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The Role of Technical Efficiency Achieving Sustainable Development: A Dynamic Analysis of Norwegian Dairy Farms

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Abstract: Growing environmental concerns have prompted governments to make sustainable choices in agricultural resource use. Evaluating the sustainability of agricultural systems is a key issue for the implementation of policies and practices aimed at revealing sustainability. This study aimed to evaluate the performance of Norwegian dairy farms, accounting for marginal effects of environmental (exogenous) variables. We adopted the dynamic parametric approach within the input distance function framework to estimate the performance of Norwegian dairy farms, focusing on the technical efficiency and determinates. For comparison, we also estimated the static parametric model, which was used by previous studies. We used unbalanced farm-level panel data for the period 2000–2018. The result shows a mean technical efficiency score of 0.92 for the dynamic model and 0.87 for the static models. The empirical result shows that the previous studies that focused on the static model reported a biased result on the performance of dairy farms. The dynamic efficiency score suggests that Norwegian dairy farms can reduce the input requirement of producing the average output by 8% if the operation becomes technically efficient. The environmental variables have a different effect on the performance of the farmers; thus, policymakers need to place special focus on these variables for the sustainable development of the dairy sector.

Keywords: productive efficiency; investment; farm management; and dairy farm

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1. Introduction

Food insecurity, climate change, and biodiversity resource loss are the main challenges to the sustainable development of mankind [1]. The primary objectives of the Norwegian agricultural and food policies, as set out in White Paper No. 11 (2016–2017), are: (1) long-term food security; (2) agriculture in all parts of the country; and (3) creating more added value along with sustainable production with reduced greenhouse gas emissions. To deliver a more resilient primary agriculture sector, national and regional governments are identifying mechanisms to support family farms to adapt to agricultural policy demands. Growing environmental concerns have prompted governments to make sustainable choices and perform sustainable actions in the economy, aimed at preventing the deterioration of the environment whilst also maintaining long-term food security and optimal utilization of production resources [2].

The concept of sustainable agriculture has become increasingly vital in agricultural policy debates and has led farmers to pay attention to the questions of the monitoring and evaluation of agricultural practices [3]. Improving the productivity and efficiency of agricultural input use is the first step in tackling the challenge of sustainable use of natural resources. Moreover, the environmental impacts of agricultural production can be reduced by efficient use of production resources or reducing losses of production resources. Consequently, measuring and evaluating farm performance accounting for environmental differences is an important task for researchers in order to make the best use of resources and to identify the best-performing farms [4]. Evaluating the sustainability of agricultural systems is a key issue for the implementation of policies and practices aimed at revealing sustainable forms of land use [5] and a key step in supporting the development of sustainable farming systems [6].

In the economics literature, there are several approaches to measuring and evaluating the performance of an agricultural system, including the Bayesian stochastic frontier approach [7], the semi-parametric approach [8], and the stochastic data envelopment analysis (DEA) approach [9], although these are not commonly used in empirical studies. There are two main approaches to measuring and evaluating the performance of an agricultural system in empirical studies: a parametric approach, such as the stochastic frontier approach (SFA), and a non-parametric approach, such as data envelopment analysis (DEA) [10]. In both methods, the basis for performance measurement is the radial contraction or expansion connecting inefficient observed points with the reference points on the production frontier [4,11]. For a sample of producers, both approaches involve estimating the 'best-practice' frontier for a specific group of farms. If the actual production point of a farm lies on the frontier, the farm is considered to have performed the best and used resources efficiently; if it lies below the frontier, then it is inefficient. The choice of estimation method has been an issue of debate and each approach has its advantages and disadvantages, see for details [12,13]. The treatment of measurement error is the critical distinction between parametric and non-parametric approaches. The SFA approach can accommodate noise, such as measurement errors due to weather, disease, and pest infestation, which are likely to be significant in farming. Moreover, the DEA approach is sensitive to outliers since the measurement error is ignored [12–14]. Since the farms in our study are sensitive to random external shocks, we chose the SFA approach to evaluate the efficiency scores and determinants of inefficiency. An extensive literature has emerged over the past several decades that addresses how to measure the best-performing farms and deviations from optimal behavior using the SFA model (see, for example [13,14]).

