Does contract farming improve the technical efficiency of urban and peri-urban dairy farmers? Evidence from Nekemte city, Ethiopia

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ABSTRACT

Purpose: The main objective of this study was to investigate the influence of contract farming on the technical efficiency of dairy farmers in urban and peri-urban areas, specifically in Nekemte City, Ethiopia.

Design/Methodology/Approach: The research design employed to obtain the data was a cross-sectional study. For data analysis, both primary and secondary sources of information were gathered. A semi-structured questionnaire was used to collect primary data. A simple random sampling technique was followed to select 181 sample dairy farm producers in urban and peri-urban areas of Nekemte city. The data analysis methods that were employed included descriptive analysis, Cobb-Douglas stochastic frontier analysis, and the propensity score matching technique.

Findings: According to the Cobb-Douglas stochastic frontier production function results, the most significant input in milk production is fodder, which has the biggest coefficient (= 0.353). The sum of the coefficients of all inputs is 0.512, and dairy farmers in the study area have been operating at decreasing returns to scale. The result of logistic regressions showed that the owner or manager's age, education, and experience are important factors that influence their decision to participate in urban dairy contract farming. The results of the propensity score matching technique showed that dairy farmers' technical efficiency increased by 0.150, or 21.52%, because of contract farming.

Conclusion: The results of the study highlight that contract farming helps dairy farmers in urban and peri-urban areas become more technically efficient.

Research Implications: The result of the study can serve as an input for policy formulation and serve as a stepping stone for other researchers.

Keywords: *Contract farming, Dairy farming, Ethiopia, Propensity score matching technique.*

1. INTRODUCTION

Globally, livestock production contributes 40% to the global agricultural Gross Domestic Product (GDP) and an estimated 30% of agricultural GDP within the developing world (Abbasi & Nawab, 2021). Ethiopia holds a large potential for dairy development. The country currently manages the largest livestock population in Africa, estimated at 29 million cattle, 24 million sheep and goats, 18 million camels, 1 million equines, and 53 million poultry (Ahmed, Simeon, & Assefa, 2004).

All available statistics suggest that the productivity of livestock in Ethiopia is among the lowest in the world. The average production for Ethiopia, 210 kilograms per year per cow, is less than a tenth of the world's productivity of 2.3 tons and about a third of Kenya's 551 kilograms per year per cow (Asfaw, Rashid, Gebremedhin, & Kennedy, 2013). Management Entity (2021) report also indicated that milk production averages only 1.35 liters per day per cow.

According to Ethiopia's livestock master roadmaps for growth and transformation, the government's overall target was to raise total cattle milk production to 7967 million litres by 2020 through genetics, feed, and health interventions to improve traditional family cow dairy production and expand and improve specialized dairy production units (Shapiro et al., 2015). The Livestock Master Plan will eventually support major transformations in

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the livestock sector, well beyond 2020, which will not only increase the availability of affordably priced animal protein for the population but might also result in negative public health, environmental, and social outcomes.

At the household level, livestock plays a critical economic and social role in the lives of pastoralists, agro-pastoralists, and smallholder farm households in the central highlands. Livestock fulfills an important function in helping people cope with shocks and accumulate wealth, and it serves as a store of value in the absence of formal financial institutions and other missing markets. In smallholder mixed farming systems, livestock provides nutritious food, additional emergency and cash income, farm outputs and inputs, and fuel for cooking food (Asfaw et al., 2013).

According to Whiting (2015) efficiency is the situation of society getting the maximum benefits from its scarce resources. The measurement of productive efficiency has important implications for the neoclassical theory of production economics and economic policy, and measuring productivity efficiency allows one to test competing hypotheses regarding sources of efficiency or differentials in productivity (Rios & Shively, 2005).

Regarding the impact of contract farming, the existing literature has found positive effects on the technical efficiency of production. Birthal and Joshi (2009) identified that contract farming is a more efficient form of production mainly due to its ability to reduce marketing and transaction costs to producers in India. Contract producers could save over 90% on costs associated with the marketing of milk and the acquisition of inputs, information, and services. They realized twice the net revenue of their independent counterparts. The average milk price under contract was marginally higher compared to the prevailing market price, suggesting no extraction of monopsonistic rent by the firm in the output market.

Saroj, Paltasingh, and Jena (2023) evaluated the returns to contract farming (CF) in the form of farm efficiency for both contract and non-contract wheat growers in Haryana, North India. They found that CF adopters are significantly more efficient than non-adopters. It also shows that farmers who don't adopt CF lose 16% of their technical efficiency. However, non-adopters would increase their technical efficiency by 12% if they adopted instead. This is attributed to CF provisions of higher quality inputs and improved production technology.

Joseph, Jakinda Otieno, Oluoch-Kosura, and Ochieng (2021) estimated and compared technical efficiency (TE) and technology gap ratios (TGRs) between contracted and non-contracted farmers of chilli peppers and spider plants in rural areas of Kenya. Their results showed that, for both spider plants and chilli contract participants had higher mean TE with respect to the meta-frontier (0.66 and 0.24) compared to non-participants (0.12 and 0.15), respectively.

