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How can dairy farmers become more revenue efficient? Efficiency drivers on dairy farms

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ABSTRACT

The aim of this article is to identify a set of efficiency drivers which can explain differences in revenue efficiency between dairy farms. To explore farm efficiency, we apply stochastic frontier analysis on a balanced panel of 212 Norwegian dairy farms. The results show that on average the farms can increase the revenue from dairy by 28 percentage points. The article identifies important drivers of revenue efficiency which the farmer can change in the short or medium run to increase efficiency. Automatic milking systems, high beef production per cow, low age at first calving and organic farming are among drivers which can explain differences in revenue efficiency between farms. Our findings have implications for both management scholars, practitioners and policy makers.

KEYWORDS: farm efficiency; stochastic frontier function; farm management; panel data; automatic milking systems; beef production

Introduction

Efficient dairy farms are important not only to the farmer, but also to the society as such, because farms contribute to work opportunities, food security, rural viability and biodiversity in the countryside. Comparing farming literature shows that technical inefficiency is present in dairy farming (Zhu *et al.*, 2012; Manevska-Tasevska *et al.*, 2013; Areal *et al.*, 2012; Barnes *et al.* 2011; Lawson *et al.* 2004; Heshmati and Kumbhakar 1994). The average efficiency and consequently profits can increase significantly if production is conducted with more intense use of inputs, or with combinations of inputs and outputs closer to optimum (see e.g. Lawson *et al.*, 2004; Heshmati and Kumbhakar, 1994). Less is known about what the causes of inefficiency at the farm level are. Profitable and efficient farming can be said to depend on the so-called managerial factor (Rougoor *et al.*, 1998) or the farmers' human and social capital (Hansen and Greve, 2015). Differences in operational and managerial practices of the farmer are particularly interesting because these actions are possible to change over a relatively short run. Consequently, identifying how differences in the operational work contribute to increased farm level efficiency is interesting, because it helps us understand how the inefficient farms can improve.

Norwegian dairy farmers participate in a program to monitor their economic performance, with Tine cooperative dairy company keeping a database of biological and financial data that indicates substantial differences exist among farmers. The data are collected for farm management, advisory and research purposes. The present research accessed Tine's database to see what may explain differences in farmers' revenue efficiency. The remainder of the paper is structured as follows: First, relevant literature data and methods are presented, then follows presentation of results, discussion and conclusion.

Literature review

The relationships between economic consequences and managerial practices on dairy farms have attracted attention in previous literature. Danish dairy farmers reporting higher frequencies of lameness, ketosis and digestive disorders were more technically efficient, while farmers reporting higher frequencies of milk fever were less efficient (Lawson *et al.*, 2004). Technical inefficiency increases and allocative inefficiency decreases as the proportion of purchased feed rises (Hansen *et al.*, 2005; Cabrera *et al.*, 2010). The actual effects of subsidies on a producer's performance are complex and vary e.g. with production (Zhu *et al.*, 2012). Similarly, while Kelly *et al.* (2013) found a positive contribution from specialization in dairy on technical efficiency, Brümmer (2001), Hadley (2006) and Hansson (2007b) found a negative effect. Technical efficiency is also positively related to the stocking rate (Kelly *et al.*, 2013), the contribution of family labor, the use of a total mixed ration feeding

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system, a low share of purchase feed and milking frequency (Cabrera *et al*., 2010). Further, technical efficiency is negatively related to farmer age and farm size (Rasmussen, 2010).

