Economic performance and efficiency determinants of crop-producing farms in Norway

Habtamu Alem
Norsk Institutt for Biookonomi, As, Norway
Gudbrand Lien
Inland Norway University of Applied Science, Lillehammer, Norway, and
J. Brian Hardaker
University of New England, Armidale, Australia

Abstract

Purpose – The purpose of this paper is to explore the economic performance of Norwegian crop farms using a stochastic frontier analysis.

Design/methodology/approach – The analysis was based on a translog cost function and unbalanced farm-level panel data for 1991–2013 from 455 Norwegian farms specialized in crop production in eastern and central regions of Norway.

Findings – The results of the analysis show that the mean efficiency was about 78–81 percent. Farm management practices and socioeconomic factors were shown to significantly affect the economic performance of Norwegian crop farms.

Research limitations/implications – Farmers are getting different types of support from the government and the study does not account for the different effects of different kinds of subsidy on cost efficiency. Different subsidies might have different effects on farm performance. To get more informative and useful results, it would be necessary to repeat the analysis with less aggregated data on subsidy payments.

Practical implications – One implication for farmers (and their advisers) is that many of them are less efficient than the estimated benchmark (best performing farms). Thus, those lagging behind the best performing farms need to look at the way they are operating and to seek out ways to save costs or increase crop production. Perhaps there are things for lagging farmers to learn from their more productive farming neighbors. For instance, those farmers not practicing crop rotation might be well advised to try that practice.

Social implications – For both taxpayers and consumers, one implication is that the contributions they pay that go to subsidize farmers appear to bring some benefits in terms of more efficient production that, in turn, increase the supply of some foods so possibly making food prices more affordable.

Originality/value – Unlike previous performance studies in the literature, the authors estimated farm-level economic performance accounting for the contribution of both an important farm management practice and selected socioeconomic factors. Good farm management practices, captured through crop rotation, land tenure, government support and off-farm activities were found to have made a positive and statistically significant contribution to reducing the cost of production on crop-producing farms in the Central and Eastern regions of Norway.

Keywords Benchmarking, Cost function, Farm management, Farm performance

Paper type Research paper

1. Introduction

The United Nation has predicted that current world population of 7.6bn is expected to reach 8.6bn in 2030, 9.8bn in 2050 and 11.2bn in 2100 (United Nations, 2017). Finding a way to meet the growing demand for food represents a major challenge for farmers,

policymakers and agricultural researchers. These global challenges also affect Norway. Increasing the quantity and quality of food in response to growing food demand requires improvement in the performance of the agricultural sector. Agricultural production growth in Norway is a topic of continuing interest to researchers and policymakers who aim to improve the economic efficiency and economic sustainability of primary agriculture. Good farm management and agronomic practices, in combination with efficient input use, are the best ways to improve farm productivity. In this context, agronomic practices are steps farms incorporate into their farm management to produce crop output. These steps include land preparation, time of sowing, crop rotation, use of new crop varieties, pest control, etc. While some practices may be designed to increase output, others may be directed to reducing labor time or costs.

Farms use different farm management/agronomic practices and resource combinations to produce crops. Thus, we can expect differences in performance between farms, with some less efficient than others. Farm inefficiency can be defined as the extent to which farmers are using more resources to produce a given level of output than the resources used by the best practice farmers.

In recent years, several studies have used "benchmarking" techniques to examine the efficiency in the agricultural sector (e.g. Kumbhakar and Lien, 2010; Koesling et al., 2008; Odeck, 2007; Flaten et al., 2010; Lien et al., 2010; Kumbhakar et al., 2014; Sipilainen et al., 2013). "Benchmarking" is defined as a measurement of the quality of an organization's policies, products, programs, strategies, etc., in comparison with standard measurements, or with similar measurements of its peers, see for detail Kumbhakar and Lovell (2000), and Coelli et al. (2005). The objectives of benchmarking are: to analyze how the more successful organizations achieve their high-performance levels; to determine what and where improvements are called for; and to use this information to improve performance. Measuring such efficiency gaps and identifying the causes can be useful to both farm managers, taxpayers, consumers and to policymakers and planners seeking to help farmers to improve their performance (Singh et al., 2016).

An investigator may not only be interested in the level of economic performance but also might want to know which factors (exogenous variables) affect the level of farm performances (Smith et al., 2006; Parmeter and Kumbhakar, 2014).

The ability of a farm manager to convert inputs into outputs via a given technology is often influenced by "exogenous variables" that characterize the environment in which production takes place (Coelli et al., 2005) (different names have been used in the economics literature for exogenous variables, such as environmental variables, z-variables and determinants of inefficiency). Thus, the accurate measurement of the economic performance of the crop farms demands an understanding of differences in the working environment. The environmental factors include farm-specific factors, such as management skill, institutional constraints and attitude to risk, or innovations that are unmeasured but can be partially represented by observable variables such as age, experience, participation in farm improvement programs and education. Environmental variables can be expected to provide farmers with various types of opportunities and challenges, which ultimately affect their level of farm performance.

In recent years, several studies have used benchmarking techniques to examine the level and determinants of inefficiency in farming. For instance, Latruffe et al. (2004) analyzed the technical efficiency and its determinants for individual farms specialized in crop and livestock production in Poland. They reported that, on average, livestock farms are more technically efficient than crop farms. Moreover, soil quality and the degree of market integration proved to be important determinants of technical efficiency. Curtiss (2000) investigated technical efficiency and competitiveness for Czech crop production for the years 1996–1998 and reported that there was a high correlation between technical efficiency and competitiveness. Moreover, market conditions, transaction costs in marketing and bargaining power were positive determinants for competitiveness. Zhu and Lansink (2008)

analyzed the impact of the CAP reforms on the technical efficiency of three crop-producing EU countries in the period 1995–2004. They reported that the mean technical efficiency was 75 percent in the Netherlands, 70 percent in Sweden and 59 percent in Germany. The ratio of crop subsidy to the total subsidy had a positive impact on the technical efficiency in the Netherlands and Sweden, but no significant impact in Germany.

Kumbhakar *et al.* (2014) estimated technical efficiency and its determinants for Norwegian grain farms for the period 2004–2008. They reported that resources were sub-optimally used. Off-farm activity, direct subsidy and entrepreneurial orientation were found to have negative effects on technical efficiency, while farm managers with more experience were likely to be more efficient than those with fewer years of farm experience. Lien *et al.* (2018) estimated technical efficiency of the Norwegian crop-producing farms observed from 1993 to 2014 and reported that the mean technical efficiency was 0.82–0.88. Moreover, off-farm work was found to decrease technical efficiency while direct subsidy payments had a positive and statistically significant effect on technical efficiency.

Previous studies of agricultural efficiency have given useful insights into farm performance. However, the contribution of farm management practices such as crop rotation to the economic performance of crop farms remains unclear. This paper contributes to the literature in a number of ways. First, we hypothesize that:

   H1. In addition to commonly used efficiency determinants (land rent, off-farm activity and direct government support), cost efficiency (CE) depends on the important farm management/agronomy practice of crop rotation.

