Research in Economics 74 (2020) 263–271

Contents lists available at ScienceDirect

Research in Economics

journal homepage: www.elsevier.com/locate/rie

Research Paper

Performance of the Norwegian dairy farms: A dynamic stochastic approach

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ARTICLE INFO

Article history:
Received 19 June 2020
Accepted 30 July 2020
Available online 7 August 2020

JEL Classification:
C23
D22
D25
M21

Keywords:
Dynamic farm management
Dairy farm
Performance
Adjustment of inputs

ABSTRACT

From a theoretical perspective, it is well stated that the farm's decision on the use of inputs depends on the farmer's ability to make an efficient decision over time. The existing literature in performance analysis of the dairy farms based on static modeling and thus ignores the inter-temporal nature of production decisions. This paper aims to construct a dynamic stochastic production frontier incorporating the sluggish adjustment of inputs, to measure the performance of dairy farms in Norway. The empirical application focused on the farm-level analysis of the Norwegian dairy sector for 2000- 2018. The dynamic frontier estimated using the system Generalized Method of Moments estimator. The analysis shows that the static model in the previous studies underestimates the performance of the dairy farms.

1. Introduction

The standard neoclassical frontier function applied in empirical efficiency models entails an assumption that all farms are fully efficient (Alem, 2018). Following the pioneering contributions by Aigner et al. (1977) and Meeusen and van Den Broeck (1977), who independently proposed the stochastic production frontier framework using cross-sectional data, the literature diverges from the standard neoclassical production function model by including two distinct error components. These two studies have suggested that given the input, there are two main causes for the deviation of the actual output of a given farm from the maximum possible or the potential output. One of the deviations (error components) is attributed to captures random shocks (noise) to a production system that is beyond the control of the producer and can affect the output, for instance, uncertainty about the weather, disease, and pest infestation. The second deviation is the inefficiency reflected in the shortfall from the maximal potential output, which is individual specific (farm-effect) interpreted as one-sided inefficiency (non-negative random variable). Thus, In Stochastic Frontier Analysis (SF) the gap between observed output and the potential output is explained in terms of both inefficiency and random errors.

Since the introduction of one-sided inefficiency within the context of SF panel data models, there has been considerable research to extend and apply the model to generate consistent and unbiased estimates (Alem, 2018). Thus, the SF model can be categorised in two based on the assumptions used. The first category is assumptions model specification such as on about the temporal behavior of the inefficiency (e.g. persistent and transit); distribution of the error terms (exponential, normal, truncated, and gamma distribution); estimation techniques such as Generalized Method of Moments (GMM); Maximum

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https://doi.org/10.1016/j.rie.2020.07.006

likelihood, etc. (see e.g. Greene (2008), and Kumbhakar et al. (2015). The second category is assumptions on the behavior of the input use (static and dynamic). This paper contributes to the literature focusing on the second category.

There exists a strand of literature focusing on estimating the performance of the farm based on a static framework assumption in which an input is used for the production process, it immediately contributes to production at the maximum possible level see (e.g. Alem et al., 2019, Kumbhakar et al., 2014, Sipiläinen et al., 2013). However, once the input is introduced in the production process, it might take some time for adjusting within the system (Minviel and Sipiläinen, 2018). Thus, comparing the performance of the farm using technical efficiency scores obtained based on the static framework is likely to produce misleading results. This is mainly because the farm's decision on the use of inputs depends on the farmer's ability to make an efficient decision over time. The dynamic SF framework relaxes the static assumption on the use of inputs.

In the literature, we can find important contributions to dynamic efficiency modeling, and the model advances have taken place in the framework of the nonparametric approach using data envelopment analysis (DEA). A nonparametric measure of dynamic efficiency first proposed by Silva and Stefanou (2003 and 2007). Silva et al. (2015) employed the adjustment cost technology to generalize the static conditional input distance function developed by Chambers et al. (1998) to a dynamic framework. Ahn et al. (2000) examine a potential link between technical innovation and productive efficiency level using a parametric dynamic approach. Recently, we can find a few important contributions of a dynamic efficiency modeling from the parametric approach (e.g. Bhattacharyya, 2012; Minviel and Sipiläinen, 2018; Serra et al., 2011).