According to the study, Nguyen, Dzator, and Nadolny (2018) estimated that the technical efficiency of tea production for contracted farmers is 59.9 percent, while, it is 55.1 percent for independent households. The results indicate that the technical efficiency of contracted farmers is higher than that of their counterparts by 4.8 percent in Vietnam. Mazhar et al. (2022) in their work, examined the influence of contract farming participation on smallholder rice farmers' technical efficiency using a cross-sectional data set of 650 respondents. We applied a stochastic frontier analysis (SFA) to examine the production frontier and inefficiency estimates. Further, propensity score matching (PSM) was used to control endogeneity and self-selection bias in technical efficiency estimates. The results reveal that the technical efficiency score of organic rice farmers in Punjab, Pakistan, is 89.7%, which can still be improved by 10.3% at the current socio-demographic characteristics and input levels. Yuan, Bi, and Zhang (2023) examined the impact of contract farming on farm household income using survey data from 610 rural households in China. The result of the propensity score matching method indicated that contract farming improves farmers' technical efficiency in agricultural production. Participation in contract farming enhances the tendency to centralize the technical efficiency of agricultural production. Selorm, Sarpong, Egyir, Mensah Bonsu, and An (2023) applied the propensity score matching technique and found that the technical efficiency levels of contract farmers were 77 percent, compared with 69 percent for non-contract farmers in the case of soybean farmers in Northern Ghana. However, there are few studies in Ethiopia examining the impact of contract farming on the efficiency of urban and peri-urban dairy production, with the majority of these studies focusing on rural agricultural activities. Contract farming is emerging as an important form of vertical coordination in Ethiopia. Supermarkets, cafeterias, and end consumers are increasingly securing their milk requirements through contracts. However, there hasn't been much investigation into the issues of efficiency and benefit distribution in contract farming. Few studies have been carried out so far and are concentrated in and around Addis Ababa, the capital city of the country. As a result, the main objective of this study was to measure the impact of contract farming on the technical efficiency of urban and peri-urban dairy farmers in the case of Nekemte City, Ethiopia.

2. LITERATURE REVIEW

The urban and peri-urban farming system (PFS) is defined as the farming system that is performed in rural areas mixed with the urban area with consequences at the territorial level and close to the urban area (EEA – European Environment Agency, 2006; FAO, 2010; Gaviglio, Filippini, Madau, Marescotti, & Demartini, 2021).

This study is based on two key theories; the principal-agent theory and transaction cost theory. According to Williamson (1986), transaction costs consist of the costs of finding a bargaining partner, negotiating a sale agreement, and monitoring/enforcing the performance of the terms of trade. To reduce risk and transaction costs, humans create institutions, writing and enforcing constitutions, laws, contracts, and regulations - so-called formal institutions and structuring and inculcating norms of conduct, beliefs, and habits of thought and behaviour informal institutions (Menard & Shirley, 2005). The interaction theory between an agent and the principal they represent focuses on structuring incentives to ensure the agent acts in the principal's best interest. In the context of law, principals do not know enough about whether (or to what extent) a contract has been satisfied, and they end up with agency costs. The solution to this information problem related to the moral hazard problem is to ensure the provision of appropriate incentives so agents act in the way principals wish.

According to Afriat (1972) efficiency is the relationship between ends and means, and it plays a crucial role in both production analysis and consumption and demand studies. Economists widely distinguish between technical efficiency and allocative or price efficiency, following pioneering work by Farrell (1957). The TE analysis assumes the feasibility of defining an optimal level of input transformation and calculates the farmer's actual ability to convert resources into output. The distance between the optimal level of efficiency and the actual farm's TE measures the technical inefficiency, which is interpreted as the failure of farms to produce the maximum output that is possible considering the inputs provided. The paper has examined issues of efficiency and equity in contract farming of milk. To visualize the impact of participation on the technical efficiency of dairy farm businesses in urban and peri-urban areas of Nekemte city, conceptually the model of interaction between explanatory variables and the outcome variables can be constructed in the framework below (for detail see Figure 1).

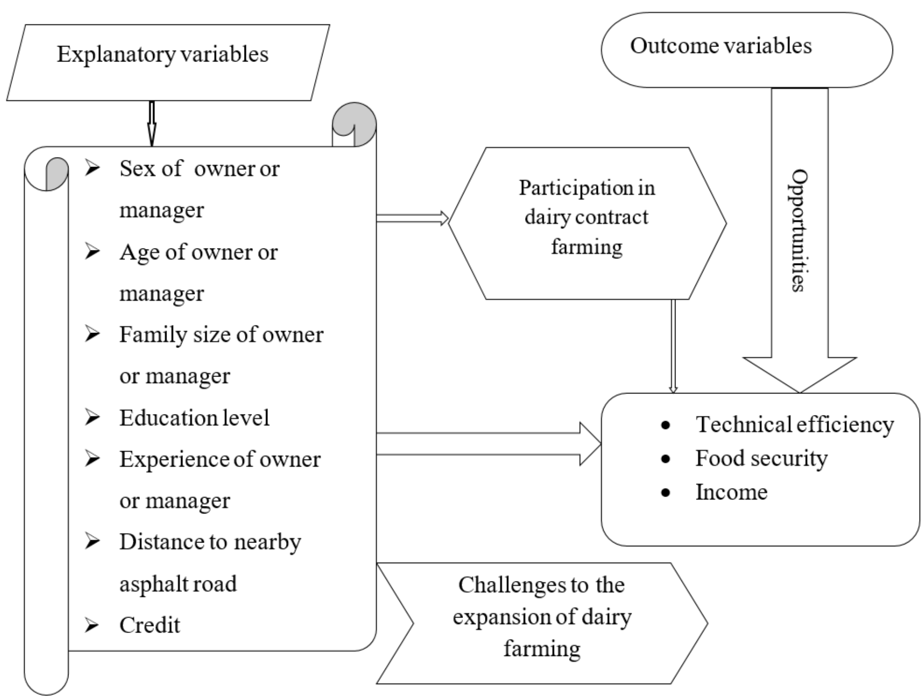

Figure 1. Diagrammatic representation of the conceptual framework.