Second, unlike previous studies, which commonly estimated the technical efficiency of farms:

   H2. We estimated the economic (cost) efficiency, which accounts for both the technical and the allocative inefficiency of each farm.

A farm achieves technical efficiency when it is able to minimize the use of inputs to produce a given amount of output so that no inputs are wasted. Allocative efficiency is achieved when the farm is able to use its inputs according to their respective relative prices. Measuring such CE gaps and identifying determinants can be useful to farm managers, policymakers, planners and advisers seeking to help farmers to improve their performance.

The rest of the paper is organized as follows: Section 2 discusses the nature of Norwegian agriculture. Section 3 addresses the approach to measuring farm performance, while Section 4 discusses model specification. Section 5 includes a discussion of the data and definitions of variables used in the cost function. Section 6 includes the results and discussion thereof. Section 7 covers conclusions and implications.

2. The nature of agricultural production in Norway
Norwegian farms are usually small and family-operated. Only 3.3 percent of the total Norwegian land area is farmland (Statistics Norway, 2013). 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 in most parts of the country and a short growing season (five months on average), growing fodder, mainly grass, has the comparative advantage in most parts of the country. On the other hand, long summer days, with sufficient rainfall, are beneficial for crop production. Moreover, the cool climate limits the spread of pests and diseases (Steinshamn *et al.*, 2016).

The primary objectives of the Norwegian agricultural and food policies, as set out in the White paper No. 11 (2016 –2017) are: long-term food self-sufficiency along with protection of the environment; creating more added value; and maintenance of small-scale farming in all regions. To achieve these objectives the government supports the farmers. The two main support instruments used by the government are border protection measures to limit or exclude

competing imports, and budgetary payments (subsidies). The budgetary support includes market price support, special tax rules for agriculture, area payments, investment grants and grants for research and extension services. Market price support for most commodities, in the form of wholesale target prices, is provided. These target prices and most budgetary payments are negotiated on an annual July/June basis between the government and representatives of the two farmers' unions (the Norwegian Farmers and Smallholders Union and the Norwegian Farmers Union), resulting in an Agricultural Agreement. Despite the various support measures, the value of support payments has been decreasing in real terms.

As in most developed countries, farming has become highly mechanized and the number of farms has been declining, with production becoming concentrated on fewer farms. According to Statistics Norway, the number of farms was 96,000 in 1991 and had declined to 42,000 in 2015. Moreover, 2.3 percent fewer farms were registered in 2016 compared to 2015. The number of farms growing only crops decreased by 29 percent over the years 2006–2016 (Statistics Norway, 2013). However, according to the NIBIO (2016) farm account survey report, the average size of farm holdings in 2015 was 37 ha, which was an increase of 8 percent compared to 2014. Moreover, the area of rented farmland has been increasing over time, and the average area of rented land per farm reported in 2015 was 17 ha (NIBIO, 2016).

The structure of farms in Norway has been regulated by the Norwegian Concession Act. Norwegian farmers face extensive farm policies which have effects on their choices of the size and scale of the farm. For example, the Norwegian Agricultural Authority manages the quantities produced of milk, meats, vegetables, potatoes, fruits and berries (Knutsen, 2007). Limited access to land and capital restricts productivity changes, as does policy regulation in the form of quantitative restrictions on milk supply.

Norwegian agriculture 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 on output-related subsidies. If that happened, it would force a dramatic and painful shift toward a more competitive agriculture. Therefore, there is a case to be made to take urgent steps to improve the productivity and management of farming.

3. Approaches to measuring farm performance

There are two main benchmarking methods in the literature to measuring the performance of farms: a parametric (econometric) approach, such as a stochastic frontier analysis (SFA); and a non-parametric approach, such as data envelopment analysis (DEA). In both methods, the basis for performance measurement is the radial contraction/expansion connecting inefficient observed points representing individual firms with reference points on the efficient frontier (There are other approaches too, for instance, Bayesian stochastic frontier (SF) (Koop and Steel, 2001), semi-parametric (Simar and Wilson, 2007) and stochastic DEA (Huang and Li, 2001), but these are not commonly used in empirical studies).

Based on a sample of producers, both the two main approaches involve estimating a "best practice" frontier for a specific industry or sample of firms. Each approach has its pros and cons. For details, see Coelli *et al.* (2005), Parmeter and Kumbhakar (2014) and Kumbhakar *et al.* (2015). The treatment of measurement error is the critical distinction between parametric and non-parametric approaches. SFA models can accommodate stochastic noise, such as measurement errors due to weather, disease and pest infestation that are likely to be significant in farming. The DEA approach is sensitive to outliers since the measurement error is ignored (e.g. 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 CE scores and determinants of inefficiency.

Depending on the nature of the data set at hand, there are two classes of SFA models. If we have only one observation per farm, then a cross-sectional model has to be chosen to

estimate the performance of each individual farm. A data set that consists of different farms that are observed at different time periods is called a panel data set. A panel data set contains more information, and therefore allows us to separate unobserved heterogeneity (farm-specific effects) from inefficiency.

Since the introduction of the SFA model by Aigner et al. (1977) and Meeusen and Van den Broeck (1977), there has been considerable research to extend the basic model, creating a new subfield in econometrics. Different SFA models have been developed based on different assumptions about the temporal behavior of the inefficiency. Reviews of much of this research are provided by Kumbhakar and Lovell (2000), Coelli et al. (2005), Greene (2008) and Kumbhakar et al. (2015).

In addition to estimating CE for each crop farm, it is useful to learn about factors that affect cost inefficiency between and within farms (Lien et al., 2018). The first SFA models that dealt with modeling the impact of exogenous variables (z-variables) on the level of inefficiency between and within farms are those of Kumbhakar et al. (1991) and Reifschneider and Stevenson (1991). In these cross-sectional models, the variance of the inefficiency term was specified as a function of a set of exogenous variables (z-variables). Later, Wang (2002) introduced a further generalization in which both the mean and variance of the inefficiency are functions of exogenous variables. For detailed reviews see Parmeter and Kumbhakar (2014) and Lien et al. (2018).

Among panel data models, the inefficiency specification used by Battese and Coelli (1995), commonly known as BC95, is frequently used in the empirical analysis of performance studies (Parmeter and Kumbhakar, 2014). Using the BC95 model, a researcher not only estimates the efficiency score, but also can investigate determinants of firm inefficiency (exogenous variables) in a single-step procedure. It is also possible to estimate the determinants of inefficiency in two steps, but that method creates biased results (Wang and Schmidt, 2002). In the single-step procedure, the parameters of inefficiency and the determinants are estimated together via maximum likelihood.

