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Measuring Technology and Performance Differentials Among the Norwegian Dairy Farms

Abstract

Purpose- The study measures the technology gap and performance of the Norwegian dairy farms accounting for farm heterogeneity

Methodology- The analysis was based on a meta-frontier and unbalanced farm-level panel data for 1991-2014 from 417 Norwegian farms specialized in dairy production in five regions of Norway.

Findings- The result of the analysis provides empirical evidence of regional differences in technical efficiencies, technological gap ratios, and input use

Practical implications- One implication for farmers (and their advisers) is that dairy farms in all regions used available technology in the area sub-optimally. Thus, those lagging behind the best performing farms need to look at the way the best performing farmers are operating. Policymakers might reduce the gap is through training, including sharing information about relevant technologies from one area to another, provided that the technologies being shared fit the working environment of the lagging area.

Findings- The paper contributes to the literature in several ways. In contrast to Battese et al. (2004), we account for farm-level performance differences by applying the model devised by Greene (2005), thus may serve as a model for future studies at more local levels or of other industries. Moreover, we are fortunate to able to use a large level of farm-level panel data from 1991- 2014.

Keywords: *Dairy farm, meta-frontier, heterogeneity, region, and technical efficiency*

Paper type: Research paper

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 (Alem, 2018; Headey, Alauddin, & Rao, 2010; Kumbhakar & Tsionas, 2011; Ma, Bicknell, & Renwick, 2019). Since the introduction of stochastic frontier (SF) analysis (Aigner, Lovell and Schmidt, 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; Alem, 2020; Lien, Kumbhakar, & Alem, 2018; and Kumbhakar, Wang, & Horncastle, 2015 for reviews). The SF model can be applied to cost, production, revenue, and distance or profit functions. Mostly, the 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 environment. Farms in different regions are likely to face different production opportunities, and technology sets may differ because of differences in resource endowments. For instance, 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 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 (Alem, Lien, Hasaker, & Guttormsen, 2019). Thus, comparing the performance of farms located in different regions obtained from single estimates across all regions is likely to produce misleading results.

Policy intervention and management advice may need to be different for different regions (groups). Thus, researchers often seek to control heterogeneity using various methods (Huang, Huang, & Liu (2014). Some researchers use statistical methods. For example, groups of similar farmers can be formed by using cluster algorithms (Álvarez, Corral, Solís, & Pérez, 2008). Others use econometric methods, for instance, heterogeneity captured by the intercept e.g. random parameter model, 'true'-fixed and 'true'-random effect models (see Alem, 2018, Greene, 2005; Abdulai & Tietje, 2007). Other researchers assume different technologies to account for heterogeneity. In this category, latent class models, and metafrontier models are widely used. 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, Jiang, & Sharp,2015, Sauer & Paul, 2013, and Baráth, & Fertő, 2015 for details). Latent class models and meta-frontier models are widely used in this category. 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 and Kumbhakar, 2004 and Alvarez et al., 2012, for details). On the other hand, the stochastic meta-frontier framework is based on the hypothesis that all producers in different locations (or other comparable groupings) have operated to the same technology (see e.g. Alem et al, 2019; Battese et al., 2004 and O'Donnell et al., 2008). All these models have advantages and disadvantages in estimating technical efficiency; however, the meta-frontier model is most commonly used for the group- or regionally based studies (Alem, et al., 2019). A meta-production function has been applied widely to evaluate the efficiency of groups of firms see for instance Wongchai, Liu, & Peng, 2012; Yaisawarng & Ng, 2014; De Witte & Marques, 2009; M.-Y. Huang & Fu, 2013; T.-H. Huang, Chiang, Chen, & Chiu, 2010; Kontolaimou & Tsekouras, 2010; and Boshrabadi, Villano, & Fleming, 2008; Mariano, Villano, & Fleming, 2011; Moreira & Bravo-Ureta, 2009; Nkamleu, Nyemeck, & Sanogo, 2006; O'Donnell et al., 2008; Sipiläinen, Kuosmanen, & Kumbhakar, 2008; Villano & Mehrabi Boshrabadi, 2010; Zhuo & Shunfeng, 2008.

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The main objective of this study is to assess the technical efficiency and technological gaps of dairy farms in different regions of Norway. We consider farm heterogeneity and compare dairy farm's performance in five Norwegian regions using the 'true' random effect model of Greene (2005) and the stochastic meta-frontier model of Battese et al. (2004).

The paper contributes to the literature in two aspects. First, in contrast to Battese et al. (2004), 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 dairy farms with observations from 1991 to 2014.

The rest of the paper is organized as follows. In section 2 the structure of Norwegian agriculture is outlined, and regional differences are noted 2. In section 3, the empirical model is described. Section 4the theoretical model used is described, 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.

2. Norwegian farm structure and regions

Norway is a mountainous and thinly populated country with only three percent of the total land area under agricultural cultivation compared to 57 percent for the European Union as a whole (Almas and Brobakk). As in many other countries, the objectives of agricultural policy in Norway are diverse and complex. The Norwegian government white paper report no.9 (2011-2012) stated that the primary goals for the Norwegian agriculture sector are to increase food production to keep up self-sufficiency at the present level and to produce food in all regions.

Except for grain production in the southeast part, Norwegian agriculture is dominated by livestock. Some 30% of the farmers in Norway are specialized in dairy farming (Fig. 1)[1]. Norwegian dairy farms are usually small, family-operated, and face hostile production environments such as harsh climate, extensive areas of rugged terrain, and short growing seasons. These 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. Subsidy programs and border protections are the two instruments the Norwegian government uses to support farmers. A milk quota system has been effective since the mid-1980s. The milk quotas were progressively reduced in Norway from about 1992 to 2002. A system of quota reallocation was introduced in 1997.

« Insert Fig 1 here »

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. Milk yield per cow in Norway is lower than in other countries for instance compares to the neighboring counties Sweden and Denmark (See Fig 2). Structural change in the Norwegian dairy sector is slower than in other Nordic countries owing to government policy that favors small farms and their wide geographic distribution (Flaten; Atsbeha, Kristofersson, and Rickertsen). The Norwegian protectionist agricultural policy is facing external pressure from the European Economic Area (EEA) and the World Trade Organization (WTO) agreements. The pressure is also coming from the Norwegian consumers who seek high-quality products at the lowest cost. Thus, improving the efficiency of use of farm production is a priority objective of farmers, researchers, and policymakers.

[1] Authors' own computation using data from the EUROSTAT Database for Norway.

Dairy farmers need to be innovative and use existing technologies efficiently to reduce production costs and to be competitive (Moreira & Bravo-Ureta, 2009).

« Insert Fig 2 here »

Norway is divided into five main regions (Fig. 3) and 19 administrative counties 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 the 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 fiords and mountains. This region also receives most of the country's rain.

« Insert Fig 3 here »

Eastern Norway (Akershus, Oppland, Oslo, Telemark, Hedmark, Vestfold, Østfold, Hedmark, 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.