The first debate in the literature is on the question of how to handle farm heterogeneity in the SFA model, since the sustainable agricultural policy intervention might be different for a different environment because of heterogeneity in farming. The common practice in the literature, if the variables are observable, is to incorporate heterogeneous production factors that affect the inefficiency level in the specification of the composed error terms. Often, however, not all the factors that affect the performance of the farm are observable, so we seldom have complete information about the production conditions. For instance, data on soil type, latitude, altitude, precipitation, distance from the service center, etc. are seldom available or are too complex to be measured by single indicators. In the recent literature, such unobserved heterogeneity was separated from farm inefficiency using econometric techniques (see, e.g., [15,16]). The other source of heterogeneity is differences in the technology used, i.e., technological heterogeneity. The fact that agricultural producers face different production environments may lead to variations in production, which might lead to differences in technology use. In the literature, we can find different techniques by which to control technology heterogeneity. Examples include the cluster algorithm technique [17]; the random parameter technique [18]; the latent class technique (see e.g., [19]); and metafrontiers (see, e.g., [20,21]). Each approach has pros and cons with respect to estimating the performance of a given sector, accounting for technology heterogeneity or regional differences [20]. In this study, we control both heterogeneities, accounting for dummies for each farm, and the estimated SFA model using Greene's [16] approach.

In the empirical application of the SFA model, the dairy sector has received much attention and performance analysis has been conducted (see, for instance, [20–23]). All these studies used a static model. The static model does not account for the contribution of investment, which allows farm managers to adjust their production decisions. The dynamic model accounts for the adjustment of quasi-fixed inputs through investment [24]. We can find in the literature both parametric and non-parametric dynamic approaches. Both kinds of approaches have pros and cons with respect to conducting dynamic efficiency measurement (see for a detailed review [4,25]). This study focuses on the parametric dynamic approach. The parametric dynamic model can be estimated in a reduced or a structural approach, which allows for firm-specific technical inefficiency levels to follow a simple autoregressive process, namely the AR (1) process (see [26,27]). The reduced form captures the dynamic aspects of a firm's behavior, but the model does not model explicitly the dynamic structure of the decision-making process [4]. The dynamic structural approach, which is mainly based on [28], provides a complete characterization of production technology. The reduced form assumes that the farm's decision on farm investment depends on the farmer's ability to make an efficient decision over time. As such, we used the dynamic distance function model to analyze the performance of Norwegian dairy farms. The purpose of this study is to evaluate the role of technical efficiency, accounting for the environmental variables that achieve the sustainable development of Norwegian dairy farms, using a dynamic stochastic approach.

This article contributes to the economics literature in the following ways. First, in contrast to [28], since farms often face differences in the soil quality, intensity of sunlight, temperature, and rainfall, we account for these farm-level heterogeneities and unobserved heterogeneities using [16], true fixed-effect model approach. Second, in this study, we account for determinants (environmental variables) of performance differences from a dynamic perspective, unlike previous studies e.g., [4].

The rest of the article is organized as follows. Section 2 addresses the conceptual framework for dynamic performance measurement. Section 3 discusses the specification of the empirical model. Section 4 discusses the data used. Section 5 discusses the estimation and results. Finally, Section 6 provides a discussion and policy implications.

2. Conceptual Framework

We can represent production technology using the production possibilities set, distance function, and production function. Following [28], the dynamic production technology set (Ψ) for time t represents an input requirement set as:

$$\Psi = \{(\mathrm{y_t}|\mathrm{K_t} : \mathrm{x_t},\ \mathrm{I_t},) : \mathrm{x},\ \mathrm{I\ can\ produce\ y_t\ given\ K_t}\} \tag{1}$$

where $\mathrm{x_t} \in \Re^K_+$ denotes a $1 \times \mathrm{K}$ vector of variable inputs, $\mathrm{y_t} \in \Re^{\mathrm{M}}_+$ stands for a $1 \times \mathrm{M}$ vector of output, $\mathrm{I} \in \Re^H_+$ represents a $1 \times \mathrm{H}$ vector of gross investment, and $\mathrm{K} \in \Re^{\mathrm{P}}_+$ represents a $1 \times \mathrm{P}$ vector of quasi-fixed inputs. The producers transform the inputs into outputs using some production technology (Ψ).