The general BC95 model for our panel data in a cost function form can be specified as:

$$\ln C_{it} = \beta_0 + f(y_{it}, w_{it}; \beta) + u_{it}(z_{it}; \delta) + v_{it}, \tag{1}$$

where $\ln C_{it}$ is the logarithm of actual costs incurred by farm i in time t; $f(y_{it}, w_{it}; \beta)$, the chosen function form (e.g. Cobb-Douglas, Translog); y_{it}, a vector of outputs; w_{it}, the vector of input prices; and β, the vector of parameters to be estimated. The component v_{it} is a symmetric disturbance (error term) capturing the effects of noises that are beyond the control of the farmers. The error term has both positive and negative effects, and satisfies the classical assumptions, i.e., $v_{it}^{iid} \sim N(0, \sigma_v^2)$, $v_{it} \perp u_{it}$. Further, u_{it} is a one-sided non-negative term, accounting for inefficiency. In the BC95 model, u_{it} is obtained by truncating (at zero) the normal distribution, i.e., $u_{it} \sim N^+(\mu_{it}, \sigma_{u_{it}}^2)$ and $\mu_{it} = z_{it}\delta$, z_{it} is a vector that includes exogenous variables associated with variability in the efficiency score and δ is an unknown parameter to be estimated.

The CE is the ratio of the minimum cost of each farm ($\exp(f(y_{it}, w_{it}; \beta) + v_{it})$) to its actual cost ($\exp(f(y_{it}, w_{it}; \beta) + u_{it} + v_{it})$). i.e. CE = $\exp(-u_{it})$. CE has a value between 0 and 1, with 1 defined a cost-efficient farm. Since only the sum of two error terms ($\varepsilon_{it} = u_{it} + v_{it}$) can be observed, the farm's cost inefficiency index can be estimated using the conditional mean of the inefficiency term, as proposed by Jondrow et al. (1982), i.e. $E[u_{it}/v_{it} + u_{it}]$.

4. Empirical model specification
Consistent with the farm efficiency literature (e.g. Christensen and Greene, 1976), we estimated a transcendental logarithmic (translog) cost function incorporating Hicks-neutral technology change. We used panel data but, to simplify the notation, we have dropped the

subscripts i and t, where i would denote firm $i = 1, \ldots, n$ and t would denote time, $t = 1, \ldots, t$. Our specification of the cost function C, including the prices of inputs $(w_j)\, j = 1, \ldots, J$, outputs $(y_k)\, k = 1, \ldots, K$, and a local wage distribution index $(r_m)\, m = 1, \ldots, M$, is:

$$
\ln C = \beta_0 + \sum_{j=2}^{J} \propto_j \ln w_j + \sum_{k=1}^{K} \beta_k \ln y_k + \sum_{m=1}^{M} \emptyset_m \ln r_m + \delta_t t
$$

$$
+ \sum_{k=1}^{K} \sum_{j=1}^{J} \propto_{kj} \ln y_k \ln w_j + \frac{1}{2} \sum_{m=1}^{M} \sum_{m=1}^{M} \emptyset_{mm} \ln r_m \ln r_m
$$

$$
+ \frac{1}{2} \left[\sum_{k=1}^{K} \sum_{k=1}^{K} \beta_{kk} \ln y_k \ln y_k + \sum_{j=2}^{J} \sum_{k=2}^{J} \beta_{jj} \ln w_j \ln w_j + \delta_{tt} t^2 \right]
$$

$$
+ \sum_{k=1}^{K} \sum_{m=1}^{M} \beta_{km} \ln y_k \ln r_m + \sum_{j=2}^{J} \sum_{m=1}^{M} \propto_{jm} \ln w_j \ln r_m
$$

$$
+ \sum_{j=2}^{J} \propto_{jt} t \ln w_j + \sum_{k=1}^{K} \beta_{kt} t \ln y_k + \sum_{m=1}^{M} \emptyset_{mt} t \ln r_m + \varepsilon. \tag{2}
$$

The error terms ε splits into two components, i.e., $\varepsilon \equiv v_{it} + u_i$. As discussed in section 3 component u_i captures cost inefficiency with $u_{it} \sim N^+(\mu_{it}, \sigma^2_{u_{it}})$. v_{it} is the error term capturing random shocks and assumed to be symmetric and to satisfy the classical assumptions i.e., $v_{it}^{iid} \sim N(0, \sigma^2_v)$. All Greek letters are parameters to be estimated. The trend variable, t, is included to capture technology change and starts with $t = 1$ for 1991 and increases by one annually.

Economic theory requires imposition of price homogeneity and symmetry restrictions on the parameters. Symmetric restrictions require $\sum_{j=1}^{J} \propto_j = 1$, and $\sum_k \beta_{kk} = \sum_j \beta_{jj} = \sum_m \emptyset_{mm} = 0$. An easy way to impose price homogeneity is to divide the all inputs prices and total cost by an arbitrary chosen input price. Thus, in Equation (2) the left-hand side is re-defined as $\ln C = \ln (C)/(w_1)$, and all input prices are re-defined as $\ln w_j = \ln (w_j)/(w_1)$, i.e., we divided all input prices and the total cost by wages before estimating the translog cost function. Given the translog specification in (2), the farm-specific cost inefficiency and marginal effects of the exogenous variables are calculated following the procedures of Jondrow *et al.* (1982) and of Wang (2002), respectively.

As discussed above in Section 3, we included exogenous determinants of farm CE in our model. The choice of variables in the final model was based on two criteria. First, we considered data availability. Many variables that could affect crop management, such as skill, education level, soil type and slope or aspect of the farmland, were not available in our data set, so could not be included. Second, we considered the literature available on the subject, for example, Latruffe *et al.* (2004), Bozoğlu, and Ceyhan (2007) and Lien *et al.* (2018). As a result, we chose the following variables:

(1) Crop rotation (z_1) – reflecting the impact of rotation system on crop and forage production, measured as the ratio of non-cereal crops such as root and legume crops to the total cropped area. We expected the farm managers' decisions to rotate the type of crop grown on the land would make a positive contribution to the performance of their farms. Our expectation is in line with other research findings that crop rotation reduces agriculture's dependence on external inputs through internal nutrient recycling, maintenance of the long-term productivity of the land (Gebremedhin and Schwab, 1998). Crop rotation can improve the fertility of the soil

(Reckling *et al.*, 2015) and can increase yields to a higher degree than pesticide intensity and tillage use (Deike *et al.*, 2008).

(2) Land tenure (z_2) – the proportion of the total farmland that is rented. Farm managers' decisions to rent land or not depend on the price of land and other factors. We expected a positive contribution to this variable because we hypothesize that well-performing farms more commonly rent extra land. Deininger and Byerlee (2011) support our hypothesis and stressed that land rental markets can help transfers of land from producers with low levels of productivity and low comparative advantage in agriculture to more efficient farmers.

(3) Off-farm activity (z_3) – the ratio of time of owner plus partner allocated to off-farm activity to the total time assigned to the farm. We expected a positive contribution from this variable on the basis that off-farm experience and income are likely to promote better farm management. Our hypothesis is supported by the literature. Off-farm income has been found to relax cash constraints and to allow farmers to spend significantly more on improved farming technologies (e.g. Pfeiffer *et al.*, 2009; Stampini and Davis, 2009).