The parametric dynamic efficiency measures mainly carried out either in a structural or reduced approach (Minviel and Sipiläinen, 2018). The structural dynamic model approach is mainly based on two methods i.e. shadow cost method (see e.g. Rungsuriyawiboon and Hockmann, 2015) and distance function method (Serra et al., 2011). A shadow cost method that relates actual observed costs shadow or behavioral costs obtained from the optimization programs. However, Serra et al. (2011) argue that the shadow cost approach does not specify the production technology directly. The dynamic distance function approach developed by Serra et al. (2011) is derived from the duality between input distance functions and cost functions which provide a complete characterization of production technology.

The reduced dynamic model approaches mainly the extension of the standard stochastic frontier model through an autoregressive process of order for the inefficiency component (see e.g. Minviel and Sipiläinen, 2018). That is, the actual productive efficiency in any period depends on the actual product in the previous period. The productive efficiency in a given farm is assumed to be related to sluggish adjustments, high adjustment costs, or uncertainty over future production conditions. Sluggish adjustments and high adjustment costs of inputs not only affect the adoption of technology innovations but can also affect the whole production process by preventing outputs from reaching the maximum possible output level (Ahn et al., 2000; Bhattacharyya, 2012). As such, in this paper, we follow the reduced dynamic model approach that follows the set up used in Ahn et al. (2000) and Bhattacharyya (2012).

The empirical application focused on the farm-level analysis of the Norwegian dairy sector. Performance analysis of the dairy sector has received much attention in the literature (see e.g. Alem et al., 2019, Minviel and Sipiläinen, 2018, Sipiläinen et al., 2013). This is mainly the sector that is highly regulated and gets support from the government which indeed measuring productive efficiency has become a key indicator to control and plan the performance of production units for both policy-makers and farmers. Dairy farms face a continuous process of technological and environmental changes that requires them to make managerial decisions in a dynamic context. The farm makes a production plan such that an objective extending far into the future is optimized. The vast literature on Norwegian farm efficiency measures has largely ignored this issue. That is, That is, the previous study estimations were based on a static setting technology specification see for instance Alem et al. (2019); Kumbhakar et al. (2008); Lien et al., 2018; Sipiläinen et al., al.(2013).

The paper contributes to the literature in several ways. First, in contrast to Bhattacharyya (2012), we used the flexible functional form for the technology estimation and applied for the agricultural sector. Second, we are fortunate to be able to use a large farm-level panel dataset of Norwegian dairy farms with observations from 2000 to 2018.

The rest of the article is organized as follows. The main theoretical and econometric models are presented in Sections 2 and 3, respectively. Section 4 addresses the application of the empirical model. Section 5 discusses the nature of Norwegian agriculture followed by a discussion of the data and definitions of variables used in the production function. Section 7 covers the empirical results and finally, Section 8 presents concluding remarks.

2. Theoretical model

Let us consider a general production function for the potential output y^*_{it} of a farm i that uses a vector of inputs x_{it} at time t.

$$y^*_{it} = f(x_{it};\beta) \tag{1}$$

Where $f(x_{it};\beta)$ is the chosen function form (e.g. Cobb–Douglas, Translog); β is the vector of technology parameters to be estimated; i= 1, …, N denotes the production unit; and t= 1, … T denotes the time.

Let y_{it} be the actual output produced by farm i at time t and let θ be the speed of adjustment of outputs.

$$y_{it} = \theta y^*_{it} \tag{2}$$

$$y^*_{it} - y_{it} = y^*_{it}(1 - \theta) \tag{3}$$

If the speed of adjustment is lower than one, then the actual output is will be lower than the potential output. For the first period of production, the actual output (y_{it}) is only θ fraction of the potential output (y^*_{it}), however for the next production period onwards, not only the θ fraction of the potential output (y^*_{it}), but also θ fraction of the potential output (y^*_{it}) for the previous period output is important. Therefore, the dynamic process of output generation can be represented by:

$$y_{it+1} = \theta y^*_{it} + \theta y^*_{it}(1-\ \theta) \text{ or } y_{it+1} = \theta y^*_{it} + (1-\ \theta)y_{it} \tag{4}$$

$$y_{it} = \theta y^*_{it} + (1-\ \theta)y_{it-1} \tag{5}$$

Substituting Eq. (1) to (5),

$$y_{it} = \theta f(x_{it};\beta) + \theta(1-\ \theta)f(x_{it-1};\beta) \tag{6}$$

Eq. (6) demonstrates that the current output depends on the current and past inputs.