Production technology can be represented by either an input or an output possibility set [29]. To characterize the production technology set (Ψ) in multiple input–output contexts, one can choose from among many appropriate functions. These alternatives can be classified as either primal or dual functional forms. The general primal representation of production technology is given by the directional distance function approach.

Figure 1 illustrates how an inefficient observation at $(\mathrm{x_t}, \mathrm{I_t})$ is anticipated by the efficiency frontier by reducing the input quantities (X) and increasing the investment (I) at the point $(\mathrm{x_t} + \dot{\beta}\mathrm{g_x}, \mathrm{I_t} + \dot{\beta}\mathrm{g_I})$. β shows the value of the dynamic directional input distance function (DIDF); that is, the level of inefficiency in resource use. The directional vector g is in the fourth quadrant, indicating that the inputs are to be contracted and the investment stimulated. In this study, we extended the [28] model as follows.

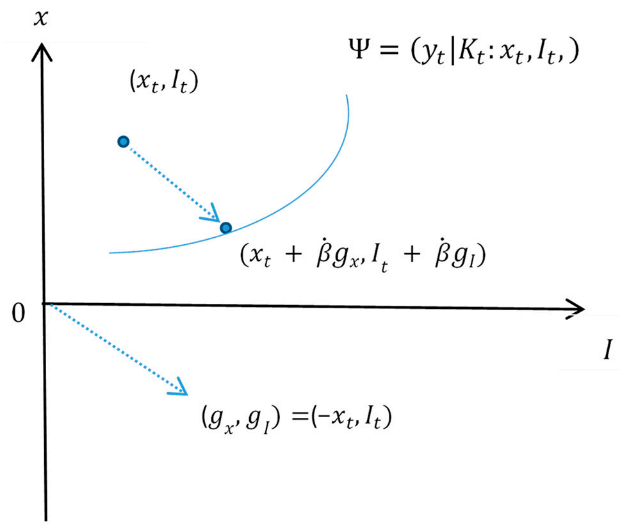

Figure 1. Illustration of the dynamic directional input distance function (DIDF).

The DIDF at any period t is defined as the maximum possible reduction of the input vector x while producing the same level of output y and farm characteristics z:

$$D_I(y_t, x_t, I_t, k_t; Z, t, \omega) = \max\left\{\left(\lambda : \frac{x_t}{\lambda}\right) \in L(y_t, x_t, I_t, k_t; Z, t, \omega)\right\} \quad (2)$$

where y_t is the output vector at time t in a given vector of investment I_t, capital stocks k_t, and variable inputs x_t. $L(y_t, x_t, I_t, k_t; Z, t, \omega)$ represents the input set while λ denotes a scalar ($\lambda \geq 1$). The value of λ measures the possible reductions in inputs, whose minimum value $\lambda = 1$ indicates that farm managers are using the inputs efficiently. The value of Z is a vector of firm characteristics, such as experience, age, size, education, etc. t is the time trend and ω denotes unobserved heterogeneity, such as individual effects. The dynamic input distance function (DIDF) in (2) must fulfil the following properties.

(a) It is non-decreasing in outputs: $D_I(\lambda y_t, x_t, I_t, k_t; Z, t, \omega) \leq D_I(y_t, x_t, I_t, k_t; Z, t, \omega), 0 \leq \lambda \leq 0$;
(b) The monotonicity condition is satisfied;
(c) It is homogeneous: $\lambda D_I(y_t, x_t, I_t, k_t; Z, t, \omega) = L(\lambda y_t, \lambda x_t, \lambda I_t, \lambda k_t; Z, t, \omega), \lambda > 0$;
(d) It is non-increasing in inputs: $D_I(y_t, \lambda x_t, I_t, k_t; Z, t, \omega) \leq D_I(y_t, x_t, I_t, k_t; Z, t, \omega)$, $\lambda \geq 0$; and
(e) It is non-decreasing in investment: $D_I(y_t, x_t, \lambda I_t, k_t; Z, t, \omega) \leq D_I(y_t, x_t, I_t, k_t; Z, t, \omega)$, $0 \leq \lambda \leq 0$.