(4) Government support (z_4) – the ratio of government assistance to the total agricultural income. We hypothesized a positive contribution from this variable because government support can motivate farm managers to invest in new technology and may facilitate such investment by easing cash flow constraints. In line with our hypothesis, there is evidence that government support helps to promote better use of economic resources (e.g. Ferjani, 2008; Kumbhakar and Lien, 2010).

5. Data

Our 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 kept by the Norwegian Agricultural Agency. The data include production and economic data collected annually by NIBIO from about 1,000 farms in all regions of Norway. The number of participants varies from year to year. Approximately 10 percent of the surveyed 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 have participated in more than 20 years, and others have started participating for the first time. To accommodate panel features in estimation, we included only those farms for which at least three consecutive years of data are available.

To assess the efficiency and productivity growth, we needed to be sure that farmers under consideration are comparable. To obtain a homogeneous group, we choose only farms in the two main cropping areas where 98 percent of the cultivated land was located. Figure 1 shows that out of the 286,000 ha of land cultivated for grain and forage production in 2012, 81 percent was located in the Eastern Norway and 17 percent in Central Norway.

The set of data used in this study is a farm-level unbalanced panel data with 3,885 observations from 455 farms specialized in the production of grain and forage crops during the period 1991–2013.

5.1 Variables in the model

The outputs in Equation (2) are grain production in kg, adjusted for quality, i.e., feed units (FU) (y_1), forage production in FU (y_2) and value of other crop outputs in Norwegian kroner (NOK) (y_3). Grain yield is an aggregate of the four main crops: barley, wheat, oats and oilseeds. FU is a measure of the physical output adjusted for differences in the quality of outputs.
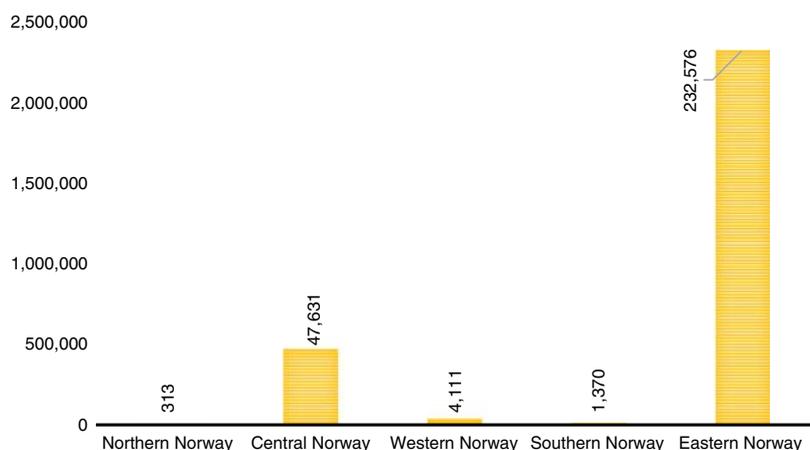
Figure 1.
Cropland in hectare
for five regions
of Norway
computed data from
Statistics Norway

1 FU is defined as 1 kg of grain with 15 percent water content. Thus, the output measure is a quality-adjusted yield of all crops in kilograms per year.

The input prices (w_j) in the cost function in Equation (2) are specified as follows: land price is based on market price for land in terms of rents paid for land at the farm level. The price of labor is the wage for hired labor. We computed the implicit prices (opportunity costs) of owned land and family labor based on data for farm-level rents and wages provided by NIBIO. We included a local wage distribution index (r) to control for regional variation in wages in our analysis. These data were provided by the Norwegian Tax Administration. The prices of materials and capital costs were constructed as Laspeyres indices based on figures provided by NIBIO. Descriptive statistics of the data are shown in Table I.

6. Estimation results and discussion
6.1 Estimation procedures and hypothesis tests
The cost function was estimated using STATA® version 14. The trend variable was normalized to be zero in the year 2013. We estimated the model for the whole sample.

Variables	Label	Unit	Eastern region	Central region	Both regions
TC	Total cost	NOK	46,016 (30,813)	36,761 (25,183)	43,624 (29,736)
y_1	Grain output	1,000 FU	68.44 (69.89)	38.50 (38.61)	60.70 (64.64)
y_2	Forage output	1,000 FU	72.96 (53.08)	87.18 (55.87)	76.63 (54.17)
y_3	Other outputs	1,000 NOK	9.52 (7.98)	8.73 (6.04)	9.32 (7.54)
w_1	Rent	NOK /hectare	2,572.60 (159.29)	1,790.60 (122.87)	2,370.50 (154.55)
w_2	Wage	NOK/hours	141.34 (31.86)	153.56 (30.35)	144.50 (31.93)
w_3	Materials price	index	66.38 (15.42)	69.51 (15.83)	67.19 (15.59)
w_4	Capita price	index	80.19 (10.31)	82.33 (10.35)	80.74 (10.36)
r	Region index	index	0.14 (0.01)	0.15 (0.01)	0.14 (0.01)
Z_1	Crop rotation	ratio	0.22 (0.07)	0.09 (0.02)	0.20 (0.07)
Z_2	Land tenure	ratio	0.27 (0.25)	0.24 (0.22)	0.26 (0.24)
Z_3	Off-farm activity	ratio	0.04 (0.09)	0.04 (0.09)	0.04 (0.10)
Z_4	Gov. support	ratio	0.26 (0.11)	0.32 (0.10)	0.28 (0.11)
Year	Trend (t)		(1 = year 1991)		
n	Sample size		2,881	1,004	3,885

Note: [a]Standard deviations in parentheses

Table I.
Descriptive statistics
(mean values[a])
for crop production
in eastern and
central regions

The estimated parameters for the translog frontier models are listed in Table VI. Various specification tests were conducted to obtain the best model and functional form for the data under analysis. A series of hypotheses about the nature of the frontier model and the consistency of the cost function with its properties were tested using Likelihood Ratios. The null hypothesis of an OLS specification was rejected at the 0.01 percent significance level. Before estimating the cost function, the skewness of the data was tested (Schmidt and Lin, 1984). The test of skewness returned a p-value of less than 0.001 showing that the null hypothesis of no skewness was confidently rejected. Therefore, we found support for a right-skewed error distribution, and hence for the SF specification of the model. We also tested the characteristics of the technology with the result that a Cobb-Douglas technology specification was rejected (see Table II). Thus, we estimated a cost function using a translog function specification.

6.2 Cost efficiency scores

Estimates of CE scores of the farms are presented in Table III. The results show that, at the means, the minimum costs are about 78 and 81 percent of the actual costs for farms in the central and eastern regions, respectively. The implication is that average actual cost per farm could be reduced by 19 to 22 percent. These results are broadly in line with other studies. Kumbhakar *et al.* (2014) estimated six different models for the Norwegian grain farming and reported that the mean technical efficiency varied from 0.64 to 0.91. Odeck (2007) found a mean technical efficiency for Norwegian grain production of 0.70 for SFA and 0.75 for DEA. Osborne and Trueblood (2006) estimated 70–86 percent inefficiency for Russian crop production. Our estimate is greater than the estimate by Onyenweaku and Okoye (2007) of an average CE of 59 percent for cocoyam farmers in Anabra state, Nigeria.