Milk yield has a positive effect on farm economic and technical efficiency (Hansen *et al*., 2005; Hansson, 2007b). However, the positive effect might be diminishing (Sipiläinen *et al*., 2009). Kumbhakar *et al*. (2009), Sipiläinen and Oude Lansink (2005), and Tiedemann and Latacz-Lohmann (2011) report lower technical efficiency on organic dairy farms than on conventional farms. However, Mayen *et al*. (2010) and Lansink and Pietola (2002) find no difference when they correct for the different technologies used. Finally, Haga and Lindblad (2018) find that organic farmers are more revenue efficient than conventional farmers. Farmer education, experience in farming and specialization contribute to efficiency on organic farms (Lakner and Breustedt 2015). Jiang and Sharpe (2014) report a significant negative relationship between capital intensity, livestock quality and cost efficiency. According to Allendorf and Wettemann (2015) a high percentage of losses, a high replacement rate and a long calving interval decreases technical efficiency, while a low age at first calving, high milk yield and high somatic cell count increases efficiency. Hansen *et al*. (2005) found that a low age at first calving, low forage-, insemination- and veterinary costs, a high fertility, milk quota filling and milk yield, and a high amount of beef produced per cow were hallmarks of economically efficient Norwegian farms. Similarly, Inchaisri *et al*. (2010) found a negative correlation between dairy farm profits and low reproductive efficiency. Finally, Steeneveld *et al*. 2012 found that automatic milking systems (AMS) do not affect technical efficiency as compared to conventional milking systems (CMS), while Hansen *et al*. (2019) find that AMS farms are more revenue efficient than CMS farms beyond 35-40 cows, but only after a transition period of four years.

Previous literature has focused little on factors that the farmer can easily change in the short-run to increase efficiency in the dairy farm operations. We denote these factors efficiency drivers. Further, except from Hansson (2007b) and Jiang and Sharp (2014), literature focusing on managerial practices and efficiency on dairy farms have focused mainly on technical efficiency, and not considered allocative and economic efficiencies. This is somewhat paradoxically, since cost efficiency and particularly allocative efficiency is considered the more problematic part of the profitability process (Hansson 2007b). Revenue efficiency is output oriented and considers both technical and allocative efficiency. Revenue efficient farmers maximize the output given the input factors available, and combine the outputs to maximize the revenue. Consequently, revenue efficiency gives us a better view of farm efficiency and how it is affected by the operational managerial practices than just technical efficiency. The aim of this paper is to identify a set of efficiency drivers which the dairy farmer can affect through managing the farm.

Material and methods

There are several approaches to analyze efficiency, both nonparametric and parametric ones. Within these categories, Data Envelopment Aanalysis (DEA) (Farrell, 1957; Charnes *et al*., 1978) and Stochastic Frontier Analysis (SFA) (Aigner, Lovell and Schmidt, 1977; Meeusen and van den Broeck, 1977) are the most common. According to Coelli *et al*. (2005) both DEA and SFA have their advantages and disadvantages, and there is no clear winner. As compared to DEA SFA allows for both unobserved variation in output due to shocks and measurement error as well as inefficiency, and according to Coelli (1995) shocks and errors can be a challenge in analyzing agricultural data. Therefore, we chose SFA in this study. Differences in efficiency can be explained by either a one-step SFA approach, or a two-step approach. However, the two-step approach has been criticized due to statistical inconsistencies (Kumbhakar and Lovell, 2000; Wang and Schmidt, 2002), and therefore we decided to use the one-step SFA approach.

SFA is a parametric method that makes use of econometric techniques to estimate the production frontier. The frontier in our setting characterizes the maximum output with various input combinations given a technology. Producers do not always optimize their production functions. Producers operating above the frontier are considered efficient, while those who operate under the frontier are considered inefficient. However, observations at the frontier does not necessarily have to be real producers, which means that even the most efficient ones can end up with an efficiency index below one. Because our main interest is the efficiency drivers, we want an output variable which reflects the value created in the dairy production. The Norwegian red breed is a combined breed, and thus it is important to include revenue from both beef and livestock in the output. Norwegian dairy farmers receive coupled subsidies which may constitute a significant part of farm revenue, particularly on small and medium sized farms. In the present study, we include the total subsidy amount received by the farmer related to dairy in the farm revenue or output, following Barnes (2008), Rasmussen (2011) and Manevska-Tasevska *et al*. (2016). Our choice to use total revenue from milk and beef production includes subsidies as output variable aligns with Kompas and Che (2006) and Allendorf and Wettemann (2015). The SFA estimates farm revenue efficiency by measuring the distance between the observed and the highest possible amount of output/ revenue that can be obtained, while keeping the amount of inputs fixed. Basically, the structure of our estimated model is equivalent to a production function, since price differences between farms are partly due to product quality differences. Regionally differentiated subsidies per liter milk also contribute to price differences.