The DIDF property mentioned above states that the outputs and the inputs vary in the same proportion. The monotonicity property is fulfilled if the first derivatives of the DIDF ≥ 0. The common way to impose the homogeneity property is to divide all the inputs by one of the inputs following [30] as follows:

$$\frac{D_I(y_t, x_t, I_t, k_t; Z, t, \omega)}{x_1} = L\left(y_t, \check{x}_{kt}, \dot{I}_t, \dot{K}_t; Z, t, \omega\right) \quad (3)$$

where $\check{x}_t$ is a vector of input ratios with $\check{x}_{kt} = \frac{x_{kt}}{X_1}$, $\forall k = 2, \ldots, K$; $\dot{I}_t = \frac{I_t}{x_1}$, and $\dot{K}_t = \frac{K_t}{x_1}$. We re-write Equation (3) in logarithm and a translog (TL) form as in [12] as

$$\ln D_I(y_t, x_t, I_t, k_t; Z, t, \omega) - \ln x_1 = TL\left(\ln y_t, \ln \check{x}_{kt}, \ln \dot{I}_t, \ln \dot{K}_t; Z, t, \omega\right) \quad (4)$$

We re-arrange Equation (4) and add the random error term (v_{it}) to make the distance function stochastic.

$$-\ln x_1 = TL\left(\ln y_t, \ln \check{x}_{kt}, \ln\dot{I}_t, \ln \dot{k}_t; Z,\ t, \omega\right) + v_{it} - \ln D_I(y_t, x_t, I_t, k_t; Z,\ t, \omega) \quad (5)$$

where v_{it} is the white noise (v_{it}), while $\ln D_I = u_{it} \geq 0$ captures the effects of technical inefficiency.

The other issue that arises from the economics literature is that if a farm observes some of its efficiency and productivity, its input choices may be influenced, resulting in an endogeneity problem with the stochastic production frontier estimation. The traditional approaches to addressing endogeneity in production function estimation that employ instrumental variables and fixed effects are problematic on both theoretical and empirical grounds. Nevertheless, an important feature of the ideas that are opposed to [31] (the Input Requirement Function) is that, in the DIDF model, inputs as regressors appear in ratios. Consequently, the inputs in ratio form in the DIDF model solve the endogeneity problem. See for more detail the [23] discussion on the endogeneity problem, which can be found in Appendix B in the supplementary data at European Review of Agricultural Economics (ERAE) online.

3. Empirical Model

Because of its flexibility, we use the translog specification of Equation (5). Thus, Equation (5) specified as a translog DIDF in log form is:

$$\begin{aligned}
-\ln x_1 = {} & \alpha_0 + \sum_{k=1}^{K} \beta_k \ln \check{x}_{k,it} + \sum_{p=1}^{P} \beta_p \ln \dot{k}_{p,it} + \sum_{h=1}^{H} \beta_h \ln \dot{I}_{h,it} + \sum_{m=1}^{M} \beta_m \ln \dot{y}_{m,it} + \beta_t D_t + \\
& \tfrac{1}{2} \sum_{K=1}^{K} \sum_{K=2}^{K} \beta_{kk} \ln x_{k,it} \ln x_{k,it} + \tfrac{1}{2} \sum_{p=1}^{P} \sum_{p=2}^{P} \beta_{pp} \ln k_{p,it} \ln k_{p,it} + \tfrac{1}{2} \sum_{h=1}^{H} \sum_{h=2}^{H} \beta_{hh} \ln \dot{I}_{h,it} \ln \dot{I}_{h,it} + \\
& \tfrac{1}{2} \sum_{m=1}^{M} \sum_{m=2}^{M} \beta_{mm} \ln \dot{y}_{m,it} \ln \dot{y}_{m,it} + \sum_{K=1}^{K} \sum_{p=1}^{P} \beta_{kp} \ln x_{k,it} \ln \dot{k}_{p,it} + \sum_{K=1}^{K} \sum_{h=1}^{H} \beta_{kh} \ln x_{k,it} \ln \dot{I}_{h,it} + \\
& \sum_{K=1}^{K} \sum_{m=1}^{M} \beta_{km} \ln x_{k,it} \ln \dot{y}_{m,it} + \sum_{p=1}^{P} \sum_{h=1}^{H} \beta_{ph} \ln \dot{k}_{p,it} \ln I_{h,it} + \sum_{p=1}^{P} \sum_{m=m}^{M} \beta_{pm} \ln \dot{k}_{p,it} \ln \dot{y}_{m,it} + \\
& \sum_{h=1}^{H} \sum_{m=1}^{M} \beta_{hm} \ln \dot{I}_{h,it} \ln \dot{y}_{m,it} + \sum_{k=1}^{K} \beta_{kt} \ln \check{x}_{k,it} D_t + \sum_{p=1}^{P} \beta_{pt} \ln \dot{k}_{p,it} D_t + \sum_{h=1}^{H} \beta_{ht} \ln \dot{I}_{h,it} D_t + \sum_{m=1}^{M} \beta_{mt} \ln \dot{y}_{m,it} D_t + \\
& \tfrac{1}{2} \beta_{tt} D_t^2 + \omega_i + v_{it} - u_{it}
\end{aligned} \quad (6)$$

where $\ln \dot{y}_{m,it}$ is a vector of potential outputs in a logarithm $(m = 1, \cdots, M)$. $\ln\check{x}_{k,it}$ is a vector of inputs in a logarithm divided by the labour input $(j = 1, \cdots, J)$ by farms $(i = 1, \cdots, N)$ and time $(t = 1, \cdots, T)$ given a vector of gross investments I_t $\left(\ln \dot{I}_{h,it} = \frac{\ln I_{ht}}{X_1}, \forall\, h = 1, \ldots, H\right)$ and a vector of initial capital stocks k_t $\left(\ln \dot{k}_{p,\ it} = \frac{\ln I_{pt}}{X_1}, \forall\, p = 1, \ldots, P\right)$ at time t as discussed above: $\ln\check{x}_{kt} = \frac{\ln x_{kt}}{X_1}$, $\forall k = 2, \ldots, K$.

β are parameters to be estimated, D_t *is the dummy variable for a time t, and* (v_{it}) *denotes the* white noise, which fulfills the classical assumption. ω_i denotes farm-level heterogeneity and $u_{it} \geq 0$ denotes efficiency, which is assumed to have a truncated normal distribution, i.e., $u_{it} \sim N^+(\mu_{it}, \sigma_u^2)$. We assume that μ_{it} is a function of a vector of firm characteristics (z_{it}), i.e., $u_{it} \sim N^+(\partial z_{it}, \sigma_u^2)$. Equation (6) was estimated using [16] true fixed-effect model specifications. Technical efficiency was calculated following the procedure of [32]

$$E(\exp(-u_{it} \mid \varepsilon_{it}) \quad (7)$$

where $\boldsymbol{\varepsilon_{it}} = v_{it} - u_{it}$

Following [33], the marginal effects of environmental variables were estimated as follows

$$(\partial E(\exp(-u_{it}/\varepsilon_{it}))/(\partial z_{itk}). \quad (8)$$

As discussed in Section 2, we imposed the homogeneity property of the technology on Equation (6) before the estimation; that is, $\sum_{k=1}^{K} \beta_k = 1$, $\sum_{k=1}^{K} \beta_{kp} = \sum_{k=1}^{K} \beta_{kh} = \sum_{k=1}^{K} \beta_{km} = 0$, while quadratic symmetric implies $\beta_{kp} = \beta_{pk}$; $\beta_{kh} = \beta_{hk}$ $\beta_{km} = \beta_{mk}$. We imposed these restrictions before the estimation.