Table III also shows the distribution of the farms in the sample according to their CE. Thus, 1 percent of the farms are only 60 percent cost efficient while 10 percent of the sample farms are 71 percent cost efficient. We also checked for differences in the efficiency scores between the eastern and central regions using a pairwise comparison of the means test.

Restrictions	Parametric restrictions	Wald test statistics	p-value
CD technology	H_0: all interaction terms are zero	941.57	0.00
Normality test/Test return of Skewness			
Schmidt and Lin (1984)		11,850.97	0.00
LR test for random effects		39,235.22	0.00

Table II.
Properties of grain and forage production technology

Percentile	Eastern region	Central region	Both regions
1	0.61	0.59	0.60
5	0.69	0.67	0.68
10	0.72	0.70	0.71
25	0.76	0.74	0.76
Mean	0.81	0.78	0.80
75	0.85	0.82	0.84
90	0.90	0.87	0.89
95	0.92	0.90	0.91
99	0.95	0.93	0.95
SD	0.07	0.06	0.07
Observations	2,881	1,004	3,885

Table III.
Cost efficiency scores for both regions and the pooled data

We found the difference to be statically significant (see Table IV). Our results also showed that the average inefficiency level was higher, on average, in the years 2000–2013 compared to the years 1991–2000 (see Table V).

6.3 Elasticities and determinants of cost inefficiency
We checked the robustness of our results by separate estimates for the two regions and different periods. The regression results in Table VII show that all the first-order terms, except materials price (w_3) and the regional index (r) are significant. The models were found to exhibit positive and highly significant first-order parameters, fulfilling the monotonicity condition as expected for a well-behaved cost function. The elasticities of costs of grain, forage, and other outputs were 0.25, 0.20 and 0.33, respectively. This means, for instance, that if grain output increases by 1 percent, costs increase by an estimated 0.25 percent, ceteris paribus. The elasticity of cost of land was 0.02 and significant at the 5 percent level. If the price of land rose by 1 percent, costs will increase by an estimated 0.02 percent, ceteris paribus. The elasticity of cost of material inputs was 0.15, but was not statistically significant. The coefficient for the price of capital (fixed input) (0.83) is the largest among other partial elasticities and statistically significant ($p < 0.001$). This result implies that crop production in Norway is capital intensive in that the percentage change in the capital price has a larger influence on the costs of crop production than the costs of other inputs. Thus, farm managers who want to improve the crop farming needs to give priority to the wise use of these costs.

The lower part of Table VI presents the coefficients estimated for the determinants included in the inefficiency effects model. The results indicate that agronomic and socioeconomic factors influence CE. Farm management practice, specifically crop rotation, was found to make a positive and significant contribution to reducing the cost of production. This result is in accord with our expectation, suggesting that crop rotation decreases the cost of production, probably via a reduction in the use of variable inputs such as fertilizer and/or by an increase in output for given amounts of input. Thus, our hypothesis is sustained. Crop rotation can improve the fertility of the soil, interrupt the life cycles of insect pests and weeds, and can help control soil-borne diseases (Reckling *et al.*, 2015; Vereijken, 1997; Melander *et al.*, 2005). Deike *et al.* (2008) claimed that crop rotations increase yields to a higher degree than pesticide intensity and tillage use.

An increase in off-farm activity was found to be associated with a significant reduction in cost inefficiency (increase in CE) among the farm households. While this result might seem to be counterintuitive, possible reasons are that off-farm activities broaden farmers' experience, leading to improved farm management, or off-farm income may relax cash

Group	Obs.	Mean	SD	t-value	p-value
Central region	1,004	0.783	0.068	−11.86	0.000
Eastern region	2,881	0.813	0.068		

Table IV.
Pairwise comparison of means of cost efficiency between eastern and central regions

Group	Obs.	Mean	SD	t-value	p-value
Central region	1,738	0.903	0.040	70.61	0.000
Eastern region	2,147	0.746	0.085		

Table V.
Pairwise comparison of means of cost efficiency between 1991–2000 and 2000–2013

Variable first order (elasticities)[a]		y_1	y_2	y_3	w_2	w_3	w_4	r	Year
Grain(y_1)	0.25*** (0.01)	0.09*** (0.01)							
Forage(y_2)	0.20*** (0.01)	−0.01 (0.01)	0.07*** (0.01)						
Other(y_3)	0.33*** (0.01)	−0.06*** (0.00)	0.00 (0.01)	0.09** (0.01)					
Rent (w_2)	0.02* (0.01)	0.03*** (0.01)	0.01 (0.01)	0.01 (0.01)	0.00 (0.01)				
Material(w_3)	0.15 (0.18)	0.21** (0.10)	−0.17 (0.11)	−0.13 (0.13)	−0.28 (0.15)	8.40* (4.47)			
Capital(w_4)	0.83*** (0.19)	−0.28** (0.11)	0.04 (0.12)	0.10 (0.14)	0.32 (0.17)	−7.02 (4.70)	5.39 (5.01)		
Region index (r)	0.13 (0.11)	0.12** (0.00)	−0.01 (0.06)	−0.10 (0.05)	−0.21** (0.00)	−0.35 (1.24)	0.71 (1.34)	0.97* (0.45)	
Year	0.02 (0.02)	−0.01*** (0.00)	−0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	−0.12* (0.06)	0.10 (0.06)	−0.00 (0.02)	0.01**(0.00)
Exogenous inefficiency determinates[b]									
Crop rotation		0.31***	(0.06)						
Land tenure		0.10***	(0.02)						
Off-farm activity		0.39***	(0.04)						
Government support		0.65***	(0.07)						
Log. L. = 122***		(0.00)			$\gamma = \sigma_u^2/\sigma_u^2 + \sigma_v^2 = 0.21$	AIC = −139	n = 3,885	BIC = 186	

Notes: [a]Elasticities (first order parameters); [b]positive efficiency score parameter estimates show that the variable has a positive effect on cost efficiency. Standard errors in parentheses. *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

Table VI.
Estimates of parameters in the Translog cost function and inefficiency determinants

constraints and allow farmers to spend significantly more on improving farming technologies (Pfeiffer *et al.*, 2009; Stampini and Davis, 2009). However, our finding is not consistent with a study of Norwegian grain farms from 1991–2005 which reported that there was no systematic difference in technical efficiency between part-time and full-time farmers (Lien *et al.*, 2010). Perhaps the different findings might be explained by our use of a longer data series, including more recent years, than that available to Lien *et al.*

The results show that government support has a positive and significant effect on the efficiency of crop production. Our finding is in line with earlier studies indicating that the subsidies help the technological development of beneficiary farms. Government support may give incentives for technological innovation that increase efficiency. In line with our results, some have claimed that better use of economic resources is achieved (Ferjani, 2008; Kumbhakar and Lien, 2010). On the other hand, other studies (e.g. Giannakas *et al.*, 2001) have shown that government payments reduce producer incentives to generate the highest possible income from farming. Neoclassical economists believe that government support distorts the allocation of resources, compared to market equilibrium and leads to higher costs of production. They argue that, in the longer run, subsidies are capitalized into higher land prices, making it harder for potential progressive new entrants to start farming. It seems that further study is needed on the specific influence of various government supports on the efficiency of resource use.

