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A Metafrontier Analysis on the Performance of Grain-Producing Regions in Norway

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Abstract: Previous application of the stochastic frontier model and subsequent measurement of the performance of the crop sector can be criticized for the estimated production function relying on the assumption that the underlying technology is the same for different agricultural systems. This paper contributes to estimating regional efficiency and the technological gap in Norwegian grain farms using the stochastic metafrontier approach. For this study, we classified the country into regions with district level of development and, hence, production technologies. The dataset used is farm-level balanced panel data for 19 years (1996–2014) with 1463 observations from 196 family farms specialized in grain production. The study used the true random effect model and stochastic metafrontier analysis to estimate region level technical efficiency (TE) and technology gap ratio (TGR) in the two main grain-producing regions of Norway. The result of the analysis shows that farmers differ in performance and technology use. Consequently, the paper gives some regionally and farming system-based policy insights to increase grain production in the country to achieve self-sufficiency and small-scale farming in all regions.

Keywords: grain production; metafrontier; panel data; regional development; technical efficiency

JEL Classification: R58; O52; Q16; C23; D24

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1. Introduction

The main objectives of Norwegian agricultural and food policies are agricultural production in all parts of the country; food security; creating more added value, and sustainable production with reduced greenhouse gas emissions. Only 3.3% of the total Norwegian land area is farmland (Statistics Norway 2020). Owing to the topography of the country, fields are often small, scattered, and difficult to cultivate, which contributes to the high costs of agricultural production. With a relatively long winter and a short growing season (five months on average) in most parts of the country, growing fodder, mainly grass, has a comparative advantage. On the other hand, long summer days, given sufficient rainfall, is beneficial for crop production. Moreover, the cool climate limits the spread of pests and diseases (Steinshamn et al. 2016). The Norwegian government supports farmers in achieving the abovementioned objectives, and the sector is so heavily subsidized that, without support, it would not be competitive with imports. There is a threat that Norway may be obliged, by international pressures, to cut back on border protection and output-related subsidies, which might force the Norwegian agricultural policy toward more competitive agriculture. Consequently, to achieve food and nutrition security at a national level, there is a need to improve the performance of farmers in all regions of Norway. Improving the performance of farmers is a key contributor to the efficient use of resources and overall productivity growth in the Norwegian economy (Lien et al. 2010).

In the economics literature, there are two main approaches[1] for measuring farm performance; that is, a parametric approach such as the stochastic frontier approach, and a non-parametric approach, such as data envelopment analysis. In both methods, the basis for performance measurement is the radial contraction or expansion, connecting inefficient observed points with the reference points on the production frontier. For a sample of producers, both approaches involve estimating the 'best-practice' frontier for a specific group of farms. If the actual production point of a farm lies on the frontier, the farm is considered as performing to its best and using resources efficiently; if it lies below the frontier, then it is inefficient. The choice of estimation method has been an issue of debate, and each approach has its advantages and disadvantages (for details, see Alem 2018; Coelli et al. 2005; Kumbhakar et al. 2015). The treatment of measurement error is the critical distinction between parametric and non-parametric approaches. The stochastic frontier approach (SFA) can accommodate noise, such as measurement errors due to weather, disease, and pest infestation that are likely to be significant in farming. The data envelopment analysis (DEA) approach is sensitive to outliers since the measurement error is ignored (Coelli et al. 2005; Barnes et al. 2009). Since farms in our study are sensitive to external random shocks, we have chosen the SFA approach to evaluate the cost efficiency scores and determinants of inefficiency. The stochastic frontier approach has been commonly used for the agricultural sector and assumes that the underlying technology is the same for all sample observations, regardless of differences in the working environment (Kumbhakar et al. 2012). Nevertheless, farms in different regions are expected to face different technology sets and input use because of differences in resource endowments (O'Donnell et al. 2008). Thus, comparing the performance of farms in different regions using single estimates across all regions is likely to produce misleading results (for details, see Alem et al. 2019).

