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Regional Differences in Technical Efficiency and Technological Gap of Norwegian Dairy Farms: a Stochastic Metafrontier Model

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Abstract

This paper compares technical efficiencies (TEs) and technological gap ratios (TGRs) for dairy farms in the Norwegian regions accounting for differences in working environments. We used the 'true' random effect model of Greene (2005) and the stochastic metafrontier approach by Huang et al. (2014) to estimate TEs and TGRs. The dataset used was farm-level balanced panel data for 23 years (1992-2014) with 5442 observations from 731 dairy firms. The results of the analysis provide empirical evidence of small regional differences in technical efficiencies, technological gap ratios, and input use. Thus, an assumption about joint underlying technology across regions seems to be quite reasonable, since our results implies that the policies in place are working effectively to keep relatively disadvantaged producers in the business. Further, the results may provide some support for the more region-specific agricultural policies, in terms of support schemes and structural regulations.

Keywords: dairy firm, metafrontier, heterogeneity, region, technical efficiency

1. Introduction

Technical efficiency estimation has been of mounting interest as a means of identifying best practice performance and of improving the efficiency of resource use (Coelli et al., 2005; Kumbhakar and Tsionas, 2011). Since the introduction of stochastic frontier (SF) analysis (Aigner et al., 1977; Meeusen and Van den Broeck, 1977), the SF model has been widely used to estimate technical efficiency in applied economic research (see Coelli et al., 2005 and Kumbhakar et al., 2015 for reviews). The SF model can be applied to cost, production, revenue, and distance or profit functions.

The traditional approach has been used to estimate efficiency scores based on the assumption that the underlying technology is the same for all sample observations, regardless of differences in operating circumstances and working environments. However, firms in different regions are likely to face different production opportunities, and technology sets may differ because of differences in resource endowments. For instance, in farming, there will often be differences in soil quality, the intensity of sunlight, temperature, and rainfall from place to place. The experience of farmers, their capital endowment, and input composition will differ between firms, even in the same region. Firms in different locations make choices from different sets of possible input-output combinations given their particular production opportunities and circumstances (O'Donnell et al., 2008). Thus, comparing the performance of firms in different regions using technical efficiency scores obtained from single estimates across all regions is likely to produce misleading results as a basis for policy interventions and as benchmarks for individual farms.

Since policy intervention and management advice may need to be different for different regions (groups), researchers often seek to control heterogeneity using various methods. Some researchers use statistical methods. For example, groups of similar farmers can be formed by using cluster algorithms (Álvarez et al., 2008). Others use econometric methods, for instance, heterogeneity captured by the intercept such as the 'true'-fixed and 'true'-random effect models (Greene, 2005).

Other researchers assume different technologies to account for heterogeneity. In this category, random parameter model, latent class models, and metafrontier models are widely used. The random parameter model[1] treats continuous parameter variation and the estimation is extremely time-consuming (Greene, 2005). Latent class models are based on the assumption that a finite number of groups are represented in the data, and different functions are estimated for each of the groups (see, e.g., Orea & Kumbhakar, 2004, Alvarez et al., 2012, Sauer & Paul, 2013, and Baráth, & Fertő, 2015 for details). On the other hand, the stochastic metafrontier framework is based on the hypothesis that all producers in different locations (or other comparable groupings) at least have access to the same technology (see e.g. Battese et al., 2004 and O'Donnell et al., 2008). All these models have advantages and disadvantages in estimating technical efficiency; however, the metafrontier model is most commonly used for group or regional studies.

Hayami (1969) and Hayami and Ruttan (1971) were among the first to conduct a cross-country time series analysis of land and labor productivity in agriculture using a meta-production function. According to Hayami and Ruttan (1971, p 82), 'the meta-production function can be regarded as the envelope of commonly conceived neoclassical production functions'. Within this framework, described in detail by O'Donnell et al. (2008), the efficiencies relative to the metafrontier production function consist of two components: 1) the distance between the observed input-output point and the group frontier, and 2) the distance between the group frontier and the metafrontier. This approach has been applied widely to evaluate the efficiency of groups of firms. For instance, it has been used in industries (Wongchai, Liu, and Peng, 2012; Yaisawarng and Ng, 2014); in infrastructure (De Witte and Marques, 2009); in finance and banking (Huang and Fu, 2013; Huang et al., 2010; Kontolaimou and Tsekouras, 2010, and Chao, Yu, Hsiung, & Chen, 2017), and in agriculture (Boshrabadi et al., 2008; Mariano et al., 2011; Moreira and Bravo-Ureta, 2010; Nkamleu et al., 2006; O'Donnell et al., 2008; Villano and Mehrabi Boshrabadi, 2010; Zhuo and Shunfeng, 2008; and Jiand and Sharp, 2015).