3. Empirical model

We choose a translog (TL) specification for our empirical analysis because of its flexibility and Eq. (1) specified as a TL production function in log form as:

$$\begin{aligned} \mathrm{lny}^*_{\mathrm{it}} = {} & \beta_0 + \sum_{\mathrm{j=1}}^{4}\beta_{\mathrm{j}}\mathrm{lnx}_{\mathrm{jit}} + \tfrac{1}{2}\sum_{j=1}^{4}\beta_{jj}\left(lnx_{jit}\right)^2 + \sum_{\mathrm{j=1}}^{4}\sum_{\mathrm{l=2}}^{4}\beta_{\mathrm{jl}}\mathrm{lnx}_{\mathrm{jit}}\mathrm{lnx}_{\mathrm{lit}} + \beta_{\mathrm{t}}\mathrm{D_t} \\ & + \tfrac{1}{2}\beta_{\mathrm{tt}} + \sum_{\mathrm{j=1}}^{4}\beta_{jt}lnx_{jit}\mathrm{D_t} \end{aligned} \tag{7}$$

where $\mathrm{y}^*_{\mathrm{it}}$ is a vector of potential outputs, x_{jit} is a vector of inputs ($j = 1, \cdots, J$) by farms ($i = 1, \cdots, N$) and time ($t = 1, \cdots, T$), all Greek letters are parameters to be estimated, and $\mathrm{D_t}$ is the dummy variable for time to capture the technological change.

The dynamic stochastic production frontier that incorporates the sluggish adjustment of inputs and the error terms can be written as:

$$\begin{aligned} \mathrm{lny}_{\mathrm{it}} = {} & (1-\ \theta)lny_{it-1} + \theta(\beta_0 + \sum_{\mathrm{j=1}}^{4}\beta_{\mathrm{j}}\mathrm{lnx}_{\mathrm{jit}} + \tfrac{1}{2}\sum_{j=1}^{4}\beta_{jj}\left(lnx_{jit}\right)^2 \\ & + \sum_{\mathrm{j=1}}^{4}\sum_{\mathrm{l=2}}^{4}\beta_{\mathrm{jl}}\mathrm{lnx}_{\mathrm{jit}}\mathrm{lnx}_{\mathrm{lit}} + \beta_{\mathrm{t}}\mathrm{D_t} + \ \tfrac{1}{2}\beta_{\mathrm{tt}}\ \ + \sum_{\mathrm{j=1}}^{4}\beta_{jt}lnx_{jit}\mathrm{D_t}) + \end{aligned} \tag{8}$$

The error-terms ε_{it} splits into two components, i.e. $\varepsilon_{it} \equiv v_{it} - u_{it}$. The component ($u_{it}$) captures transient (time-varying) and producer specific inefficiency with $u_{it} \sim N^+(\mu, \sigma_u^2)$. v_{it} is the idiosyncratic error term capturing random shocks and assumed v_{it} is symmetric and to satisfy the classical assumptions i.e., ${v_{it}}^{iid} \sim N(0, \sigma_v^2)$. . All Greek letters are parameters to be estimated. The trend variable, t, is introduced to capture the effect of technological change and starts with $t = 1$ for 2000 and increases by one annually.

4. Application

The dynamic stochastic production frontier model in Eq. (8) includes the dependant variable and one period lagged dependant variable ($\mathrm{lny_{it}}$ and lny_{it-1}) which both are the function of the error term (ε_{it}). The lagged dependent variable is an endogenous regressor by construction in Eq. (8). Thus, the conventional fixed effect estimator is biased and inconsistent. To deal with this problem, the Generalized Method of Moments (GMM) estimator in the spirit of Arellano and Bond (1991) and Blundell and Bond (1998) are predominantly applied in practice for that consistently estimates Eq. (8). GMM uses a set of moment conditions relating to the first differenced regression equation, and another set of moment conditions for the regression equation in levels (See for example Bhattacharyya, 2012).

