Are Organic Farms Less Efficient? The Case of Estonian Dairy Farms

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Abstract

The paper investigates the technical efficiency of conventional and organic dairy farms in Estonia in the period 2006–2015 using Farm Accountancy Data Network. We analyse self-selection into organic farming using the propensity-score-matching approach and explicitly test the hypothesis that organic and conventional farms apply homogeneous technology. We find that organic farms are less efficient. However, the difference in technical efficiency between organic and conventional farms decreases substantially when the technical efficiency assessment incorporates the use of the appropriate technology. The lack of growth of technical efficiency over time indicates that there might be a lack of knowledge in organic milk production that hinders its development. Since technical efficiency increases with farm size, it is important that organic dairy farms increase their scale.

Keywords

Production function, technical efficiency, milk production, propensity score matching.

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Introduction

The adoption of organic farming practices has gained increasing attention both in policy and scientific circles. According to the organic farming paradigm, a farm is a balanced unit, wherein production-, environment-, and human activities are integrated (Tzouvelekas et al., 2001; Mareth et al., 2016). Organic livestock production is associated with several limitations compared to conventional systems. In most cases, it also assumes organic crop production on the farm. During summers, cows need to be grazed, which is a constraint for larger farms. There is usually not enough grassland around the holding and grazing many cows requires additional labour. In organic livestock production natural insemination is preferred to artificial insemination, and the use of hormones or other preparations for heat synchronization is not allowed. The use of veterinary medicine for preventing disease is prohibited. After curing animals with medical preparations, the sale of milk is banned for twice as long as in conventional systems. Feed for animals must not contain GMOs, antibiotics, growth stimulators, or hormone preparations. Calves must be fed with natural milk for three months (Leming et al., 2011; Palts and Vetemaa, 2012; Nehring et al., 2021).

The difference in productivity of conventional and organic production systems may be due to technological differences, technical inefficiency, or both. Critics of organic production claim that conventional farms are clearly winners in terms of crop yield efficiency, while organic farm advocates claim that organic farms are more energy efficient (De Ponti et al., 2012). The milk yield of dairy cows on organic farms is on average 30% less than on conventional farms in the EU (European Parliament, 2018).

The profitability of organic agriculture can be attributed to several factors. First, organic farmers do not rely on synthetic fertilizer and pesticide inputs, which can be costly. In addition, organic foods enjoy a price premium over conventionally produced foods, meaning that organic farmers can often get more for their yield (Kumbhakar et al., 2009). However, the more restricted use of specific inputs in organic production increases costs, makes organic farms less productive, and, unless higher output prices compensate for lower productivity, reduces their profitability. Seufert et al. (2012) showed that crop yields are typically smaller in organic farms than in conventional farms, but the difference in some cases may be very small.

A wealth of literature has evaluated the factors affecting the TE of EU dairy farming (e.g., Madau et al., 2017; Čechura et al., 2021; Kroupová Žáková and Trnková, 2020). Most of the TE comparisons between organic and conventional farms utilize data about traditional inputs (land, materials) and outputs (milk, grain, etc.) and assume that the same technology is used (e.g., Tzouvelekas et al., 2001, Kumbhakar et al., 2009). Pietola and Oude Lansink (2001) point out that the choice to transition to an organic production system might be more likely among conventional farms that have lower productivity. Sipiläinen and Oude Lansink (2005) suggested that when comparing conventional and organic farms several factors need to be controlled for, including farm location, to avoid selection bias. Other studies have suggested that organic dairy farms have lower TE compared to conventional farms (Oude Lansink et al., 2002; Ricci Maccarini and Zanoli, 2004; Djokoto, 2015).

One of the key issues of efficiency analysis is the technological heterogeneity among farms. This is especially important if we want to compare the performance between organic and conventional farms. The issue of technology choice (conventional dairy farms converting to an organic system or vice versa) has been considered already by Breustedt et al. (2011). Nehring et al. (2021). They found that both conventional and organic larger dairy farms had higher TE, and that size of the farm was related to its economic viability. Kargiannis et al. (2012) found that conventional and organic farms are similarly efficient considering their production technologies.

Estonia is a good case study to compare the TE of organic and conventional dairy farms. Dairy is one of the main production branches in Estonian agriculture with the highest average milk yield per cow in the EU. The competitiveness of organic production systems is an increasingly prominent area of interest as the EU's Farm-to-Fork Strategy has defined the aim of increasing the share of area that is organically farmed of total utilized agricultural area to 25 per cent by 2030 (European Commission, 2020). EU Member States such as Austria and Estonia (22 per cent) have almost reached this target (Moschitz et al., 2021).