Using this method, estimates of the gap between the group frontiers and the metafrontier can be used to design performance improvements that involve a change in the production environment. Changes in production environment might be made by the government (infrastructure, relaxing labor laws, etc.) or by firms in the industries (e.g., move production to some more favorable place). However, as O'Donnell et al. (2008) pointed out, both governments and firms have reduced possibilities in some sectors to change their production environments. For example, in agriculture, the government can do very little about geographical differences in soil quality, and farmers are normally not able to move their production to other geographical regions. Such limitations must be kept in mind when interpreting the results of a regional focused metafrontier analysis in agriculture.

The primary objectives of Norwegian agricultural policy are long-term food self-sufficiency, protection of the environment and of farming in all regions. We focused our analysis on dairy farming. Knowledge about the performance of dairy producing farms at the regional level could help policy makers introduce better-targeted agricultural policy and systems in Norway. Thus, the aim of this study is to assess the technical efficiency and technological gaps of dairy farms in different regions of Norway, using a recently introduced stochastic metafrontier model of Huang et al. (2014).

The rest of the paper is organized as follows. In section 2, the theoretical model used is described and the empirical model is described in section 3. In Section 4 the structure of Norwegian agriculture is outlined and regional differences are noted, while in section 5, the data are described and the variables used in the production function are defined. Empirical estimation and results are presented in section 6. Finally, section 7 is a discussion of findings and conclusions.

[1] Some researchers have employed Bayesian estimators which is resemble the random parameter model by assuming a stochastic model with exponential distributed inefficiency. Readers who are interested may refer to Koop and Steel (2001), Tsionas (2002), and Assaf (2011).

2. Theoretical model

Battese et al. (2004) and O'Donnell et al. (2008) introduced the modern metafrontier production-function model. Their model was estimated in two steps: in the first step a stochastic frontier analysis (SFA) model was used to estimate the group frontiers; then in the second step a date envelopment analysis (DEA) was used to estimate the metafrontier. The second step DEA procedure has some drawbacks, since it does not account for firm heterogeneity and data noise in the estimation, and the results do not include statistical properties of the estimated parameters. Noting these drawbacks, Huang et al. (2014) introduced a new two-step approach using SFA to estimate both the group frontiers in step one and the metafrontier in step two. Within this framework, it is also possible to include *z* or production environment variables in both steps. We applied the estimation framework of Huang et al. (2014) in this study.

Application

A general conventional stochastic production frontier model is given by:

$$y_{it} = f(x_{it}, \beta)e^{(v_{it}-u_{it})} \tag{1}$$

where y_{it} is the output produced by firm *i* at time *t* = 1,2 …,*T*, x_{it} is a vector of factor inputs, *i* = 1, 2, …, *N* for firm at time *t*, β is a vector of unknown parameters to be estimated, v_{it} is the stochastic (white noise) error term, and u_{it} is a one-sided error representing the technical inefficiency of firm *i* at time *t*. Both v_{it} and u_{it} are assumed to be independently and identically distributed (iid) with variances σ_v^2 and σ_u^2, respectively. The main assumption for estimating technical efficiency (TE) using conventional production frontier for equation (1) is that firms operate under the same working environment. Violation of this assumption biases TE estimates (Orea and Kumbhakar, 2004).

To deal with this potential problem in the case of dairy farms operating in different environments in different regions, suppose we have *k* regions in a given sector. We can then estimate group stochastic frontiers for each region as follows:

$$y_{it}^k = f^k\left(x_{it}^k, \beta^k\right)e^{(v_{it}^k-u_{it}^k)} \quad i=1,2, \ldots, N(k) \tag{2}$$

where y_{it}^k denotes the output level for farm *i* for the k^{th} region in the t^{th} time period; x_{it}^k is the input vector; v_{it}^k represent the error term and is assumed to be iid and distributed as $v_{it}^k \sim N(0,\ \sigma_{vk}^2)$. u_{it}^k is a one-sided error representing the technical inefficiency and distributed as $u_{it}^k \sim N^+\left(0,\ \sigma_{vk}^2\left(z_{it}^k\right)\right)$ where z_{it}^k denotes inefficiency or production environment determinants; and β^k is a vector of unknown parameters for the k^{th} region. These parameters are to be estimated using the 'true' random effect model of Greene (2005) to account for farm effect (unobserved heterogeneity) within the region. The technical efficiency of the i^{th} farm relative to the region–*k* frontier can be computed, following Greene (2005), as:

$$TE_{it}^k = \frac{y_{it}^k}{f^k(x_{it}^k, \beta^k)e^{(v_{it}^k)}} = \frac{f^k\left(x_{it}^k, \beta^k\right)e^{(-u_{it}^k)}}{f^k\left(x_{it}^k, \beta^k\right)} = e^{-u_{it}^k} \tag{3}$$

where TE_{it}^k is a measure of the performance of the individual farm (*i*) relative to the regional group-frontier.