Arellano and Bond (1991) argue that additional instruments can be obtained in a dynamic panel data model if one utilizes the orthogonality conditions that exist between lagged values of lny_{it-1} and the disturbances error term (ε_{it}). Let us illustrate this with the simple autoregressive model:

$$\mathrm{lny_{it}} = \alpha lny_{it-1} + \ \beta_{\mathrm{j}}\mathrm{lnx_{jit}}\ + \varepsilon_{it} \quad i = 1, \cdots, N \text{ and } t = 1, \cdots, T \tag{9}$$

Bludell and Bond (1998) and Bhattacharyya (2012) suggested that the first differences of the two or more-period lagged dependent variables are valid instruments for the equation in levels, and two or more period lagged dependent variables in levels are relevant instruments for the equation in first differences. To get a consistent estimate of δ as N $\rightarrow\infty$ with T fixed, we first difference (9) to eliminate the individual effects is

$$\mathrm{lny_{it}} - lny_{it-1}\ = \alpha(lny_{it-1} - lny_{it-2}) + \ \beta_{\mathrm{j}}\left(\mathrm{lnx_{jit}} - \mathrm{lnx_{jit-1}}\right)\ +\ \varepsilon_{it} - \varepsilon_{it-1} \tag{10}$$

and note that $(\varepsilon_{it} - \varepsilon_{it-1})$ is MA (1) with a unit root. For $t = 3$, the first period we observe this relationship, we have

$$\mathrm{ln}y_{it-3} - lny_{it-2} = \alpha(lny_{it-4} - lny_{it-3}) + \beta_{\mathrm{j}}\left(\mathrm{lnx}_{\mathrm{jit-3}} - \mathrm{lnx}_{\mathrm{jit-2}}\right) + \varepsilon_{it-2} - \varepsilon_{it-3} \tag{11}$$

In this case, lny_{it-1} and $\mathrm{lnx}_{\mathrm{jit-2}}$ are a valid instrument, since they are highly correlated with $(lny_{it-4} - lny_{it-3})$ and $(\mathrm{lnx}_{\mathrm{jit-3}} - \mathrm{lnx}_{\mathrm{jit-2}})$ respectively, but not correlated with $(\varepsilon_{it-2} - \varepsilon_{it-3})$ as long as the ε_{it} are not serially correlated. One can continue in this fashion, adding an extra valid instrument with each forward period, so that for period T, the set of valid instruments becomes $(lny_{it-1},\ldots, lny_{it-T}, T-2)$ and $(\mathrm{lnx}_{\mathrm{jit-1}},\ldots, \mathrm{lnx}_{\mathrm{jit-}T}, T-2)$.

We estimate Eq. (8) using a one-step GMM estimator following the above procedure. The Arellano and Bond (1991) test is applied to the residuals in differences to test for second-order autocorrelation. Moreover, Sargan's J test is used to determine the validity of the overidentifying restrictions.

All variables expressed in Eq. (8), each variable is divided by its geometric mean which allows for a possibility of the TL first-order parameters directly interpreted as partial production elasticities at the geometric mean of the data (Coelli et al., 2005). The trend variable is normalized to be zero in the year 2018. Various specification tests of hypotheses about the parameters in the frontier and the inefficiency model were performed using the generalized likelihood ratio (LR) test statistic.

Since only the sum of two error terms $(\varepsilon_{it} = v_{it} - u_{it})$ can be observed in Eq. (8), the farm's technical efficiency index can be estimated using the conditional mean of the efficiency term, proposed by Battese and Coelli (1988), i.e. $\mathrm{E}(\exp(-\mathrm{u}_{\mathrm{it}}\varepsilon_{\mathrm{it}})$. The static model with time-variant technical efficiency as given in Eq. (8) is estimated as a fixed-effects model and accordingly, the technical efficiency is estimated using Battese and Coelli (1988). For empirical application, we used Norwegian dairy farm data.

5. The nature of Norwegian agriculture

The primary objectives of Norwegian agricultural and food policies, as set out in White Paper no. 11 (2016–2017), are long-term food security; agricultural production in all parts of the country; creating more added value; and sustainable production with reduced greenhouse gas emissions. Consumers are to be provided with wholesome, high-quality products and the production process should be mindful of aspects related to the environment, public health, and animal welfare (OECD, 2017). Due consideration is given to the idea that farmers, as self-employed individuals, should have opportunities for the same income development as others in society. To achieve these objectives, the government supports the farmers. As in most developed countries, farming has become highly mechanized and the number of farms has been declining, with production becoming concentrated on fewer farms. According to a 2017 Statistics Norway report, in 1991, there were 96 000 farms; this declined to 42 000 in 2015. Moreover, 2.3% fewer farms were registered in 2016 compared to 2015. The number of farms growing only crops decreased by 29% during the period 2006–2016. Moreover, the average farm size increased from 14.7 ha in 1999 to 23.9 ha in 2016 (Statistics Norway, 2017). In 1991, the number of dairy cows stood at 342 000, compared to 224 000 in 2015, while the number of dairy farms decreased from 27 625 to 8 860 over the same period.

