2013), Adane Et Al., (2015) (-) – Bardhan And Sharma (2013) (No Effect) – Nega And Simeon (2006)
3. Cows	The number of cows each farmer has, discrete, in heads.	(+) – Lawson *et al.* (2004a), Lawson *et al.* (2004b), Sarabia *et al.*, (2009), Al-Sharafat (2013), Adane *et al.*, (2015), Nega And Simeon (2006), Girma (2019)
4. Forage Area	The source of roughage for feeding, continuous, in square meters.	(+) – Lawson *et al.* (2004a), Lawson *et al.* (2004b), Nega And Simeon (2006) (No Effect) – Adane *et al.*, (2015)
5. Dairy Feeds	Quantities of feeds used for lactating purposes, continuous, in bags (each bag contains 25 kilograms)	(+) – Lawson *et al.* (2004a), Lawson *et al.* (2004b), Nega And Simeon (2006), Sarabia *et al.*, (2009), Al-Sharafat (2013)
6. Time	A time dummy was included to capture technological change, 0 = 2017, 1 = 2020	(+) - Piesse *et al.,* (1996), Del Corral *et al.*, (2011), Kellermann And Salhofer (2014), Moreira And Bravo-Ureta (2016), Skevas *et al.*, (2018)

Table 2. List of technical inefficiency variables and their expected parameter signs according to literature

Explanatory Variable	Description, Type, Unit	Expected Sign, Hypotheses
1. Age	Age of farmer, discrete, in years	(+) – Lawson *et al.* (2004a), Lawson et al. (2004b) Palacpac et al., (2015) (-) – Lawson *et al.* (2004), Nega and Simeon (2006), Bardhan and Sharma (2013) (No effect) – Adane *et al.*, (2015), Girma (2019)
2. Education	Farmer's years in formal schooling, discrete, years	(+) – Nega and Simeon (2006), Al-Sharafat (2013), Adane *et al.* (2015), Girma (2019) (No effect) – Bardhan and Sharma (2013)

Table 2. Continued

3. Vermicomposting	Dummy variable taking the value of 1 if the farmer practices vermicomposting or disposes of his/her farm's generated manure to producers of vermicast, 0 if otherwise	(-) First known attempt as explanatory variable of technical inefficiency.
4. Waste segregation	Dummy variable taking the value of 1 if the farmer practices waste segregation for his/her other farm wastes e.g. packaging of drugs, biologics, feeds, and artificial insemination (AI) paraphernalia, 0 if otherwise	(-) First known attempt as explanatory variable of technical inefficiency.
5. Cleaning frequency	The estimated number of times the farmer cleans the animal housing or pens, discrete, count	(-) First known attempt as explanatory variable of technical inefficiency.

To verify whether inefficiency exists among the sample, the likelihood-ratio test of inefficiency error term with H_0: $\sigma_u = 0$ was evaluated using $\bar{\chi}^2$. Failing to reject the null hypothesis indicates the absence of technical inefficiency and the implication that the production function can be estimated using ordinary least squares instead of the maximum likelihood estimation method (MLE).

The significance of the model for the panel data case was identified through Wald χ^2 statistic with degrees of freedom equal to the number of explanatory variables of the production function with H_0: $\beta_k = \theta = 0$ while H_A: at least one of the explanatory variables of the production function is ≠ 0. On the other hand, for the separate cross-section data for 2017 and 2020, model significance was also determined through Wald χ^2 statistic with degrees of freedom equal to the number of explanatory variables of the production function with H_0: $\beta_k = 0$ while H_A: at least one of the explanatory variables of production function is ≠ 0. Finally, significant regressors were identified through the *z*-test and were evaluated if consistent with economic theory.

Technical Efficiency Analysis

Assuming inefficiency is present in the model and that the state of technology was different for 2017 and 2020, separate MLEs for stochastic production function with technical inefficiency model were generated for the two years. Cobb-Douglas was also applied as the functional form of the production function. The inefficiency error term was assumed to follow an exponential distribution. Significant variables of the technical inefficiency model were determined through the reported results of the *z*-test. A negative coefficient estimated meant that the attached regressor had an inverse relationship with the farmer's technical inefficiency and, thus, could increase TE. The opposite is true if the estimated coefficient had a positive sign. Post-estimation was performed through STATA to predict the farmers' TE rating.