To estimate the stochastic metafrontier function that envelops all the frontiers of the *k* regions using the approach of Huang et al. (2014), in step 2 we specified the following SFA:

$$\hat{f}^k\left(x_{it}^k, \beta^k\right) = f^M\left(x_{it}^k, \beta\right)e^{(v_{it}^M-u_{it}^M)} \tag{4}$$

where the $\hat{f}^k(x_{it}^k, \beta^k)$ are the predictions from the group-frontiers from step 1 in (2). In other words, each vector of group-frontier predictions is stacked together in one vector for the whole sample. In this model v_{it}^M represent the error term and is assumed to be *iid* as $v_{it}^M \sim N(0,\ \sigma_{vM}^2)$; u_{it}^M is a one-sided error representing the technical inefficiency and distributed as $u_{it}^M \sim N^+\left(0,\ \sigma_{vM}^2(z_{it}^M)\right)$ where z_{it}^M denotes the region-specific determinants for the technology gap component; and β is a vector of unknown parameters to be estimated for the metafrontier.

As discussed in detail in Huang et al. (2014), at a given input level x_{it}^k, the observed output y_{it}^k of the *i*-th farm relative to the metafrontier consists of three components i.e. $\frac{y_{it}^k}{f^M(x_{it}^k,\beta)} = TGR_{it}^k \times TE_{it}^k \times e^{v_{it}^M}$, where $TGR_{it}^k = \frac{f^k(x_{it}^k,\beta^k)}{f^M(x_{it}^k,\beta)}$ is technological gap ratio, $TE_{it}^k = \frac{f^k(x_{it}^k,\beta^k)e^{(-u_{it}^k)}}{f^k(x_{it}^k,\beta^k)} = e^{-u_{it}^k}$ is the firm's technical efficiency, and $e^{v_{it}^M} = \frac{y_{it}^k}{f^M(x_{it}^k,\beta)e^{-u_{it}^k}}$ is the random noise component.

In summary, the two-step approach to estimate the metafrontier proposed by Huang et al. (2014) consists of two SFA regressions, i.e.:

$$lny_{it}^k = f^k(x_{it}^k, \beta^k) + v_{it}^k - u_{it}^k\ , i = 1,2, \dots, N_k\ ; t = 1, 2, \dots, T \tag{5}$$

$$ln\hat{f}^k(x_{it}^k, \beta^k) = f^M(x_{it}^k, \beta) + v_{it}^M - u_{it}^M\ , \forall i, t\ k = 1,2, \dots, K \tag{6}$$

where $ln\hat{f}^k(x_{it}^k, \beta^k)$ is the estimate of the region-specific frontier from equation (5). Since the estimates $ln\hat{f}^k(x_{it}^k, \beta^k)$ are region specific, the regression (5) is estimated *K* times, one for each region ($k = 1,2, \dots, K$). These output estimates from all *K* regions are then pooled to estimate (6).

The metafrontier should be larger than or equal to the group-specific frontier, i.e. $f^k(x_{it}^k, \beta^k) \leq f^M(x_{it}^k, \beta^k)$. The estimated TGR must be less than or equal to unity:

$$T\hat{G}R_{it}^k = \hat{E}(\left(e^{-U_{it}^M} \middle| \hat{\varepsilon}_{it}^M\right)) \leq 1 \tag{7}$$

where $\hat{\varepsilon}_{it}^M = ln\hat{f}^k(x_{it}^k, \beta^k) - ln\hat{f}^M(x_{it}, \beta)$ are the estimated composite residuals of (6). The technical efficiency of the i^{th} farm to the metafrontier (MTE) is equal to the product of the estimated TGR (7) and the estimated individual farm's technical efficiency (3), i.e.

$$M\hat{T}E_{it}^k = T\hat{G}R_{it}^k \times \widehat{TE}_{it}^k \tag{8}$$

3. Empirical model

We estimated the second order flexible transcendental logarithmic (TL) function (Berndt and Christensen, 1973). The region-*k* frontier in (5) specified as a TL function is:

$$lny_{it}^k = \beta_0^k + \sum_{j=1}^{4} \beta_j^k lnx_{jit} + \frac{1}{2}\sum_{j=1}^{4} \beta_{jj}^k \left(lnx_{jit}\right)^2 + \sum_{j=1}^{4}\sum_{l=2}^{4} \beta_{jl}^k lnx_{jit}\, lnx_{lit} + \beta_t^k t + \frac{1}{2}\beta_{tt}^k + \sum_{j=1}^{4} \beta_{jt}^k\, lnx_{jit} t + \theta_i^k + v_{it}^k - u_{it}^k \tag{9}$$