Livestock dominates Norwegian agriculture in all regions and about 30% of the farmers in Norway specialize in dairy farming (Alem et al., 2019). Over the past three decades, various regulatory schemes have been established to align aggregate milk production with domestic demand (Jervell and Borgen, 2000). From 1977 to 1983, dairy farmers who voluntarily stabilized or reduced their supply of milk relative to a base year obtained a bonus. However, over these years, aggregate milk supply increased. To avoid the overproduction of milk for the domestic market, the government introduced a two-price scheme in 1983. The quotas limited the amount of milk farmers could sell at full price. Until 1990, investments for the development and entry of new generations of farming families entitled some farmers to obtain an additional (free) quota. Many farmers expanded to beef production (by purchasing calves or suckler cows) to use idle resources (such as land, buildings, and labor) that had previously been used for dairy cows. In 1996, the government implemented a system for restricted redistribution of milk quotas using regionally based, regulated quota sales. Initially, the government managed the quota transfer; however, from 2002, a portion of the quota could be sold and bought between farmers. Leasing of milk quotas has been allowed since 2009. There is an upper limit on the milk quota per farm, though this limit has been changed several times. Norwegian agriculture is so heavily subsidized that, without support, it would not be competitive with imports. There is a threat that Norway may be obliged by international pressures to cut back on border protection and output-related subsidies. This would force a dramatic and painful shift towards more competitive agriculture. Therefore, there is a case to be made to urgently take steps to improve the productivity and management of farming.

6. Data

The data source is the Norwegian Farm Accountancy Survey collected by the Norwegian Institute of Bioeconomy Research (NIBIO). It includes farm production and economic data collected annually from about 1000 farms.[1] There is no limit on the number of years a farm may be included in the survey. However, for various reasons, approximately 10% of the surveyed farms are replaced per year.

[1] The number of participants varies from year to year. For example, in 1991 data were collected from 1049 farms but in 2013 the number of farms was 924.

Table 1
Descriptive statistics (mean values per farm) for dairy farms (2000–2018).

	Mean	Standard deviations
Output variable		
Total revenue in NOK*	1,567,332	1,021,241
Input variables		
land in hectare	34.4	20.4
labor in hours	3534	940
Materials in NOK	502,254	322,294
Capital in NOK	484,443	267,996
Observation	5327	

* NOK = Norwegian kroner, 2015 values.