Agricultural policy intervention might be different for different production environments and different farming systems because of heterogeneity. There are two common sources of farm heterogeneity which need to be accounted for in performance analysis (Baráth and Fertő 2015). The first source of heterogeneity is the heterogeneity of production conditions among sample farms. The possible solution for this heterogeneity is to include control variables in the production or cost function if the (approximate) production conditions can be observed (Coelli et al. 2005). Often, however, not all the factors that affect the performance of the farm are observable, so we seldom have comprehensive information about the production conditions. For instance, data on soil type, latitude, altitude, precipitation, distance from the service center, and the like are seldom available or are too complex to be measured by single indicators. In the recent literature, such unobserved heterogeneity can be separated from farm inefficiency using econometric techniques (Greene 2005b). The second source of heterogeneity results from differences in the technology used, i.e., technological heterogeneity. The fact that agricultural producers face different production environments may lead to a variation in the crops produced. For instance, farms located in dry regions might plant a crop variety that can resist drought. Consequently, differences between working environments mean differences in technology use. The assumption that all farms use identical technology might not be true; hence, there is a need to account for technology heterogeneity. In the economics literature, we can find different techniques to control technology heterogeneity. For instance, using cluster algorithms technique (Álvarez et al. 2008); using random parameter technique (Greene 2005a); latent class technique (see e.g., Orea and Kumbhakar 2004); and metafrontier (see, e.g., O'Donnell et al. 2008). Each approach has pros and cons regarding estimating the performance of the given sector in accounting for technology heterogeneity or regional differences, though the metafrontier approach is commonly used for regionally-based studies (Alem et al. 2019).

[1] There are other approaches, for instance, the Bayesian stochastic frontier (Koop and Steel 2001), semi-parametric (Simar and Wilson 2007), and stochastic DEA (Huang and Li 2001), though these re not commonly used in empirical studies.

A metafrontier model has produced promising results in agriculture when focusing on the dairy sector (see, e.g., Moreira and Bravo-Ureta 2010). Therefore, this study aims to measure the performance and regional technology gaps of Norwegian crop-producing farms located in different regions. In the economics literature, the paper contributes as follows. First, we controlled unobserved farm-level heterogeneity using the Greene (2005b) model in addition to controlling technological heterogeneity unlike, for instance, Battese et al. (2004). Second, we used a stochastic metafrontier approach for the crop sector. As far as we know, this is the first study of regional performance differences conducted for the crop sector and a Nordic country[2]. Third, we take advantage of large farm-level panel data from Norwegian grain-producing farms observed from 1996 to 2014.

This paper is organized as follows. Section 2 describes the theoretical model used. Sections 3 and 4 introduce the empirical model and the data used. Section 5 presents the empirical estimation and results. Finally, Section 6 presents our conclusions and the policy implications.

2. Theoretical Model

As discussed in the introduction, we used a stochastic production frontier for this study. A general 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 crop 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 error term; and u_{it} represents the technical efficiency of farm i. Both v_{it} and u_{it} are assumed to be independent and identically distributed (*iid*) with variance σ_v^2 and σ_u^2, respectively, that means the variables have the same probability distribution and are mutually independent. The assumption used to estimate the performance of the farm for Equation (1) is that farms in all regions operate under the same working environment. A violation of common technology assumption biases the estimates (for details, see, e.g., Orea and Kumbhakar 2004).

We can minimize the technology heterogeneity by forming relatively homogeneous groups (k regions) and estimate separate functions using the Greene (2005b) model to account for unobserved heterogeneity within the region as follows:

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

where y_{it}^k is the crop output for farm i in the tth period for the kth region; x_{itk} denotes the input vector for farm i at time t in region k; v_{itk} represents the error; u_{itk} denotes the inefficiency of farm i at time t in region k; and β^k is a vector of unknown parameters to be estimated for the kth region. As stated above, β^k can be estimated using the Greene (2005b) model to account for the farm effect within the region (unobserved heterogeneity). If we assume the exponent of the production frontier in Equation (2) is linear in β^k, then the technology can be represented for instance using a Cobb–Douglas or translog function (see Section 3). After estimating Equation (2) for each region separately, it is important to test whether the regions share the same technology using a log-likelihood ratio test.

The technical efficiency (TE_{it}^k) of the ith farm to the region–k frontier can be computed, following Alem et al. (2019), as

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

[2] Nordic countries include Norway, Sweden, Denmark, Iceland, and Finland.

