sSOURCE OF TOTAL FACTOR PRODUCTIVITY CHANGE: AN EMPIRICAL ANALYSIS OF GRAIN PRODUCING REGIONS IN NORWAY

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Abstract
In this article, we estimate the progress of Total Factor Productivity (TFP) in the Norwegian grain production sector. Previous studies conducted in TFP estimation can be criticized for estimated production function relied on the assumption that the underlying technology is the same for all regions and firms face similar environmental conditions. In reality, agricultural firms in different regions resource endowment, adoption of new technology, and innovation might be different because of farmers face different production opportunities. For this study, we classified the country into two main grain producing regions with district level of development, and hence production technologies. We used farm level balanced panel data for 19 years (1996-2014) with 1463 observations from farms specialized in grain production. We applied the 'true' fixed effect stochastic frontier model to estimate region level efficiency and source of productivity changes. The result of the analysis shows that there has been a productivity improvement in the sector, and technical change has had the main source of productivity change.

Keywords: *Productivity, Technology, sustainable development, and Region*
JEL Classifications: *R58, O52, Q16, and C23*

1. Introduction

The primary objectives of the Norwegian agricultural policy are long-term food self-sufficiency; protect the environment and small-scale farming in all regions. Grain production in the country is mainly based on small-scale family farms. The production conditions are tougher due to Nordic climate, scattered and steep land that is not convenient for crop production. Thus, the

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cost of grain production is very high which leads little competency of the family farms in the open market. As a result, to achieve the agricultural policy objectives, the sector has been heavily subsidized (OECD, 2016). Improving the performance of firms have been pivotal concern for policymakers, farmers, and researchers for the development of the agricultural sector

The economic performance of a firm commonly measured using efficiency and productivity. Assessing the drivers of productivity growth is critical for business and economic policy. Their identification allows monitoring of firms and can guide policymakers in their decisions. Hence, an abundant literature has sought to decompose various sources of productivity growth into technical change, efficiency change, and scale change (see for e.g. Alvarez, del Corral, & Tauer, 2012).

Few studies have been conducted focusing on productivity growth of Norwegian grain producers (see for instance Odeck, 2007 and 2009). The study can be criticized for focusing on estimates a single frontier model working under the same production frontier (technology). Even if the functional forms were flexible with these studies, a standard technology for all regions in Norway is unlikely to happen. In reality farm experience, capital endowment, and input use may differ even between farmers in the same area. A single frontier function estimation encompassing every sample observation may not be appropriate because the estimation may be biased due to the technology might not likely to represent the 'true' technology (O'Donnell et al., 2008; Orea & Kumbhakar, 2004).

In general, the structure of the Norwegian grain production raises some interesting questions that need an answer. Has there been any productivity progress in Norwegian food production in the last decade? Is there any potential for improving the efficiency of the Norwegian grain farm operators in different regions? To this end, an assessment of food producers' performances as compared to others facing the same condition is of interest to the subsidizers (decision-makers). The rationale is twofold; (1) the farmers can learn from the front-runners how best to utilize their resources efficiently, and (2) the decision makers can gain insight on the potential for resource savings. More knowledge about the performance of grain producing firms at the regional level could help policymakers introduce better-targeted agricultural systems. The analysis based on balanced farm-level data collected in Norwegian regions in the period 1996-2014.

The rest of the paper organized as follows. Section two presents the theoretical framework of the study followed by section three describes the empirical model while section four discusses the data and definition of variables used in the production function. Empirical estimation and results presented in section five. The final section encompasses a summary of our findings and conclusions.

2. Theoretical Framework

Previous performance studies have used different approaches to measure and decomposing TFP. The various approaches employed in the literature have been classified by Diewert (1981) using index numbers (the Divisia, Malmquist, Tornquist, Luenberger, and Fisher), nonparametric methods using linear programming; parametric methods using cost and production functions. A Recent measure of TFP change seeks to decompose TFP change into different sources. A decomposition of TFP change first proposed by Kumbhakar (1996) and decomposed into Technical change (TC), Scale change (SC), Technical efficiency (TE), and price change components. Following this approach, different papers decompose TFP change into four principal components commonly using Malmquist and Divisia Index. For instance, Balack (2001) using Malmquist index and decomposed TFP into Technical change (TC) - shows operating on a new frontier and captures the improvement in the best practices through the adoption of new technologies. Efficiency change (EC) - shows the firm's ability to use available technology, for instance, inefficient farmers lately adopting the existing technology. Scale or size change (SC) - shows movements along the frontier and a decrease in average cost of production. Mix effect- which is very common in the multiple-input-multiple-output firm. It measures the effects of change in the composition of inputs and output over time.