Our results indicate that land tenure also plays an important role in explaining CE differentials among crop producers. In particular, the greater the proportion of the leased land, the higher is the CE. One possible reason might be that productive and efficient farms are spreading the costs of fixed factors such as tractors over larger areas by renting more land. Deininger and Jin (2009) found that land rental markets can help to move toward a more economic distribution of operational farm sizes through transfers of land from producers with low levels of productivity and low comparative advantage in agriculture to more efficient farmers. Following such transfers, agricultural output and incomes will be higher for those renting (Deininger and Byerlee, 2011).

Although, as noted, crop rotation was found to have positively and significantly contributed to reducing the cost of production in both regions, the magnitude of crop rotation contribution in the central region at 0.96 is higher than the 0.29 contribution in the eastern region (Table VII). Moreover, the importance of crop rotation in the latest

Elasticities	Eastern (1991–2013)	Central (1991–2013)	For the year (1991–2000)	For the year (2001–2013)	Both regions (1991–2013)
Grain(y_1)	0.26*** (0.01)	0.18*** (0.01)	0.30** (0.01)	0.23*** (0.01)	0.25*** (0.01)
Forage(y_2)	0.19*** (0.01)	0.21*** (0.02)	0.21*** (0.02)	0.15*** (0.01)	0.20*** (0.01)
Other(y_3)	0.31*** (0.01)	0.44*** (0.01)	0.35*** (0.02)	0.36*** (0.02)	0.33*** (0.01)
Rent (w_2)	0.03*** (0.01)	0.03*** (0.02)	0.03*** (0.01)	0.07*** (0.01)	0.02*** (0.01)
Material (w_3)	0.09 (0.22)	0.47* (0.27)	0.01 (0.42)	0.55 (0.35)	0.15 (0.18)
Capital (w_4)	0.85*** (0.23)	0.58** (0.28)	0.97** (0.42)	0.44 (0.35)	0.83*** (0.19)
Region index (r)	0.01 (0.91)	0.28 (0.52)	−0.02 (0.16)	0.31** (0.16)	0.13 (0.11)
Exogenous inefficiency determinates					
Crop rotation	0.29*** (0.06)	0.96*** (0.35)	0.19** (0.07)	0.97*** (0.14)	0.31*** (0.06)
Land tenure	0.09*** (0.04)	0.11*** (0.03)	0.05 (0.03)	0.16*** (0.04)	0.10*** (0.02)
Off-farm activity	0.37*** (0.02)	0.49*** (0.08)	0.46*** (0.02)	0.43*** (0.02)	0.39*** (0.04)
Government support	0.62*** (0.08)	0.94*** (0.13)	0.32** (0.11)	0.72*** (0.09)	0.65*** (0.07)
Mean cost efficiency	0.81	0.71	0.90	0.75	0.83

Notes: [a]The second-order parameters in the TL are dropped, to save space, but are available from the authors on request. Standard errors in parentheses. *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

Table VII.
Estimates of parameters and determinants of efficiency by region and year[a]

farming period, (2001–2013), was higher than in the previous decade (1991–2000). We found no significant difference between regions, but the contribution of land tenure increased over time. Perhaps scale economies increased over time with the spread of larger and more powerful farm machinery. We found no statistical difference in the positive contribution of off-farm activities between regions or over time. However, the contribution of government support to CE was higher in the central region (0.94) and increased for the years 2001–2013 (0.72). The reasons for these differences are unclear at present.

7. Conclusion and implication of the study

The aim of this study was to investigate whether farm management and socioeconomic factors contributed to improving the performance of crop farms in Norway. We found that farm resources were widely used sub-optimally, i.e., 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.

The findings revealed that agronomic and socioeconomic factors affect the cost-efficient level of crop production. A good agronomic practice – crop rotation – was found to have made a positive and statically significant contribution to reducing cost. Moreover, the magnitude of crop rotation contribution was higher in the central region and increased over time in all regions. Off-farm activity positively and significantly enhanced the performance of the farms, and farmers renting land are more cost-efficient than those not doing so. Our analysis also confirms that government support has an association with improved CE, probably by relaxing farmers' financial and liquidity constraints, enabling them to purchase new technologies that can enhance farm crop output. We also found that farmers renting land is more cost-efficient than those not doing so.

7.1 Implications of the study

One implication for farmers (and their advisers) is that many of them are less efficient than the estimated benchmark (best performing farms). Thus, those lagging behind the best performing farms need to look at the way they are operating and to seek out ways to save costs or increase crop production. Perhaps there are things for lagging farmers to learn from their more productive farming neighbors. For instance, those farmers not practicing crop rotation might be well advised to try that practice.

More cost-efficient farms likely to be financially sustainable, and also that more cost-efficient farms will contribute to the goal of food self-sufficiency. Thus, policymakers need to help farmers improve their efficiency. This can be done by facilitating the distribution and sharing of information on good farm management. Since it appears that farmers' management is improved with off-farm experience and/or income, it suggests a need for more focus on the benefits of off-farm work. Policies that promote the development of non-farm businesses and other employment opportunities in rural areas are therefore important to enable more farm people to get local jobs. Since subsidies have a positive effect on efficiency, policymakers should maintain or extend subsidies that help farmers to invest and innovate. Most Norwegian farms are small and several policy measures are in place that holds back structural change, making it hard for operators to reap the scale economies we expect to exist in mechanized crop farming. Policies that limit the transfer of farmland by sale might be reconsidered if improving CE is considered more important than perpetuating a traditional farming culture. Policymakers might also usefully seek and implement measures to facilitate successful farmers sharing their experience with others.

For both taxpayers and consumers, one implication is that the contributions they pay that go to subsidize farmers appear to bring some benefits in terms of more efficient production that, in turn, increase the supply of some foods so possibly making food prices more affordable.

Researchers need to seek out data to explore further the causes of differences in efficiency between farms in order to better identify ways of closing the gaps. Our results show that there is a need to gather more data to be able to identify more farming practices, besides crop rotation, that lead to more efficient production. Similarly, more studies are needed to find out what the farmers in the central region do well so that successful practices might be extended farmer in the eastern region.

It appears that the structure of crop farming in Norway, with a preponderance of relatively small farms, is likely to be having an adverse effect on efficiency. That effect may be partially overcome via a healthy rental market. It may well be useful to investigate the operation of this market to see whether any impediments to land renting exist that might be removed and whether there are issues about the security of tenure that need to be addressed.

Farmers are getting different types of support from the government and our study does not account for the different effects of different kinds of subsidy on CE. Different subsidies might have different effects on farm performance. To get more informative and useful results, it would be necessary to repeat the analysis with less aggregated data on subsidy payments.