To choose between fixed effects or random effects models a Hausman test was applied. The test showed no significant differences between the fixed and random coefficients ($p=0.275$), and thus the random effects model yields the most efficient estimates. Using a random effects model also has the advantage that the analysis can be performed in one step, as compared to the fixed effects model. Estimation of the stochastic frontier panel data under the random effects framework can be done by imposing distributional assumptions on the random components, and estimate the parameters by maximum likelihood. Thus, the inefficiency term u_i is truncated normally distributed from 0 and downwards. This ensures that $u_i \geqslant 0$. Further we assume that the production frontier follows a Cobb- Douglas (CD) product function, which is commonly applied in agriculture (see e.g. Battese and Coelli, 1995; Pitt and Lee, 1981). In case of SFA it is possible to choose between several production function models: CD, CES, translog, generalised Leontief, normalized quadratic and its variants. The translog and the CD production functions are the two most common functional forms used in empirical studies of production, including frontier analyses (Battese and Broca 1997).

Compared to e.g. a translog production function, the CD is restrictive in the properties it imposes upon the production structure, such as an elasticity of substitution equal to unity. The translog also opens up for interaction effects between input variables and second order effects. On the other hand, the CD functional form is relatively easy to estimate and interpret. The wrong choice of production function may influence the results. However, while the absolute level of the technical efficiency is quite sensitive to distributional assumptions, rankings are less sensitive (Battese and Broca, 1997). In this study ease of estimation is important because we included up to 22 efficiency drivers in addition to the five input variables. Even with this relatively simple functional form we sometimes had trouble getting the model to converge. Further, ease of interpretation is important because our main interest is to explore the efficiency drivers, not the efficiency level per se.

Our one-step parametric SFA model with farms indexed i, and two periods 2012 and 2013, indexed t=1,2, is defined as

$$\begin{aligned}\ln(\text{total dairy revenues}_{it}) &= \beta_0 + \beta_1\ln(\text{working hours}_{it}) \\ &+ \beta_2\ln(\text{milk quota}_{it}) + \beta_3\ln(\text{cowshed capacity}_{it}) \\ &+ \beta_4\ln(\text{forage acreage}_{it}) + \beta_5\ln(\text{variable costs}_{it}) \\ &+ \delta\text{year2013} + (v_{it} - u_i),\end{aligned} \quad (1)$$

where v_{it} is the error term, $v_{it} \sim N(0, \sigma_v^2)$ and $u_i \sim N^+(\mu, \sigma_u^2)$. We assume that the expected value of the inefficiency term μ is a function of the vector of the efficiency drivers $\mathbf{z}_m$ (m=1,…,22), and a vector of unknown coefficients $\boldsymbol{\gamma}_m$

$$\mu = \gamma_0 + \sum_{m=1}^{M} \gamma_m z_m \quad (2)$$

In a SFA model with output- oriented specification, the inefficiency term u_i represents the log difference between the maximum attainable output and the actual output (Kumbhakar *et al.* 2015). After estimating the model, the JLMS estimator of inefficiency $E(u_i|\epsilon_i)$ (Jondrow *et al.* 1982; Kumbhakar and Lovell, 2000) is applied to estimate the inefficiency of each farm. Finally, each farm is assigned a revenue efficiency index based on the estimated value of u_i.

$$\text{Revenue efficiency} = e^{-E(u_i|\epsilon_i)} \quad (3)$$

The model (1) has a log- log form, and the estimated coefficients (β_1,…,β_5) can therefore be interpreted as elasticities, or the percentage change in total revenue as the corresponding input factor changes by one percent. By summing the estimated coefficients of the input factors one obtains the return to scale, or the percentage increase in total revenue as all input factors increase proportionally. Bayes Information Criteria (BIC) is used to choose between different models, and the model is estimated using STATA.

