Regional differences in technical efficiency and technological gap of the Norwegian dairy farms: a stochastic meta-frontier model

Alem, H.[a,d], Lien, G.[b,a], Hardaker, B. J.[c], and Guttormsen, A.[d] [1]

Abstract

This paper compares Technical efficiency (TEs) and Technological gap ratio (TGRs) for dairy farms in regions of Norway, accounting for differences in working environments. We used the stochastic meta-frontier approach of Huang et al. (2014) to estimate TEs and TGRs to account for regional heterogeneity, and the 'true' random-effect model of Greene (2005) to account for farm effects. The dataset used was farm-level balanced panel data for 24 years (1991–2014), with 5,442 observations from 731 dairy farms. The results of the analysis provide empirical evidence of small regional differences in TEs, TGRs, and input use. Furthermore, the results may provide support for the more regionally specific agricultural policy, in terms of support schemes and structural regulations.

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[a]Norwegian Institute of Bioeconomy Research, Norway   habtamu.alem@nibio.no
[b] Inland Norway University of Applied Sciences, Norway   gudbrand.Lien@inn.no
[c] University of New England, Armidale, N.S.W., Australia   j.brian.hardaker@gmail.com
[d] Norwegian University of Life Science, Norway , atle.guttormsen@nmbu.no

1. Introduction

Technical efficiency estimation is of growing interest as a means of identifying best-practice performance and of improving the efficiency of resource use (Coelli et al., 2005; Kumbhakar & Tsionas, 2011). Since the introduction of stochastic frontier analysis (Aigner et al., 1977; Meeusen & 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 used to estimate efficiency scores is based on the assumption that the underlying technology is the same for all the sample observations, regardless of differences in operating circumstances and working environments. However, farms 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 the composition of input will differ between farms, even in the same region. Farms 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 farms 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 or groups, researchers often seek to control heterogeneity using various methods. Some researchers use statistical methods. For example, similar farmers can be grouped using cluster algorithms (Álvarez et al., 2008). Others use econometric methods, for instance, heterogeneity

captured by intercepts such as the 'true'-fixed and 'true'-random effect models (Greene, 2005a, and 2005b). Other researchers assume different technologies to account for heterogeneity. In this category, the random parameter model, latent class models, and meta-frontier models are widely used. The random parameter model[2] treats continued parameter variation and the estimation is extremely time-consuming (Greene, 2005a). 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., Alvarez et al., 2012, Baráth & Fertő, 2015, Orea & Kumbhakar, 2004; and Sauer & Paul, 2013 for details). On the other hand, the stochastic meta-frontier framework is based on the hypothesis that 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 for estimating technical efficiency; however, the meta-frontier 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 labour 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, as described in detail by O'Donnell et al. (2008), the efficiencies relative to the meta-frontier 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 meta-frontier. This approach has been widely applied y to evaluate the efficiency of productive groups. For instance, it has been used in industries (Wongchai, Liu & Peng, 2012; Yaisawarng & Ng, 2014); in infrastructure (De Witte &

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[2] Some researchers have employed Bayesian estimators that resemble the random parameter model in assuming a stochastic model with exponentially distributed inefficiency. For further information, refer to Koop and Steel (2001), Tsionas (2002), and Assaf (2011).

Marques, 2009); in finance (Kontolaimou & Tsekouras, 2010, Chao, Yu, Hsiung & Chen, 2017), and in agriculture (Boshrabadi et al., 2008; Mariano et al., 2011; Moreira & Bravo-Ureta, 2010; Nkamleu et al., 2006; O'Donnell et al., 2008; Villano & Mehrabi, 2010; Zhuo & Shunfeng, 2008; Jiand & Sharp, 2015).

Using this method, estimates of the gap between the group frontiers and the meta-frontier can be used to design performance improvements that involve a change in the production environment. Such change might be generated by the government (infrastructure, relaxing labour laws, etc.) or by farms in the industries (e.g., move production to a more favourable place). However, as O'Donnell et al. (2008) point out, both governments and farms 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 regionally focused meta-frontier analysis in agriculture.