References

Aigner, D., Lovell, C.K. and Schmidt, P. (1977), "Formulation and estimation of stochastic frontier production function models", *Journal of Econometrics*, Vol. 6 No. 1, pp. 21-37.

Barnes, A., Moran, D. and Topp, K. (2009), "The scope for regulatory incentives to encourage increased efficiency of input use by farmers", *Journal of Environmental Management*, Vol. 90 No. 2, pp. 808-814.

Battese, G.E. and Coelli, T.J. (1995), "A model for technical inefficiency effects in a stochastic frontier production function for panel data", *Empirical Economics*, Vol. 20 No. 1, pp. 325-332.

Bozoğlu, M. and Ceyhan, V. (2007), "Measuring the technical efficiency and exploring the inefficiency determinants of vegetable farms in Samsun province, Turkey", *Agricultural Systems*, Vol. 94 No. 3, pp. 649-656.

Christensen, L.R. and Greene, W.H. (1976), "Economies of scale in the US electric power generation", *Journal of Political Economy*, Vol. 84 No. 4, pp. 655-676.

Coelli, T.J., Rao, D.S.P., O'Donnell, C.J. and Battese, G.E. (2005), *An Introduction to Efficiency and Productivity Analysis*, Springer Science & Business Media, New York, NY.

Curtiss, J. (2000), "Technical efficiency and competitiveness of the Czech agricultural sector in late transition – the case of crop production", *Proceedings KATO Symposium*, Berlin, November 2-4.

Deike, S., Pallutt, B., Melander, B., Strassemeyer, J. and Christen, O. (2008), "Long-term productivity and environmental effects of arable farming as affected by crop rotation, soil tillage intensity, and strategy of pesticide use: a case-study of two long-term field experiments in Germany and Denmark", *European Journal of Agronomy*, Vol. 29 No. 4, pp. 191-199.

Deininger, K. and Byerlee, D. (2011), *Rising Global Interest in Farmland*, The World Bank, Washington, DC.

Deininger, K. and Jin, S. (2009), "Securing property rights in transition: lessons from the implementation of China's rural land contracting law", *Journal of Economic Behavior & Organization*, Vol. 70 No. 1, pp. 22-38.

Ferjani, A. (2008), "The relationship between direct payments and efficiency on Swiss farms", *Agricultural Economics Review*, Vol. 9 No. 1, pp. 93-102.

Flaten, O., Lien, G., Koesling, M. and Løes, A.-K. (2010), "Norwegian farmers ceasing certified organic production: characteristics and reasons", *Journal of Environmental Management*, Vol. 91 No. 12, pp. 2717-2726.

Gebremedhin, B. and Schwab, G. (1998), "The economic importance of crop rotation systems: evidence from the literature", Staff Paper 98-13, Michigan State University, Department of Agricultural Economics, East Lansing, MI.

Giannakas, K., Schoney, R. and Tzouvelekas, V. (2001), "Technical efficiency, technological change and output growth of wheat farms in Saskatchewan", *Canadian Journal of Agricultural Economics/ Revue Canadienne d'agroeconomie*, Vol. 49 No. 2, pp. 135-152.

Greene, W.H. (2008), "The econometric approach to efficiency analysis", *The Measurement of Productive Efficiency and Productivity Growth*, Vol. 1 No. 2, pp. 192-250.

Huang, Z. and Li, S.X. (2001), "Stochastic DEA models with different types of input-output disturbances", *Journal of Productivity Analysis*, Vol. 15 No. 2, pp. 95-113.

Jondrow, J., Lovell, C.A.K., Materov, I.S. and Schmidt, P. (1982), "On the estimation of technical inefficiency in stochastic frontier production function model", *Journal of Econometrics*, Vol. 19 No. 2, pp. 233-238.

Knutsen, H. (2007), *Norwegian Agriculture: Status and Trends 2007*, Norwegian Institute of Bioeconomy Research, Oslo.

Koesling, M., Flaten, O. and Lien, G. (2008), "Factors influencing the conversion to organic farming in Norway", *International Journal of Agricultural Resources, Governance, and Ecology*, Vol. 7 No. 1, pp. 78-95.

Koop, G. and Steel, M.F. (2001), "Bayesian analysis of stochastic frontier models", in Badi, H. and Baltagi, A., Gutierrez, L. (Eds), *Companion to Theoretical Econometrics*, Blackwell Publishing Ltd, Oxford, pp. 520-573.

Kumbhakar, S.C. and Lien, G. (2010), "Impacts of subsidies on farm productivity and efficiency", in Ball, E., Fanfani, R. and Gutierrez, L. (Eds), *The Economic Impact of Public Support to Agriculture: An International Perspective*, Springer, New York, NY, ch. 6, pp. 109-124.

Kumbhakar, S.C. and Lovell, C.K. (2000), *Stochastic Frontier Analysis*, Cambridge University Press, New York, NY.

Kumbhakar, S.C., Ghosh, S. and McGuckin, J.T. (1991), "A generalized production frontier approach for estimating determinants of inefficiency in US dairy farms", *Journal of Business & Economic Statistics*, Vol. 9 No. 3, pp. 279-286.

Kumbhakar, S.C., Lien, G. and Hardaker, J.B. (2014), "Technical efficiency in competing for panel data models: a study of Norwegian grain farming", *Journal of Productivity Analysis*, Vol. 41 No. 2, pp. 321-337.

Kumbhakar, S.C., Wang, H.-J. and Horncastle, A. (2015), *A Practitioner's Guide to Stochastic Frontier Analysis Using Stata*, Cambridge University Press, New York, NY.

Latruffe, L., Balcombe, K., Davidova, S. and Zawalinska, K. (2004), "Determinants of technical efficiency of crop and livestock farms in Poland", *Applied Economics*, Vol. 36 No. 12, pp. 1255-1263.

Lien, G., Kumbhakar, S.C. and Alem, H. (2018), "Endogeneity, heterogeneity, and determinants of inefficiency in Norwegian crop-producing farms", *International Journal of Production Economics*, Vol. 201 No. 3, pp. 53-61.

Lien, G., Kumbhakar, S.C. and Hardaker, J.B. (2010), "Determinants of off-farm work and its effects on farm performance: the case of Norwegian grain farmers", *Agricultural Economics*, Vol. 41 No. 6, pp. 577-586.

Meeusen, W. and Van den Broeck, J. (1977), "Efficiency estimation from Cobb-Douglas production functions with composed error", *International Economic Review*, Vol. 18 No. 2, pp. 435-444.

Melander, B., Rasmussen, I.A. and Bàrberi, P. (2005), "Integrating physical and cultural methods of weed control examples from European research", *Weed Science*, Vol. 53 No. 3, pp. 369-381.

NIBIO (2016), *Resultatkontroll for gjennomføringen av landbrukspolitikken: Budsjettnemda for jordbruket*, Norwegian Institute of Bioeconomy Research, Oslo (In Norwegian).