Source: Developed by the researcher based on literature (2023).

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3. METHODOLOGY OF THE STUDY

Nekemte is one of the Oromia regional state cities found in the East Wollega zone with a total coverage area of 53.8 KM2 or 5380 hectares. According to Nekemte Town Administration Office, the total population of the town is 138,127. Of which 69,400 are males while 68,727 are females. It is located 328 km in the western direction from the center state capital- Addis Ababa. The city altitude ranges in between 1960 meters to 2170 meters from the lowest gorge area of the city through to the maximum hill point of the city area, respectively. The annual rainfall average of the city ranges between 1500 mm-2200 mm. The city divides into six sub-cities. The current boundary of Nekemte city is surrounded by rural peasant association villages on all sides.

According to the Nekemte town administration office, the town is divided into seven sub-towns Darge, Bake Jama, Burqa Jato, Bakanisa Kese, Chalalaki, Sorga, and Keso. The town has a latitude and longitude of 9°5′N 36°33′E (for detail see Figure 2). Its average annual rainfall is 1854.9 mm, and the average temperature ranges from 140 C to 260 C (Melese, Solomon, & Amsalu, 2017).

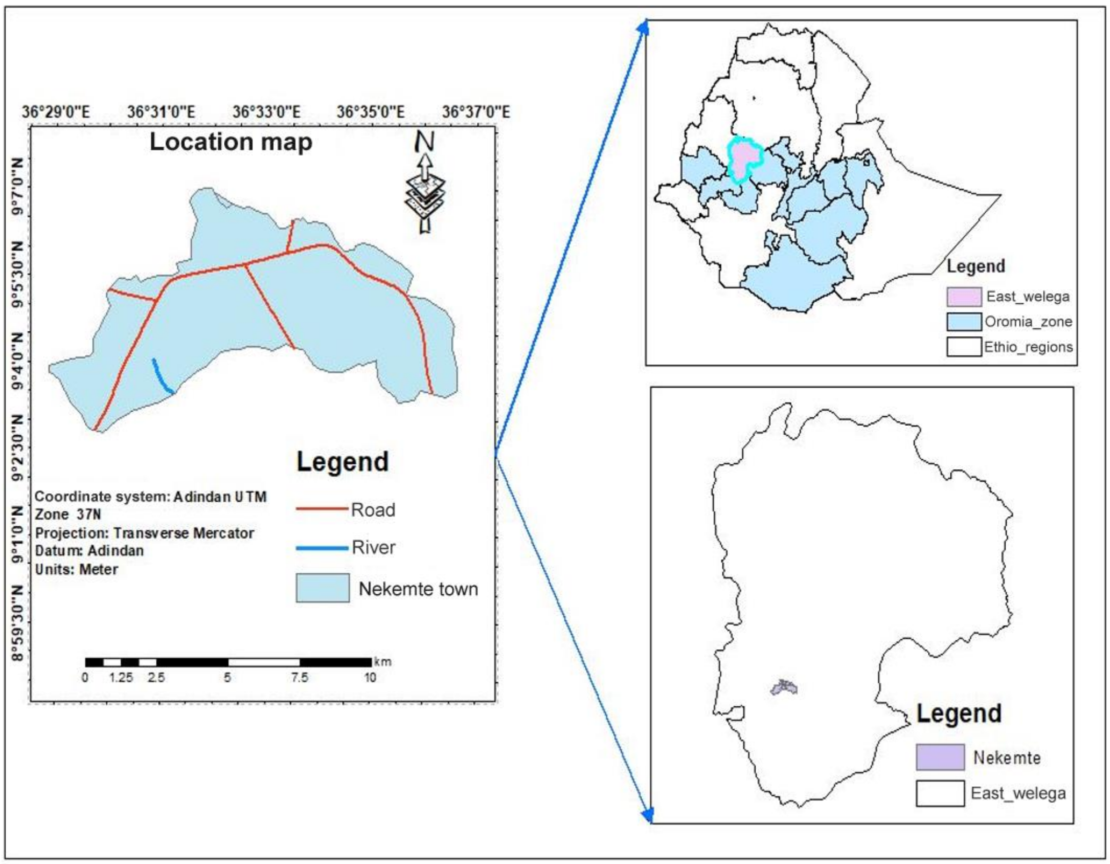

Figure 2. Map of the study area.

The major objective of this study is to measure the impact of participation in dairy contract farming on the level of technical efficiency of dairy farmers in urban and semi-urban areas of Nekemte city. To this end, both descriptive and explanatory research designs were applied in this study.

Both primary and secondary data were used in this study. Primary data were collected from dairy farmers in the urban and peri-urban areas. Primary data were collected using a semi-structured questionnaire to collect both qualitative and quantitative data from dairy farm owners/managers of the study area. Such data include demographic characteristics, socioeconomic characteristics, participation in different group activities, and the associated income generated in cash and in-kind from engaged group membership.

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The study used a simple random sampling design. Lists of dairy farmers in urban and peri-urban areas of Nekemte city were obtained from the kebeles, and representative samples were selected based on simple random sampling techniques.

The required sample size was determined by using Kothari (2004) sample size determination formula, where the exact number of households in each Kebele, or the sampling frame, is known. It was used to provide more accurate and estimated samples selected in the study area. Kothari (2004) developed a formula to determine the sample size, taking into account the heterogeneity of the population, which included both participants and non-participants. The formula is:

$$n=\frac{z^2*N*p*q}{(N-1)e^2+z^2*p*q}=\frac{(1.96)^2*341*0.5*0.5}{(341-1)0.05^2+(1.96)^2*0.5*0.5}=181$$

Where N = population, n= sample size, z= the value of standard variation at a given confidence level and to be worked out from the table showing the area under normal curve, p = sample proportion, q= 1 - p, e = given precision rate or acceptable error (Kothari, 2004).