As indicated above, the primary objectives of Norwegian agricultural policy are long-term food self-sufficiency, and the protection of the environment and of farming in all regions. We focused our analysis on dairy farming; however, the method can be applied to other agricultural production activity in Norway. Knowledge of the performance of dairy farms at the regional level could help policymakers introduce better-targeted agricultural policies and systems in Norway. In light of this, the aim of this study is to assess the technical efficiency and technological gaps on dairy farms in different regions of Norway using the recently introduced stochastic meta-frontier model of Huang et al. (2014).

The paper contributes to the literature in a number of ways. First, in contrast to Huang et al. (2014), we account for farm-level heterogeneity (unobserved heterogeneity) by applying the model devised by Greene (2005a, 2005b). Second, we are fortunate to be able to use a large

farm-level panel dataset of Norwegian crop-producing farms with observations from 1991 to 2014.

The rest of the paper is organised as described in what 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 estimations and results are presented in Section 6. Finally, Section 7 comprises a discussion of the findings and the conclusion.

2. Theoretical model

Battese et al. (2004) and O'Donnell et al. (2008) introduced the modern meta-frontier production-function model. As noted above, the meta-frontier model allows control of heterogeneity by establishing homogeneous groups within the sample. The model is estimated in two steps: in the first step, a stochastic frontier analysis (SFA) model is used to estimate the homogenous group frontiers; then, in the second step, linear programming is used to estimate the meta-frontier. The second step procedure has some drawbacks. Since a linear programming approach used, it is not possible to include the determinants (the production environment) of regional differences. In addition, programming techniques do not isolate idiosyncratic shocks and thus the results are susceptible to random noise, and no statistical properties can be ascertained (Huang et al., 2014). 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 meta-frontier in step two. With this framework, it is possible to include z or production environment variables in both steps. We apply the estimation framework of Huang et al. (2014). Moreover, unlike Huang et al. (2014), we account for farm-level heterogeneity in the first step using Greene's (2005b) model.

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 farm i at time $t = 1,2 \ldots,T$, x_{it} is a vector of factor inputs, $i = 1, 2, \ldots, N$ for the farm 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 farm 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 TE using conventional-production frontier for equation (1) is that farms operate in the same kind of working environment. Violation of this assumption biases TE estimates (Orea & 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 in the kth region in the tth time period, x_{it}^k is the input vector, v_{it}^k represents the error term and is assumed to be iid as $v_{it}^k \sim N(0, \sigma_{vk}^2)$. u_{it}^k is a one-sided error representing technical inefficiency and is 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 kth region. These parameters are to be estimated using the 'true' random-effect model of Greene (2005a) to account for the farm effect (unobserved heterogeneity) within the region. The TE of the ith farm relative to the region k frontier can be computed, following Greene (2005b), as:

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

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 meta-frontier function that envelops all the frontiers of the *k* regions, we use the approach of Huang et al. (2014). In step 2 we, therefore, specify the following SFA:

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

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 as one vector for the whole sample. In this model, v_{it}^M represents 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 term representing technical inefficiency and is 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 meta-frontier.

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 meta-frontier consists of three components, that is,

$\frac{y_{it}^k}{f^M(x_{it}^k,\beta)} = TGR_{it}^k \times TE_{it}^k \times e^{v_{it}^M}$, 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 farm's TE, and $e^{v_{it}^M} = \frac{y_{it}^k}{f^M(x_{it}^k,\beta)e^{-u_{it}^k}}$ is the random noise component.