The aim of the paper is to contribute to the literature to the debate on of the TE of organic farms using Estonian dairy sector as an example. We pay special attention on the differences in technology between organic and conventional farms using treatment effect approach. Whilst pervious studies have focused on the Western European countries, our attempt is the first to analyse a highly efficient dairy sector in a Central and Eastern European country.

Materials and methods

Methodology

The first step in our investigation is to estimate TE. Since the pioneering work of Aigner et al. (1977) and Meeusen and van den Broeck (1977), efficiency measurement using stochastic frontier models has become a standard approach of applied economists. However, traditional efficiency models assume that all firms face a common frontier, and the only differences result from the intensity of input use (Tsionas, 2002; Alvarez et al., 2012). As our aim is to estimate TE for dairy farms and to compare organic and conventional farms, the assumption of common technology is strong. To account for unobserved heterogeneity, conventional panel data models such as fixed-effects or random-effects models are suitable (Pitt and Lee, 1981; Schmidt and Sickles, 1984). However, these models have the following limitations: (i) the treatment of the inefficiency term as time-invariant, which raises a fundamental identification problem, and (ii) they fail to distinguish between cross-individual heterogeneity and inefficiency (Abdulai and Tietje, 2007; Greene, 2005). To account for these limitations, Greene (2005) proposes two stochastic frontier models that are time-variant and that distinguish unobserved heterogeneity from the inefficiency component. These models are called 'true' fixed-effects (TFE) and 'true' random-effects (TRE) models. However, as pointed out by Greene (2005), TFE models might produce biased individual effects and efficiency estimates because the presence of the individual effects creates an incidental parameter problem. In contrast, TRE models produce unbiased inefficiency estimates, therefore we apply a TRE model in line with that of Kostlivý and Fuksová's (2019). The TRE model can be specified as:

$$y_{it} = \alpha + \mathrm{f}(x_{it}, \beta) + w_i + v_{it} - u_{it}, \qquad (1)$$

where y_{it} is the log of output (revenue) for farm i at time t; α is a common intercept; $\mathrm{f}(x_{it}, \beta)$ is the production technology; x_{it} is the vector of inputs (in logs); β is the associated vector of technology parameters to be estimated; v_{it} is a random two-sided noise term (exogenous production shocks) that can increase or decrease output (ceteris paribus); and $u_i > 0$ is the non-negative one-sided inefficiency term. The parameters of the model are estimated with the maximum likelihood (ML) method using the following distributional assumptions:

$$u_{it} \sim N^{+}(0, \sigma_{it}^{2}) = N^{+}\left(0,\ exp\left(w_{u0} + z'_{u,it} w_u\right)\right) \quad (2)$$

$$v_{it} \sim N^{+}(0, \sigma_{v}^{2}) \quad (3)$$

$$w_{it} \sim N^{+}(0, \sigma_{w}^{2}) \quad (4)$$

The term u_i in the Equation (1) measures technical inefficiency in the sense that it measures the shortfall in output from its maximal possible value given by the stochastic frontier ($f(x_{it}, \beta) + v_{it}$). The estimation of u_i contains the specific heterogeneity; to disentangle these effects we applied the JLMS technique (Jondrow et al., 1982). This implies calculating the conditional distribution of u_{it} given $\varepsilon_{it} = v_{it} - u_{it}$ for each observation.

Mayen et al. (2010) emphasize two important methodological issues when comparing the TE of organic and conventional farms: self-selection into organic farming, and formal testing of the homogeneous technology assumption. They propose using a matching approach instead of a Heckman-type model to address the self-selection issue. Following their suggestion, we employ propensity score matching (PSM) to predict the probability of a farm being an organic farm based on observed covariates for both organic and conventional farms. The method balances the observed covariates between the organic group and conventional farmers based on the similarity of their predicted probability of being organic farmers. The aim of PSM matching is to find a comparison group of organic farmers from a sample of conventional farmers that is closest (in terms of observed characteristics) to the sample of organic farmers. Estimating the treatment effects based on the propensity score matching (PSM) requires two assumptions. The first is the Conditional Independence Assumption (CIA), which states that for a given set of covariates participation is independent of potential outcomes. A second condition is that the average treatment effect for the treated (ATT) is only defined within the region of common support. This assumption ensures that treatment observations have comparison observations "nearby" in the propensity score distribution. Following Mayen et al. (2010) we perform a formal test to resolve the potential endogeneity problem and test the validity of the assumption of homogeneous technology using an organic dummy in the production frontier.