In this study, N = 341, z= 1.96, p= 0.5, q= 1-0.5= 0.5, e = 0.05

Therefore, the sample size for this study was 181.

STATA 15 software was used to analyze the data entry, data management, and descriptive statistics of the study findings.

Since agricultural production exhibits random shocks and it is necessary to separate the influence of stochastic variables from the resulting estimates of technical inefficiency, dairy farmers have adopted stochastic frontier analysis to measure their technical efficiency.

The stochastic frontier model was originally proposed for the analysis of the panel data by Battese and Coelli (1995) and simultaneously by Aigner, Lovell, and Schmidt (1977) and Meeusen and Broeck (1977) for the cross-sectional data, which is considered in this study, is defined by

$$Yi = exp\,(Xi\,\beta + v_i - u_i) \quad (1)$$

Where Yi denotes the output for the ith sample farm

Xi is a (1 x K) vector whose values are functions of inputs and explanatory variables for the i^{th} farm

β is a (K x 1) vector of unknown parameters to be estimated

V_i is assumed to be independent and identically distributed random errors that have a normal distribution with mean zero and unknown variables $\delta^2{}_V$, that is vi ~ N(0, $\delta^2{}_V$) and U_i s are non-negative unobservable associated with the technical inefficiency of production. Such that for a given technology and levels of inputs, the observed output falls short of its potential output (Ui~ N (0, $\delta^2{}_u$), or it is a one-sided error term (U ≥ 0) efficiency component that represents the technical inefficiency of the farm.

Technical efficiency of an individual farmer or farm is defined as the ratio of observed output and the corresponding frontier output, given the state of available technology, and presented as follows:

$$\mathrm{TEi} = \frac{\mathrm{Yi}}{f(\mathrm{Xi}{:}\beta)\exp(\varepsilon)}=\frac{f(Xi;\beta)(\varepsilon i=Vi-Ui)}{f(Xi;\beta)\,exp(Vi)}=exp(-\mu) \qquad (2)$$

Where f (Xi; β). exp (vi-ui) is the observed output (Y) and F (Xi; β).exp (vi) is the frontier output (Y*). Pursuing Battese and Coelli (1995) the error term (vi) permits random variations in output due to factors outside the control of the farmer, like weather and diseases, as well as measurement error in the output variable, and is assumed to be identically, independently, and normally distributed with mean zero and constant variance ($\delta^2{}_V$); i.e., vi ~ N (0, $\delta^2{}_V$).

The major objective of this study is to examine the impact of participation in dairy contract farming on technical efficiency. To analyze such types of impact, econometric models such as regression discontinuity design, Heckman's two-stage model, and semi-parametric methods (difference-in-difference approach, propensity score matching) are widely used. The lack of observational data for the control group motivated the choice of PSM for this study, necessitating the creation of a statistical comparison group based on a model of the probability of participation in dairy contract farming. The propensity score approach can reduce bias in observational studies (Rosenbaum, 1987;Rosenbaum & Rubin, 1985;Rubin & Thomas, 1992) through the identification of non-users who are similar to users in all relevant pre-access characteristics. Matching helps to find a group of treated individuals (participants) similar to the control group (non-participants) in all relevant pre-treatment characteristics where they only participated in dairy contract farming and the other group did not. Detailed specifications of PSM are found in Caliendo and Kopeinig (2008). The estimation process was done using psmatch2 in STATA 15.

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The impact of an individual's participation in dairy contract farming is measured by the difference between potential outcomes with and without access:

$$\Delta_i = Y_{1i} - Y_{0i} \qquad (3)$$

Where states 1 and 0 correspond to participants and non-participants, respectively. The variable Y represents the technical efficiency score of the individual dairy farmer.

To evaluate the impact of participation in dairy contract farming on the population, we may compute the average treatment effect (ATE):

$$ATE = E(Y_1 - Y_0) \qquad (4)$$

Most often, we want to compute the average treatment effect on the treated (ATT):

$$ATT = E[\Delta_i] = E(Y_1 - Y_0 \,/\, D = 1) \qquad (5)$$

Where D = 1 refers to the treatment.

Many of these parameters depend on counterfactual outcomes, making them unobservable. For instance, we can rewrite ATT as:

$$ATT = (Y1|D = 1) - E(Y0|D = 1) \qquad (6)$$

Where ATT in Equation 6 is the average outcome for participant in dairy contract farming if they sell their dairy products on contractual basis.

3.1. Assumption and Data Requirements of PSM

For the matching method to be valid, two key assumptions should be satisfied. These are Conditional Independence (CIA) and the presence of common support (Khandker, Koolwal, & Samad, 2010).

Conditional Independence: There is a set X of covariates, observable to the researcher, such that after controlling for these covariates, the potential outcomes are independent of the treatment status:

$$(Y_i; Y_o) \perp D|Xi \qquad (7)$$

The above Equation 7 is simply the mathematical notation after controlling for X; the treatment assignment is "as good as random." The CIA is crucial for correctly identifying the impact of the program since it ensures that the treated and untreated groups differ, and these differences may be accounted for to reduce the selection bias. This enables the construction of a counterfactual for the treatment group using the untreated units.

Common Support: For each value of X, there is a positive probability of being both treated and untreated:

$$0 < P(D = 1 \mid X) < 1 \qquad (8)$$

Equation 8 indicates that even in the case of a randomized experiment, participants selected for treatment may choose not to be treated or may not comply with all aspects of the treatment regime. In this sense, even a randomized trial may involve bias in evaluating the effects of treatment, and non-experimental methods may be required to adjust for that bias. An appropriate matching algorithm matches the treated group with the non-treated group for each value of X when the assumptions of unconfoundedness and common overlap are satisfied.