Scale Efficiency Analysis

Following the separate estimation of the frontier production function for 2017 and 2020, separate output elasticity coefficients for input variables and hence, scale elasticity for 2017 and 2020 were calculated. Scale elasticity is also known as returns to scale (RTS), which is the proportionality of change in output after the amounts of all inputs in production have been changed by the same factor. If a proportionate increase in all inputs results in a more than proportionate increase in output, then the scale elasticity is greater than 1, and therefore, production exhibits increasing returns to scale. This means that the farmer can still take advantage of economies of scale since outputs can still be increased via operational scale adjustment. Consequently, the inverse scenario describes decreasing returns to scale. In this scenario, increasing consumption of all inputs does not display scale efficiency as it increases output level but by a lower rate. Finally, production is said to exhibit constant returns to scale when the proportionate increase in all inputs results in the same proportionate increase in output, hence the optimal scale elasticity (Coelli *et al.*, 2005).

Technological Change Analysis

The panel data case was used to determine if there is a technological change between 2017 and 2020 as captured by the time dummy variable parameter. Technological advancements are deemed reflective of the effectiveness of the PCC's research and development program.

TFP Change Decomposition

The process of TFP decomposition in this study is performed following the methods for stochastic frontier analysis by Quilloy (2019). For TFP decomposition purposes, the production function with technical inefficiency can be specified as follows based on Kumbhakar *et al.* (2000):

$$y_{it} = f(x_{it}, t)\exp(-u_{it}) \tag{5}$$

where i is the index of observation units, t is the index for the time period, y_i denotes output quantity per observation, and x_i is a vector of explanatory input variable for each observation. The function f represents the frontier production function while the $\exp(-u_{it})$ denotes technical inefficiency.

Accordingly, as cited by Briones *et al.* (2014), technological change (TC) and TEC are derived as follows:

$$TC_{it} = \frac{\partial \ln f(x_{it}, t)}{\partial t} \tag{6}$$

$$TEC = \frac{-\partial u_{it}}{\partial t} \tag{7}$$

Letting $\lambda_j = \varepsilon_j / RTS$; $RTS = \sum_j f_j x_j = \sum_j \partial \ln f / \partial \ln x_j$ and using the definition of TFP growth as $T\dot{F}P = \dot{y} - \sum_i^N s_i \dot{x}_i$, the full expression for TFP growth is derived as

$$T\dot{F}P = (RTS - 1) \sum_j \lambda_j \dot{x}_j + TC + TEC + \sum_j (\lambda_j - s_j) \dot{x}_j \ . \tag{8}$$

Equation (8) decomposes TFP growth and price effects, the last term at the right-hand side of the equation, although price effects were not included in this study since complete input prices were not gathered.

Given the availability of panel data and using a time dummy variable, technological progress between 2017 and 2020 was empirically confirmed if the estimated coefficient of the time dummy is statistically significant and is equal to θ x 100%. Technical efficiency change, which was provided to be statistically significant using paired sample t-test, was measured simply as the percent difference between the farmers' mean TE in 2020 and 2017. Scale efficiency change was computed following the first term of the right-hand side of Equation (8). Microsoft Excel was used to compute the TFP change.

Results and Discussion

Description of respondents' socio-demographic characteristics revealed that the majority of the respondents were male, married, and serves as heads of their households with an average size of five. Furthermore, most of them have buffalo dairy farming as their main income source. Their average family income is PHP 32,052.02 per month. Their average age, years in education, and dairy farming experience are 51, 11.11, and 12.55 years, respectively.

Mean milk production output and input levels were summarized in Table 3, which showed that there is a significant growth in milk production (at 5% probability level) between 2017 and 2020. All inputs did not change significantly although the forage area decreased in nominal terms.

Table 3. Milk production output and input description for the years 2017 and 2020

Variables	Mean			Change
	Both Periods	2017	2020	2020 – 2017
Milk (L)	2,586.27	2,009.20	3,163.34	1154.14**
Capital	1,265,306.12	1,264,427.02	1,266,185.23	1758.21^{ns}
Labor	629.66	597.27	662.05	64.77^{ns}
Cows	3.60	3.41	3.80	0.39^{ns}
Forage area	1,802.15	1,872.25	1,732.05	-140.20^{ns}
Dairy feeds	48.59	46.33	50.85	4.53^{ns}

Note: ***, **, * - significant at 1%, 5% and 10% probability levels, respectively using paired sample t-test of two means; ^{ns} – not significant at 10% probability level.