Following Battese et al. (2004), we can estimate the technical efficiency of the ith farm relative to the metafrontier:

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

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

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

The metafrontier function defined by (4) and (5) is a production function of specified functional form that does not fall below the deterministic function for the stochastic frontier models of the involved regions (O'Donnell et al. 2008). For Equation (5) to hold, the metafrontier 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 metafrontier function were estimated by solving the optimization problem as follows:

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

subject to $\ln f(x_{it}, \beta^{*}) \geq \ln f(x_{it}, \hat{\beta}^{k})$ for all k = 1, 2, ... , K where $\ln f(x_{\,it}, \hat{\beta}^{k})$ is the logarithm of the estimated deterministic component of the stochastic frontier for the kth 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 Equation (6) can be solved by linear programming as follows:

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

subject to $(x_{it}, \beta^{*}) \geq \left(x_{it}, \hat{\beta}^{k}\right)$ for all k = 1, 2, ... , K where $\overline{x}$ is the row vector of means of the elements of the x_{it} vectors overall for i farms in all t periods for the kth region (Battese et al. 2004). Once Equation (7) is solved using linear programming, we can express Equation (2) in terms of the metafrontier function in Equation (4), as follows:

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

In Equation (8), the first part on the right-hand side is the technical efficiency relative to the stochastic frontier for the kth region in Equation (3). The second part on the right-hand side of Equation (8) is the technological gap ratio (TGR) for the ith farm in the kth region in the tth period, i.e.,

$$TGR_{it}^{k} = \frac{e^{x_{it}\beta^{k}}}{e^{x_{it}\beta^{*}}}. \tag{9}$$

Equation (9) shows that the TGR is the ratio of the output for the frontier production function for the kth region compared to the potential output defined by metafrontier function, given observed inputs (O'Donnell et al. 2008). An alternative expression for the technical efficiency of the ith farm to the metafrontier (TE_{it}^{*}) is given by

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

Equation (10) shows that the technical efficiency for each region relative to the metafrontier (TE_{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), TGR equal to 1 implies that regions are using the available technology in the country efficiently. The TGR value is between 0 and 1.

3. Empirical Model

We used the translog function which is widely used in applied econometrics (Berndt and Christensen 1973) as follows:

$$\ln(\mathrm{y_{it}}) = \beta_0 + \sum_{\mathrm{k}=1}^{4} \beta_k \ln x_{kit} + \sum_{\mathrm{k}=1}^{4}\sum_{\mathrm{l}=1}^{4} \beta_{kl} \ln x_{kit} \ln x_{lit} + \beta_t t + \frac{1}{2}\beta_{tt} t^2 \quad (11)$$

$$+ \frac{1}{2}\sum_{\mathrm{k}=1}^{4} \beta_{kk} (\ln x_{kit})^2 + \sum_{\mathrm{k}=1}^{4} \beta_{kt} \ln x_{kit} t + \theta_i^k + v_{it}^k - u_{it}^k$$

where y_{it} denotes a vector of crop-outputs at a time "t" and x_{it} denotes the vector of inputs used in time t. As stated above, v_{it} is the error term and u_{it}^k denotes the efficiency term while β are parameters to be estimated. θ_i^k captures farm-specific unobserved heterogeneity. Equation (11) were estimated using a single-stage maximum likelihood estimator based on Greene (2005b) and the technical inefficiency (TE_{it}^k) estimated following Jondrow et al. (1982) using farm-level data, which is discussed in the next section.

4. Data

The Norwegian Institute of Bioeconomy Research (NIBIO) conducts a survey every year to collect farm-level production and economic data. The survey covers the five regions of Norway in all farm size and farm types. For the implementation of the Norwegian agricultural policy, the country is divided into five main regions based on geographical and climatic conditions. Eastern Norway is relatively highly populated as the capital city, Oslo, is in this region. The region is characterized 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 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. Northern Norway is characterized by wide inland plains, dark winters, and the midnight sun in summer. Central Norway is located between Northern Norway and the southern part of the country and, so, shares characteristics of both north and south. Western Norway is the region with most of Norway's fjords and mountains and the region that receives most of the country's rain.