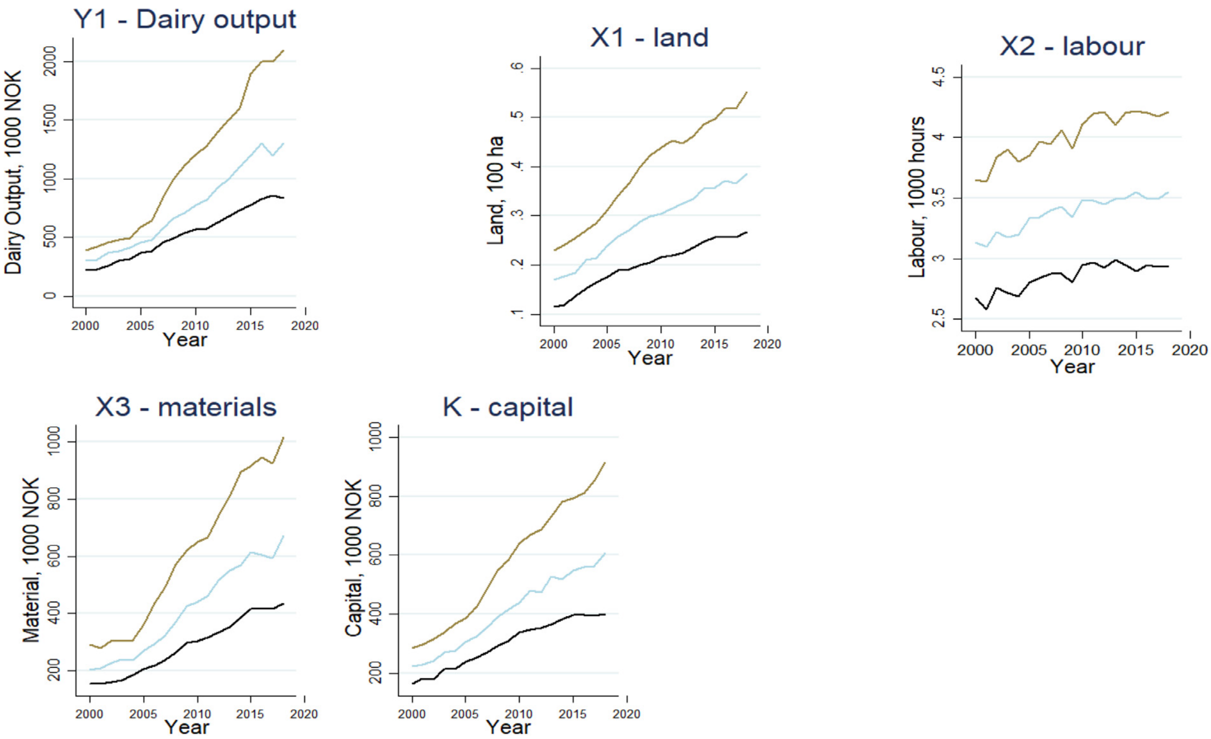

Fig. 1. The median, first and third quantile values (middle, bottom, and top lines) of outputs and inputs.

The dataset used is an unbalanced panel of 5323 observations on 663 Norwegian dairy farms involved in the production of dairy output for the year 2000–2018. To ensure that milk output is the main farm output, we select those farms whose milk sales represent at least 80% of total farm income. The variables selected for this analysis contain one output variable and four input variables. Output (y) includes dairy production, which represents total farm revenue from milk and dairy products, exclusive of direct government support. The output is valued in Norwegian kroner (NOK) and adjusted to 2015 values using the consumer price index (CPI). The TL production function in the empirical model (8) is specified with the following four input variables. Farmland (x_1), defined as productive land (both owned and rented) in hectares and labor (x_2), measured as the total labor hours used on the farm, including hired labor, owners' labor, and family labor. Materials (x_3), including fertilizers, feed, oil and fuel products, electricity, expenses for crop and animal protection, construction materials and other costs; and fixed cost (x_4), including fixed cost items plus maintenance costs on-farm capital tied up in machinery, buildings, and livestock. All costs are measured in NOK adjusted to 2015 values. Maintenance and costs associated with the hiring of machines are registered annually.

To accommodate panel features with farm information over several years in the estimation, only those farms for which at least three years of data were available were included in the analysis. A summary of the output and input variables is shown in Table 1. Fig. 1 shows the input and output for the year 2000–2018. All inputs, investment, and outputs increase for the study period.

Table 2
Estimated parameters for the dynamic model and its Static counterpart.

	Dynamic model		Static model	
	Estimated value	*Robust Std. error*	Estimated value	*Robust Std. error*
Elasticities				
y_{t-1} (lagged output)	0.488***	0.011		
x_1 (Land)	0.140***	0.009	0.256***	0.009
x_1 (Labour)	0.034***	0.008	0.056***	0.008
x_3 (Materials)	0.233***	0.006	0.420***	0.007
x_4 (capital)	0.105***	0.006	0.268***	0.007
t (Time-trend)	0.013***	0.001	0.034***	0.000
AR (1)	−2.849***			
AR (2)	0.244			
Sargan test	22.730			
Nr. of instruments	20			
Technical efficiency	0.970	0.022	0.919	0.073
Number observation	5327		5327	

* *p<0.10*, ** *p<0.05, and* *** *p<0.01*.
*The second-order parameters in the TL are dropped, to save space, but is available from the authors.

7. Results and discussion

7.1. Model specification tests

Parameter estimates for the dynamic model are reported in Table 2. As a baseline for comparisons, Table 2 also reports parameter estimates for the static counterpart of the dynamic model. The dynamic model differs from the static one mainly in the fact that it accounts for lagged decisions and that it does include lagged dependant variable and estimated using GMM.

Various specification tests were conducted to obtain the best model and functional form for the data under analysis.[2] First, we tested the null hypothesis that there are no technical efficiency effects in the models for the five regions and the pooled data. The null hypothesis was rejected. That test confirmed that technical inefficiency constitutes the largest share of total error variance. Second, LR tests for all SF models for each region and the pooled data revealed that a simplification of the translog (TL) to Cobb-Douglas functional form was rejected. Thus, the TL functional form was retained.