Description of their waste management practices revealed that for both 2017 and 2020, vermicomposting and waste segregation were practiced by 27% and 92% of the respondents, respectively. Meanwhile, the average cleaning frequency was around twice daily. Descriptive statistics for the technical inefficiency model are presented in Table 4 below.

Table 4. Descriptive statistics of technical inefficiency model independent variables for the years 2017 and 2020

Variables	Mean			Min	Max
	Both Periods	2017	2020	2017	2020
Age	49.45	47.95	50.95	30	78
Education	11.11	11.11	11.11	4	17
Vermicomposting	0.27	0.27	0.27	0	1
Waste segregation	0.92	0.93	0.91	0	1
Cleaning frequency	1.86	1.86	1.86	0	1

For the other waste management practices, the spreading of manure was practiced the most, followed by recycling wastewater as liquid fertilizer, maintaining wastewater lagoon, and basic composting.

Results of separate MLE of the stochastic production function with inefficiency effects for 2017 and 2020 were shown in Table 5. Among the factors of production, cows, forage area, and dairy feeds were statistically significant as explanatory variables of milk output in 2017. Meanwhile, in 2020, cows and dairy feeds were the statistically significant inputs. An advantage of the Cobb-Douglas functional form is that the parameter estimates of the inputs already represent their partial elasticities. The coefficient of ln of cows in 2020 indicates that increasing the number of cows by 10% will result in a 6.9% increase in milk output. Model estimates for 2017 and 2020 were both found to be statistically significant at a 1% probability level given the Wald Chi-Squared test statistic. Furthermore, the statistically significant LR test statistic for both 2017 and 2020 led to the rejection of the null hypothesis that errors due to inefficiency were zero, justifying the use of the frontier method.

Table 5. MLE of the stochastic frontier production function for the 2017 and 2020 cross-section and the panel data case

Variables	2017		2020		Panel	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
ln capital	-0.0991^{ns}	0.1061	0.0570^{ns}	0.0663	-0.0137^{ns}	0.0620
ln labor	-0.1527^{ns}	0.2591	0.2787^{ns}	0.2650	0.1158^{ns}	0.1976
ln cows	0.3941^{**}	0.1935	0.6895^{***}	0.1475	0.7477^{***}	0.1243
ln forage area	0.2581^{**}	0.1285	0.0010^{ns}	0.1218	0.0955^{ns}	0.0976
ln dairy feeds	0.4262^{***}	0.1245	0.0005^{*}	0.0003	0.0005^{ns}	0.0003
Time					0.4860^{**}	0.1953
_cons	6.2849^{***}	2.1253	5.0233^{**}	2.0917	5.7588^{***}	1.5529
lnsig2v					-0.9924^{***}	0.3366
_cons	-1.1483^{**}	0.4828	-1.4250^{***}	0.3997		
lnsig2u					-0.8665^{**}	0.4786
Age	-0.0146^{ns}	0.0390	0.0075^{ns}	0.0415		
Education	-0.0610^{ns}	0.1639	-0.0311^{ns}	0.1505		
Vermicomposting	-0.8350^{ns}	1.2480	-0.0670^{ns}	1.1873		
Waste segregation	1.6662^{ns}	2.4678	2.5301^{ns}	2.9085		
Cleaning	-0.6657^{ns}	0.7256	-1.1111^{*}	0.6755		
_cons	-0.0135^{ns}	3.7228	-1.5605^{ns}	4.3553		
sigma_v	0.5632	0.1360	0.4904	0.0980	0.6088	0.1025
No. of obs.	44		44		88	
Wald Chi-Squared(5)	44.01^{***}		50.77^{***}		63.26^{***}	
Log likelihood	-50.57		-48.17		-111.31	
LR test, $\sigma_u = 0$: $\bar{\chi}^2(01)$	1.72*		4.46^{**}		2.98^{**}	

Note: ln – natural logarithm; ***, **, * - significant at 1%, 5% and 10% probability levels, respectively; ^{ns} – not significant at 10% probability level.

Predicted TE scores of farmers for 2017 and 2020, respectively, ranged from 0.11 to 0.89 and from 0.06 to 0.93. Mean TE slightly declined from 0.65 in 2017 to 0.64 in 2020, but the change was not statistically significant based on the paired sample *t*-test, and therefore, TEC is zero. The negative coefficient of cleaning frequency, the sole statistically significant predictor of technical inefficiency, indicates that increasing cleaning frequency will increase TE, which is consistent with economic expectation since cleaning prevents the occurrence of mastitis. Distribution and descriptive statistics of the TE scores are provided in table 6 below.