The dataset used in this study is farm-level balanced panel data for 19 years (1996–2014) with a total of 1463 observation. To assess the technical efficiency and productivity growth, we need to be sure that farms under consideration are comparable. Most farms that are engaged in grain production are located in the eastern and central regions of Norway. The 2012 statistics show that three is 2,325,765 decare of cultivated land (Figure 1). Among this, 81% is based in the east and 17% in central regions (SSB 2016). Thus, to obtain a homogenous group of farms, only farms specialized in grain production in Eastern and Central Norway that reported their account data for the period 1996–2014 were selected.

The production data contained crop output, which includes grain output (y) and is represented by farm revenue from grain and grain products (sales + farm use + farmhouse consumption). Grain output is an aggregate of four main species: barley, wheat, oats, and oilseed species. The aggregate is quality-adjusted and is measured in FU (feed units) as defined by the Norwegian Institute of Bioeconomy Research (NIBIO). Cultivated land ($x_{1)}$ is productive land (both owned and rented) in decare. Labor (x_2) is the total labor hours used on the farm, which includes hired labor and owners, and family labor. Variable farm input (x_3) is input like fertilizers, feed, oil and fuel products, electricity, expenses for the plant, constructive materials, and other costs, deflated by the CPI to 2014 Euro prices. Capital (X_4) is expenditure on fixed-cost items plus depreciation and maintenance costs for on-farm capital tied up in machinery and buildings. All values were deflated by the consumer prices index to 2014 Euro prices. The summary and definitions of both the output and input variables are shown in Table 1.

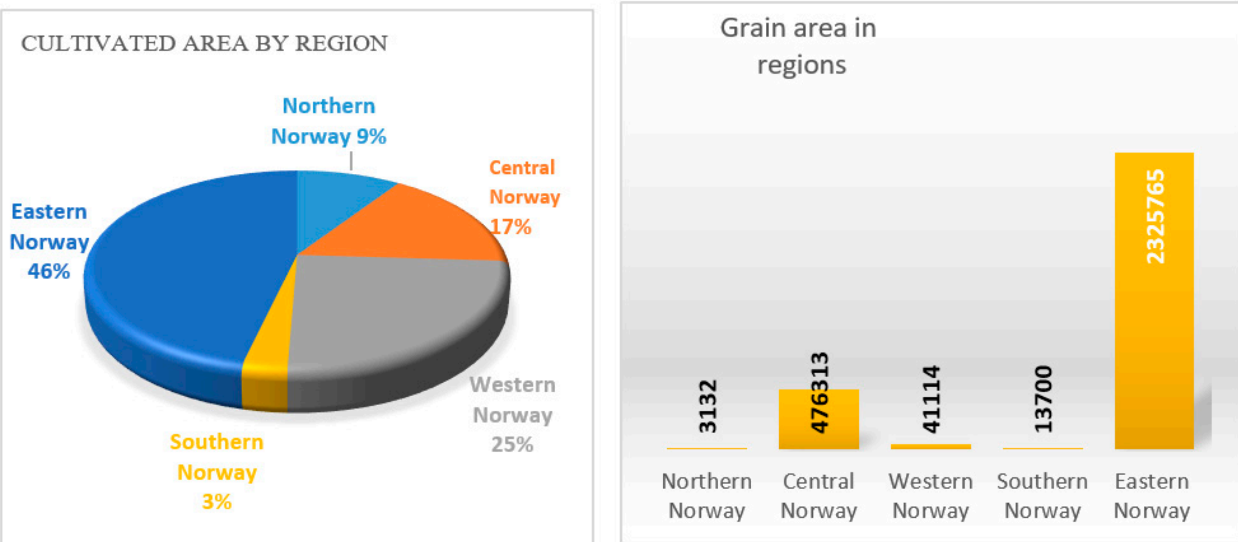

Figure 1. Five regions total cultivated and grain land in 2012, computed data from Statistics Norway (2016).

Table 1. Descriptive statistics (mean value) for crop production in two regions (1996–2014).

Region	Output (In €2014)	Land ($\times1$) (0.1 Hectare)	Labor ($\times2$) (In Hours)	Var. Cost ($\times3$) (In €2014)	Fixed Cost ($\times4$) (In €2014)	N
Eastern Norway	33,527.50	342	991	9391.00	15,917.40	1292
Std. Dev.	(23,694)	*(212)*	*(634)*	*(6403)*	*(10,372)*	
Central Norway	28,547.30	282	676	6195.50	11,755.20	171
Std. Dev.	*(13,664)*	*(85)*	*(222)*	*(2808)*	*(5762)*	
Norway	32,945.40	335	954	9017.50	15,430.90	1463
Std. Dev.	*(22,804)*	*(202)*	*(606)*	*(6179)*	*(10,032)*	

Source: Author's calculations.