Other researchers using Divisia index and decompose TFP change into four components. For example, Kumbhakar and Lozano-Vivas used the production frontier model to decompose the Divisia TFP growth into Technical efficiency change (EC), technical change (TC), allocative efficiency change (AEC) and scale change (SC) component (Kumbhakar & Lozano-Vivas, 2005). On the other hand, Brümmer et al. (2002) decomposed the Divisa TFP change into EC, TC, AEC and SC component using output distance function. Using input distance function Karagiannis et al.(2004)

decompose Divisia TFP change into the same four components (Karagiannis, Midmore, & Tzouvelekas, 2004). For all these studies can be criticized for not considering technological heterogeneity and the research relied on the assumption that the underlying technology is the same for all regions. For this study, we examined regional differences and used a production function approach. Total factor productivity change is the sum of Technical change (TC), Efficiency change (EC), Scale change (SC), and Allocative efficiency change. *TFP* change connected to the technology are $\boldsymbol{TC+SC+TEC}$, which is the focus of this study.

The first source of TFP change could be technical change (TC), which results from a shift in the frontier. TC shows operating on a new frontier and captures the improvement in the best practices through the adoption of new technologies, for instance, new crop varieties. The second source of TFP change due to efficiency change (EC), which shows improved effectiveness in the firm's ability to use available technology. EC shows moving towards the frontier due to improved farm management, for example, the form of reducing resource wastage. An intensive agricultural extension, inefficient farmers, lately adopting the currently available technology is improving efficiency. If technical inefficiency is time-invariant, $(i.e. -\partial u/\partial t \; = 0)$ then EC does not affect the TFP change. The third component is due to a change in scale efficiency change (SC). SC shows movements along the frontier. SC shows improvement in the scale of operations of the firm and its movement towards technologically optimum scale of operation (Coelli et al., 2005). Allocative efficiency component of TFP change captures either deviation of input prices from the value of their marginal products in the allocation of inputs. Allocative efficiency is not computing for this study because of input prices data at farm level is not available.

3. Empirical Model

The translog production function for region-*k* frontier is:

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

where $\beta_{kl} = \beta_{lk}$ for all k and l; y is a vector of grain outputs in log form, x_i is a vector of inputs in log. All Greek letters are parameters to be estimated. The white noise error term v_{it} is added to allow for random measurement error in Eq. (1). The term v_{it} is symmetric and assumed to satisfy the classical assumptions, i.e. $v_{it} \overset{iid}{\sim} N(0, \sigma_v^2), v_{it} \perp u_{it}$. U_{it}^k is the non-negative variable representing technical inefficiency for each region. The trend variable, t, include capturing Hicks-neutral technology change starts with T=96 for 1996 and increases by one annually. We treated α_i^k as fixed parameters that are not part of inefficiency according to Greene (2005) 'true fixed-effect' frontier model. We also estimated assuming α_i^k treated as a random variable, which allows technical inefficiency to vary over time and employ the 'true' random-effects frontier model (referred to as TRE) (Greene, 2005). We conducted Hausman test to choose the random and fixed effect model. Moreover, the test shows that true random effect rejected in the two regions. As a result, we estimated our data based on the true fixed effect stochastic frontier model.

All data for the TL model expressed as deviations from their sample mean, which makes it possible to interpret the first-order parameters directly as partial production elasticities at geometric mean of the data (Coelli et al., 2005). The trend variable is normalized to be zero in the year 2014. All other variables normalized before taking the logarithms by dividing each variable by its mean values in 2014. Various specification tests of hypotheses of the parameters in the production frontier function and the inefficiency model performed using the generalized likelihood-ratio test statistic. The firm's inefficiency estimated using the conditional mean of the inefficiency term proposed by Jondrow et al., (1982). Technical efficiency (TE_{it}^k) is equal to one if firms in region k have an inefficiency effect equal to zero and is less than one otherwise. We calculated TFP change components from the Eq. (1) as follows: Technical change or frontier shift (TC $= \frac{\partial \ln y}{\partial t}$) $= \varphi t + \sum_{k=1}^{4} \delta_k \ln x_{it}$; EC (technical efficiency change) = $\frac{-\partial U_{it}^k}{\partial t}$. All variables are normalized so that the first-order parameters can be interpreted as production elasticities at geometric mean(ε_j). The sum of the elasticities shows the returns to scale (RTS) .i.e. RTS=$\sum_{k=1}^{4} \beta_k$.