Table 6. Distribution and descriptive statistics of farmers' technical efficiency rate

Efficiency Class/ Descriptive Statistics	Number Of Farmers		Percent	
	2017	2020	2017	2020
0.00 - 0.09	0	1	0.00%	2.27%
0.10 - 0.19	2	3	4.55%	6.82%
0.20 - 0.29	1	0	2.27%	0.00%
0.30 - 0.39	3	3	6.82%	6.82%
0.40 - 0.49	2	1	4.55%	2.27%
0.50 - 0.59	5	6	11.36%	13.64%
0.60 - 0.69	7	7	15.91%	15.91%
0.70 - 0.79	17	15	38.64%	34.09%
0.80 - 0.89	7	7	15.91%	15.91%
0.90 - 1.00	0	1	0.00%	2.27%
Min TE	0.11	0.06		
Max TE	0.89	0.93		
Mean TE	0.65	0.64		
SD	0.19	0.22		

Since most of the included determinants in the efficiency effects model failed to explain the variabilities in dairy farmers' TE, other data available were used to group the farmers and spot possible relationships which can be considered and can serve as a guide to the exploration of factors influencing TE in future studies. Included in the list are the technical inefficiency determinants and other data, which were also collected through the same survey instruments as previously discussed. These are summarized in Table 7.

Table 7. Farmer technical efficiency distribution based on identified farm and farmer characteristics or variable

Characteristics/ Variables	Description	Mean TE 2017	Mean TE 2020
Age	> Average Age (2017=47.95 Years; 2020=50.95 years)	0.66 (20)	0.67 (20)
	≤ Average Age (2017=47.95 Years; 2020=50.95 years)	0.64 (24)	0.63 (24)
Education	> Average Education (2017 and 2020 = 11.11 years)	0.67 (18)	0.66 (18)
	≤ Average Age (2017 and 2020 = 11.11 years)	0.64 (26)	0.63 (26)
Vermicomposting	Yes	0.71 (12)	0.60 (6)
	No	0.63 (32)	0.65 (38)
Waste segregation	Yes	0.64 (41)	0.62 (40)
	No	0.79 (3)	0.86 (4)
Distance	Shorter Distance to Philippine Carabao Center National Headquarters (PCC-NHQ) (San Jose and Munoz)	0.64 (31)	0.65 (31)
	Longer Distance to PCC-NHQ (Other Municipalities)	0.67 (13)	0.64 (13)
Other income	Yes	0.64 (39)	0.66 (39)
	No	0.73 (5)	0.51 (5)
Drugs and biologics	Yes	0.64 (39)	0.70 (28)
	No	0.70 (5)	0.54 (16)
Cooperative officer	Yes	0.68 (18)	0.65 (16)
	No	0.63 (26)	0.64 (28)
Price per liter	> Average Price (2017=49.92 pesos; 2020=65.36 pesos)	0.65 (33)	0.57 (20)
	≤ Average Price (2017=49.92 pesos; 2020=65.36 pesos)	0.64 (11)	0.70 (24)
Environmental seminar	Yes	0.63 (38)	0.65 (41)
	No	0.76 (6)	0.60 (3)
Spends on feed inputs	> Average Annual Spending (2017= 9,242.84 pesos; 2020= 24,046.35pesos)	0.69 (15)	0.67 (17)
	≤ Average Annual Spending (2017= 9,242.84 pesos; 2020= 24,046.35pesos)	0.63 (29)	0.63 (27)

Numbers in parentheses () represent the frequency count of respondents in the group.

For both production years, farmers whose age and years of education are above the sample means have posted higher average TE scores than their younger and less-schooled counterparts. However, it was earlier found that age and education are not statistically significant determinants of farmers' TE. This piece of information suggests older and more educated farmers are more technically efficient and could be regarded as an opportunity by the younger and less-schooled farmers. When grouped by vermicomposting practice, distance to PCC National Headquarters, presence of other income sources, use of drugs and biologics, the selling price per liter, and attendance to an environmental seminar relative to buffalo farming, it was observed that farmers exhibit varying results between 2017 and 2020 wherein, on the average, farmers in the affirmative group are higher than their respective counterparts in one year but became lower on the other. This further validates the difficulty of pinpointing the factors influencing farmers' TE. Furthermore, an unfavorable scenario was depicted pertaining to the practice of waste segregation. The table indicates that, for both 2017 and 2020, farmers who do not practice proper waste segregation are, on the average, more technically efficient than those who do. This is inconsistent with this study's assumption that good environmental practices positively affect dairy productivity and must be further examined in future studies.