4. Data

We used farm-level data collected by the Norwegian Institute of Bioeconomy Research (NIBIO). The empirical analysis was based on data collected from 663 dairy farms for the years 2000–2018, with a total of 5327.

The choice of variables in the final model was based on two criteria. First, we considered data availability. Second, we considered the literature available on the subject; for instance, [4,10,23]. Thus, the dynamic production technology was modeled in terms of two outputs and five inputs (land, labour, materials, capital assets, and gross investments). Dairy output (y1) is the total farm revenue from milk and dairy products. Other outputs (y2) include crops and other outputs the farm produced. Labor (x_1) was measured as the total number of labor hours used on the farm. Farmland (x_2) is in hectares. Materials (x_3) include the implicit value index for feed and electricity used for milk production. Capital assets (K) account for the implicit quantity index, which was obtained by deflating the value of machinery, buildings, and livestock at the beginning of the year. Gross investment (I) includes the flow of investments during a year. The datasets contain observations with zero values for investments. Thus, to use a flexible functional form (Translog), following the literature (see, for instance, [25,34] we transformed the value; that is, $\ln\left(I + \sqrt{I^2 + I}\right)$. All values are adjusted to 2015 values. Our dynamic analysis estimated both the level of performance and the environmental variables that caused the difference. Thus, in addition to output and input variables, we included four variables as covariates in our efficiency model to account for exogenous variables. These are (i) the financial structure of the farm, measured as the ratio of debt to an asset; (ii) government support in Norwegian Kroner (NOK); (iii) farm experience, measured in a year; and (iv) farm owners' off-farm income, measured in NOK. A summary of the descriptive statics is presented in Table 1.

Table 1. Descriptive statistics for the main variables used in the empirical analysis (2000–2018).

Variables	Mean	Std. Deviation
Output Variables		
Dairy revenue in 1000 * NOK (y_1)	969.031	696.191
Other output in 1000 NOK (y_2)	32.497	60.651
Input Variables		
Land in hectares (x_1)	34.404	20.438
Labour in 1000 h (x_2)	3.534	0.940
Materials in 1000 NOK (x_3)	535.469	402.353
Capital in 1000 NOK (K)	503.570	312.117
Investment in 1000 NOK (I)	449.655	605.403
Exogenous Variables		
Debt to Asset Ratio (Z_1)	0.400	0.181
Subsidy in 1000 NOK (Z_2)	533.134	228.512
Farm experience in a year (Z_3)	27	10
Off-farm income in 1000 NOK (Z_4)	0.671	0.331
Observations 5327		

* NOK = Norwegian kroner in 2015. 1 NOK = 11 EUR. Source: Author's calculation.

5. Results and Discussion

The dynamic and static counterparts' estimates are presented in Table 2. Before we estimated the models, the variables were normalized to the geometric mean; thus, parameters can be interpreted as partial elasticities at the point of approximation. The linear parameters for inputs and outputs have the sign expected from the theory, namely positive for inputs and negative for outputs, and all are statically significant at the 1% level. The estimated partial elasticity of dairy output to land input (x_2) is significant, with a value of 0.242 for the dynamic model and 0.147 for the static model, which means that the cost of land input represents on average 14%–24% of the total cost in the sample, ceteris paribus. The highest partial elasticity was found in both models for material input (x_3), i.e., 0.359 for the dynamic model and 0.416 for the static model. The partial elasticity for capital inputs (x_4) had a value of 0.184 for the dynamic model and 0.209 for the static model. Moreover, the partial elasticity of investment (I) was positive and statistically significant (0.005), which shows that dairy farm investment accounts for 21%–18% at the sample mean, ceteris paribus. The distance elasticity for dairy output (y_1) was significant, with values of −0.453 for the dynamic model and −0.535 for the static model. This result shows that a 1% increase in dairy output leads to a 0.45–0.53 increase in total costs, ceteris paribus. Moreover, the distance elasticity for other outputs (y_2) was significant, with values of −0.007 for the dynamic model and −0.009 for the static model. The coefficients for the time trend were statistically significant at the 1% level, with values of 0.005 for the dynamic model and 0.001 for the static model, which implies that the dairy sector in Norwegian agriculture has made technological progress during the period 2000 to 2018 at the rate of 0.1%–0.5% per annum. The partial elasticity for investment (0.005) and the coefficient of the trend variable (0.005) were both positive and significant at the 1% level. The positive value indicates that investment-based technical progress occurred during the years 2000–2018. A similar result was reported by [22] for genetics-based investment in Icelandic dairy farms from 1997 to 2006.