Then, the two-step approach to estimate the meta-frontier as proposed by Huang et al. (2014) consists of two SFA regressions:

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

$$lnf^k(x_{it}^k, \beta^k) = f^M(x_{it}^k, \beta) + v_{it}^M - u_{it}^M, \forall i, t \ k = 1, 2, \ldots, K \qquad (6)$$

where $lnf^k(x_{it}^k, \beta^k)$ is the estimate of the region-specific frontier from the equation (5). Since

the estimates $lnf^k(x_{it}^k, \beta^k)$ are region specific, regression (5) is estimated K times, one for each

region$(k = 1, 2, \ldots, K)$. These output estimates from all K regions are then pooled to estimate

(6).

The meta-frontier should be larger than or equal to the group-specific frontier, that is,

$f^k(x_{it}^k, \beta^k) \leq f^M(x_{it}^k, \beta^k)$. The estimated TGR must be less than or equal to unity:

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

where $\hat{\varepsilon}_{it}^M = lnf^k(x_{it}^k, \beta^k) - lnf^M(x_{it}, \beta)$ are the estimated composite residuals of (6). The TE

of the ith farm to the meta-frontier is equal to the product of the estimate of the TGR in Eq. (7)

and the individual farm's estimated TE in Eq. (3), that is, $M\hat{T}E_{it}^k = T\hat{G}R_{it}^k \times \widehat{TE}_{it}^k$.

3.   Empirical model

We estimate the second-order flexible TL function (Berndt & Christensen, 1973). The region k

frontier in (5) specified as a TL function is:

$$lny_{it}^k = \beta_0^k + \sum_{j=1}^{4} \beta_j^k lnx_{jit} + \frac{1}{2}\sum_{j=1}^{4} \beta_{jj}^k (lnx_{jit})^2 + \sum_{j=1}^{4}\sum_{l=2}^{4} \beta_{jl}^k lnx_{jit} \, lnx_{lit} + \beta_t^k t$$
$$+ \frac{1}{2}\beta_{tt}^k \quad + \sum_{j=1}^{4} \beta_{jt}^k \, lnx_{jit} t + \theta_i^k + v_{it}^k - u_{it}^k \qquad (8)$$

where y_{it} is a vector of dairy outputs, x_{jit} is a vector of inputs $(j = 1, \cdots, J)$ by farms

$(i = 1, \cdots, N)$ over time $(t = 1, \cdots, T)$, and all the 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   symmetrical   and   is   assumed   to   satisfy   the   classical   assumptions,   that   is,

$v_{it} \overset{iid}{\sim} N(0, \sigma_v^2), v_{it} \perp u_{it}$. The term u_{it}^k is specified as $u_{it}^k \sim N^+\left(0, \sigma_{vk}^2(z_{it}^k)\right)$, and θ_i^k is a

farm-specific component for capturing time-invariant unobserved heterogeneity, which is assumed to have an iid normal distribution. The model is estimated using the TRE frontier model[3] (Greene, 2005), and it extends the conventional stochastic frontier model by disentangling the farm effect (unobserved heterogeneity) from TE. The trend variable, t, is introduced to capture the effect of technological change and starts with $t = 1$ for 1991 and increases by one annually. The same estimation model is used to estimate (6), but $\ln y_{it}^k$ in (8) is replaced by $\ln \hat{f}^k(x_{it}^k, \beta^k)$. The models are estimated using LIMDEP software.

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 normalised as zero in the year 2014, and all other variables are normalised before calculating the logarithm by dividing each variable by its mean value. Various specification tests of hypotheses about the parameters on the frontier and in the inefficiency model are performed using the generalised LR test statistic.