4. RESULTS AND DISCUSSION

This chapter deals with data presentation, descriptive analysis, and econometric analysis.

Table 1. Description of dummy variables used in the model.

Variables	Category	Do you sell your milk outputs on a contractual basis to users/Consumers?			Chi-square test
		No	Yes	Total	
Sex of the owner or manager	Female	16(50%)	16(50%)	32(100%)	0.393
	Male	58(56.31%)	45(43.69%)	103(100%)	
	Total	74(54.81%)	61(45.19%)	135(100%)	
Have you received credit last year?	No	27(52.94%)	24(47.06%)	51(100%)	0.116
	Yes	47(55.95%)	37(44.05%)	84(100%)	
	Total	74(54.81%)	61(45.19%0	135(100%)	

Source: Computed from own survey data (2023).

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Sex of the Owner or Manager: Of the total female dairy farmers, 16(50%) of them are selling their milk outputs on a contractual basis to users/consumers. Table 1, further revealed that of the total male dairy farmers in the study area, 45 (43.69%) of them are selling their milk output on a contractual basis to users or urban consumers (for detail see Table 1).
Credit: Of those dairy farmers who received credit 37 (44.05%) were selling their milk products on a contractual basis, and from those dairy farmers who received no credit, 24 (47.06%) were not selling their milk products on a contractual basis.

Table 2. Description of variables used in the model.

Variable name	**Do you sell your milk outputs on a contractual basis to users/Consumers?**			**St. err**	**t value**
	Mean of no. (n1=74)	**Mean of yes (n2=61)**	**Difference**		
Age	44.014	42.049	1.965	1.234	1.6
Family size	5.676	5.459	0.217	0.43	0.5
Education level	8.46	10.082	-1.623	0.528	-3.05***
Work experience	4.243	5.787	-1.544	0.598	-2.6**
Distance to nearby asphalt road	545.811	525.737	20.073	76.543	0.25
Technical efficiency	0.629	0.783	-0.155	0.018	-8.35***

Note: ***, & ** shows significant at 1% and 5%, respectively
Source: Computed from own survey data (2023).

Age: Age is one of the demographic factors that is useful to describe households and provide clues about the age structure of the sample and the population. Age is usually considered in determinants of participation studies with the assumption that older people have more experiences, which enables them to easily adopt new technologies. On the other hand, younger farmers are more likely to adopt new technology because they have had more schooling than the older generation. In our case, the average age of the participants in dairy contract farming was 42.1 years, while it is about 44.01 years for non-participants. The t-test of age between participants and non-participants was found to be insignificant. That means there is no statistical mean difference between participants and non-participants in terms of age.
Family Size: Family size in this study refers to the number of members who are currently living within the family. Large family size is an indicator of the availability of labor if the majority of the family members are within the age range of the active labor force. The availability of labor in the household is again one of the important resources in dairy farming. The average family size of participants in dairy contract farming was 5.459 persons, while it is about 5.676 persons for non-participants. The t-test revealed no significant difference in family size between participants and non-participants.
Education Level: The education status of the household head is the most common and important variable that is found to explain participation in dairy contract farming. Education can influence the productivity of producers and the innovations of new ideas. Education has the power to change the knowledge, skills, and attitudes of dairy farmers. It also enhances the analytical and problem-solving skills of farmers. In addition, education enhances the locative ability of decision-makers by enabling them to think critically and use information sources efficiently. Hence, literate producers are expected to be in a better position to get and use information that contributes to improving their participation in urban dairy contract farming. According to the survey results, on average adopters, have about 10.082 grades of formal education while non-participants have 8.46 grades of formal education in the study area. The t-test result indicates that the education level of households was found to be significant between participants and non-participants at a 1% level of significance. That means participants in dairy contract framing have a higher level of education compared to non-participants (Table 2).
Work Experience: Experience in dairy farming is taken to be the number of years that an individual was continuously engaged in milk production. Farmers' experience in dairy farming is expected to increase their demand for yield. The participants had an average of 5.787 years of dairy production experience, while non-participants had an average of 4.243 years. The t-test (t = 2.6) of the dairy farm experience between participants and non-participants was significant at a 5% confidence interval (Table 2).

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Distance to a Nearby Asphalt Road: It refers to the distance of the dairy farming center/shop from the nearby asphalt road in kilometers. It determines the decision to participate or not in dairy contract farming. Those dairy farmers nearer to asphalt roads are in a better position to participate in urban dairy contract farming. It is expected that households nearer to the road will probably incur lower transaction costs and can easily participate in dairy contract farming.
Technical Efficiency: The estimated farm-level technical efficiency for participant and non-participant dairy farmers was 78.3 percent and 62.9 percent, respectively (Please refer to Table 2). The results also showed a statistically significant difference between participants and non-participants, with a significance level of less than 1%. This value indicates that technical efficiency is larger for farmers who participated in urban dairy farming compared with non-participants.

4.1. Estimation of the Stochastic Cobb-Douglass Production Function

Individual technical efficiency levels in dairy farmers were estimated using the stochastic frontier production function. Three different distributional assumptions, half-normal, truncated normal, and exponential, were made for the distribution of the error term, ui. The chibar^2 (01), AIC, and BIC results confirmed that the Cobb-Douglas production frontier assuming an exponential distribution fits the data well. The input variables used in the stochastic frontier production model were the number of lactating cows, shade size, labor, and fodder. As indicated in Table 3, the result of the model showed that the input variables estimated under the Cobb Douglas production function, such as the number of lactating cows, labor, and fodder statistically and significantly affected the level of milk output at less than a 1% significance level. The details of the estimated result of stochastic frontier model are given in Table 3 below. The signs of the coefficients of the stochastic frontier were as expected, except for the negative parameter, the number of laborers used.