Table 2. Dynamic and static model parameters estimates and marginal effects estimates.

Variables	Dynamic Model		Static Model	
	Estimated Value	**Robust Std. Error**	**Estimated Value**	**Robust Std. Error**
Elasticities				
x_2 (Land)	0.242 ***	0.008	0.147 ***	0.007
x_3 (Material)	0.359 ***	0.009	0.416 ***	0.009
K (Capital)	0.184 ***	0.007	0.209 ***	0.008
I (Investment)	0.005 ***	0.000		
y_1 (Dairy output)	−0.453 ***	0.012	−0.535 ***	0.009
y_2 (Other output)	−0.007 ***	0.001	−0.009 ***	0.001
D (year)	0.005 ***	0.001	0.001	0.001
Constant	0.112 ***	0.006	0.160 ***	0.004
Marginal effects of determinates on technical efficiency [b]				
Debt to asset ratio	0.469 ***	0.111	0.892 ***	0.160
Subsidy	0.002 ***	0.000	0.002 **	0.000
Farm experience	−0.001 ***	0.002	−0.004 ***	0.002
Off-farm activity	0.000	0.000	0.001	0.000
Different tests of the technology				
Welch test comparing mean TE	22.836 ***	0.000		
LR test of random effect	3480 ***	0.000	2562 **	0.000
Cobb–Douglas technology	1285 ***	0.000	985 ***	0.000
Log. Likelihood	5291 ***	0.000	3984 ***	0.000
Technical Efficiency	0.902	0.115	0.876	0.124
Number observation	5327		5327	

$p < 0.10$, ** $p <$ 005, and *** $p < 0.01$; The second-order parameters in the translog (TL) were dropped to save space, but are available from the authors on request. [b] Positive efficiency score parameter estimates show that the variable has a negative effect on technical efficiency.

The negative of the inverse of the sum of the partial output elasticities provides a measure of the economies of scale (EOSs) [34], which are referred to as ray scale economies [35];

i.e., $\mathrm{EOS} = -\left[\sum_{m=1}^{2} \frac{\partial \ln D_I}{\partial \ln y_{mit}}\right]^{-1}$. If the EOS > 1, the technology exhibits an increasing return; if the EOS < 1, the technology exhibits a decreasing return; and if the EOS = 1, the technology exhibits a constant return [36]. The results show that the EOS is higher than 1 in both the dynamic model and the static mode; thus, the dairy farm technology for the years 2000–2018 exhibits increasing returns to scale for the average farm. Similar results were reported by [37].

The estimated marginal effects of environmental variables on technical efficiency are reported in Table 2. The result indicates that, apart from off-farm income, all environmental variables included in the model are significantly correlated with technical efficiency in milk production and, thus, the sustainability of the dairy sector. The debt–asset ratio had a significant negative effect on the technical efficiency of Norwegian milk producers. It was expected that those farmers who received credit would help to invest in the dairy sector. Debt helps dairy farms relax capital constraints and can smooth the flow of income during difficult years [38,39]. However, the result suggests that dairy farms with higher debt incur higher costs, which reduce their technical efficiency. There is no consensus in the economics literature on the relationship between debt and technical efficiency. For instance, earlier results obtained by [23] support our finding; however, [25] reported a positive correlation between technical efficiency and debt-to-asset ratio.