The AR (2) test statistic (p-value =0.81), as reported in column (1) of Table 2 corresponds to the test of the null hypothesis that the residuals in the first-differenced regression exhibit no second-order serial correlation. Following the test procedure proposed by Arellano and Bond (1991), a negative first-order serial correlation in the equation in first differences is expected and the AR (1) test statistic supports that. Thus, the random shocks to the sectors are not serially correlated and the estimation results are consistent. The Sargan (1958) and Hansen (1982) J-statistic which is used to determine the validity of the overidentifying restrictions and statistic for testing exogeneity of the instrumental variables, as reported in column (1) of Table 2, supports the validity of the instruments (p-value = 0.302). The GMM system estimation uses internal instruments for estimation, and thus, there can be several valid instrumental variables. Thus, the set of instrumental variables for which the Sargan test of exogeneity was the most powerful.

7.2. Elasticities

Table 2 shows the parameters of dynamic and static model estimates. Both models exhibited positive and highly significant first-order parameters, fulfilling the monotonicity condition for a well-behaved production function. The estimated elasticity of dairy output to land input (x_1) is significant with values of 0.140 and 0.256 for dynamic and static models, respectively. If the land input increase by 1% in the dynamic model, the dairy output will increase by an estimated 0.14%, ceteris paribus. The estimated elasticities of dairy output to labor input (x_2) were 0.034 and 0.056 for dynamic and static models, respectively. The estimated elasticities of dairy output to material input (x_3) were 0.233 and 0.420 for dynamic and static models, respectively. The coefficients of the materials (x_3) are the largest among other partial production elasticities statistically significant ($p < 0.001$) in both models. These results imply that the percentage change in materials has a larger influence on dairy production compared to other farm inputs. The static model result is consistent with results in the literature, for instance, Alem et al. (2019). The partial elasticity of capital cost (x_4) was positive and statically significant a value of 0.105 and 0.268 for dynamic and static models, respectively.

The result in Table 2 also shows that the one period lagged output has a significant positive effect on the current output, where output is measured in logarithm. Using the estimated value of $(1-\theta) = 0.488$, the actual change in the output of a sector in any period is 52% of the change in output that is needed to catch up with the potential output in that

[2] Tests are not reported here due to space but are available upon request from the principal author.

Table 3
Distribution of technical efficiency scores.

Percentile	Dynamic model	Static model	Difference
1%	0.901	0.647	0.254
5%	0.947	0.764	0.183
10%	0.958	0.818	0.140
25%	0.968	0.895	0.073
Mean	0.970	0.919	0.051
75%	0.978	0.968	0.010
90%	0.981	0.978	0.003
95%	0.983	0.982	0.001
99%	0.997	0.990	0.007
Std.devation	0.017	0.073	
Observations	5327	5327	
Welch test comparing mean TE		49.85***	

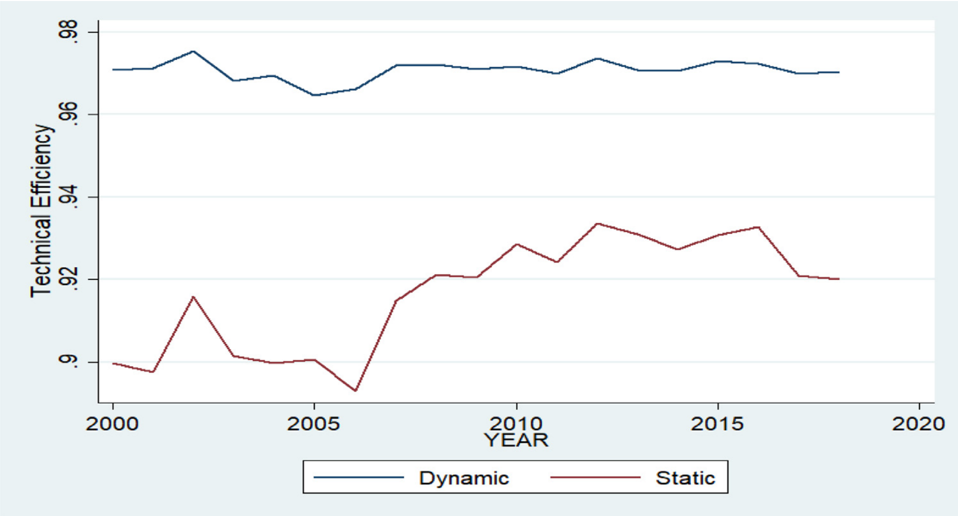

Fig. 2. Yearly average technical efficiencies for dynamic and static models.

period. Further, an estimate of $(1-\theta)$ is statistically significant at the 1% level indicating that the speed of adjustment is significantly different from unity. Assuming similar speeds of adjustment for inputs across sectors, this result supports the partial adjustment scheme for output and suggests that the static model is a misspecified one for this sample. The coefficients for the time trend (0.013) implies that the productivity of dairy farms resource use increased on average by 1.3% over the period 2000 −2018.