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Table 3. Stochastic frontier result.

Input variables	Half normal model			Exponential distribution model			Truncated distribution model		
	Coefficient	Standard error	Z-value	Coefficient	Standard error	Z-value	Coefficient	Standard error	z
Ln of number of lactating cows	0.268***	0.069	3.86	0.273***	0.065	4.200	0.27***	0.06	4.20
Ln of shade size in m2	0.08	0.057	1.41	0.085	0.054	1.570	0.08	0.05	1.57
Ln labour used	-0.207***	0.069	-3.02	-0.199***	0.066	-3.010	-0.20***	0.07	-3.01
Ln fodder used	0.363***	0.099	3.67	0.353****	0.094	3.750	0.35***	0.09	3.75
Constant term	0.65	0.465	1.4	0.562	0.437	1.290	0.56	0.44	1.29
/lnsig2v	-2.379***	0.295	-8.06	-2.324***	0.229	-10.16	-425.97***	2765.57	-0.15
/lnsig2u	-1.351****	0.345	-3.91	-2.395***	0.373	-6.410	4.86***	6.47	0.75
sigma_v	0.304***	0.045	6.781	0.313***	0.036	8.742	7.18***	6.48	1.11
sigma_u	0.509***	0.088	5.791	0.302***	0.056	5.355	129***	835.06	0.15
sigma2	0.352***	0.073	4.812	0.189***	0.029	6.548	0.999***	0. .0049	203.29
lambda	1.672***	0.123	13.54	0.965***	0.082	11.834	128.90	835.06	0.15
LR test of sigma_u=0: Chibar2(01) = 4.57** Number of observation= 135 Chi-square = 47.8*** Akaike crit. (AIC) =167.702				Chibar2(01) = 7.26*** Chi-square = 51.781*** Akaike crit. (AIC) = 165.011			Wald chi2(4) = 51.78*** Log-likelihood = -75.506054 AIC = 167.0121		

Note: * **, & ** show significant at 1%, & 5, respectively.
Source: Computed from own survey data (2023).

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The coefficients of inputs would have an elasticity interpretation if the stochastic production function were specified in logarithmic form. Accordingly, fodder is the most important input in dairy farms. Here, partial elasticity indicates the relative importance of every factor in milk output. Moreover, the sum of the coefficients of the inputs is 0.512. As such, a 1% increase in all the specified inputs will lead to about a 0.512% increase in milk output. This indicates that the urban dairy farmers in the study area are operating at a decreasing return to scale. This implies that if all the resources used in the production process increase in the same proportion, the output will increase by less than the proportionate amount.

A STATA post-estimation command calculates predictions of an individual dairy farmer's technical efficiency. The technical efficiency score of each dairy farmer score was used as an outcome variable in propensity score matching to evaluate the effect of participation in dairy contract farming on technical efficiency.

In PSM estimation, the following steps were performed:

First, a probability model of participation in dairy CF was estimated to calculate the propensity score of each dairy farm owner/manager.

In this section, the selected explanatory variables were used to estimate the probit regression model and to examine the determinants of participation in dairy contract farming. The probit model can be used when dependent variable is binary (also called dummy), which takes value 0 or 1, and it is a nonlinear regression model that forces the output (predicted value) to be either 0 or 1 (Gujarati & Porter, 2009). Hence**,** a probit and logit model was fitted to estimate the effects of the hypothesized explanatory variables on the probabilities of participation in dairy contract farming.

If the assumptions of logistic/probit regression analysis are not met, we may have problems, such as biased coefficient estimates or very large standard errors, and these problems may lead to invalid statistical inferences. So, before we use our model to make any statistical inference, check that our model fits sufficiently well and checks for influential observations that have an impact on the estimates of the coefficients (Verbeek, 2004).

To test goodness of fit test, the researcher used the likelihood ratio test, and as it can be seen in the logit/probit estimate table, the LR Chi^2 value of the model is very high (Chi-square = 26.826 for logistic regression and Chi-square = 26.922 for probit regression) with the p-value of 0.000. This indicates that the model as a whole is statistically significant. However, our analysis was made using probit regression since Akaike crit. (AIC) = 174.97 for probit regression is lower than that of Akaike crit. (AIC) = 175.070 for probit regression (for detail refer to Table 4).

Table 4. Logistic/ probit regression result.

Independent variables	**Logit model**			**Probit model**		
	Coef.	**St. err.**	**dy/dx**	**Coef.**	**St. err.**	**dy/dx**
Sex of owner or manager *	-0.874	0.487	-0.215	-0.529	0.296	-0.208
Age of owner or manager ***	-0.104	0.032	-0.026***	-0.064	0.019	-0.025
Family size of owner or manager	-0.073	0.08	-0.018	-0.045	0.049	-0.018
Education level ***	0.225	0.07	0.055***	0.136	0.041	0.054
Experience of owner or manager ***	0.169	0.06	0.042***	0.101	0.035	0.040
Distance to nearby asphalt road	-0.0005	0.0005	-0.0001	-0.025	0.240	-0.0001
Credit	-0.051	0.4	-0.013	-0.024	0.24	-0.0001
Constant	2.668	1.699		1.675	1.017	
Mean dependent variable = 0.452 SD dependent variable = 0.500 Pseudo r-squared = 0.144 Number of obs. = 135 Chi-square = 26.826 Prob > chi2 =0.000 Akaike crit. (AIC) = 175.070 Bayesian crit. (BIC) =198.312				Mean dependent var =0.452 SD dependent var =0.500 Pseudo r-squared = 0.145 Number of obs. =135 Chi-square =26.922 Prob > chi2 =0.000 Akaike crit. (AIC) = 174.97 Bayesian crit. (BIC) = 198.216		

Note: *** shows significant at 1%.
Source: Computed from own survey data (2023).