Data

For the purpose of the empirical analysis we used data from the Estonian Farm Accountancy Data Network (FADN), which was obtained from the Estonian Agricultural Research Centre. The database consists of an unbalanced panel of dairy farms for the period 2006–2015.

The production function $f(x_{it}, \beta)$ in our models is specified with the following input variables: *Labour* is hours of labour used on the farm, measured as total number of hours worked, including management, family, and hired workers; Land is agricultural area in hectares; *Variable inputs* is variable farm inputs, measured by total specific costs (variable costs), deflated by the consumer price index (CPI) to 2006 Euro prices; *Capital* is farm-fixed and capital costs, also deflated by the CPI to 2006 Euro prices; and t(1;...; 10) is a time trend. Farm total output (*Output*) in euros was used as an output variable, which was deflated by the producer price indices of agricultural products for agricultural goods.

The z-variables in this study are the following: *Share of rented land* is the share of rented land of the farmer's total agricultural land in a year; *Share of paid labour* is the share of paid labour in total labour input. *Farm size* is the size of the farm classified according to FADN size groups.

Summary statistics and the statistical significance of tests on equality of means for continuous variables and equality of proportions for binary variables of organic and conventional farms are reported in Table 1. There are significant differences in farm characteristics between conventional and organic farms. Calculations indicate that, on average, organic farms are smaller in terms of output and input use and receive smaller subsidies than conventional farms. Other characteristics are also significantly different, except for the age of farmers. However, the matched conventional farms exhibit similar characteristics to the organic farms.

	Conventional			Organic			Matched conventional[a]		
	N	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev.
Production function variables									
Output (euros)	1834	295743.9	636586.8	289	33260.4***	53014.9	289	115891.7	350027.7
Capital (euros)	1834	70292.1	145277	289	17111.2***	31833.9	289	31063.9***	93155.9
Variable inputs (euros)	1834	208876.2	471940	289	29685.1***	37763.5	289	76318.5	212012.9
Land (hectare)	1834	413.3	709.6	289	171.1***	182.5	289	190.9***	390.8
Labour (AWU)	1834	10.5	17.6	289	2.9***	2.8	289	4.8	9.8
Heteroskedasticity variables in the inefficiency function									
Share of rented land	1830	0.5	0.31	289	0.54***	0.32	289	0.55	0.34
Share of paid labour	1834	0.45	0.43	289	0.27***	0.37	289	0.26	0.37
Heteroskedasticity in error component variables									
Farm size	1834	7.58	2.64	289	6.14***	1.52	289	5.99***	2.3
Additional variables for PSM analysis									
Age (year)	1820	53.4	11.5	289	53.7	10.9	289	53.4	11.9
Owner (0/1)	1834	0.7	0.46	289	0.86***	0.35	289	0.83	0.37
Natura 2000 (0/1)	1834	0.08	0.27	289	0.20***	0.4	289	0.14	0.35
Total subsidies (euros)	1834	62255	105879	289	31370***	32643	289	31425	74129

Note: Asterisks denote a statistically significant difference with the organic mean at the 1 percent (***) level,

[a] The subsample of conventional farms matched to organic farms on the basis of the estimated PSM analysis

Source: Own estimations, data: Farm Accountancy Data Network (Estonia)

Table 1: Descriptive statistics of variables.

Results and discussion

Self-selection test

First, we test whether there is a reason to consider self-selection into organic farming for the full sample. Thus, we employ a Durbin-Wu-Hausman (DWH) test of the endogeneity of the organic dummy variable included in the Equation (1). The resulting chi-squared statistic from an F test is 6.46 with 1 degree of freedom (p-value = 0.011). Therefore, we reject the null hypothesis that the organic dummy is exogenous at the 5% level.

PSM analysis

We start with a description of the results of matching procedures. We selected the age of farmers, ownership, total agricultural subsidies, economic farm size, the share of paid labour in total labour, and the share of rented land in total agricultural land, located in Natura 2000 areas, and county dummies to control for regional heterogeneity as the covariates to ensure appropriate similarity between organic and conventional farms without violating the assumption of common support.