3. Theoretical model

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 …, T, x_{it} is a vector of factor inputs, i = 1, 2, …, N for farms at time t, v_{it} is the stochastic (white noise) error term, and u_{it} is a one-sided error representing the technical inefficiency of farm i. Both v_{it} and u_{it} are assumed to be independently and identically (*iid*) distributed with variance σ_v^2 and σ_u^2, respectively. The main assumption estimating technical efficiency (TE) using conventional production frontier for equation (1) is that farms in all regions included in the frontier operate under the same working environment. Violation of this assumption biases TE estimates (Orea and Kumbhakar, 2004). We minimize the heterogeneity of the working environment (technology use) by forming relatively homogeneous groups (region) and estimate separate functions as follows:

Suppose we have k regions in a given sector. Following the procedure of Battese et al., (2004), we can estimate the stochastic frontier for each region as follows:

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

where y_{it}^k denotes the output level for farm i in the t^{th} time for the k^{th} region; x_{itk} is the input vector for farm i at time t in region k; v_{itk} represents the error term and is assumed to be independently and identically distributed as a random variable with mean zero and variance σ_{vk}^2; u_{itk} is a one-sided error representing the technical inefficiency of farm i at time t in region k; 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. If we assume the exponent of the production frontier in equation (2) is linear in the parameter vector β^k, then the technology can be represented in a suitable functional form, for instance using a Cobb-Douglas or Translog function (see section 3). After estimating the frontier in equation (2) for each region separately, it is important to test whether or not the regions share the same technology using a log-likelihood ratio test. The technical efficiency of the i^{th} farm to the region–k frontier can be computed, following Greene (2005), as:

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

where TE_{it}^{k} is a measure of the performance of the individual farm (i) relative to the regional frontier. A stochastic meta-frontier is a frontier function that envelops all the frontiers of the k regions. To compare the individual technical efficiency of the i^{th} farm relative to the meta-frontier, we used the stochastic meta-frontier production approach, as developed by Battese et al. (2004) whereby the meta-frontier is expressed by:

$$y_{it}^{*} = f(x_{it},\beta^{*}) \equiv e^{x_{it}\beta^{*}},\ i=1, 2 \ldots N, \text{ and } t = 1, 2, \ldots, T \tag{4}$$

where y_{it}^{*} is the meta-frontier output; $f(\cdot)$ is a specified functional form; and β^{*} denotes the vector of parameters for the meta-frontier function that satisfies the following constraint

$$f(x_{it}\beta^{*}) \geq f(x_{it}\beta^{k}) \qquad \text{for all } k = 1, 2, \ldots, K. \tag{5}$$

The meta-frontier function defined by equation (4) and equation (5) is a production function of specified functional form that does not fall below the deterministic function for the stochastic frontier models of the regions involved (O'Donnell, Rao, and Battese). For equation (5) to hold, the meta-frontier production function is estimated using either linear or quadratic programming, as discussed in detail in Battese et al. (2004). For this study, we applied the linear programming method and the $\hat{\beta}^*$parameters of the meta-frontier function were estimated by solving the optimization problem as follows:

$$\min_{\beta^*} \sum_{t=1}^{T} \sum_{i=1}^{N} \left[\ln f(x_{it}, \beta^*) - \ln f\left(x_{it}, \hat{\beta}^k\right)\right] \quad (6)$$

subject to: $\ln f(x_{it}, \beta^*) \geq \ln f\left(x_{it}, \hat{\beta}^k\right)$ for all k =1, 2,…, K

where $\ln f\left(x_{it}, \hat{\beta}^k\right)$ is the logarithm of the estimated deterministic component of the stochastic frontier for the k^{th} region. The frontier can be estimated using the pooled datasets by including observation in all regions. Given that $f(x_{it}, \beta^*)$ in equation (6) is log-linear in the parameters, the optimization problem in (6) can be solved by linear programing as follows:

$$\min_{\beta^*} \sum_{t=1}^{T} \sum_{i=1}^{L} [(\bar{x}, \beta^*)] \quad (7)$$

subject to: $(x_{it}, \beta^*) \geq \left(x_{it}, \hat{\beta}^k\right)$ for all k=1, 2…, K

where $\bar{x}$ is the row vector of means of the elements of the x_{it} vectors overall i farms in all t periods for the k^{th} region (Battese et al., 2004). Once equation (7) is solved using linear programing, we can express equation (2) in terms of the meta-frontier function in equation (4), such that

$$y_{it} = e^{-u_{itk}} \left[\frac{e^{x_{it}\beta^k}}{e^{x_{it}\beta^*}}\right] e^{x_{it}\beta^* + v_{itk}} \quad (8)$$

In (8), the first part on the right-hand side is the technical efficiency relative to the stochastic frontier for the k^{th} region in equation (3). The second part on the right-hand side of equation (8) is the technological gap ratio (TGR) for the i^{th} farm in the k^{th} region in the t^{th} period (Battese and Rao, 2002; Battese et al., 2004), i.e.:

$$TGR_{it}^{k} = \frac{e^{x_{it}\beta^k}}{e^{x_{it}\beta^*}} \quad (9)$$

Equation (9) shows that the TGR is the ratio of the output for the frontier production function for the k^{th} region compared to the potential output defined by the meta-frontier function, given observed inputs (Battese and Rao, 2002). The detailed theoretical framework is shown in Figure 1. An alternative expression for the technical efficiency of the i^{th} farm, to the meta-frontier (TE_{it}^{*}) is given by

$$MTE_{it}^{*} = TE_{it}^{k} \times TGR_{it}^{k} \tag{10}$$

« Insert Fig 4 here »

Equation (10) shows that the technical efficiency for each region relative to the meta-frontier (MTE_{it}^{*}) is a product of each farm's technical efficiency for each region (TE_{it}^{k}) and each farm's technology gap ratio (TGR_{it}^{k}). According to Battese et al. (2004), 'an increase in TGR implies a decrease in the gap between the region frontier and the meta-frontier. The TGR value is between 0 and 1.

4. Empirical model

We estimated the second-order flexible transcendental logarithmic (TL) function. This functional form is widely used in applied econometric (Berndt and Christensen, 1973) and is a local second-order approximation to any arbitrary twice differentiable production function with no a priori restrictions substitution between the inputs like Cobb -Douglas. The region-*k* frontier in a TL function is:

$$\ln(\mathrm{y_{it}}) = \beta_0 + \sum_{\mathrm{k=1}}^{4} \beta_k \ln x_{kit} + \sum_{\mathrm{k=1}}^{4} \sum_{\mathrm{l=1}}^{4} \beta_{kl} \ln x_{kit} \ln x_{lit} + \beta_t t + \frac{1}{2}\beta_{tt} t^2 + \frac{1}{2}\sum_{\mathrm{k=1}}^{4} \beta_{kk} (\ln x_{kit})^2 + \sum_{\mathrm{k=1}}^{4} \beta_{kt} \ln x_{kit} t + \boldsymbol{\theta_i^k} + v_{it}^k - u_{it}^k \qquad (11)$$

where y is a vector of dairy outputs, x_i is a vector of inputs 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. $v_{it} \overset{iid}{\sim} N(0, \sigma_v^2), v_{it} \perp u_{it}$. The term u_{it}^k is a non-negative variable representing technical inefficiency for the particular region, and $\boldsymbol{\theta_i^k}$ is a farm-specific component to capture time-invariant unobserved heterogeneity, assumed to have an iid normal distribution. We allow technical inefficiency to vary over time and employ the 'true'[2] random-effects (TRE) frontier model Greene (2005).