4. Data

We used farm level balanced panel data for 19 years (1996-2014) with a total of 1463 observations from the Norwegian farm accountancy survey collected by the Norwegian Institute Bioeconomy Research (NIBIO). The data include agricultural production and economic data collected annually divided into five regions, farm size classes, and types of farms. 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 located in the Eastern and central regions of Norway. Thus, to obtain a homogenous group of farms, only farms specialized in grain production from East and Central Norway reported their account data for the period 1996-2014 were selected.

The production data contained one output variable and four input variables. Output (y) includes grain production, which represented by the total farm revenue from grain and grain products (sales + farm use + farmhouse consumption) exclusive of government support. Grain output is an aggregate of four main species: barley, wheat, oats, and oilseeds species. All output valued in Norwegian kroner (NOK) and deflated to 2014 revenues using the consumer price index (CPI). We used four inputs for our analysis. Farmland (x_{1}) is productive land (both owned and rented) in a hectare. Labor (x_2) is the total labor hours used in the farm, which includes hired labor and owners, and family work. Variable input (x_3) inputs like fertilizers, feed, oil and fuel products, electricity, expenses for plant and other costs, deflated by the CPI to 2014 NOK prices. Capital costs (X_4) are expenditure on fixed cost items plus depreciation and maintenance costs on farm capital tied up in machinery, buildings. All values deflated by the CPI to 2014 NOK prices. Maintenance and costs associated with the hiring of machines and land are registered annually. Depreciation costs calculated as a percentage of historical costs with different rates for different capital assets, for instance, land, is estimated with discount percentages of zero while machines are at 10 percent.

5. Estimation and Results

5.1. Specification tests

Various specification tests were conducted to obtain the best model and functional form for the data under analysis (Table 1)

Table 1: Properties of grain and forage production technology

Restrictions	**parametric restrictions**	**chi2**	**p-value**	**Decision**
CD technology*	H_0: All interaction terms are zero			
East region		2.99	0.0004	reject H_0
Central region		4.21	0.0057	reject H_0
Constant RTS*	H_0: $\sum_j^k \beta_j = 1$, and $\sum_j^k \gamma_{jl} = \sum_j^k \delta_{jl} = 0$			
East region		30.94	0.0000	reject H_0
Central region		0.08	0.7858	not reject H_0
Hick's technology	H_0: $\alpha_{jt} = 0$			
East region		12.74	0.0000	reject H_0
Central region		2.68	0.0588	not reject H_0
Test return of Skewness	Schmidt & Lin (1984) test			
East region		359.34	0.0000	reject H_0
Central region		25.18	0.0002	reject H_0
Hausman test				
East region		66.27	0.0000	reject H_0
Central region		59.25	0.0000	reject H_0

F test, RTS= Returns to scale*

Before estimating the production function, the skewness of the data tested based on Schmidt & Lin (1984). The test return of Skewness with a P value is less than 0.001 shows the null hypothesis of no skewness confidently rejected in both regions. Moreover, we tested the null hypothesis (H_0) that there are no technical efficiency effects in the models for two regions and pooled data examined. The null hypothesis rejected, in which the LR is greater than the (mixed) chi-square value of 5.412. Therefore, we have found support for a right-skewed error distribution, and the skewness is statistically significant. Thus, the result confirms the rejection of the null hypothesis of no skewness in the OLS residuals. Therefore, we estimated the model with the parametric distributional assumptions of v_i and u_i. LR tests for all SFA models for each region and the pooled data reveal that a simplification of the characteristics of the technology Cobb-Douglas (CD) technology specification is rejected in both regions. Table 1 shows results of all test of the property of production technologies. Thus, the analysis of the study based on translog functional form for the two regions and the pooled data.

The hypothesis that all regions grain farming share the same technology was rejected. We used the likelihood ratio test (LR), where L(H0) is the value of the log-likelihood function for the stochastic frontier estimated by pooling the data for the two regions (i.e. 48), and L(HA) is the sum of the values of the log-likelihood functions estimated separately from the regional production frontiers i.e. 86. The LR statistic such that LR = -2 [ln{L(H0)}-ln{L(HA)}] = 38. The LR test gives a likelihood ratio of 38 that is a strongly significant rejection of the null hypothesis and indicates that the technology used in East and Central regions were not the same. As a result, we estimated the two areas separately. Hausman tests conducted to select the appropriate model for our data. The test result shows that in the two regions and the pooled data, the chi-square is colossal so that reject the null hypothesis (reject random effects as inconsistent). Thus, the analysis of the paper based on the 'true' fixed effect model framework.