The first challenge in PSM analysis is to identify the appropriate matching algorithm. The most used matching algorithms that involve a propensity score are the following: Nearest Neighbour Matching, Radius Matching, Stratification Matching, and Kernel Matching. As the quality of a given matching technique depends strongly on the dataset, the selection of a relevant matching technique is based on three independent criteria: i) standardized bias (Rosenbaum and Rubin, 1985); ii) a t-test (Rosenbaum and Rubin, 1985); and, iii) joint significance and pseudo R2 (Sianesi, 2004). Our estimations suggest that the various methods produce very similar results, but nearest-neighbours (N1) matching is the best matching algorithm in all cases[1].

Table 2 presents the probit estimates of the organic propensity equation. The model has a McFadden pseudo R^2 value of 0.205, and 87.05% of the cases are correctly classified. Some variables are statistically significantly associated with being an organic dairy farm. Farms with a greater share of rented land and those located in Natura 2000 areas are more likely to be organic. On the other hand, farm size is negatively associated with organic production. Some county dummies are also highly significant.

We use the probit estimates to generate a propensity score – i.e., the predicted probability of being organic – for each farm. We then create a subsample of conventional farms by selecting for each organic farm the conventional farm with a propensity score

[1] We applied the STATA psmatch2 programme developed by Leuven and Sianesi (2012).

closest to that of the organic farm. The resulting subsample of matched conventional farms consists of 289 farms. These farms are on average less than half the size of the original conventional dairy sample in terms of outputs and use of inputs (Table 2). Compared to the organic farms, the matched conventional dairy farms are still statistically different in terms of capital and input use and farm size.

Variable	coefficients
Age	-0.006
Owner	0.056
Farm size	-0.179***
Natura 2000	0.510***
Share of rented land	0.270*
Share of paid labour	-0.033
Total subsidies	0.000
County dummies	
39 Harju	1.420***
44 Hiiu	0.907***
49 Ida-Viru	0.516*
51 Järva	-0.371
57 Lääne	0.054
59 Lääne-Viru	-0.148
65 Põlva	-0.312
67 Pärnu	0.313
70 Rapla	-0.537*
74 Saare	0.835***
78 Tartu	0.848***
82 Valga	0.066
84 Viljandi	0.545*
86 Võru	0.078
constant	-0.629
N	2108
Pseudo R^2	0.205

Note: Asterisks denote statistical significance at the 10% (*), 5% (**), and 1% (***) levels.
Source: Own estimations, data: Farm Accountancy Data Network (Estonia)

Table 2: Probit estimates of the propensity to produce organic milk.

In the next step we employed a balancing property test (t-test) to check statistically the comparability of the two groups of farms in terms of observable covariates (Caliendo and Kopeinig, 2008). Our estimations confirm that the matching algorithm that was applied considerably increased the comparability of the two farms groups, making counterfactual analysis more realistic (Appendix, Table A 1). After matching, the differences between the two groups in terms of covariates became insignificant.

We apply a DWH test of the endogeneity of the organic dummy variable included in equation (1) over the PSM subsample. The resulting c hi-squared statistic from an F test is 1.901 with 1 degree of freedom (p-value = 0.168). Thus, we cannot reject the null hypothesis that the organic dummy is exogenous, and we conclude that the PSM approach appropriately generates a subsample of conventional farms to which organic farms are randomly assigned.

Stochastic frontier analysis

We chose a translog specification of the $f(x_{it}, \beta)$ function in the empirical analysis because of its flexibility. We used log values for the input variables in the translog production function. Prior to taking logs, the x-variables were scaled (divided by their geometric means). Table 4 presents the results of the stochastic frontier models estimated on the full sample and the PSM subsample of dairy farms. We estimate two different models for each sample. First, we assume that both organic and conventional dairy farms have the same production technology. Second, we estimate a model that allows the organic and conventional production technologies to differ. Using the model for both the full sample and the PSM subsample that allows for different technologies, we test the restriction that the organic intercept and slope shifters are jointly equal to zero. The resulting chi-squared statistic from a Wald test is 4.53 and 4.45 with 5 degrees of freedom for the full sample and PSM subsample (p-value = 0.033 and 0.034). Thus, we reject the null hypothesis that the organic intercept and slope shifters are jointly equal to zero at conventional significance levels. In other words, we reject the hypothesis of a homogeneous technology for organic and conventional dairy farms.