The above model 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 1991 and increases by one annually.

All data for the TL model are expressed as deviations from their geometric 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 the logarithm by dividing each variable by its mean value. Technical efficiency (TE_{it}^k) is equal to one if firms in region k have an inefficiency effect equal to zero. 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.

[2] The term 'true' is used in the literature on fixed and random effect models, and is fully explained in Greene (2005a, 2005b).

5. Data

The data source is the Norwegian Farm Accountancy Survey collected by the Norwegian Institute of Bioeconomy Research (NIBIO). The survey participants are selected from a list of farmers, randomly drawn from the register of grants run by the Norwegian Agricultural Agency. The data include production and economic data collected annually by the Norwegian Institute of Bioeconomy Research (NIBIO) from about 1,000 farms in all regions of Norway. The number of participants varies from year to year. For example, in 1991 data has been collected from 1049 firms, but in 2014 it was 924 firms. Approximately 10 % of the survey farms are replaced per year to incorporate changes in the population of farms in Norway. Participation in the survey is voluntary. There is no limit on the number of years a farm is included in the study. Some of the farmers participated for more than 20 years, and others have started participating for the first time. The data used for our empirical analysis is farm-level balanced panel data for 1991-2014 with 2208 observations from 417 dairy farms. 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 2014 values using the consumer price index (CPI). The production function $f(x_{it};\beta)$ in the empirical model (11) is specified with the following four input variables. Farmland (x_1), defined as productive land (both owned and rented) in hectares. Labor (x_2) is measured as the total labor hours used in the farm, including hired labor, owners' labor, and family labor. Variable inputs (x_3) include fertilizers, feed, oil and fuel products, electricity, expenses for crop and animal protection, construction materials, and other costs. Capital inputs (x_4) are expenditures on fixed costs items plus depreciation and maintenance costs on-farm capital tied up in machinery, buildings, and livestock. Maintenance and costs associated with the hiring of machines and land are recorded annually. All costs are measured in NOK adjusted to 2014 values.

« Insert Table 1 here »

6. Estimation and results

This section describes the results of the estimation of the frontiers for the individual regions and associated technical efficiency (TE) measures. TE measures were estimated separately for each of the five regions and for pooled data using the TRE model implemented using the software Stata version 14. The meta-frontier was estimated using the software SHAZAM version 10, following O'Donnell et al. (2008). Various specification tests were conducted to obtain a better 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. Also, the 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 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 which theoretical framework for our study, we used the likelihood ratio (LR) and Bartlett's equal variance tests, and the two tests show a similar result. For instance, following Gourieroux et al. (1982), we estimated the likelihood ratio test (LR). L(H0) was the value of the log-likelihood function for the stochastic frontier estimated by stochastic production frontiers estimated using the pooled data for the five regions (i.e. 437), and L(HA) was the sum of the values of the log-

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

likelihood functions estimated separately from the regional production frontiers i.e. 861. The LR statistic such that L = -2 [ln{L(H0)}- ln{L(HA)}] = 848. The LR statistics is 848 which is a strong rejection of the null hypothesis that the dairy farms from the five regions operate on the same production frontier. This shows that the conventional stochastic production frontiers 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 concerning the meta-frontier instead of the pooled stochastic frontier framework. The meta-frontier is the valid framework to compare the groups under analysis (O'Donnell, Rao, and Battese, 2008; Moreira and Bravo-Ureta, 2009). Moreover, we conducted Hausman tests on whether the errors are correlated with the regressors, the null hypothesis is they are not. The chi-square is small and not significant so that accept the null hypothesis, reject fixed-effects models in favor of the random effect model i.e. the assumption of orthogonality in RE is working.

6.1. Input elasticities

Table 2 in the appendix shows the result of TRE model estimation for five regions and the pooled data. The table also includes the results of the linear programming for the meta-frontier. 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 variable inputs in all regions of Norway, and the pooled data, are the largest among other partial production elasticities, and they are all statically significant. These results imply that the percentage change in variable inputs has a larger influence on dairy production compared to other farm inputs. This result is consistent with other studies (Cuesta, 2000; Moreira and Bravo-Ureta, 2009). The estimated elasticity of dairy output to land input (x_1) is significant in all regions except in the central region, with values ranging from 0.04 to 0.27.

« Insert Table 2 here »

The estimated elasticities of dairy output to labor input (x_2) were 0.14 for the northern region, 0.12 for the south of the country, and 0.17 for the central region. All were found to be statically significant. However, labor input was not statistically significant in the eastern and western regions, consistent with the findings in the study by Kumbhakar et al. (2008) of Norwegian dairy farming for the period 1976 to 2005. The partial elasticity of fixed inputs (x_4) was positive and statically significant in all regions with a minimum value of 0.10 in the southern region and a maximum value of 0.21 in the western region.

6.2. Technical changes and returns to scale

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, 201). 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 in the study period. In all areas, the production frontier was shifting out at an increasing rate. This result is consistent with other studies, for instance, Moreira and Bravo-Ureta (2010). The annual percentage change in output due to TC was estimated to be between 0.05- 0.07%.

The coefficients for returns to scale (RTS) were less than 1 for all regions and the pooled data (Table 2). However, a log-likelihood test did not reject a constant return to scale (CRS) ($\sum_{k=1}^{4} \beta_k = 1$). A similar result was reported in the technological gap study of New Zealand dairy farms ((Jiang and Sharp, 2015). However, our findings contrast with the studies of Norwegian dairy farms by (Atsbeha et al., 2015; Løyland and Ringstad,2001) who reported increasing returns to scale. Our finding is more rational because in Norway it is hard to expand dairy herd size (cow numbers) because of the milk quotas imposed since 1983 and with no redistribution of quotas before 1997 (Sipiläinen et al., 2014).

6.3. Technical efficiency to the regional frontier (TE_i) and the meta-frontier (MTE^*_{it})

The estimated technical efficiency scores and technology gap ratio (TGR) are summarized in Table 3. The technical efficiency scores show the relative managerial performance like calving interval, the length of the dry period, and age at the first calv using the existing technology in each region. Farms in the central region achieved the highest mean technical efficiency (0.94), with minimum variation (SD = 0.04) followed by the western region (0.92). The average TE score of 0.86 in the eastern region implies that dairy farms can reduce the input requirement of producing the average output by 14 % if their operation becomes technically efficient, given its regional technology. i.e, if all dairy farms in the eastern region operated by 100 percent TE, the same volume of milk could have been produced with approximately 14 percent fewer inputs.