Finally, potentially affecting the TE of farmers positively were their feedstuff spending behavior and their leadership involvement in their cooperatives. As shown for both years, farmers who spent on feeding inputs (e.g. supplementary improved forages, legumes, and vitamins and minerals) more than the sample's average have higher TE scores. This is a promising finding suggesting the inclusion of more feeding practices as determinants of TE in future studies. Such practices include supplementary feeding (e.g. improved forages, legumes, and concentrates), silage making as feedstock during the dry period, twice-a-day milking, use of milk replacer, use of urea, molasses, and mineral block (UMMB), and feeding of vitamins and minerals. Apparently, holding governance or management positions in the cooperative such as being a member of the board of directors, could also affirmatively influence TE and must be explored further on the possible reasons for its inclusion in succeeding TE analyses.

Given the sum of partial elasticities, it was found that farmers were producing at decreasing returns to scale in 2017 with scale elasticity equal to 0.81. Meanwhile, farmers were able to transition to increasing returns to scale in 2020 when their scale elasticity equaled 1.03. It is expected in dairy farming that changes in returns to scale will follow the changes in average cow-holding since it is the main input that sets the intensity of the use of the other supporting inputs such as forage, feeds, and labor. Given that the average cow-holding of farmers increased from around four in 2017 to roughly five in 2020, the overall returns to scale adjustment just means that at that specific transition, the intensity of use of inputs was improved such that potential returns after increasing the inputs altogether will provide a slightly higher proportionate increase in milk production. Following the scale efficiency change formula, which is the first term of the right-hand side of Equation 8, SEC was found to be -0.52%.

Finally, technological progress was confirmed based on the statistically significant coefficient of the time dummy variable estimated using the panel data case of the production function shown in Table 5. The positive coefficient means that there is 48.60% technological progress between 2017 and 2020 or an average of 12.15% annually. Suspected reasons include (1) the effects of the five-year Korea International Cooperation Agency (KOICA) co-funded Dairy Herd Improvement (DHI) Program, which culminated in 2018, wherein, breeding efficiency, AI and technical services provision, and linkages with local government units (LGUs) were enhanced; (2) the technology lag benefits coming from the boost in PCC's research funding since 2008 after it was given the additional mandate of serving as the national lead agency for livestock and biotechnology pursuant to DA Administrative Order No. 9 s. 2008; and (3) the process innovation effect of digitalization through the iREB Database, which provides complete production and financial performance analyses to aid farmers in making better business decisions. These innovations were considered the general factors that shifted the dairy buffalo milk production frontier upward. However, a study dedicated to the direct attribution of technological progress to specific innovations must be empirically established separately. Though not included in this study, technological innovations that enhance the environmental factors affecting milk production could also shift the frontier and, thus, is ideal to be studied separately.

TFP decomposition, based on the foregoing results of its sources, was shown in Table 8. TFP growth is at 48.08% for the entire 4-year period covered or an average of 12.02% annually.

Table 8. TFP change decomposition of dairy buffalo milk production in Nueva Ecija, Philippines

TFP Component	Total Change Rate (%)	Average Annual Change Rate (%)
Technological change	48.60	12.15
Technical efficiency change	0.00	0.00
Scale efficiency change	-0.52	-0.13
Total factor productivity change	48.08	12.02

Moreover, the observed output growth between 2017 and 2020 was further decomposed into TFP growth and input usage growth. Exhibited in Table 9 was the input usage growth computed at 9.53%, derived by adding the product of input use growth and its respective partial elasticity. Since panel data is assumed for the decomposition formula, partial elasticities used were the parameters estimated through the panel data case. The sum of TFP growth and output growth from input usage growth matches the observed change rate from 2,009.20 liters in 2017 to 3,163.34 liters in 2020, which is about 57%.