5. Estimation Results and Discussion

Technical efficiency (TE) estimates were obtained from the stochastic frontier model and estimated separately for the two regions and the pooled data following the procedure for the 'True' random effect model (Greene 2005b) using STATA version 14. The metafrontier estimated using SHAZAM version 10 following O'Donnell et al. (2008). The results of the analysis are discussed below.

5.1. Input Elasticity and Technological Change

The estimated parameters of the stochastic frontier (SF) translog function specified in Equation (11) for estimation for the two regions and the pooled data are reported in Table 2.

Table 2 also shows the results of the linear programming estimates for the metafrontier. All variables are normalized; that is, we divide all variables by their geometric mean value before their logarithms. Consequently, the first-order parameters are interpreted as production elasticities at the geometric mean. The coefficient for the land is the largest among other partial production elasticities in all regions of Norway and statically significant ($p < 0.001$). The results imply that the percentage change in the land has a larger influence on grain production compared to other inputs. As a result, any intervention to improve the grain sector needs to prioritize these inputs. On the other hand, the estimated elasticity of grain output for labor input (x_2) is 0.17 in the eastern region, and 0.27 in the central region, which are statically significant at $p < 0.001$. The partial elasticity of grain output for variable input is statically significant ($p < 0.001$) for both regions. Moreover, the partial elasticity of fixed input (x_4) in all regions is positive and statically significant in all regions, with a minimum value of 0.12 in the eastern region and 0.17 in central regions.

Table 2. Parameter estimates for the translog function and the metafrontier.

		Eastern Norway		Central Norway		Pooled Data		Metafrontier
				S. Frontier				
β_1	x_1(land)	0.64 ***	(0.05)	0.77 ***	(0.16)	0.65 ***	(0.04)	0.36
β_2	x_2 (labor)	0.17 ***	(0.03)	0.27 ***	(0.03)	0.15 ***	(0.03)	0.51
β_3	x_3 (V.cost)	0.12 ***	(0.03)	0.09 ***	(0.01)	0.12 ***	(0.03)	1.35
β_4	x_4 (F.cost)	0.12 ***	(0.03)	0.17 *	(0.08)	0.12 ***	(0.03)	0.01
β_{11}	$x_1 * x_1$	0.50 **	(0.18)	1.05	(0.90)	0.12 ***	(0.03)	−0.52
β_{22}	$x_2 * x_2$	0.11	(0.06)	0.25	(0.22)	0.57 ***	(0.17)	0.21
β_{33}	$x_3 * x_3$	0.04	(0.05)	0.001	(0.08)	0.06	(0.05)	0.01
β_{44}	$x_4 * x_4$	−0.01	(0.08)	0.23	(0.28)	0.01	(0.07)	0.03
β_{12}	$x_1 * x_2$	−0.06	(0.07)	−0.10	(0.40)	−0.05	(0.08)	−0.83
β_{13}	$x_1 * x_3$	−0.14	(0.09)	−0.25	(0.33)	−0.17 *	(0.08)	0.06
β_{14}	$x_1 * x_4$	−0.15	(0.09)	−0.15	(0.22)	−0.20 *	(0.08)	−1.30
β_{23}	$x_2 * x_3$	0.02	(0.04)	0.37	(0.26)	0.02	(0.04)	−1.40
β_{24}	$x_2 * x_4$	0.02	(0.05)	−0.17	(0.30)	0.01	(0.05)	1.28
β_{34}	$x_3 * x_4$	0.09	(0.07)	0.01	(0.10)	0.11 *	(0.06)	0.57
β_t	t	0.09 ***	(0.00)	0.03 ***	(0.00)	0.03 ***	(0.00)	0.63
β_{tt}	$t * t$	0.01 ***	(0.00)	0.01 ***	(0.00)	0.01 ***	(0.00)	0.64
δ_1	$t * x_1$	−0.03	(0.02)	−0.05 *	(0.02)	−0.03 *	(0.01)	−0.65
δ_2	$t * x_2$	0.01	(0.01)	0.02 *	(0.01)	0.02	(0.01)	−0.22
δ_3	$t * x_3$	−0.02 *	(0.01)	0.004	(0.01)	−0.02 **	(0.01)	0.59
δ_4	$t * x_4$	−0.00	(0.01)	−0.03	(0.03)	−0.003	(0.01)	−0.61
α_0	_cons	−0.39 ***	(0.03)	−0.28 ***	(0.05)	−0.37 ***	(0.03)	0.89
U-sigma		−3.77 ***	(0.15)	−3.86 ***	(0.59)	−3.79 ***	(0.14)	
V-sigma		−3.06 ***	(0.07)	−4.54 ***	(0.47)	−3.12 ***	(0.07)	
Theta		0.16 ***	(0.01)	0.14 ***	(0.03)	0.16 ***	(0.01)	
Sigma_u		0.15 ***	(0.01)	0.14 ***	(0.04)	0.15 ***	(0.01)	
Sigma_v		0.22 ***	(0.01)	0.10 ***	(0.02)	0.22 ***	(0.01)	
Lambda		0.70 ***	(0.02)	1.04 ***	(0.06)	0.70 ***	(0.02)	
Log-L		−216 ***		43 ***		−215 ***		
RTS		1.06		1.33		1.04		
N		1292		171		1463		