« Insert Table 3 here »

The TE scores are not comparable with each other unless we assume the underlying technology is the same in all regions. If we assume farmers in all regions have access to the same underlying technologies, we can make the following comparison. Farmers in the eastern and southern regions had the lowest mean TEs. Maximum variation was recorded in the eastern region (SD = 0.14). Despite the restrictive assumptions, these results can be rationalized to some extent. For example, farmers in western, central, and northern regions received higher government support and performed better within their regions, which is in line with other studies indicating that subsidies help beneficiary farms to perform better. Government assistance was found to help productivity gains from increased technical efficiency by Zhu et al., 2006; Ferjani, 2008; Kumbhakar and Lien, 2010 and Rizov et al., 2012. Lawson et al. (2004) reported that efficient farms (best-performing farms) replace cows more frequently, enroll heifers in production at an earlier age, and have shorter calving intervals (Lawson, Agger, Lund, & Coelli, 2004).

The mean technical efficiency (TE) for all regions estimated using the conventional stochastic production frontiers was 0.87 with moderate variation (SD=0.11). The estimate is close to what was found in TE studies reported in the literature, for instance, Swedish dairy farms 0.89 (Hansson & Öhlmér, 2008) and New England dairy farms 0.83 (Bravo-Ureta and Rieger, 1991). However, our result is lower than the TE estimates for Danish dairy farms 0.97 (Lawson, et al., 2004) and higher than the estimates obtained for Icelandic dairy farms 0.76 (Atsbeha, Kristofersson, & Rickertsen, 2015).

The difference between the average technical efficiency scores from the regional and meta-frontier model (MTE_{it}^{*}) are also shown in Table 3. If we compare the technical efficiency to the meta-frontier, the value is contrary to what we observed in the technical efficiency reported within the regions (TE_i). The average SF analysis of technical efficiency of the central region to the meta-frontier was only 0.33 for the years 1991-2014. By contrast, the highest TE was found in the eastern region (0.80). Dairy farms in the eastern region were performing better compared to other regions. We lack relevant data and information to point to the exact reason for this finding. However, in the eastern region there exist a large share of milking-robots and the possibility of off-farm work and access to skilled hired labor are good. These factors may contribute to a well-developed agricultural knowledge system, close relations with the farm technology industry, and a strong belief in technology. All these factors may contribute to high production efficiency relative to other regions.

Moreover, previous empirical literature shows that dairy cattle breed and feeding practices give different milk yields which might have differences in farm-level performance in the regions. For instance, a comparison analysis conducted between two cattle breeds shows that the Norwegian Red (NRF) breed partitions more feed energy to milk production than the Black sided Tronder and Nordland Cattle (STN) breed. The research also showed that the NRF breed grazes in areas with more nutrient-rich vegetation compared to STN (Sæther). A study conducted to estimate the contribution of genetic improvement of biological inputs through breeding on the performance of dairy farms reported that on average productivity growth Icelandic dairy farms by 0.3 % per year due to genetic-based technological change (Atsbeha et al., 2015). Hannson and Öhlmér (2008) reported that operational managerial practices like breeding (breeds and breed percentage) and feeding practices (feed ration and mix of forage) contribute to improving efficiency at Swedish dairy farms.

6.4. Technology gap ratios (TGR)

Estimates of the mean values of TGR (Table 3) vary even more widely among regions than the average technical efficiency estimates in the meta-frontier model. A similar result was reported by (Boshrabadi, et al., 2008; Víctor et at., 2010). The eastern region achieved the highest TGR (0.93), which means farms in the eastern region are closer to the meta-frontier compared to farms in other regions. Conversely, the lowest average TGR score was for the central region (0.35) followed by the western region (0.53). The TGR values ranged from maxima of 1.00 for the eastern, southern, and northern regions, showing that some farmers were producing the maximum outputs as indicated by the meta-function, given the current technology in the dairy sector. By contrast, the maximum TGR values for the central and western regions ranged only up to 0.53 and 0.88, respectively. Even the most efficient farmers in these regions were far from the meta-frontier.

7. Conclusion and Policy Implications

The objective of the paper was to compare technical efficiency for dairy farms in the five Norwegian regions using a stochastic meta-frontier approach. The results of the analysis show that technical efficiency scores and technology gap ratios are different for the five regions. This finding has not been shown in previous dairy efficiency studies in Norway. The production techniques were found to have exhibited constant returns to scale in all regions, and the rate of technological change was discovered to increase at an increasing rate (section 6). Moreover, the partial production-elasticity for variable inputs was the largest compared to other partial inputs in all regions of Norway. This result suggests that the percentage change in variable farm inputs such as feed seems to offer the best way to improve dairy productivity in all regions.

The results suggest that dairy farms in all regions used available technology in the area sub-optimally, i.e. some farmers produced lower outputs from the inputs they used or used more inputs to produce the same output, compared to the best performing farmers. The average technical efficiency score ranges from 0.94 in the central region and 0.86 in the eastern region, and these results are statically different from each other. Farms in the central and western regions had the highest technical efficiency on average, given the technology available across the regions. It seems farms in these regions were exhibited better management of inputs performance like calving interval, the length of the dry period, and age at the first calv. However, comparing performances across all regions, the lowest technological gap ratios were found in the central and western regions.

The policy implication of the study is two-fold: first for dairy farmers located in the central and western regions are far from the estimated meta-frontier, then one possible way policymakers might reduce the gap is through training, including sharing information about relevant technologies from one area to another, provided that the technologies being shared fit the working environment of the lagging area. Second, The production frontiers for eastern and southern regions are relatively near to the meta-frontier. Thus, these two regions might need to be increased investment to promote local research to develop new dairy technologies like genetic technology that improve productivity (shift the frontier outwards). On the other hand, it may be that the east and south regions have advantages such as weather conditions and other geographically related circumstances compared to farms in other areas. Hence, some of the dairy technologies they use may not fit other regions, suggesting that agricultural policies that aim to encourage efficient dairy production, such as innovation of improved technology (like breeding, bull selection, and improved feed varieties) through research and development, need to account the environmental differences between regions.

Finally, we have not to a large extent analyzed or discussed the reasons for the considerable differences in the technology gap between regions because of data limitation. According to O'Donnell et al. (2008), the technology sets can differ because of differences in economic infrastructure (e.g., access to markets), resource endowments (e.g., quality of soils, climate, and energy resources), physical, human and financial capital (e.g., size and quality of the labor force, and type of machinery), and other characteristics in which production take place. It is a task for future research to assemble or collect the needed further data on the genetic quality of dairy herd and feeding practices to better identify reasons for regional differences. Moreover, we estimated the meta-frontier using the non-parametric approach, thus it is also a need for further analysis if the values are different by estimating using a parametric approach.