Table 9. Output elasticity of significant input variables using panel data and their respective mean utilization growth rates

Variable	ε_j	λ (ε_j/RTS)	$\bar{x}$ (2017)	$\bar{x}$ (2020)	$\dot{x}$	(λ*$\dot{x}$)
Ln capital	-0.0137	-0.0145	1,264,427	1,266,185	0.14%	-0.0000
Ln labor	0.1158	0.1225	597.27	662.05	10.84%	0.0133
Ln cows***	0.7477	0.7906	3.41	3.80	11.33%	0.0896
Ln forage area	0.0955	0.1010	1872.25	1732.05	-7.49%	-0.0076
Ln dairy feeds	0.0005	0.0005	46.33	50.85	9.77%	0.0000
RTS	0.9458					
Total (λ*$\dot{x}$)						0.0953

Summary and Conclusion

This study attempted to determine if the dairy buffalo subsector has the potential to increase its productivity by analyzing the total factor productivity of dairy buffalo milk production in Nueva Ecija, Philippines. Milk production and waste management data for the years 2017 and 2020 were gathered from 44 randomly selected dairy buffalo milk producers in Nueva Ecija. Assuming the presence of technical inefficiency in the model, the parametric stochastic frontier analysis was applied to a Cobb-Douglas production function with an inefficiency effects model, further assuming that the inefficiency error term follows an exponential distribution. Using Stata v.14 software, parameters of the production function and the technical efficiency model were estimated using MLE. Technological progress was estimated by including a time dummy variable in the regressors of the production function in the panel data case. For the technical efficiency analysis, separate production functions with the technical inefficiency model were estimated for farmers in 2017 and 2020. Subsequently, the TE scores of each farmer were predicted. Year-specific scale effects, as defined by returns to scale, were identified by estimating separate production functions for 2017 and 2020.

Results of the stochastic frontier analysis revealed that the statistically significant factors of milk production were cows, forage areas, and dairy feeds. The parameter estimate for cows in 2020 indicates that increasing the cow heads by 10% will result in a 6.9% increase in milk production.

Technical efficiency analysis revealed that cleaning frequency positively affected farmers' TE in 2020, while none of the regressors explained technical inefficiency in 2017. The mean of the predicted farmer TE scores were 0.65 and 0.64 for 2017 and 2020, respectively. Paired sample t-test showed that there was no TEC between the two periods. Farmer's feedstuff spending behavior and leadership involvement are found to potentially explain their

TE and should be further explored in future studies. For the scale efficiency analysis, production shifted from decreasing returns to scale in 2017 with a scale elasticity of 0.8117 to increasing returns to scale in 2020 with a scale elasticity of 1.0268. Following the scale efficiency change formula, it was found that TFP growth from scale efficiency change is equal to -0.52% or -0.13% annually. Finally, the statistically significant coefficient of the time dummy variable based on the MLE of the production function using panel data confirmed a 48.60% technological progress or an annual average of 12.15%. KOICA co-funded DHI Project from 2013 to 2018, declaration of PCC as the lead agency for livestock and biotechnology per the DA AO 9 s. 2008, and digitalization efforts such as the iREB Database for farmers, were suspected as the general source of technological progress that flowed from 2017 to 2020.

Overall, the TFP of dairy buffalo milk production in Nueva Ecija grew by 48.08% between 2017 and 2020, or an average of 12.02% annually. Technological change is the main driver of TFP growth, but the TE of farmers allowed them to reach only an average of 65% of their maximum attainable output based on the upward-shifting state of technology.

These results concluded that there is a potential to increase dairy buffalo milk productivity through TFP, particularly through technological progress. Realizing that technical inefficiency exists among dairy farmers and that it did not improve between 2017 and 2020, increasing TFP can still be achieved by improving farmers' TE (i.e., improving their cleaning frequency practice).

Recommendations

Empirically establishing that TFP growth in dairy buffalo milk production is only due to technological progress, PCC should continue investing in its Genetic Improvement and Research for Development Programs. However, since output growth from technological progress is not instantaneous due to some lag, research for development programs may take on a new paradigm giving more emphasis to applied research especially feeding practices. Given the farmers' low and stagnant TE, maximum attainable outputs given the improving state of technology were not achieved. With this, a shift of some resources from technology development towards technology adoption in the form of training and extension services provision is recommended. As per the scale efficiency, the slightly increasing returns to scale in 2020 suggests that farmers have started to operate on a better scale. It is an opportune time, therefore, for farmers to produce more by scaling up their production and taking advantage of economies of scale. Furthermore, given that the input cows are reporting the highest output elasticity coefficient, the notion of increasing their dairy cow holding is also encouraged, however, an increase in profitability is another issue and will require further analysis—factoring in the prices of dairy inputs and the milk output. For future studies, the attribution of technological progress to specific factors is considered essential. The inclusion of environmental factors such as temperature and rainfall to production inputs while capturing environmentally smart practices such as the installation of the air-cooling system, better housing, and wallowing pond as determinants of farmers' TE are also viable improvements to this study.

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