4. Norwegian dairy farms and regions

4.1. Norwegian dairy farms: changing patterns

In Norway, the northernmost country in Europe, livestock production is the dominant agricultural activity in all regions, and only some 30% of the farms specialise in dairy farming. Norwegian dairy farms are usually small-scale compared to other developed countries, family-operated, face extensive areas of rugged terrain, and they have short growing seasons for feed

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[3] In this study, we used the 'true' random-effect model and not the 'true" fixed-effect model. Estimates (not reported here) show reasonably low correlation between farm/firm effects and the regressors (less than approximately 0.5). In addition, we used an unbalanced panel in which 25% of the sample has four or fewer observations per farm (i.e. 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.

production. These problems contribute to the high costs of production. The Norwegian government provides significant support to the agricultural sector and dairy farms are among the most 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 concentrated on fewer farms. Yet, structural change in the Norwegian dairy sector is slower than in other Nordic countries owing to government policy that favours small farms and their wide geographic distribution (Atsbeha et al., 2015; Flaten, 2002).

In the dairy sector, various regulatory schemes have been established to align the supply of milk production to domestic milk demand (Jervell & Borgen, 2000). A fall in the demand for milk in 1980 together with a reduction in consumer subsidies for milk resulted in a large surplus in 1982 (Kumbehakar et al., 2008). To avoid the overproduction of milk for the domestic market, the government imposed a restrictive quota scheme in 1983 to limit the amount of milk farmers could sell. A quota-trading system was introduced in 1996 for the redistribution of milk quotas at the regional level. The system allows 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 assigned a quota for how much milk it can produce. Subsidy and other price regulations are determined every year by negotiations between the government and farmers' representatives, which is referred to as the agricultural settlement.

Norwegian protectionist agricultural policy is facing external pressure from European Economic Area and World Trade Organization agreements. Pressure is also coming from Norwegian consumers who seek high-quality milk products at the lowest cost. There is no guarantee that Norwegian agriculture policy in the future will lead to cost-effective and more competitive dairy production against foreign products. Thus, improving 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 & Bravo-Ureta, 2010).

4.2. Norwegian regions

Norway extends 1,750 km between 58 degrees north to 71 degrees north (further than the distance from Rome to Oslo), with considerable variation in elevation. There is a contrast between the coastal area (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 based on geographical and climatic conditions (see Figure 1 in the Appendix). Northern Norway (Finnmark, Troms, and Nordland) is characterised by wide inland plains, dark winters, and midnight sun in summer. Central Norway (Nord-Trøndelag and Sør-Trøndelag) is located between Northern Norway and southern part of the country, and so shares characteristics of 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 as the capital city, Oslo, is located in this region. The region is characterised by relatively hot summers and cold winters. Compared to the other regions, the land here is flatter and more suitable for crop production. Southern Norway (Vest-Agder and Aust-Agder) shares most of the characteristics of the Eastern region but is not as suitable for crop production as the fields are scattered and the terrain is more rugged.

5. Data

The data used for our empirical analysis is farm-level unbalanced panel data for 1991–2014, with 5,442 observations from 731 dairy farms. The data source is the Norwegian farm

accountancy survey, collected annually by NIBIO. To accommodate panel features with farm information over several years of estimation, only those farms for which at least three years of data were available are included in the analysis. A summary of the output and input variables is shown in Table 1.

Table 1 Descriptive statistics (mean values per farm) for dairy farms in five regions and for the whole sample (1991–2014)

	Norway	Eastern Norway	Southern Norway	Western Norway	Central Norway	Northern Norway
Output variable	900,253	889,986	909,399	812,047	998,693	904,915
Total revenue (NOK, excl. direct subsidies[**])	(662,372)	(607,733)	(758,417)	(768,207)	(647,536)	(514,957)
Input variables						
Land (hectares)	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)	3,464	3,532	3,228	3263	3,665	3,585
	(1,001)	(1,013)	(1,016)	(1,082)	(965)	(843)
Materials (NOK[*])	168,492	178,498	154,429	145,968	188,663	171,906
	(113,130)	(117,469)	(108,343)	(119,938)	(111,103)	(100,622)
Capital cost (NOK)	268,361	275,877	264,614	247,005	287,906	266,130
	(301,085)	(377,658)	(419,718)	(438,047)	(400,702)	(367,115)
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)	379,232	382,439	316,482	346,258	385,359	451,685
	(198,957)	(184,358)	(172,184)	(206,528)	(154,808)	(235,986)
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 contact	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	5,442	1,324	864	1,125	1,013	1,116