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Appendix

Table 1 Descriptive statistics (mean values per farm) for dairy farm in five regions (1991-2014)

Region	N	Output (y)*	Land (x_1) (Hectare)	Labor (x_2) (In hours)	Var. Inputs (x_3)*	Capital inputs(x_4)*
Eastern	552	447985	23.6	3555	258800	288482
Stand. Dev		*(290699)*	*(111)*	*(890)*	(184697)	*(180456)*
Southern	456	402617	20.5	3037	239083	243612
Stand. Dev		*(293204)*	*(117)*	*(1016)*	*(166380)*	*(172551)*
Western	456	367293	15.9	2956	209966	196862
Stand. Dev		*(255697)*	*(84)*	*(867)*	*(131419)*	*(128922)*
Central	264	463344	22.4	3591	255631	267535
Stand. Dev		*(262465)*	*(84)*	*(843)*	*(143010)*	*(123853)*
Northern	480	449833	22.6	3633	284128	282394
Stand. Dev		*(229369)*	*(110)*	*(967)*	*(143441)*	*(171449)*
Norway	2208	424189	21.7	33346	249770	256466
Stand. Dev		*(270483)*	*(110)*	*(970)*	*(159120)*	*(164584)*

*in 2014 Norwegian Kroner

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

	Eastern Norway	***Southern Norway***	***Western Norway***	***Central Norway***	***Northern Norway***	***Pooled data***	***Meta-frontier***
x_1*(land)*	0.24***	0.27***	0.13**	0.04	0.09*	0.07***	0.19
	(0.04)	(0.05)	(0.05)	(0.06)	(0.04)	(0.02)	
x_2*(labor)*	0.09	0.12*	0.07	0.17*	0.14*	0.16***	0.11
	(0.05)	(0.05)	(0.05)	(0.07)	(0.06)	(0.03)	
x_3*(V. cost)*	0.50***	0.39***	0.57***	0.54***	0.56***	0.50***	0.41
	(0.03)	(0.04)	(0.04)	(0.05)	(0.04)	(0.02)	
x_4*(C. cost)*	0.13***	0.10**	0.21***	0.12***	0.18***	0.18***	-0.07
	(0.03)	(0.04)	(0.03)	(0.05)	(0.03)	(0.02)	
x_{11}	0.43**	0.25	-0.32	-0.41	-0.33	-0.13	0.53
	(0.15)	(0.16)	(0.18)	(0.29)	(0.17)	(0.09)	
x_{22}	-0.19	0.06	-0.61***	-0.08	0.09	-0.19	-0.07
	(0.27)	(0.17)	(0.18)	(0.35)	(0.21)	(0.11)	
x_{33}	0.38***	0.64***	0.01	0.23	-0.15	0.23***	0.57
	(0.08)	(0.14)	(0.13)	(0.12)	(0.15)	(0.05)	
x_{44}	-0.03	-0.23	0.53***	0.15	-0.14	0.28***	0.02
	(0.11)	(.15)	(0.11)	(0.24)	(0.13)	(0.06)	
x_{12}	0.35*	0.33*	-0.07	-0.02	0.03	0.06	0.11
	(0.11)	(0.14)	(0.14)	(0.22)	(0.15)	(0.07)	
x_{13}	-0.48***	-0.70***	0.24*	-0.40**	-0.05	-0.10*	-0.42
	(0.09)	(0.10)	(0.11)	(0.12)	(0.12)	(0.05)	
x_{14}	-0.07	0.24*	-0.03	0.19	0.25*	-0.07	-0.09
	(0.07)	(0.10)	(0.11)	(0.20)	(0.12)	(0.05)	
x_{23}	-0.08	-0.13	0.03	-0.10	-0.05	0.09	-0.07
	(0.10)	(0.11)	(0.12)	(0.16)	(0.15)	(0.06)	
x_{24}	-0.08	-0.09	0.25*	-0.03	0.08	0.04	-0.03
	(0.11)	(0.12)	(0.11)	(0.2)	(0.13)	(0.06)	
x_{34}	0.04	0.05	-0.39***	-0.14	0.11	-0.23***	-0.38
	(0.06)	(0.11)	(0.10)	(0.14)	(0.11)	(0.04)	
t	0.004	0.003	-0.002	0.009**	-0.003	0.004***	0.19
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.001)	
t^2	0.005***	0.006***	0.005***	0.005***	0.007***	0.005***	-0.13
	(0.001)	(0.00)	(0.00)	(0.001)	(0.001)	(0.000)	
tx_1	0.04*	0.02	-0.02	0.04	-0.02	0.005	0.30
	(0.01)	(0.01)	(0.01)	(0.03)	(0.02)	(0.01)	
tx_2	-0.002	0.02	-0.04***	0.05*	-0.04**	-0.02*	0.03
	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	
tx_3	0.02	0.01	0.05***	0.03*	0.04**	0.03***	-0.06
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	
tx_4	0.002	-0.01	0.02	-0.005	0.01	0.02**	0.07
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	
cons	-0.11*	-0.16***	-0.10***	-0.24***	-0.05	-0.11***	0.11
	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.02)	

(continued)

U-sigma	-3.61***	-4.06***	-5.12***	-5.76***	-4.26***	-3.93***
	(0.14)	(0.17)	(0.36)	(0.52)	(0.18)	(0.08)
V-sigma	-5.14***	-5.18***	-4.54***	-4.12***	-5.03***	-4.34***
	(0.20)	(0.23)	(0.17)	(0.13)	(0.18)	(0.07)
Theta	0.13***	-0.22***	0.14***	0.10***	0.13***	-0.16***
	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Lambda	2.15***	1.75***	0.75***	0.75***	1.47***	1.22***
	(0.16)	*(0.02)*	*(0.02)*	*(0.02)*	*(0.12)*	*(0.01)*
Log-L	145***	167***	221***	118***	210***	437***
RTS	0.97	0.88	0.98	0.88	0.97	0.91
N	552	456	456	264	480	2208

*Standard errors in parentheses * $p<0.05$, ** $p<0.01$, and *** $p<0.001$; RTS = returns to scale*

Table 3 Technical efficiency (TE) and Technology gap ratios estimate for dairy farms in five regions

	Region					All regions (pooled)
	Eastern	Southern	Western	Central	Northern	
TE to the regional frontier (TE_i)						
Mean	0.86	0.86	0.92	0.94	0.89	0.87
Std. Dev.	0.14	0.12	0.06	0.04	0.57	0.11
Minimum	0.18	0.21	0.63	0.10	0.16	0.21
Maximum	0.99	0.99	0.99	0.99	0.99	0.99
Technology gap ratio (TGR)						
Mean	0.93	0.89	0.54	0.35	0.61	
Std. Dev.	0.10	0.14	0.17	0.15	0.20	
Minimum	0.66	0.46	0.23	0.11	0.25	
Maximum	1.00	1.00	0.88	0.53	1.00	
TE to the meta-frontier ($\boldsymbol{MTE}^{*}_{\mathbf{it}}$)						
Mean	0.80	0.76	0.50	0.33	0.54	
Std. Dev.	0.01	0.02	0.01	0.01	0.11	
Minimum	0.12	0.10	0.14	0.01	0.04	
Maximum	0.99	0.99	0.87	0.52	0.99	
Number of observations	552	456	456	264	480	2208