5.2. Technical efficiency

Table 2 shows the estimated average technical efficiency for the two regions and pooled data.

Table 2: Technical efficiency estimate for grain production in the two regions

Region	Mean	Std. Dev.	Minimum	Maximum	N
Eastern region	0.88	0.06	0.29	0.99	1292
Central region	0.87	0.10	0.39	0.98	171
Both regions	0.88	0.06	0.29	0.99	1463

The average technical efficiency score of 0.87 indicates grain output by about 87 percent of the potential, given its regional technology. The result is in line with other studies. For example, a study of grain farming in Norway estimated on six different models and reported the mean technical efficiency varies from 0.64 to 0.91(Kumbhakar et al., 2012). Another study focusing on comparison of SF and DEA on Norwegian grain production reported a mean technical efficiency of 0.70 and 0.75 for SF and DEA models, respectively (Odeck, 2007). Our result indicates that there are farms that produced lower outputs from the inputs they used or used more inputs to produce the same output, compared to the best performing farms.

5.2. Total factor productivity (TFP) Change

Average TFP in the two regions shows in Table 3. The result indicates that overall average annual TFP growth rate in grain production during the period 1996- 2014 was different from region to region.

Table 3. Mean TFP change and its components (in percent)

Variable	Eastern region	Central region	Both regions
Technical change (TC)	0.025	0.012	0.024
Std. Dev.	(0.015)	(0.003)	(0.010)
Efficiency change (EC)	0.0001	0.0004	0.0001
Std. Dev.	(0.001)	(0.0002)	(0.001)
Scale change(SC)	0.001	0.003	0.001
Std. Dev.	(0.012)	(0.002)	(0.001)
TFP change	0.025	0.012	0.024
Std. Dev.	(0.014)	(0.005)	(0.003)
Returns to scale (RTS)	0.670	0.820	0.730
Std. Dev.	(0.000)	(0.000)	(0.000)
Sample size(n)	1292	171	1463

Table 3 shows that TFP increase by 0.03 percent per annum for the East. The result is in contrast with previous studies. For instance, a survey carried out in the Polish Agriculture reported TFP decreased by 2% over the period 1996 to 2000 (Latruffe, Davidova, & Balcombe, 2008). Moreover, Baráth and Fertő said a decline TFP in the European agriculture from 2004 to 2013 (Baráth & Fertő, 2016). TFP increased mainly due to positive contributions from technical change components. However, the contribution of technical efficiency change and scale change to TFP was almost zero. The estimated result shows that technological change (TC) in eastern region was 0.025 percent per annum. Odeck (2007) reported a higher technological change of 1.067 for the Norwegian grain production for the period 1987-1997. However, the result is a contrast to reports in other studies, for instance, a survey carried out in the Polish Agriculture TC decreased by 6 % over the period 1996 to 2000 (Latruffe et al., 2008). The contribution of the scale change to TFP was small but positive (0.001).

TFP in the central region increased by 0.012 % per annum. TFP increased mainly due to positive contributions from technical change and scale change components. However, the contribution of efficiency change in both regions almost zero which shows that the performance of the grain farms not changing over time (time-invariant). Thus, need more extension work on farmers to adopt the exiting improved technology in each region. The estimated result shows that technological change (TC) was increased by 0.012 % per annum, which is lower than the eastern region. However, the contribution of the scale change to TFP was small but higher than the East region (0.003).

6. Conclusion

We used farm level data and estimated source of TFP considering regional differences. The analysis of the paper shows that average technical efficiency of 0.88 and 0.87 in the eastern and central regions, respectively. The average technical efficiency score of 0.87 indicates grain output by about 87 percent of the potential, given its regional technology. Therefore, there is a potential for improving the Norwegian grain farm through reducing firm inefficiency.

TFP increased by 0.03 and 0.01 percent per annum for the eastern and central regions, respectively. TFP increased mainly due to positive contributions from a technical change in the two regions. The contribution of technical change in the eastern region two times higher than the central region. The contribution of the scale change to TFP was small but positive. The technology in the eastern region exhibit decreasing returns to scale while in the central region it is constant returns to scale. The magnitude and source of TFP and policy implications differed from region to region so that there is a need for regionally based intervention for the sustainable improvement of the agricultural sector.

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