[*] NOK = Norwegian kroner, 2010 values
[**] Standard deviations are in parentheses

The data used for this analysis contains 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 NOK and is adjusted

to 2010 values using the consumer price index. The TL production function in empirical model (8) is specified using the four input variables described next. Farmland (x_1), defined as productive land (both owned and rented) in hectares, and labour (x_2), measured as the total labour hours used on the farm, including hired labour, owners' labour, and family labour. Materials (x_3), including fertilisers, feed, oil and fuel products, electricity, expenses for crop and animal protection, construction materials and other costs; and fixed costs (x_4), including fixed cost items, plus maintenance costs of 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.

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 the number of years the person has been a farmer, which is based on the number of years he/she has owned the farm; direct government support in a specified year (z_2), measured in NOK; the number of cows on the farm (z_3); and the farmer's debt/asset ratio (z_4). We include two region-specific environmental variables. The regional grant index (z_5) is a region-specific index used to specify the price-level milk-producers will be paid for the produced milk. The region with the most favourable conditions for milk production (part of Western Norway) is assigned level 0, while the region with least favourable conditions for milk production (part of Finnmark in the Northern region) is assigned level 10. Other regions are graded between these extremes. Lastly, we include an indicator for the local or regional off-farm contacts (z_6). This variable was based on a 2009 farmer survey to obtain attitudinal and behavioural data to supplement the panel of 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 incorporation within this environment. It is expected

that those with more contacts (a higher score for these questions) are more likely to be aware of and to take up improved technologies. The farmers were asked to respond to the questions on a Likert-scale that ranges from 1 (little contact) to 7 (much contact). Our single variable was derived by taking a simple average of the farmer's responses to these four questions. We assumed that this regional off-farm contacts variable (z_6) was constant over time, and we further assumed it was constant within a county, that is, we used the average of the observed farm responses within a county as a proxy for the whole county.

6. Estimation results and discussion

Various specification tests were conducted to obtain the best model and functional form for the data under analysis.[4] First, we tested the null hypothesis that there are no TE 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 OLS. Second, LR tests for all SF models for each region and the pooled data revealed that a simplification of the TL to Cobb-Douglas functional form was rejected. Thus, the TL functional form was retained. Finally, as the appropriate theoretical framework for our study, we used the LR and Bartlett's equal variance tests. These two tests showed similar results. We found a strong rejection of the null hypothesis that 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 TE scores across the regions. Therefore, any efficiency comparison across the regions should be undertaken using a meta-frontier model rather than to the pooled stochastic frontier model.

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[4] The tests are not reported here due to space constraints, but are available upon request from the principal author.

Table 2 shows the result of TRE model estimation for the five regions, the pooled data model, and the meta-frontier model. For all regions, the models exhibit 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 other partial production elasticities. These results imply that the percentage change in materials has a larger influence on dairy production than other farm inputs. This result is consistent with other studies (Cuesta, 2000; Moreira & 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) are 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 land input has the largest influence compared to the partial elasticities of other inputs. If land input increases by 1% in the southern region, dairy output will increase by an estimated 0.4%. The partial elasticity of capital cost (x_4) is positive and statically significant in all regions, with a minimum value of 0.11 in the eastern region and a maximum value of 0.19 in the central region.