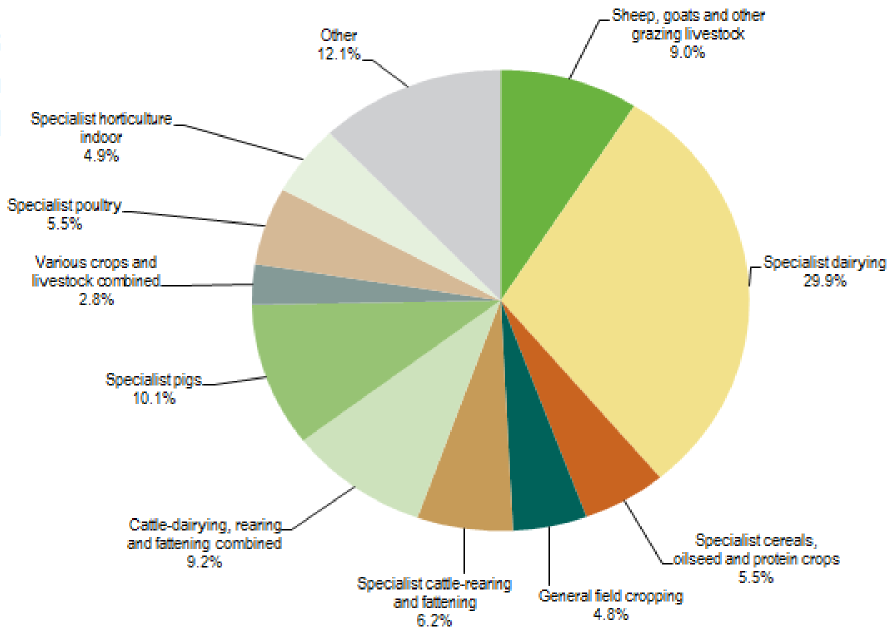

Fig. 1. Farm structure in Norway computed from Eurostat database, 2013.

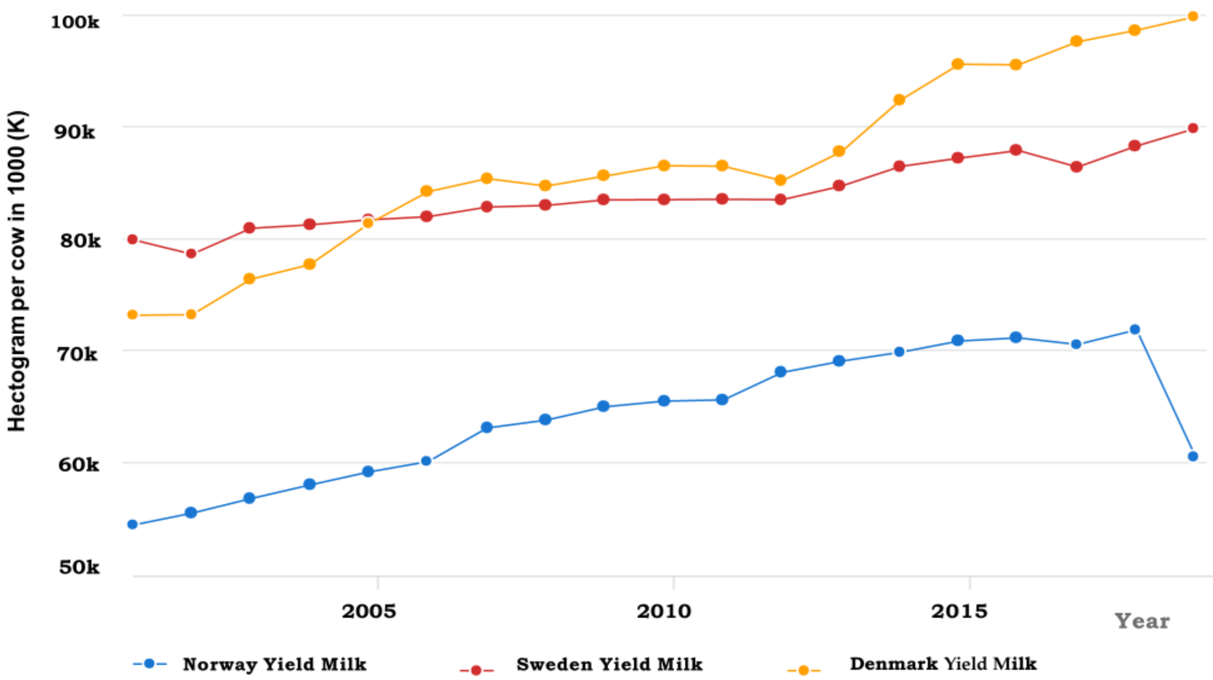

Figure 2. Norway yearly milk yield compared to Sweden and Denmark (Source: computed from FAOSTAT)

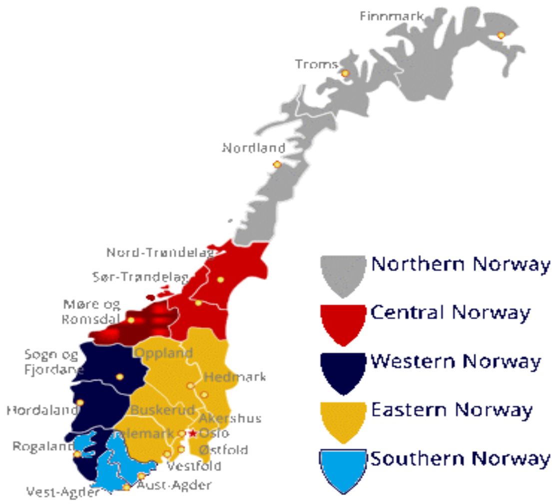

Fig. 3. Five geographical regions of Norway, source Norway at home, 2015.

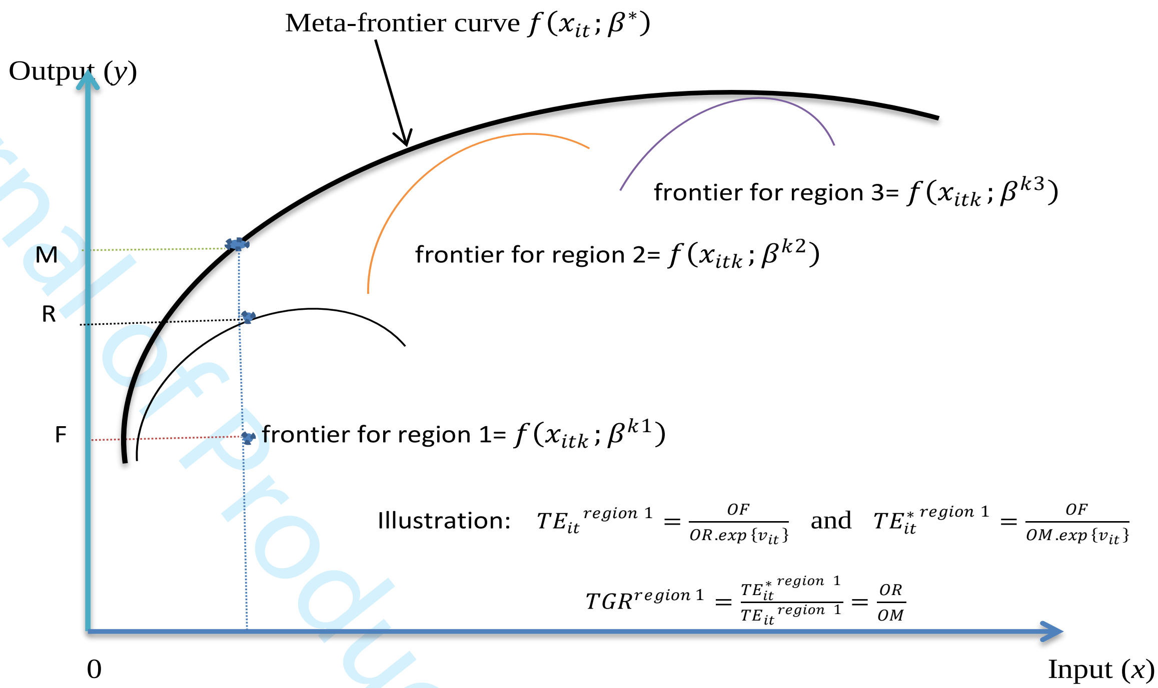

Fig. 4. Meta-frontier curve and frontier for regions based on (O'Donnell, Rao, and Battese, 2008)