Because all variables have been normalized by their respective sample mean prior to taking logarithms, the first-order estimates β_i can be interpreted as partial production elasticities, showing how much the output would increase in percentage terms if the use of the respective input was increased by 1%. Table 3 shows that variable inputs have the largest partial production elasticity in all models (0.61–0.77). Labour inputs have second highest elasticity in the full sample, whilst capital inputs play a more important role in the PSM subsample. The elasticities of capital and variable inputs are higher in the PSM subsample compared to those of the full sample. Interestingly, the time variable is insignificant for all specifications, implying the lack of changes in technological progress.

The share of rented land and the share of paid labour has a statistically significant effect on the statistical variances. As the share of rented land (share of paid labour) increases, inefficiency variance increases (decreases). When farm size increases, inefficiency variance decreases.

To assess TE differences between organic and conventional dairy farms we evaluate the stochastic frontiers at the means of discretionary inputs for all farms. The means and standard errors of the TE measured under different methodological assumptions are presented in Table 4, (columns 2-5).

	Full sample		PSM subsample	
	1 same technology	2 different technology	3 same technology	4 different technology
Capital	0.129***	0.134***	0.217***	0.224***
Variable inputs	0.643***	0.607***	0.774***	0.706***
Land	0.066***	0.105***	-0.124	-0.094
Labour	0.201***	0.179***	0.157*	0.176**
Capital* Variable inputs	-0.131***	-0.187***	-0.123	-0.157*
Capital*Land	-0.065*	-0.085**	-0.032	-0.088
Capital*Labour	0.059	0.104**	0.014	0.071
Variable inputs*Land	-0.142***	-0.070	-0.547***	-0.436**
Variable inputs*Labour	-0.238***	-0.229***	-0.512***	-0.551***
Land*Labour	0.316***	0.119	0.595***	0.538***
time	0.001	0.002	-0.003	0.004
time*Capital	-0.009	-0.003	0.029	0.029
time*variable input	0.027***	0.028***	-0.038	-0.036
time*Land	-0.003	-0.009	-0.010	-0.005
time*Labour	0.004	0.003	0.053**	0.048**
time[a]	0.004**	0.003**	0.007	0.006
Capital[a]	0.057***	0.075***	0.070**	0.093***
Variable input[a]	0.120***	0.118***	0.360***	0.317***
Land[a]	0.066**	0.104***	0.211*	0.208
Labour[a]	-0.062	0.014	-0.014	-0.003
organic		-0.291***		-0.436***
Capital*organic		0.031		0.008
Labour*organic		0.127*		-0.052
Land*organic		-0.145*		0.088
Variable inputs*organic		-0.026		-0.135
constant	12.448***	12.476***	12.491***	12.575***
Usigma				
Share of rented land	1.263***	0.708***	1.317***	1.376***
Share of paid labour	-2.180***	-2.060***	-1.346***	-1.411***
constant	-2.877***	-2.759***	-2.490***	-2.568***
Vsigma				
Farm size	-0.505***	-0.513***	-0.412***	-0.455***
constant	0.541**	0.482**	-0.554	-0.312
Theta				
constant	0.251***	0.225***	0.262***	0.250***
N	2307	2095	567	567
Log simulated-likelihood	-781.2324	-548.033	-345.553	-334.688

Note: Asterisks denote statistical significance at the 10% (*), 5% (**), and 1% (***) levels.
[a] The authors apply the Stata sfpanel command developed by Belotti et al. (2013).

Source: Own estimations, data: Farm Accountancy Data Network (Estonia)

Table 3: Results of SFA models.

Column 6 of the Table 4. displays the difference in the mean technical efficiency of organic and non-organic farms. Column 7 presents the significance of the Kruskal-Wallis test. The null hypothesis of the test is that the difference in TE means is not statistically significant. For the full sample, when we assume homogeneous technologies (row 4, Table 4), we find that the organic technology is 7.7% less productive than the technology used by conventional farms. The difference in TE decreases to 5.3% but it remains statistically significant when allowing for different technologies (row 5, Table 4.). This means that the best-practice organic farms are not able to produce as much as conventional dairy farms operating at the production frontier. In both cases, the significant Kruskal-Wallis p-values reject the mean equality null hypothesis, concluding that non-organic farm TE means are significantly higher than that of their organic counterpart, regardless of the assumptions we make on technology.