Age of the Owner or Manager of the Dairy Farm: The age of a dairy farm owner or manager negatively and significantly affected the participation decision of dairy farmers in contract farming at less than a 1% probability level. It shows that a one-year increase in the age of the respondent would result in a 2.5 percent decrease in the probability of being a participant in dairy contract farming. The possible explanation could be that as a dairy farm business owner's age increases, their access to information decreases because of a decrease in their mobility, especially in running income-generating activities. Moreover, their achievement motivation and level of aspiration diminish with age. The result is consistent with Fita, Trivedi, Patel, Tassew, and Joshi (2013) and contradicts the findings of Mosisa, Legesse, Haji, and Bekele (2020).

Education: Education is one of the important indicators of human capital and has a positive and significant effect at the 1% level of significance, implying that dairy farm business owners who are better in educational attainment were found to be more likely to participate in than illiterate persons were. The probable justification is that an educated person gains better skills, experience, and knowledge, and this again helps them to engage in diversified income strategies. Each additional year of education for the household head increases the probability of this by 5.4%. The findings align with the research by Rondhi, Aji, Hasan, and Yanuarti (2020) which demonstrated a significant positive impact of education on broiler farmers' participation in CF in Indonesia. Nazifi and Hussain (2021) also found that the extent of participation in contract farming is higher among youth than old persons.

Dairy Farm Experience: The experience of dairy farm owners is one of the factors that affect participation in dairy contract farming. Experience is taken to be the number of years that an individual was continuously engaged in the dairy farm business. Dairy farming businesses' experience is expected to increase their demand for yield. That is, experienced farmers are expected to have greater access to productive resources (such as land and labor), be able to apply improved production technologies, and faster in dairy contract farming than inexperienced farmers. The probability of adopting and intensifying improved maize varieties positively and significantly correlates, at a 10% significance level, with farm experience. Each additional year of dairy farm business experience of the owner increases the probability of participation in dairy contract farming by 0.4%. This is consistent with the research results of Fita et al. (2013) that farmers learn more from their previous experiences of milk production and rectify them in the ensuing years to improve their technical efficiency of milk production. Nazifi and Hussain (2021) also found that farming experiences increase the extent of participation in maize contract farming.

4.2. Results of Propensity Score Matching

Ensuring the balance of propensity scores across treatment and comparison groups is the second step in PSM estimation. In setting the common support conditions, the minima and maxima comparison was made. The estimated propensity scores as shown in Table 2, varies between 0 and 1. In setting the common support conditions, the minima and maxima comparison was made. As shown in Table 5, the estimated propensity scores vary between 0.139 and 0.967 with a mean of 0.55 for participants and between 0.022 and 0.808 with a mean of 0.368 for non-participant dairy farmers (see Table 5). Then, the common support region would lie between 0.139 and 0.808. In other words, households whose estimated propensity scores are less than 0.139 and larger than 0.808 are not considered for the matching exercise. Because of this results restriction, 14 households (4 of participants and 10 from non-participants) were dropped from the analysis in estimating the average impact of participation in dairy contract farming on dairy farming technical efficiency (see Table 6).

Table 5. Distribution of estimated propensity scores.

Groups	Observation	Mean	Standard deviation	Minimum	Maximum
Non- contract participants	74	0.368	0.2	0.022	0.808
Contract participants	61	0.55	0.187	0.139	0.967
All dairy farmers	135	0.451	0.214	0.022	0.967

Table 6. Common support region.

Sample	Off-support the common support region	On common support region	Total
Untreated (Non-participants)	10	64	74
Treated (Participants)	4	57	61
Total	14	121	135

Source: Computed from own survey data (2023).

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Having completed the estimation of the propensity scores and the common support region, the next step is seeking an appropriate matching estimator (or algorithm).

Table 7. Performance of the different matching algorithms.

Matching estimator		Matching performance criteria			Mean bias
		Balancing test*	Pseudo-R2	Matched sample size	
Kernel	Bwidth (0.01)	7	0.037	83	11.1
	Bwidth (0.05)	7	0.007	121	5.2
	Bwidth (0.1)	7	0.005*	121	5.4
Nearest neighbor	Neighbour(1)	7	0.022	121	10
	Neighbour(2)	7	0.025	121	8.9
	Neighbour(3)	7	0.013	121	8.2
Caliper or radius	Radius caliper (0.01)	7	0.038	83	11.1
	Radius caliper (0.05)	7	0.005*	121	4.7
	Radius caliper (0.1)	7	0.006	121	5.9

Note: * shows matching algorithms with the largest matched sample size, high balancing test, low pseudo R-squared and lowest mean bias.

Different alternatives of matching estimators were conducted to match the treatment households and control households that fall in the common support region. For the final selection, there are three most important criteria that were suggested by Deheija and Wehba (2002). The first criterion is the balancing test, which suggests that a matching estimator should balance all explanatory variables (i.e., the results show an insignificant mean difference between the two groups). The second criterion is choosing the smallest value of pseudo- R2, and the largest number of matched sample sizes is preferred. Based on the above-stated criterion, the best matching estimator was Caliper or Radius, with Radius caliper (0.05) being chosen since it balances all of the explanatory variables (i.e., results in insignificant mean differences between the two groups), bear a low pseudo-R2 value, and results in a large matched sample size (see Table 7).