The result also indicates that the marginal effects subsidy has a negative and significant correlation with the technical efficiency of dairy production. Similar results reported in other studies, such as [25], suggest that "public subsidies could distort the timing of the adjustment decision". We were expecting the support to relax dairy farms' financial and liquidity constraints and encourage investment. Previous studies in the economics literature provide mixed evidence of the effect of government support on-farm level technical efficiencies. For instance, reference [40] report that subsidies received by dairy farms in Spain, Portugal, and Italy have helped them to achieve better performance. On the other hand, several studies focusing on dairy farms report that government payments reduce producers' incentives to generate the highest possible income from farming (see, for example, [41–43]. However, our analysis does not account for any differential effects of different types of direct subsidy on efficiency, so the result should be interpreted with caution. However, dairy farmers obtain different types of support from the government, and our study does not account for the different effects of different kinds of subsidies on technical efficiency. As expected, the marginal effect of experience is positive and statistically significant, which shows that more experienced farmers are likely to be more efficient than those with fewer years of experience. Our findings are supported by other studies in the literature (e.g., [44,45]).

Table 3 reports the estimated technical efficiency scores. Most farmers fall in the 0.80 to 0.90 efficiency range. This implies that a large range of dairy farms are technically inefficient. The mean technical efficiency score is 0.92 for the dynamic model and 0.87 for the static model. The results of the Welch test are reported in Table 3. These results show that there is a statistically significant difference between the dynamic and static efficiency scores. The dynamic efficiency score suggests that Norwegian dairy farms can reduce the input requirement of producing the average output by 10% if the operation becomes technically efficient. Ref. [30] report similar results for French dairy farms.

Table 3. The distribution of technical efficiency scores for the dynamic and static models.

Percentile	Dynamic Model	Static Model	Difference
1%	0.384	0.366	0.018
5%	0.696	0.634	0.062
10%	0.774	0.726	0.048
25%	0.869	0.842	0.027
Mean	0.920	0.872	0.026
75%	0.974	0.954	0.020
90%	0.999	0.968	0.031
95%	0.999	0.972	0.027
99%	0.999	0.982	0.017
S. deviation.	0.115	0.124	
Observation	5327	5327	
Welch test for the dynamic and static models: 22.836			

Source: Author's calculation.

6. Conclusions and Policy Implications

Growing environmental concerns have prompted governments to make sustainable choices. Measuring and improving the performance of farms in their production resource use is crucial to sustainable agricultural development. This study focused on measuring the performance of dairy farms in Norway from the dynamic and the static perspective. We also estimated the marginal effects of environmental variables on the performance of the farmers. The dynamic model allows us to account for farm management decisions through investments. We used unbalanced farm-level panel data for the years 2000–2018. The result shows that, in both models, farmers used resources inefficiently. The empirical result shows that the technical efficiency estimated using the dynamic model (92%) was significantly different from that estimated using the static model (87%). This is interpreted to mean that the minimum costs for the years 2000–2018 were about 92% for the dynamic model and 87% for the static model of the actual dairy output. Thus, the dynamic model better estimates the performance of the dairy farms in Norway considering the farm managers' decisions on investment.

The empirical results show that milk producers used the available technology sub-optimally. Thus, there is a possibility to improve the use of existing technology and investment in sustainable agricultural development. If all dairy farms follow an efficient and sustainable pathway, it is possible to reduce wastage of production resources by 8% to 13%. Sustainable pathways, such as facilitating experience sharing among farms, can allow less-experienced dairy farms to learn from the best-performing farms. Experienced farmers are likely to be more efficient in using production resources than those with fewer years of experience, which suggests that policy-makers should encourage the exchange of information to improve the efficiency of low-performing farms.

The empirical analysis shows that some of the environmental variables included in the model, such as subsidized and indebted dairy farms, are negatively correlated with the performance of the farmers. Thus, policy-makers should consider and revise the subsidy and credit system if there is some imperfection in it. However, the results of these findings should be interpreted more narrowly since dairy farmers receive different types of subsidy and credit based on various criteria, and we could not identify the effect of such differences. Different types of credit and subsidy might have different effects on farm performance; thus, it would be necessary to repeat the analysis with less aggregated data on debt and subsidy payments.

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