When weLat two rows of Table 4. present TE estimates corrected for self-selection bias, that is efficiency estimated on the PSM subsample. Where webut assume homogeneous technology, we find the TE of organic farms to be 76.2%, which is six percentage points lower than for conventional farms (row 7, Table 4.). The difference between average TE on organic and conventional dairy farms is still statistically significant at the 0.01 level, and is larger in magnitude under the homogeneous technology assumption than otherwise. It follows that Thus, a false assumption of homogeneous technology causes a downward bias in the estimate of TE on organic farms relative to that on conventional farms (row 7, Table 4.).

Finally, we estimate TE for each farm based on the estimated frontiers for the PSM subsample assuming different technology and compare the TE of organic and conventional dairy farms. Measured against the appropriate frontier, we find that average technical efficiency is 71.9 % on organic farms and 75.7 % on conventional farms. A Kruskal-Wallis test suggests the difference in mean TE is not statistically significant (row 8, Table 4.).

Discussion

In Estonia, only 2% of dairy cows are raised using organic production systems, while 22% of the utilized agricultural area is organic. One of the reasons for the small share of organic dairy farms in Estonia may be the dominant size of dairy farms. The Estonian dairy sector is dominated by relatively large conventional farms (Viira et al., 2015; Luik and Viira, 2016). Our results confirm that larger farms are less likely to be organic in Estonia, which may be related to difficulties with applying certain organic production practices (e.g., grazing) in large diary units.

We use PSM to compile a valid set of conventional farms for comparing TE on organic and conventional dairy farms. Matching improved significantly the comparability of the organic and conventional farms. However, matched conventional dairy farms used more capital and variable inputs compared to similar organic farms. While variable input use could be associated with differences in intensity of production, the differences in capital may refer to a lower level of investment and older production facilities on organic farms. For organic farms, this could be an advantage in the short term, but in the longer term raises question about their economic viability.

Most earlier studies that compared the productivity of organic and conventional farms found that organic farms have lower productivity (Kumbhakar et al., 2009; Mayen et al., 2010; Oude Lansink et al., 2002; Tiedemann and Latacz-Lohmann, 2011). Sipiläinen and Oude Lansink (2005) found a 10% efficiency gap between organic and conventional dairy farms, and Kumbhakar at al. (2009) found that organic farms were 5% less efficient than conventional farms.

	conventional farms		organic farms			
	Mean	Std. Dev.	Mean	Std. Dev.	difference in means	Kruskal-Wallis
Full sample						
same technology	0.828	0.002	0.751	0.009	0.077	0.0001
different technology	0.828	0.002	0.775	0.009	0.053	0.0001
PSM subsample						
same technology	0.762	0.007	0.703	0.011	0.059	0.0009
different technology	0.757	0.007	0.719	0.011	0.038	0.2385

Source: Own estimations, data: Farm Accountancy Data Network (Estonia)

Table 4: Means and standard deviations of technical efficiency.

We find that the organic farms are on average about 8% less technically efficient than conventional farms if we assume that they use homogeneous technology. If we assume that the technology on organic and conventional farms differs, the TE of organic farms is 5% lower than on conventional farms. Therefore, we can make an unambiguous conclusion about the heterogeneity of technology on organic and conventional farms. In this case, however, the difference in TE decreases, but remains statistically significant. This confirms that the best-practice organic farms are not able to produce as much as conventional dairy farms operating at the production frontier. In this, our results are consistent with other findings (Kumbhakar et al., 2009).

This productivity difference could explain why Estonian dairy farms prefer conventional production practices. However, productivity differences are not as high as differences in yields (De Ponti et al., 2012; Seufert et al., 2012). This suggests that if the policy aim is to increase organic dairy farming, additional support is needed. However, if the aim is to increase the share of organic farms among dairy farms, one should also consider the time needed for adjustment. Sipiläinen and Oude Lansink (2005) found that after the conversion to organic farming, farm efficiency increases for 6-7 years, indicating the presence of a learning effect. An increase in the TE of organic farms was also found by Kostlivý and Fuksová (2019). The presence of a learning effect justifies the conversion subsidies for organic farms.

After evaluating TE for each farm, and comparing the results of organic and conventional dairy farms, we find that average TE is 71.9% on organic farms and 75.7% in conventional farms. This difference in mean TE was not statistically significant. One of the erroneous assumptions that can be made when comparing organic and conventional dairy farms is the assumption of homogeneous technology. If one acknowledges that organic and conventional dairy farms use different technology, the differences in TE become insignificant. This suggests that more attention should be paid to technology differences in organic and conventional production systems.