where y_{it} is a vector of dairy outputs, x_{jit} is a vector of inputs $(j = 1, \cdots, J)$ by farms $(i = 1, \cdots, N)$ and time $(t = 1, \cdots, T)$, and all Greek letters are parameters to be estimated. The white noise error term v_{it} is added to allow for random measurement error. The term v_{it} is symmetric and assumed to satisfy the classical assumptions, i.e. $v_{it} \overset{\text{iid}}{\sim} \mathrm{N}(0, \sigma_{\mathrm{v}}^2), v_{it} \perp u_{it}$. The term u_{it}^k is specified as $u_{it}^k \sim \mathrm{N}^+\left(0,\ \sigma_{vk}^2\left(z_{it}^k\right)\right)$, and θ_i^k is a farm-specific component to capture time-invariant unobserved heterogeneity, assumed to have an iid normal distribution. The model is estimated using the TRE frontier model[2] (Greene, 2005), and it extends the conventional stochastic frontier model by disentangling farm effect (unobserved heterogeneity) from technical efficiency. The trend variable, *t*, capturing Hicks-neutral technology change, starts with *t* = 1 for 1992 and increases by one annually. The same estimation model is used to estimate (6), but $\ln y_{it}^k$ in (9) is replaced by $\ln \hat{\mathrm{f}}^k\left(x_{it}^k, \beta^k\right)$. The models were estimated with the software LIMDEP.

All data for the TL model are expressed as deviations from their sample means, which makes it possible to interpret the first-order parameters directly 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 2014, while all other variables are normalized before taking logarithms by dividing each variable by its mean value. 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.

4. Norwegian dairy farms and regions

Norwegian dairy farms: changing pattern

In Norway, the northernmost country in Europe, livestock production is the dominant agricultural activity in all region, and some 30% of the farms are specialized in dairy farming. Norwegian dairy farms are usually small-scale compared to other developed countries, family-operated, and face extensive areas of rugged terrain, and they have short growing seasons for feed production. These problems contribute to the high costs of production. The Norwegian government provides significant support to the agricultural sectors and dairy farms are among the more heavily supported farmers. Most dairy farms produce both milk and meat, although the latter is mainly a by-product. The number of dairy farms has been declining, and production has been concentrating in fewer farms. Yet the structural change in the Norwegian dairy sector has been slower than in other Nordic countries owing to government policy that favors small farms and their wide geographic distribution (Atsbeha et al., 2015; Flaten, 2002).

In the dairy sector, various regulatory schemes have been set up to align the supply of milk production to the domestic milk demand (Moxnes and Borgen, 2000). A fall in the demand for milk from 1980 together with a reduction in consumer subsidies on milk resulted in a large surplus in 1982 (Kumbehakar et al., 2008). To avoid overproduction of milk for the domestic market, the government imposed a restrictive quotas scheme in 1983 to limit the amount of milk farmers could sell. A quota-trading system was introduced in 1997 for redistribution of milk quotas at the regional level. The system allowed quotas to be traded among dairy farms within the region at administratively set uniform prices, although the prices are different in different regions. Each dairy farm is annually

[2] In this study, we used the 'true' random effect model and not the 'true" fixed effect model. Estimates showed (not reported here) reasonable low correlation between farm/firm effects and the regressors (less than approximately 0.5). In addition, we used an unbalanced panel where 25% of the sample had four or less observations per farm (i.e. a panel data with a large share of short time period/time series). In cases like this, based on Clark and Linzer (2015), a fixed effect model exacerbates measurement error bias and the random effect model is preferable. Another drawback of the features of fixed-effects models is that they cannot be used to investigate time-invariant causes of the dependent variables.

assigned a quota for how much milk it can sell. Subsidy and other price regulations are every year determined by the negotiations between the government and farmers' representatives, which is called the agricultural settlement.

The Norwegian protectionist agricultural policy is facing external pressure from the European Economic Area (EEA) and the World Trade Organization (WTO) agreements. Pressure is also coming from the Norwegian consumers who seek high-quality milk product at lowest cost. Thus, improving the efficiency in dairy farm production is a priority objective of farmers, researchers, and policymakers. Dairy farmers need to be innovative and to use available technologies efficiently to reduce production costs (Moreira and Bravo-Ureta, 2010).