Table 2
Estimates for parameters of the translog stochastic frontier model by region and the pooled data, along with the coefficients of the meta-frontier

	Eastern Norway	***Southern Norway***	***Western Norway***	***Central Norway***	***Northern Norway***	***Pooled data***	***Meta-frontier***
x_1*(land)*	0.24***	0.27***	0.13**	0.04	0.09*	0.07***	0.19
	(0.04)	(0.05)	(0.05)	(0.06)	(0.04)	(0.02)	
x_2*(labor)*	0.09	0.12*	0.07	0.17*	0.14*	0.16***	0.11
	(0.05)	(0.05)	(0.05)	(0.07)	(0.06)	(0.03)	
x_3*(V. cost)*	0.50***	0.39***	0.57***	0.54***	0.56***	0.50***	0.41
	(0.03)	(0.04)	(0.04)	(0.05)	(0.04)	(0.02)	
x_4*(F. cost)*	0.13***	0.10**	0.21***	0.12***	0.18***	0.18***	-0.07
	(0.03)	(0.04)	(0.03)	(0.05)	(0.03)	(0.02)	
x_{11}	0.43**	0.25	-0.32	-0.41	-0.33	-0.13	0.53
	(0.15)	(0.16)	(0.18)	(0.29)	(0.17)	(0.09)	
x_{22}	-0.19	0.06	-0.61***	-0.08	0.09	-0.19	-0.07
	(0.27)	(0.17)	(0.18)	(0.35)	(0.21)	(0.11)	
x_{33}	0.38***	0.64***	0.01	0.23	-0.15	0.23***	0.57
	(0.08)	(0.14)	(0.13)	(0.12)	(0.15)	(0.05)	
x_{44}	-0.03	-0.23	0.53***	0.15	-0.14	0.28***	0.02
	(0.11)	(.15)	(0.11)	(0.24)	(0.13)	(0.06)	
x_{12}	0.35*	0.33*	-0.07	-0.02	0.03	0.06	0.11
	(0.11)	(0.14)	(0.14)	(0.22)	(0.15)	(0.07)	
x_{13}	-0.48***	-0.70***	0.24*	-0.40**	-0.05	-0.10*	-0.42
	(0.09)	(0.10)	(0.11)	(0.12)	(0.12)	(0.05)	
x_{14}	-0.07	0.24*	-0.03	0.19	0.25*	-0.07	-0.09
	(0.07)	(0.10)	(0.11)	(0.20)	(0.12)	(0.05)	
x_{23}	-0.08	-0.13	0.03	-0.10	-0.05	0.09	-0.07
	(0.10)	(0.11)	(0.12)	(0.16)	(0.15)	(0.06)	
x_{24}	-0.08	-0.09	0.25*	-0.03	0.08	0.04	-0.03
	(0.11)	(0.12)	(0.11)	(0.2)	(0.13)	(0.06)	
x_{34}	0.04	0.05	-0.39***	-0.14	0.11	-0.23***	-0.38
	(0.06)	(0.11)	(0.10)	(0.14)	(0.11)	(0.04)	
t	0.004	0.003	-0.002	0.009**	-0.003	0.004***	0.19
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.001)	
t^2	0.005***	0.006***	0.005***	0.005***	0.007***	0.005***	-0.13
	(0.001)	(0.00)	(0.00)	(0.001)	(0.001)	(0.000)	
tx_1	0.04*	0.02	-0.02	0.04	-0.02	0.005	0.30
	(0.01)	(0.01)	(0.01)	(0.03)	(0.02)	(0.01)	
tx_2	-0.002	0.02	-0.04***	0.05*	-0.04**	-0.02*	0.03
	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	
tx_3	0.02	0.01	0.05***	0.03*	0.04**	0.03***	-0.06
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	
tx_4	0.002	-0.01	0.02	-0.005	0.01	0.02**	0.07
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	
cons	-0.11*	-0.16***	-0.10***	-0.24***	-0.05	-0.11***	0.11
	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.02)	
U-sigma	-3.61***	-4.06***	-5.12***	-5.76***	-4.26***	-3.93***	
	(0.14)	(0.17)	(0.36)	(0.52)	(0.18)	(0.08)	
V-sigma	-5.14***	-5.18***	-4.54***	-4.12***	-5.03***	-4.34***	
	(0.20)	(0.23)	(0.17)	(0.13)	(0.18)	(0.07)	
Theta	0.13***	-0.22***	0.14***	0.10***	0.13***	-0.16***	

	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Lambda	2.15***	1.75***	0.75***	0.75***	1.47***	1.22***
	(0.16)	*(0.02)*	*(0.02)*	*(0.02)*	*(0.12)*	*(0.01)*
Log-L	145***	167***	221***	118***	210***	437***
RTS	0.97	0.88	0.98	0.88	0.97	0.91
N	552	456	456	264	480	2208

*Standard errors in parentheses * p<0.05, ** p<0.01, and *** p<0.001; RTS = returns to scale*

Table 3 Technical efficiency (TE) and Technology gap ratios estimate for dairy farms in five regions

	Region					All regions (pooled)
	Eastern	Southern	Western	Central	Northern	
TE to the regional frontier (TE_i)						
Mean	0.86	0.86	0.92	0.94	0.89	0.87
Std. Dev.	0.14	0.12	0.06	0.04	0.57	0.11
Minimum	0.18	0.21	0.63	0.10	0.16	0.21
Maximum	0.99	0.99	0.99	0.99	0.99	0.99
Technology gap ratio (TGR)						
Mean	0.93	0.89	0.54	0.35	0.61	
Std. Dev.	0.10	0.14	0.17	0.15	0.20	
Minimum	0.66	0.46	0.23	0.11	0.25	
Maximum	1.00	1.00	0.88	0.53	1.00	
TE to the meta-frontier ($\mathbf{TE}^{*}_{\mathbf{it}}$)						
Mean	0.80	0.76	0.50	0.33	0.54	
Std. Dev.	0.01	0.02	0.01	0.01	0.11	
Minimum	0.12	0.10	0.14	0.01	0.04	
Maximum	0.99	0.99	0.87	0.52	0.99	
Number of observations	552	456	456	264	480	2208