Table 2. Estimates for the parameters of the translog stochastic frontier model by region, for the pooled data model, and for the meta-frontier*

	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 *(Materials)*	.330***	.280***	.359***	.273***	.342***	.324***	.320***
	(0.012)	(0.018)	(0.017)	(0.016)	(0.017)	(0.006)	(0.001)
x_4 *(Fixed cost)*	.112***	.131***	.163***	.189***	.146***	.154***	.148***
	(0.010)	(0.013)	(0.010)	(0.010)	(0.012)	(0.004)	(0.001)
t (Time trend)	.008***	.009***	.010***	.007***	.009***	.008***	.009***
	(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 variables							
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)	
No. of 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	435	655	666	635	3,034	11,101
N	1,324	864	1,125	1,013	1,116	5,442	5,442

*Standard errors in parentheses * 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 on request.

b. Technological 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 & Ho, 2010). The parameter associated with time-squared (t^2) are 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 is shifting out at an increasing rate, that is, 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 and Lien (2013) and Moreira and Bravo-Ureta (2010). The overall annual percentage change in output due to TC is estimated to be approximately 0.01.

c. Technical efficiency and the technology gap ratio

The estimated TE scores and TGRs are summarised in Table 3. Farms in all regions achieved high mean technical efficiencies (0.91–0.89). Similar studies reported mean TEs of 0.92 and 0.82 for North and South Island New Zealand dairy farms, respectively (Jiang & Sharp, 2015).

Table 3 Technical efficiency and technology gap ratio estimates 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 meta-frontier (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

The average TE score of 0.91 in the eastern region implies that these dairy farms produce only 91% of the maximum possible (frontier) output, given the input used. That is, an average dairy farm can increase its output by around 10% if it becomes technically efficient. Although the LR test implies that farmers in the different regions do 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 TE for all regions estimated using the conventional stochastic production frontiers is 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 & Öhlmér, 2008), and for New England dairy farms – 0.83 (Bravo-Ureta & 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., 2015).

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

The average TE scores for the regional frontier model (TE_{it}) and meta-frontier 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 TE scores for the period 1991–2014 against the meta-frontier (MTE_{it}) vary from 0.87 to 0.89. As discussed in detail in the theoretical part of this paper, the mathematical expression for MTE_{it} is a product of the TGR and the regional-level TE (TE_{it}).

d. 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 bottom of Table 2 shows the estimates for the farm-specific and region-specific environmental variables of technical inefficiency.

The farming experience was found to increase TE in all regions, as indicated by the negative and statistically 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 report that farm managers with more experience are likely to be more efficient. However, this result is in contrast to an earlier study (Kumbhakar & Lien, 2010), which failed to find any statistically different effects of experience on TE for Norwegian dairy farming.

The results suggest that government support has not helped dairy farms to achieve greater TEs in all regions, as indicated by the negative and statistically significant parameter estimates. This may reflect an investment effect that occurs through the relaxing of financial constraints to purchase new technologies that can enhance milk yield or lower production costs. Previous studies have provided mixed evidence of the effect of subsidies on TE. For instance, inconsistent with our findings, Latruffe et al. (2016) report that subsidies received by dairy farms in Spain, Portugal, and Italy have helped them to achieve greater TE. 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, Lachaal, 1994; Hadley, 2006; Ferjani, 2008; and Zhu et al., 2012). However, 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 a 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 are apparently able to use technologies that are more technically efficient, as has also been found in other studies (e.g., Gerber &Franks, 2001).

A higher share of long-term debts in total assets (debt/asset) reduced TEs in all regions. Our results are contrary to some other research findings. For instance, Barnes (2008) and Zhu et al. (2012) report that debt/asset increases TE because farms can invest in assets that are more efficient. On the other hand, very high debt can also limit efficient production, a factor that is supported in our study and by earlier studies of Norwegian and Finnish dairy farms (Sipiläinen et al., 2013).

The two region-specific environmental variables of technical inefficiency show different results. The regional grant index (z_5), which specifies what price-level region the milk-producers are located in, negatively contributed to regional TE. This is in line with our expectation and with the literature; see, for instance, Špička and Smutak (2014). Farms in the most disadvantaged regions – those granted higher milk prices – are less efficient than farms in regions more favourable for dairy production. On the other hand, local off-farm contacts (z_6) contribute positively to regional differences. Our results are in line with other findings that show 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 technology and management gaps (Dinar et al., 2007).