Norwegian regions

Norway covers a distance of 1750 km between 58 degrees N to 71degreees N (further than the distance from Rome to Oslo), with considerable variation in elevation. There is a contrast between coastal areas (relatively cool summers and mild winters) and inland conditions (relatively warm summers and cold winters). For the implementation of agricultural policy the country is divided into five main regions and 19 administrative counties. These divisions are based on geographical and climatic conditions. Northern Norway (Finnmark, Troms, and Nordland) is characterized by wide plains inland, dark winters and summer midnight sun. Central Norway (Nord-Trøndelag and Sør-Trøndelag) is located between North Norway and southern part of the country, and so shares characteristics from both north and south. Western Norway (Møre and Romsdal, Sogn and Fjordane, Hordaland, and Rogaland) is the region with most of Norway's fjords and mountains. The region receives most of the country's rain and the largest flat lowland area (Jæren) is also located in this region. Eastern Norway (Akershus, Oppland, Oslo, Telemark, Hedmark, Vestfold, Østfold, and Buskerud) is relatively highly populated because the capital city Oslo is located in this region. The region is characterized by relatively hot summers and cold winters. The land is flatter and more suitable for crop production compared to other regions. Southern Norway (Vest-Agder and Aust-Agder) shares most of the characteristics of the Eastern region but is not so suitable for crop production because the fields are scattered and the terrain more rugged.

5. Data

The data used for our empirical analysis is farm-level unbalanced panel data for 1992-2014 with 5442 observations from 731 dairy firms. The data source is the Norwegian farm accountancy survey, collected annually by the Norwegian Institute of Bioeconomy Research (NIBIO). To accommodate panel features with farm information over several years in 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.

The data used 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 2010 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; 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 costs items plus maintenance costs on farm capital tied up in machinery and buildings. All costs are measured in NOK adjusted to 2010 values. Maintenance and costs associated with the hiring of machines are registered annually.

Table 1. Descriptive statistics (mean values per farm) for dairy farms in five regions and for the whole sample (1992-2014).

	Norway	Eastern Norway	Southern Norway	Western Norway	Central Norway	Northern Norway
Output variable	900253	889986	909399	812047	998693	904915
Total revenue (NOK, excl. direct subsidies**)	(662372)	(607733)	(758417)	(768207)	(647536)	(514957)
Input variables						
Land (hectare)	27.5	29.3	24.6	22.4	30.4	30.1
	(17.7)	(18.5)	(17.7)	(18.0)	(16.4)	(16.0)
Labour(hours)	3464	3532	3228	3263	3665	3585
	(1001)	(1013)	(1016)	(1082)	(965)	(843)
Materials (NOK*)	168492	178498	154429	145968	188663	171906
	(113130)	(117469)	(108343)	(119938)	(111103)	(100622)
Fixed cost (NOK)	268361	275877	264614	247005	287906	266130
	(301085)	(377658)	(419718)	(438047)	(400702)	(367115)
Farm-specific environmental variables						
Farming experience (years)	28.1	28.1	28.7	28.2	26.8	28.8
	(10.4)	(10.7)	(11.7)	(10.0)	(10.2)	(9.1)
Subsidy (NOK)	379232	382439	316482	346258	385359	451685
	(198957)	(184358)	(172184)	(206528)	(154808)	(235986)
Number of cows	19.0	18.6	20.7	17.6	21.3	17.7
	(11.1)	(9.8)	(14.1)	(12.1)	(10.7)	(8.5)
Debt/asset ratio	0.40	0.37	0.43	0.37	0.38	0.44
	(0.17)	(0.19)	(0.17)	(0.19)	(0.16)	(0.14)
Region-specific environmental variables						
Regional grant index	3.99	3.37	2.05	3.99	2.92	7.22
	(2.10)	(1.26)	(1.31)	(0.14)	(0.97)	(1.62)
Regional off-farm contacts	5.18	5.23	5.34	4.98	5.14	5.24
	(0.19)	(0.18)	(0.32)	(0.21)	(0.03)	(0.18)
N	5442	1324	864	1125	1013	1116

* NOK = Norwegian kroner, 2010 values.
**Standard deviations are in parenthesis.

In the analysis, both farm-specific and region-specific environmental or *z*-variables are included. The farm-specific *z*-variables considered for farm-level efficiency consist of farmer's experience (z_1), measured as number of years as a farmer, which is based on how many years he/she has owned the farm business); government support within a year (z_2), measured in NOK; number of cows on the farm (z_3); and the farmer's debt/asset ratio (z_4). We included two region-specific environmental variables. Regional grant index (z_5) is a region-specific index used to specify what price-level milk-producers will be paid for the milk they sell. The region with favourable conditions for milk production (part of Western Norway) is assigned (by the government) level 0, while the region with least favourable conditions for milk production (part of Finnmark in Northern region) is assigned level 10. Other regions are graded between these extremes. Lastly, we included an indicator for the local or regional off-farm contacts (z_6). This variable was based on a farmer survey in 2009 to obtain attitudinal and behavioural data to supplement the farm accountancy survey panel data used in this study. One sub-set of questions, comprised four questions about personal contacts with neighbours and people living outside the local community, and about the agricultural environment in the local community and corporation within this environment. It is expected that those with more contacts (higher score on these questions) are more likely to be aware of and to take up improved technologies. The farmers were asked to respond on a Likert-scale from 1 (little contact) to 7 (much contact) on these questions. Our single variable was derived by taking a simple average of the farmer's responses on these four questions.