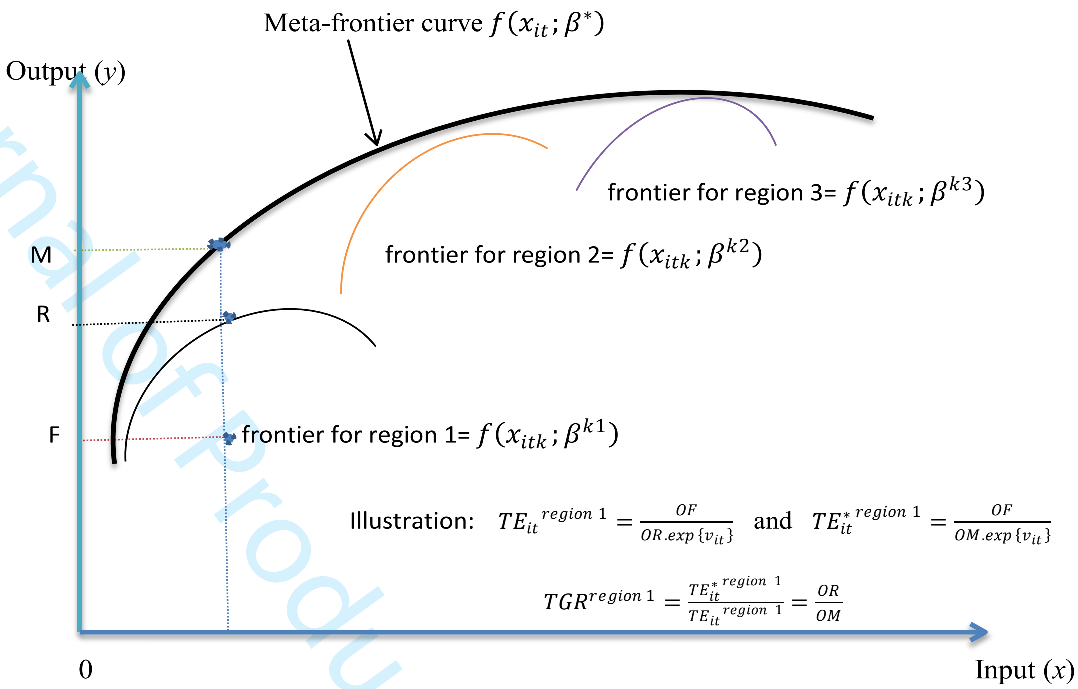

Fig. 1. Meta-frontier curve and frontier for regions based on (O'Donnell et al., 2008)

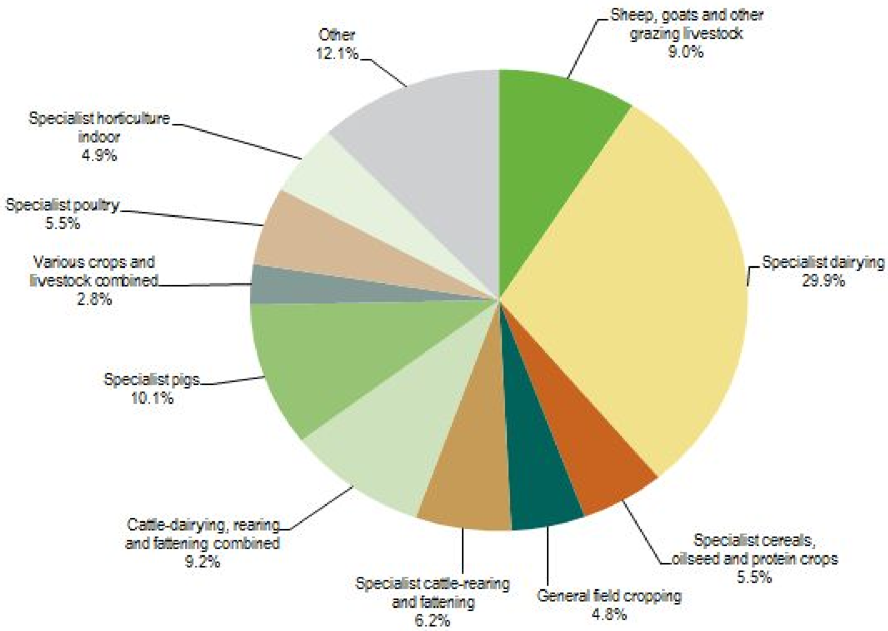

Fig. 2. Farm structure in Norway computed from the Eurostat database, 2013.

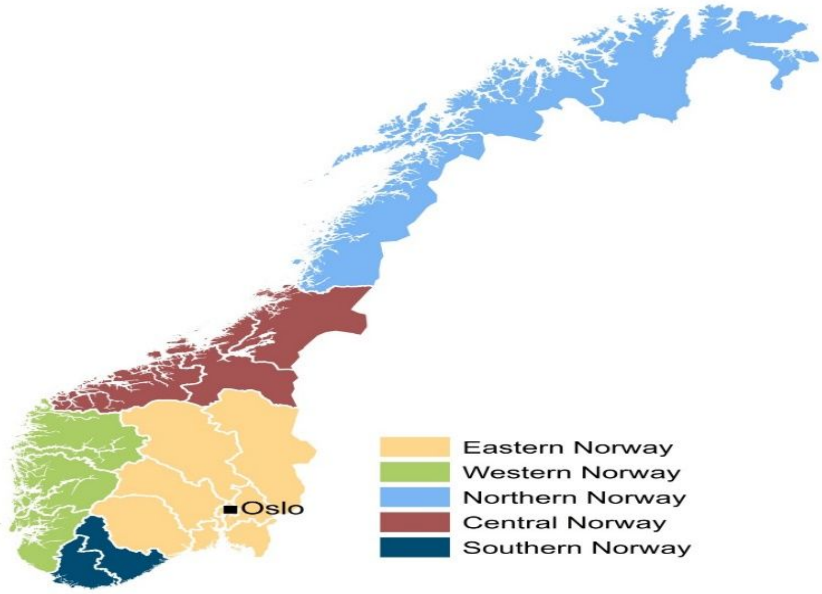

Fig. 3. Five geographical regions of Norway

Table 1 Descriptive statistics (mean values per farm) for dairy farm in five regions (1991-2014)

Region	N	Output (y)*	Land (x_1) (Hectare)	Labor (x_2) (In hours)	Var. Inputs (x_3)*	Fixed inputs(x_4)*
Eastern	552	447985	23.6	3555	258800	288482
Stand. Dev		*(290699)*	*(111)*	*(890)*	(184697)	*(180456)*
Southern	456	402617	20.5	3037	239083	243612
Stand. Dev		*(293204)*	*(117)*	*(1016)*	*(166380)*	*(172551)*
Western	456	367293	15.9	2956	209966	196862
Stand. Dev		*(255697)*	*(84)*	*(867)*	(*131419*)	*(128922)*
Central	264	463344	22.4	3591	255631	267535
Stand. Dev		*(262465)*	*(84)*	*(843)*	*(143010)*	*(123853)*
Northern	480	449833	22.6	3633	284128	282394
Stand. Dev		*(229369)*	*(110)*	*(967)*	*(143441)*	*(171449)*
Norway	2208	424189	21.7	33346	249770	256466
Stand. Dev		*(270483)*	*(110)*	*(970)*	*(159120)*	*(164584)*

*in 2014 Norwegian Kroner