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; RTS = returns to scale. Source: Author's calculations.

Wang and Ho (2010) showed that the estimated time trend variable is the average annual rate of technical change (TC). As indicated in Table 2, the estimated parameter for time for the two regions is positive and significant. These show that the rate of TC increases at an increasing rate over time. The only significant interaction parameter with time (t) for the eastern region is when time interacts with variable input (x_3). The negative value suggests that technological change (TC) has been variable and input-saving over the last 19 years and, thus, TC is non-neutral. On the other hand, the interaction parameter with time (t) for the central region with land and labor are statically significant ($p < 0.05$). The negative value of tx_1 suggests that technological change (TC) in the central region has been land-saving over the last 19 years but not labor-saving.

The sum of the functional-coefficient for the translog function at the geometric mean is 1.06 and 1.04 for the eastern region and the pooled data, respectively. Since constant returns to scale (CRS) is not rejected at any reasonable level of significance (Table 2), $\sum_{k=1}^{4} \beta_k = 1$ reveals that grain production exhibits constant returns to scale for the eastern region. In line with this finding, the study conducted by Lien et al. (2010) on the determinants of off-farm work and its effects on farm performance on the case of Norwegian grain farmers was unable to conclude that there were increasing returns to scale (Lien et al. 2010). On the other hand, the central region displays increasing returns to scale ($\sum_{k=1}^{4} \beta_k = 1.33$) since constant returns of scale were rejected at 5% of significance (Table 2). A study conducted on Norwegian grain farms for the period 1972–1996 reported increasing returns to scale (Løyland and Ringstad 2001). Our findings do not lend support to previous studies that have concluded that there are increasing and decreasing scale economics in the Norwegian grain production industry. The results for scale economics and policy implications differed from region to region such that there is a need for regionally based analysis.

5.2. Technical Efficiency and Technology Gap Ratio (TGR)

The value of technical efficiency for grain production for the region (TE_i) estimated by the SFA model is shown in Table 3. Farms in the central and eastern regions achieved the mean technical efficiency of 0.87 and 0.88, respectively. The average technical efficiency score of 0.87 indicates grain output by about 87% of the potential given its regional technology. There are no regional-level studies for the crop sector in the literature for comparison. However, if we consider the same technology assumption in our model, the result is in line with other studies, for example, a study of grain farming in Norway that estimated a single frontier model is working under a common production frontier (technology) for six different models and reported that the mean technical efficiency varies from 0.64 to 0.91 (Kumbhakar et al. 2012). Other studies focusing on the comparison of SFA and DEA on Norwegian grain production reported a mean technical efficiency of 0.70 and 0.75 for SFA and DEA models, respectively (Odeck 2007).

Table 3. Technical efficiency estimates for grain production in two regions.

Region	Mean	Std. Dev.	Minimum	Maximum	N
Eastern Norway	0.88	0.06	0.29	0.98	1292
Central Norway	0.87	0.10	0.39	0.98	117
All regions	0.88	0.06	0.29	0.98	1463

Source: Author's calculations.