6. Estimation and results

Various specification tests were conducted to obtain the best model and functional form for the data under analysis.[3] 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, suggesting the appropriateness of the SF approach as opposed to ordinary least square (OLS). 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. Finally, to choose the appropriate theoretical framework for our study, we used likelihood ratio (LR) and Bartlett's equal variance tests. These two tests showed similar results. We found the strong rejection of the null hypothesis that the dairy farms in the five regions operate on the same production frontier. The implication is that a conventional stochastic production frontier estimated using the pooled data should not be used to compare technical efficiency scores across the regions. Therefore, any efficiency comparison across the regions should be undertaken with respect to a metafrontier model rather than to the pooled stochastic frontier model.

Input elasticities

Table 2 shows the result of TRE model estimation for five regions, the pooled data model, and the metafrontier model. For all regions, the models exhibited positive and highly significant first-order parameters, fulfilling the monotonicity condition for a well-behaved production function. The coefficients of the SFs for materials in all regions of Norway (except Southern Norway), and for the pooled data, are the largest among all partial production elasticities. These results imply that the percentage change in materials has a larger influence on dairy production than any other farm inputs (except for the southern region). This result is consistent with other studies (Cuesta, 2000; Moreira and Bravo-Ureta, 2010). The estimated elasticity of dairy output to land input (x_1) is significant in all regions, with values ranging from 0.15 to 0.40. The estimated elasticities of dairy output to labour input (x_2) were 0.11 for the northern and the southern regions, 0.20 for the central region, 0.07 for the eastern region and 0.19 for the western region. In the southern region, the coefficient of labour input has the largest influence compared to the partial elasticities of other inputs. If the labour input increase by 1% in the southern region, dairy output will increase by an estimated 0.4%. The partial elasticity of fixed cost (x_4) was positive and statically significant in all regions with a minimum value of 0.11 in the eastern region and maximum value of 0.19 in the central region.

Technical changes

Technological change (TC) shows the change in productivity due to the adoption of new production practices. The first-order coefficients of the time trend variable are estimates of the average annual rate of TC (Wang and Ho, 2010). The parameter associated with time-squared (t^2) was positive and significant for all regions, indicating that the rate of TC increased at an increasing rate over the period of the data (Table 2). In all areas, the production frontier was shifting out at an increasing rate, i.e., there is an increase in the use of improved dairy farm technology in all regions of Norway. This result is consistent with other studies, for instance, Sipiläinen, Kumbhakar, & Lien (2014); Moreira and Bravo-Ureta (2010). The overall annual percentage change in output due to TC was estimated to be about 0.01.

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

Table 2. Estimates for parameters of the translog stochastic frontier model by region, for the pooled data model, and the metafrontier.[×]

	Eastern Norway	*Southern Norway*	*Western Norway*	*Central Norway*	*Northern Norway*	*Pooled data*	*Meta-frontier*
Elasticities							
x_1 *(Land)*	.280***	.395***	.256***	.267***	.147***	.257***	.266***
	(0.012)	(0.017)	(0.016)	(0.012)	(0.014)	(0.005)	(0.001)
x_2 *(Labour)*	.068***	.114***	.185***	.202***	.112***	.131***	.139***
	(0.012)	(0.020)	(0.019)	(0.019)	(0.021)	(0.007)	(0.001)
x_3	.330***	.280***	.359***	.273***	.342***	.324***	.320***
(Materials)	(0.012)	(0.018)	(0.017)	(0.016)	(0.017)	(0.006)	(0.001)
x_4	.112***	.131***	.163***	.189***	.146***	.154***	.148***
(Fix. cost)	(0.010)	(0.013)	(0.010)	(0.010)	(0.012)	(0.004)	(0.001)
t	.008***	.009***	.010***	.007***	.009***	.008***	.009***
(Time-trend)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
t^2	.004***	.004***	.003***	.005***	.004***	.004***	.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.0001)	(0.000)
Farm-specific environmental variable							
Experience	-.081*	-.369***	-0.086	-.142*	-.111*	-.162***	
	(0.042)	(0.061)	(0.079)	(0.074)	(0.062)	(0.023)	
Subsidy	.275***	.439***	.598***	.344***	.307***	.293***	
	(0.061)	(0.068)	(0.115)	(0.077)	(0.044)	(0.020)	
Numb. Cows	-1.873***	-1.329***	-2.730***	-2.232***	-2.599***	-1.768***	
	(0.288)	(0.177)	(0.406)	(0.310)	(0.268)	(0.090)	
Debt/Asset	.519**	.895***	.571**	.978***	.597***	.847***	
	(0.204)	(0.265)	(0.283)	(0.344)	(0.223)	(0.096)	
Region-specific environmental variable							
Regional grant index							1.588***
							(0.305)
Regional off-farm contacts							-37.85***
							(6.999)
Log-L	817.58	435.04	655.67	666.92	635.32	3034.82	11101.12
N	1324	864	1125	1013	1116	5442	5442