7. Conclusion

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

Estimates of the mean values of TGRs are very close to 1 (varying at the mean between 0.96 and 0.98), with no large differences between regions. A value of 1 is equivalent to a point where the individual region frontier coincides with the meta-frontier. Comparing performances across all regions, the lowest TGRs are found in the western regions (0.96, on a scale from 0 to 1). The regional grant index, which specifies what price-level region the milk-producers are located in, negatively contributes to regional TE. Farms in the most disadvantaged regions, those granted higher milk prices, are less efficient than farms in regions more favourable for dairy production. On the other hand, local off-farm contacts contribute positively to regional differences, which shows that local off-farm contacts and contact with the advisory service improve farm performance.

Moreira and Bravo-Ureta (2010) suggest that, if the production frontier for farmers in a particular area is far from the meta-frontier, then one way policymakers might reduce the gap is through training, including sharing information about relevant technologies from one area to

another, if the technologies being shared fit the working environment of the lagging area. Such policy intervention might work for some Norwegian dairy farmers who appear to be lagging in the technologies they are using. Moreira and Bravo-Ureta (2010) also suggest that regions that are already performing closer to the meta-frontier might benefit from additional investment to shift the frontier upwards. The production frontiers for all regions are relatively near the meta-frontier (0.98). Thus, all regions might require increased investment in local research to develop new dairy technologies that improve productivity.

The TGR was estimated using a single output framework. It might be interesting to see if the results are different if the meta-frontier were estimated in multiple input-output frameworks. Thus, the limitations of this study suggest important topics that could benefit from further study.

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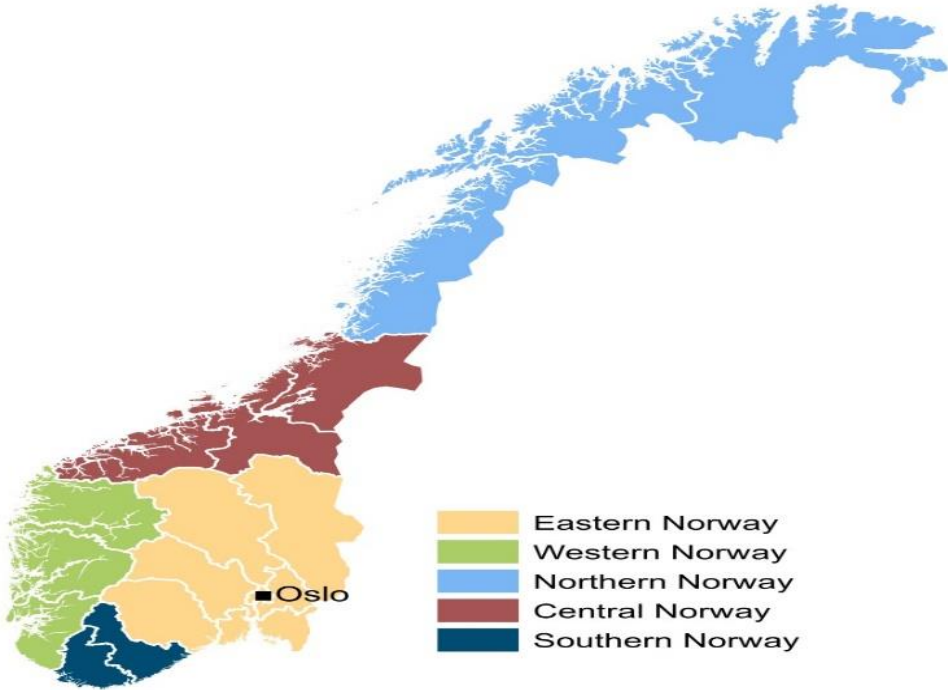
Appendix

Figure 1. The five geographical regions of Norway