The choice of an organic system is influenced by number of factors, including personal preferences. Organic farming might also be preferred by society, thus social norms might be a factor that affects the technology choice of farmers. As part of the EU Farm-to-Fork Strategy, organic farming will be promoted, and at least 25% of the EU's agricultural land shall be under organic farming by 2030 (Purnhagen et al., 2021). While Estonia (22%) has almost reached the target of 25% (Moschitz et al., 2021), there is still much room for an increase in organic milk production in Estonia. To achieve this, additional economic incentives are needed (Uuematsu and Mishra, 2012).

Conclusion

In recent years the number of organic farms and share of organic land of all utilized agricultural area has increased in Estonia. Despite this, the share of organic dairy farms remains small, and the average milk yield per cow is lower on organic farms than traditional ones. In this context, we compared the TE of organic and conventional dairy farms using FADN data from 2006–2015. The findings showed that organic and conventional farms differ in size and technology. Therefore, organic dairy farms have a different production frontier to conventional farms. It is important to acknowledge this difference in future studies that compare organic and conventional agricultural production.

Our results reveal that there has been a lack of technological progress in organic dairy farming in Estonia. While it has previously been shown that after conversion from conventional to organic farming there is a transition or learning period during which TE increases, the lack of progress in the Estonian case indicates that there might be a lack of knowledge related to organic milk production that hinders the development of this type of farming, which may also discourage conventional dairy farms from converting to organic production. This situation requires the attention of policy makers.

According to our findings, TE increases with farm size. Therefore, it is important that organic dairy farms also increase their scale and become more efficient. In addition to farm payments that compensate productivity differences, it is therefore also important to implement policy measures that facilitate the development of organic farms.

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Appendix

Variable	Unmatched	Mean		t-test	
	Matched	Treated	Control	t	p > t
Age	U	53.723	53.394	0.648	0.91
	M	53.723	53.38	0.36	0.718
Owner	U	0.858	0.706	5.40	0.000
	M	0.858	0.844	0.47	0.636
Natura 2000	U	1.204	1.077	6.90	0.000
	M	1.204	1.192	0.36	0.717
Farm size	U	6.138	7.571	-9.01	0.000
	M	6.138	6.175	-0.22	0.822
Share of rented land	U	0.543	0.504	2.09	0.037
	M	0.5436	0.533	0.38	0.706
Share of paid labour	U	0.270	0.446	-6.55	0.000
	M	0.270	0.280	-0.30	0.763
Total subsidies	U	31370	62384	-4.93	0.000
	M	31370	32718	-0.29	0.769
39.id_county	U	0.186	0.014	14.85	0.000
	M	0.186	0.144	1.38	0.169
44.id_county	U	0.034	0.015	2.28	0.023
	M	0.034	0.035	-0.08	0.937
49.id_county	U	0.051	0.042	0.69	0.488
	M	0.051	0.058	-0.37	0.711
51.id_county	U	0.020	0.088	-3.97	0.000
	M	0.020	0.028	-0.59	0.557
57.id_county	U	0.048	0.062	-0.94	0.347
	M	0.048	0.063	-0.81	0.421
59.id_county	U	0.027	0.112	-4.45	0.000
	M	0.027	0.043	-1.02	0.309
65.id_county	U	0.010	0.036	-2.33	0.020
	M	0.010	0.014	-0.46	0.645
67.id_county	U	0.169	0.155	0.61	0.545
	M	0.169	0.180	-0.34	0.733
70.id_county	U	0.041	0.164	-5.52	0.000
	M	0.041	0.059	-0.98	0.326
74.id_county	U	0.179	0.078	5.60	0.000
	M	0.179	0.175	0.14	0.888
78.id_county	U	0.055	0.018	3.82	0.000
	M	0.055	0.049	0.31	0.759
82.id_county	U	0.038	0.058	-1.43	0.154
	M	0.038	0.034	0.21	0.838
84.id_county	U	0.062	0.044	1.33	0.185
	M	0.062	0.052	0.50	0.620
86.id_county	U	0.058	0.067	-0.56	0.577
	M	0.058	0.041	0.94	0.346

Source: Own estimations, data: Farm Accountancy Data Network (Estonia)

Table A1: Comparison of farm groups without and with matching