*Standard errors in parentheses * p<0.10, ** p<0.05, and *** p<0.01; RTS = returns to scale*
[×] *The* second-order parameters in the TL are dropped, to save space, but is available from the authors on request.

Technical efficiency and technology gap ratio

The estimated technical efficiency scores and technology gap ratios (TGRs) are summarized in Table 3. Farms in all regions achieved high mean technical efficiencies (0.91-0.89). Similar results reported mean TEs of 0.92 and 0.82 for North and South New Zealand dairy farms, respectively (Jiang and Sharp, 2015). The average TE score of 0.91 in the eastern region implies that these dairy farms are producing only 91% of the maximum possible (frontier) output, given the inputs used. That is, an average dairy farm could increase its output by around 10% (=0.09/0.91) if it became technically efficient.

Although the LR-test implied that farmers in the different regions did not have access to the same underlying technologies, the TE scores are almost the same across all regions. Therefore, we can conclude that, in all regions, there is no evidence that many dairy producers are lagging far behind the most efficient producers in each region.

The mean TEs for all regions, estimated using the conventional stochastic production frontiers, was 0.90. The estimate is close to what was found in TE studies reported in the literature, for instance, for Swedish dairy farms 0.89 (Hansson and Öhlmér, 2008) and for New England dairy farms 0.83 (Bravo-Ureta and Rieger, 1991). However, our result is lower than the TE estimate for

Danish dairy farms 0.97 (Lawson et al., 2004), but higher than the estimate obtained for Icelandic dairy farms 0.76 (Atsbeha et al., 2012).

Table 3. Technical efficiencies and Technology gap ratios estimate for dairy farms in five regions.

	Regions					**Norway**
	Eastern Norway	Southern Norway	Western Norway	Central Norway	Northern Norway	
TEs to the regional frontier (TE_{it})						Pooled
Mean	0.91	0.89	0.90	0.91	0.90	0.90
Std. Dev.	0.06	0.07	0.06	0.05	0.07	0.06
Minimum	0.66	0.47	0.54	0.57	0.45	0.48
Maximum	0.99	0.99	0.99	0.99	0.98	0.99
Technology gap ratio (*TGR*)						
Mean	0.98	0.97	0.96	0.98	0.98	
Std. Dev.	0.01	0.02	0.02	0.01	0.01	
Minimum	0.96	0.87	0.84	0.94	0.92	
Maximum	1.00	1.00	1.00	1.00	1.00	
TEs to the metafrontier ($\boldsymbol{MTE_{it}}$)						Meta
Mean	0.89	0.87	0.87	0.89	0.88	0.88
Std. Dev.	0.06	0.08	0.07	0.05	0.07	0.06
Minimum	0.65	0.45	0.47	0.55	0.45	0.45
Maximum	0.97	0.97	0.98	0.98	0.96	0.98

Estimates of the mean values of TGR (Table 3) are very close to 1 (varying at the mean between 0.96 and 0.98), with no big differences between regions. A value of 1 is equivalent to a point where the individual region frontier coincides with the metafrontier. Boshrabadi et al. (2008) in Iran and Moreira and Bravo-Ureta (2010) in Argentina, Chile, and Uruguay reported similar results. The TGR values ranged from maxima of 1.00 for all regions, showing that some farms were producing the maximum outputs as indicated by the meta-function, given the current technology in the dairy sector.

The average technical efficiency scores for the regional frontier model (TE_{it}) and metafrontier model (MTE_{it}) are very similar to each other, since the TGR estimates are close to 1, as also shown in Table 3. The average overall technical efficiency scores for the years 1992-2014 against the metafrontier (MTE_{it}) vary from 0.87 to 0.89. As explained above, the mathematical expression for MTE_{it} (eq. 9) is a product of the TGR and the region level technical efficiency (TE_{it}).

Determinants of farm- and region-specific efficiency

Even though the TEs are at about the same level across regions, as discussed above, there are differences between regions in terms of the determinants of the TE scores. The lower part of Table 2 shows the estimates of the farm-specific and region-specific environmental variables of technical inefficiency.