Table 4 shows the most interesting feature of the analysis, which illustrates the difference between the average technical efficiency of the regional frontier and the metafrontier model (TE*). For instance, the average SF technical efficiency of eastern Norway to the metafrontier was only 0.52 for the years 1996–2014. The results show that farmers in the east are much less efficient compared with the metafrontier. The highest efficiency compared with the metafrontier is reported in the central region (0.71).

Table 4. Technical efficiency to the region (TE_i), the metafrontier (TE*), and technology gap ratio (TGR).

Regions	TEi	TE*	TGR	N
Eastern Norway	0.88	0.52	0.59	1292
Central Norway	0.87	0.71	0.82	117

Source: Author's calculations.

Estimates of the mean values of the TGR vary even more widely than the average technical efficiency estimates in the metafrontier model. A similar result was reported, for instance, in (Boshrabadi et al. 2008). The TGR for each region is reported in Table 5. The results show that farms in the central region achieved the highest TGR (0.82) with minimum variation (SD = 0.28). Conversely, the lowest average TGR score was estimated for Eastern Norway (0.59). The value TGR ranges from a minimum of 0.27 in the central region and with a maximum of 1 for all regions.

Table 5. Technology gap ratio (TGR) for grain production.

Regions	Mean	SD	Variance	Minimum	Maximum	N
Eastern Norway	0.59	0.30	0.09	0.39	1.000	1292
Central Norway	0.82	0.28	0.08	0.27	1.000	117

Source: Author's calculations.

In general, as we discussed in the theoretical part of the paper, a lower (higher) TGR value implies a larger (smaller) technology gap between the individual frontier and the metafrontier. The TGR score of 1 indicates that the farmer is applying the best technology available in the region, i.e., a TGR score equal to 1 is equivalent to a point where the individual region frontier coincides with the metafrontier. The TGR score of 1 in all Norwegian regions indicates that it is possible to produce maximum grain output as represented by the metafrontier, given the status of the environment. An important policy implication of efficiency analysis for the different regions is to ascertain, by increasing productivity, gains attained by increasing technical efficiency, i.e., catching up (Battese et al. 2004; O'Donnell et al. 2008). Therefore, policymakers could minimize the gap between the farmers in the eastern region through training and knowledge sharing (transfer) within the region. This policy intervention helps farmers achieve the highest possible output on the metafrontier given the current technology available in the grain farming sector. On the other hand, grain firms located in those regions near the metafrontier need additional investment in research to develop new technology. The analysis shows the central regions of Norway fall, relatively, in the latter situation.

6. Conclusions and Policy Implications

This paper aimed to measure the performance and regional technology gaps of Norwegian crop-producing farms located in different regions. We controlled unobserved heterogeneity and technological regional differences using Greene (2005b) and metafrontier models, respectively. The empirical analysis is based on balanced farm-level panel data for 19 years (1996–2014) with 1463 observations from 196 family farms specialized in grain production. The estimated average technical efficiency is 0.88 for the eastern region and 0.87 central regions. The results suggest that grain farms in all regions suboptimally use available technology in the area, given the regional technology. The study also shows that TGR is different for the two grain-producing regions of Norway. The results show that farmers in the eastern region (0.59) are much further from the metafrontier compared to the central region (0.82), which suggests that farmers in different regions use different production technologies according to the resource endowments and environmental situation of the region. Consequently, intervention to improve the grain sector in Norway demands these technology differences in the regions be considered.

Policymakers could minimize the gap for farmers within the eastern regions through training and knowledge sharing (transfer) within the region, which allows the inefficient grain-producing farms to learn from the best-performing farms. Moreover, technology adoption and information transfer from the central to the eastern region is crucial to reduce the gap. This policy intervention helps farmers achieve the highest possible output on the metafrontier with the current technology available in the agricultural sector. Grain-producing farms in the central region are near to the frontier and, thus, additional investment in new technology development is required for relative improvements in farm performance. This policy intervention helps farmers in the central region to use new technology to shift the production frontier upwards and improve grain production performance in the region.

TGR was estimated using a single output framework. It might be interesting to see if the results are different if the metafrontier was 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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