7.3. Technical efficiency

The estimated technical efficiency (TE) scores are reported in Table 3. The average TE score of 0.97 while the static one is 0.92. The Welch test, reported in Table 3, indicates the dynamic and the static efficiency scores are significantly different. As the dynamic efficiency scores are higher, this suggests that, in our sample, the static model underestimate the performance of the dairy farms. Considering the dynamic TE score which implies that these dairy farms producing only 97% of the maximum possible (frontier) output, given the input used. That is an average dairy farm can increase its output by around 3 if it becomes technically efficient. In the static case, the estimated scores suggest that farmers could improve their technical efficiency level by 8 percent on average without increasing their input use. Table 3 also shows the distribution of the farms in the sample according to their technical efficiency. Thus, for instance, 1% of the farms are only 90% and 0.65% technical efficient for dynamic and static models respectively. While 10% of the sample farms are 95% and 0.82% technical efficient.

Fig. 2 shows that the yearly average of TE scores in which the dynamic model scores are higher than those from the static model. A similar result also reported in Similar results have been reported for instance see Minviel and Sipiläinen (2018).

The TE score for Norwegian regions and farm size reported in Tables 4 and 5, respectively. The results show that there is no significant difference in regions and farm sizes for the two different models. A similar result reported Alem et al. (2019)

Table 4
Technical efficiency scores by region.

Regions	Dynamic model	Static model	Number of Observations
Eastern Norway Lowlands	0.968 (0.019)	0.928 (0.058)	442
Eastern Norway other parts	0.971 (0.015)	0.913 (0.070)	865
Agder and Rogaland -Jæren	0.974 (0.001)	0.951 (0.054)	304
Agder and Rogaland -other parts	0.967 (0.021)	0.888 (0.096)	539
Western Norway	0.971 (0.018)	0.913 (0.082)	1132
Trøndeland -Lowlands	0.973 (0.013)	0.937 (0.051)	388
Trøndeland -other parts	0.972 (0.016)	0.928 (0.058)	676
Northern Norway	0.969 (0.017)	0.920 (0.071)	981
All regions	0.970 (0.017)	0.919 (0.073)	5327

Standard errors in parentheses.

Table 5
Technical efficiency scores by Farm size.

Regions	Dynamic model	Static model	Number of Observations
$<$ 10 hectar of land	0.964 (0.024)	0.786 (0.113)	125
10- 20 hectar of land	0.971 (0.019)	0.900 (0.080)	1091
20- 30 hectar of land	0.972 (0.012)	0.921 (0.062)	1514
30- 50 hectar of land	0.970 (0.015)	0.928 (0.062)	1725
$>$ 50 hectar of land	0.968 (0.023)	0.941 (0.071)	872
All farm size	0.970 (0.017)	0.919 (0.073)	5337

Standard errors in parentheses.

8. Conclusion

The existing literature in performance analysis based on static modeling and thus ignores the inter-temporal nature of production decisions. This study departs from static modeling by developing a dynamic stochastic framework to investigate the performance of farms focusing on Norwegian dairy farms. This formwork allows accounting for the dynamic nature of the environment in which dairy farms operate. The empirical application focused on the farm-level analysis of the Norwegian dairy sector using panel data for the year 2000–2018. The result shows that the dynamic production model provides a more realistic approach to measure the performance of the Norwegian dairy farm, where sluggish adjustment of inputs is a very credible phenomenon. The average technical efficiency score of 0.97 for the dynamic model while the static one is 0.92. The Welch test, reported in Table 3, indicates the dynamic and the static efficiency scores are significantly different. As the dynamic efficiency scores are higher, this suggests that, in our sample, the static model underestimate the performance of the dairy farms. Considering the dynamic TE score which implies that these dairy farms producing only 97% of the maximum possible (frontier) output, given the input used. That is an average dairy farm can increase its output by around 3 if it becomes technically efficient. In the static case, the estimated scores suggest that farmers could improve their technical efficiency level by 8 percent on average without increasing their input use

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.rie.2020.07.006.

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