The farming experience was found to increase technical efficiency in all regions, as indicated by the negative and statically significant parameter estimates for this variable. The values differ from region to region, with the highest score found in the southern region (0.37) and the lowest in the eastern and western regions (0.08-0.09). These results support the findings of other studies, for example, Wilson et al. (2001), who reported that farm managers with more experience are likely to be more efficient. However, this result is in contrast to an earlier study of Kumbhakar and Lien (2010), who failed to find any statistically different effects of experience on TE for Norwegian dairy farming.

Our results suggest that Government support has not helped dairy farms to achieve greater TEs, as indicated by the positive and statistically significant parameter estimates. Previous studies have provided mixed evidence on the effect of subsidies on technical efficiency. For instance, inconsistent with our finding, Latruffe et al. (2016) reported that subsidies received by dairy farms in Spain, Portugal, and Italy have achieved greater technical efficiency. On the other hand, several studies focusing on dairy farms reported that government payments reduce producers' incentives to generate the highest possible income from farming (see for example Lachaal, 1994, Hadley, 2006, Ferjani, 2008, and Zhu et al., 2012). Our analysis does not account for any differential effects of different types of direct subsidy on efficiency so that the result should be interpreted with caution.

The size of the farm, measured by the number of cows in the herd, was found to have a positive and statically significant effect on TEs. As might be expected, it seems that farms with larger herds are more efficient compared to those with fewer animals. Larger farms apparently are able to utilize technologies that are more technically efficient, as also found in other studies (e.g., Tauer et al., 1987; Gerber and Franks, 2001, and Kirner et al., 2007).

A higher ratio of long-term debts to total assets (debt/asset) reduced TEs in all regions. Our result is contrary to some other research findings. For instance, Barnes (2008) and Zhu et al. (2012) reported that debt/asset increased technical efficiency because firms can invest in assets that are more efficient. On the other hand, very high debt can also limit efficient production, as is supported in our study and by earlier studies of Norwegian and Finnish dairy farms (Sipiläinen et al., 2014).

The two region-specific environmental variables of technical inefficiency show different results. Regional grant index (z_5), which specifies what price-level region in which the milk-producers are located, negatively contributed to regional technical efficiency. This is in line with our expectation and the literature; see for instance Špička and Smutak (2014). Farms in more disadvantaged regions – those granted higher milk prices are less efficient than farms in more favourable regions for dairy production. On the other hand, local off-farm contacts (z_6) contribute positively to regional differences. Our result is in line with other findings that local off-farm contacts and contact with the advisory service improve farm performance (e.g., Hussain et al., 1994; O'Neill et al., 1999). Farm extension has a significant effect on closing both the technology and management gaps (Dinar et al., 2007).

The subsidy/government support effect on efficiency is most negative in Western Norway while the herd size effect is most positive in the same region. Perhaps in this most productive dairy production region, the historical subsidy regime has hampered efficiency, while ongoing structural change (through milk quota renting, renting land, merging of farms, etc.) has improved farm-specific efficiency. The same pattern seems not to be so strong in other regions of Norway. These results may provide some support for a more region-specific agricultural policy, in terms of support schemes and structural regulations. However, more research is needed before such a conclusion could be substantiated.

7. Discussion and conclusion

The objective of the paper was to compare technical efficiency for dairy farms in the five Norwegian regions using a recently introduced a stochastic metafrontier approach. The results of the analysis show that TE scores and TGRs are somewhat different for the five regions. This finding has not been shown in previous dairy efficiency studies in Norway. The estimated average TE score ranges from 0.91 for the eastern and central region to 0.89 for the southern region. The results suggest that dairy farms in all regions used available technology in the area sub-optimally, i.e. there are farmers who produced lower outputs from the inputs they used or used more inputs to produce the same output, compared to the best performing farmers in their region. Farms in the eastern and central regions had the highest TE on average, given the technology available across all regions, but the differences between regions were small. Farming experience and size of the farm increased TE in all regions, while government support and debt/asset ratio decreased the performance. The government support effect on efficiency was most negative in Western Norway while the size effect was most positive in this region.

Dairy farming in Norway is, for the most part, a relatively a mature and ‘intensive’ industry, with the cows housed much of the year and fed purchased or conserved feed. In such a case, we would expect differences in efficiency to arise mainly from the production and conservation of feed and from access to markets for purchased feed and for selling milk. Insofar as these regional differences are compensated for by regionally differentiated subsidies, it is not surprising that regional differences in TE are somewhat small. Of course, that does not imply that all regions are more or less equally internationally competitive. Farmers in those regions getting higher prices or more subsidies would be in the most trouble if dairy farming were to be deregulated. Our study implies that the policies in place are working effectively to keep relatively disadvantaged producers in the business. However, these policies are preventing market forces from leading to adjustments that may will be unavoidable, and more painful than they need have been, has not the high protection of the less efficient been in place.

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