The next step after choosing the performing algorithm is balancing the distribution of relevant variables in both groups. The main purpose of the propensity score estimation is not to obtain a precise prediction of selection in the treatment but rather to balance the distribution of the relevant variables in both groups. The balancing powers of the estimations are ensured by different testing methods, such as reduction in the mean standardized bias between the matched and unmatched households. Results in Table 8 show that after matching, the differences are no longer statistically significant, suggesting that matching helps reduce the bias associated with observable characteristics.

Table 8. Balancing test.

Independent variables	Mean			t-test		V(T)/V(C)
	Treated	Control	%bias	t	P>|t|	
Sex of the manager /Owner	0.754	0.790	-8.3	-0.45	0.653	.
Age of the manager/Owner	42.14	41.821	4.5	0.26	0.797	1.27
Family size	5.597	5.504	3.7	0.19	0.847	1.32
Education level	9.947	9.875	2.4	0.14	0.887	0.97
experience	5.368	5.421	-1.5	-0.08	0.936	0.93
Distance to asphalt road	500.35	509.04	-2	-0.11	0.91	1.34
Access to credit	0.596	0.649	-10.7	-0.57	0.57	.

The final step in the PSM process is to estimate treatment effects on the outcome variable in the matched sample through a t-test. After controlling for pre-participation differences, it has been found that, on average, participating CF has increased technical efficiency of dairy farmers by 0.15. This means that dairy CF has increased the technical efficiency of participating households by 21.5% (Refer to Table 9). Focus group discussions also confirmed that participants are enjoying considerable benefits in terms of livestock and other asset ownership

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since they started producing milk and milk products on a contractual basis. This finding is consistent with the findings of T Birthal and Joshi (2009) and Joseph et al. (2021) found that contract participants had higher mean TE compared to non-participants. Begum (2005) also compared non-contract and contract poultry farms' income and concluded that if small farmers enter into the CF system, they obtain substantial income gains.

Table 9. Effect of dairy CF on technical efficiency of dairy farmers.

Sample	Treated	Controls	Difference	S.E.	T-stat
Unmatched	0.845	0.706	0.139	0.020	7.070***
ATT	0.847	0.697	0.150	0.024	6.260***
ATU	0.716	0.853	0.137	.	.
ATE		0.143		.	.

Note: *** shows significant at 1%.

The sensitivity test is the final step used to investigate whether the causal effect estimated from the PSM is susceptible to the influence of unobserved covariates. The result of sensitivity report is given in Table 10.

Table 10. Rosenbaum bounds sensitivity analysis.

Gamm*a	Sig+	Sig-	t-hat+	t-hat-	CI+	CI-
1	2.90E-15	2.90E-15	0.5	0.5	0.5	0.5
2	1.70E-08	0	0.5	0.5	-4.30E-07	0.5
3	3.30E-06	0	-4.30E-07	0.5	-4.30E-07	1
4	0.00005	0	-4.30E-07	1	-4.30E-07	1
5	0.0002	0	-4.30E-07	1	-4.30E-07	1
6	0.0007	0	-4.30E-07	1	-4.30E-07	1
7	0.002	0	-4.30E-07	1	-4.30E-07	1
8	0.003	0	-4.30E-07	1	-4.30E-07	1
9	0.005	0	-4.30E-07	1	-4.30E-07	1
10	0.007	0	-4.30E-07	1	-4.30E-07	1

Note: * Gamma-log odds of differential assignment due to unobserved factors.
Sig+ - upper bound significance level.
Sig- - lower bound significance level.
t-hat+ - upper bound Hodges-Lehmann point estimate.
t-hat- - lower bound Hodges-Lehmann point estimate.
CI+ - upper bound confidence interval (a= 0.95).
CI- - lower bound confidence interval (a= 0.95).

The legitimacy of propensity score analysis is based on the assumption of strongly ignorable treatment assignment that assumes all relevant covariates are employed in the treatment assignment and the bias due to the unmeasured covariates is ignorable. The sensitivity analysis in Table 10 shows that the impact result estimates are insensitive to unobserved selection bias. That means for all outcome variables estimated, at various levels of critical values of gamma, the p-critical values are significant, which further indicates that we have considered important covariates that affected both participation and outcome variables. We could not get the critical value gamma where the estimated ATT is questioned even if we have set it largely up to 10. Thus, we can conclude that our impact estimates (ATT) are insensitive to unobserved selection bias and are a pure effect of participation in dairy contract farming.

5. CONCLUSIONS AND POLICY IMPLICATIONS

The main objective of this study was to measure the effect of dairy contract farming on the technical efficiency of dairy farmers in urban and peri-urban areas of Nekemte City. To achieve the stated objective, data was collected from both primary and secondary data sources. Primary data was collected using a semi-structured questionnaire. The study employed a simple random sampling technique to select 181 dairy farmers. Descriptive, logistic regression, and propensity score matching techniques were used for data analysis. The result of the logistic regression model indicated that age, education, and dairy farm experiences statistically significantly affected

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participation in dairy contract farming. The PSM result further indicated that the technical efficiency of dairy contract farmers is higher than that of non–contract dairy farmers. This study's finding suggests that milk producers should establish sustainable contracts with consumers or end users. Other issues that may need to be addressed include the provision of training and livestock management skills to enhance dairy farmers' efficiency.

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The author confirms that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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The author declares that there are no conflicts of interests regarding the publication of this paper.

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