Odeck, J. (2007), "Measuring technical efficiency and productivity growth: a comparison of SFA and DEA on Norwegian grain production data", *Applied Economics*, Vol. 39 No. 20, pp. 2617-2630.

Onyenweaku, C.E. and Okoye, B.C. (2007), "Technical efficiency of small-holder cocoyam farmers in Anambra State, Nigeria: a translog stochastic frontier production function approach", *International Journal of Agriculture and Rural Development*, Vol. 9 No. 1, pp. 1-6.

Osborne, S. and Trueblood, M.A. (2006), "An examination of economic efficiency of Russian crop production in the reform period", *Agricultural Economics*, Vol. 34 No. 1, pp. 25-38.

Parmeter, C.F. and Kumbhakar, S.C. (2014), "Efficiency analysis: a primer on recent advances", *Foundations and Trends in Econometrics*, Vol. 37 No. 3, pp. 191-385.

Pfeiffer, L., López-Feldman, A. and Taylor, J.E. (2009), "Is off-farm income reforming the farm? Evidence from Mexico", *Agricultural Economics*, Vol. 40 No. 2, pp. 125-138.

Reckling, M., Hecker, J.-M., Bergkvist, G., Watson, C.A., Zander, P., Schläfke, N. and Maire, J. (2015), "A cropping system assessment framework – evaluating effects of introducing legumes into crop rotations", *European Journal of Agronomy*, Vol. 76 No. 1, pp. 186-197.

Reifschneider, D. and Stevenson, R. (1991), "Systematic departures from the frontier: a framework for the analysis of firm inefficiency", *International Economic Review*, Vol. 32 No. 3, pp. 715-723.

Schmidt, P. and Lin, T.-F. (1984), "Simple tests of alternative specifications in stochastic frontier models", *Journal of Econometrics*, Vol. 24 No. 3, pp. 349-361.

Simar, L. and Wilson, P.W. (2007), "Estimation and inference in two-stage, semi-parametric models of production processes", *Journal of econometrics*, Vol. 136 No. 1, pp. 31-64.

Singh, S.K., Burgess, T.F. and Heap, J. (2016), "Managing performance and productivity for organizational competitiveness", *International Journal of Productivity and Performance Management*, Vol. 65 No. 6 pp. 744-872.

Sipiläinen, T., Kumbhakar, S.C. and Lien, G. (2013), "The performance of dairy farms in Finland and Norway for 1991-2008", *European Review of Agricultural Economics*, Vol. 41 No. 1, pp. 63-86.

Smith, N., Smith, V. and Verner, M. (2006), "Do women in top management affect firm performance? A panel study of 2,500 Danish firms", *International Journal of Productivity and Performance Management*, Vol. 55 No. 7, pp. 569-593.

Stampini, M. and Davis, B. (2009), "Does nonagricultural labor relax farmers' credit constraints? Evidence from longitudinal data for Vietnam", *Agricultural Economics*, Vol. 40 No. 2, pp. 177-188.

Statistics Norway (2013), "Agriculture, forestry, hunting, and fishing", available at: www.ssb.no/en/jord-skog-jakt-og-fiskeri (accessed November 25, 2017).

Steinshamn, H., Nesheim, L. and Bakken, A.K. (2016), "Grassland production in Norway: the multiple roles of grassland in the European bioeconomy", *Proceedings of the 26th General Meeting of the European Grassland Federation, Trondheim*, pp. 15-25.

United Nations (2017), "World population prospects: the 2017 revision, key findings and advance tables", Working Paper No. ESA/P/WP/248, Department of Economic and Social Affairs, Population Division, New York, NY.

Vereijken, P. (1997), "A methodical way of prototyping Integrated and Ecological Arable Farming Systems (I/EAFS) in interaction with pilot farms", *European Journal of Agronomy*, Vol. 7 No. 1, pp. 235-250.

Wang, H.J. (2002), "Heteroscedasticity and non-monotonic efficiency effects of a stochastic frontier model", *Journal of Productivity Analysis*, Vol. 18 No. 3, pp. 241-253.

Wang, H.J. and Schmidt, P. (2002), "One-step and two-step estimation of the effects of exogenous variables on technical efficiency levels", *Journal of Productivity Analysis*, Vol. 18 No 1, pp. 129-144.

Zhu, X. and Lansink, A.O. (2008), "Technical efficiency of the crop farms under the various CAP reforms: empirical studies for Germany, the Netherlands and Sweden", available at: http://ageconsearch.umn.edu/bitstream/6589/2/cp08zh01.pdf (accessed May 21, 2017).

Further reading

Almas, R. and Brobakk, J. (2012), "Norwegian dairy industry: a case of super-regulated co-operativism. Rethinking agricultural policy regimes: food security, climate change and the future resilience of global agriculture", *Research in Rural Sociology and Development*, Vol. 18 No. 1, pp. 169-189.

Chang, H.-H. and Mishra, A. (2008), "The impact of off-farm labor supplies on food expenditures of the farm household", *Food Policy*, Vol. 33 No. 6, pp. 657-664.

Diewert, W.E. (1998), "Index number issues in the consumer price index", *The Journal of Economic Perspectives*, Vol. 12 No. 1, pp. 47-58.

Dillon, J.L. (1980), "The definition of farm management", *Journal of Agricultural Economics*, Vol. 31 No. 2, pp. 257-258.

Flaten, O. (2002), "Alternative rates of structural change in Norwegian dairy farming: impacts on costs of production and rural employment", *Journal of Rural Studies*, Vol. 18 No. 4, pp. 429-441.

Godfray, H.C.J., Beddington, J.R., Crute, I.R., Haddad, L., Lawrence, D., Muir, J.F. and Toulmin, C. (2010), "Food security: the challenge of feeding 9 billion people", *Science*, Vol. 327 No. 5967, pp. 812-818.

Mishra, A.K. and Sandretto, C.L. (2002), "Stability of farm income and the role of nonfarm income in US agriculture", *Review of Agricultural Economics*, Vol. 24 No. 1, pp. 208-221.

Sipiläinen, T., Kumbhakar, S.C. and Lien, G. (2014), "The performance of dairy farms in Finland and Norway for 1991-2008", *European Review of Agricultural Economics*, Vol. 41 No. 1, pp. 63-86.

Norwegian Agriculture Agency (2011/2012), "Agriculture and food policy", White Paper No. 9, available at: www.regjeringen.no/en/id4/ (accessed June 20, 2015).

About the authors

Habtamu Alem (PhD in Economics) is Researcher in the Division for Food Production and Society, Department of Business Economics and Management, Norwegian Institute of Bioeconomy Research (NIBIO), Norway. Habtamu Alem is the corresponding author and can be contacted at: habtamu.alem@nibio.no

Gudbrand Lien is Professor of Economics at Faculty of Economics and Organization Science, Inland Norway University of Applied Sciences , Lillehammer, Norway and he is also working as Senior Researcher in NIBIO, Norway.

J. Brian Hardaker is Emeritus Professor of Agricultural Economics at the University of New England, Armidale, NSW, Australia.