According to Statistics Norway (2013) the inflation rate was moderate, 1.6 percent from 2012 to 2013, and therefore we do not deflate the monetary values. Further, since the analysis comprises two years only, it is reasonable to assume time- invariant revenue inefficiency. Possible heteroscedasticity in SFA models is usually reduced when taking logs of the dependent variable. Thus, plots of the predicted variable against the residuals show no patterns indicating heteroscedasticity. When the distribution of inefficiency depends upon a set of efficiency drivers, it is important to check for possible correlation between the inputs and these drivers (Parmeter and Kumbhakar, 2014). For example, it could be that the inefficiency term is correlated with farm specific variables in terms of capital, land etc. A preliminary analysis shows a mean absolute value of the Pearson correlation coefficient of 0.137. This level is slightly above the limit of low correlation, and well below the limit of moderate correlation (Cohen, 1988). The absolute values range from 0.017 to 0.242, still well below the limit of moderate correlation (Cohen, 1988).

To aid the interpretation of the results and to identify the best practice in dairy farming, we apply the method used in Kompas and Che (2006) and Lien *et al.* (2007). First, we rank the farms according to their efficiency index. Then we define the lowest 25th percentile as the low efficient group (L), and the highest 25th percentile as the highly efficient group (H). The rest are in the medium efficient group (M). This classification yields three groups of 53, 53 and 106 farms respectively. We use t- tests and chi square tests to detect possible significant differences between the three groups.

Our data set is a balanced panel of 212 Norwegian dairy farmers in 2012 and 2013. Panel data have advantages over cross sectional data as it allows to control for unobservable heterogeneity (Schmidt and Sickles, 1984). Further, repeated measurement of each farm reduces the estimated standard errors of the estimates, which results in more reliable estimates. Farms with obvious irretrievable erroneous recordings, of a kind that might affect the results, were excluded. The study population covers most of Norway, with most farmers located in Eastern- Norway, Western- Norway and Mid-Norway. Altogether 22 percent of the farms are joint operations. A comparison of the study population and the average Norwegian dairy farms in 2012/2013 showed that while the farms in our panel have 31 cows and deliver 218770 liters of milk, the average Norwegian farm had 24 cows and delivered 148763 litres of milk. Thus, the farms in our study are slightly larger than the average Norwegian dairy farm.

Altogether five inputs are considered: labour, cowshed capacity, forage acreage, milk quota and total variable costs. Coelli *et al.* (2005) claim that labour and capital are the most important inputs in analyses of efficiency. Labour includes all hours worked by both family members and hired staff. Capital includes farm land, buildings, machinery and other manufacturing equipment. However, in the farm accountancy these assets are most often assessed for tax purposes, and therefore the figures do not necessarily reflect their operational values. For example, choice of depreciation rate is often a result of adaptation to the tax scheme, and asset values and depreciation rest on historic costs. To deal with such problems Coelli *et al*. (2005) recommends use of proxies for capital. Thus, we use cowshed capacity, forage acreage and milk quota as proxies for capital. Following Hansen *et al*. (2005) cowshed capacity is used as a proxy for capital allocated to cowsheds. It is calculated based on the average number of animals in each age category in each year, multiplied by the space recommended for each animal relative to the space of a cow. It is expressed in cow units. A potential disadvantage of using this measure is that building capital and machinery capital are not necessarily fully proportional to the number of cows. However, we think it is at least as good as tax values. Forage is an important input factor in dairy farming, thus acreage of grassland included pasture is used as a proxy for capital. Acreage used for grain, vegetables etc. is left out because revenues and costs related to arable crops is not considered in this study. Further, milk quotas are important for determining farm revenues in Norway. Previous research has shown that some farmers do not manage to fill the milk quota, and this reduces their efficiency (Hansen *et al*., 2005). Quotas also represent a significant capital on dairy farms. Following Areal and Balcombe (2012) the farms' milk quota is used as a proxy for capital. Finally, total variable costs are included as an input. Variable costs include purchased concentrate, fertilizers, seeds, dairy consumables and veterinary and insemination costs. A possible limitation of our study is that we omit some fixed costs such as e.g. costs related to administration, book keeping, electricity, fuel, insurances, freight, maintenance of buildings and so on. We chose to do so because our main interest is to identify efficiency drivers related to the production of milk and beef itself. In that respect we think the most relevant fixed costs are represented in our study.

Based on our professional knowledge and literature findings we explore the following efficiency drivers: age of cows at first calving, insemination costs per litre milk delivered to dairy, percentage of milk quota delivered to dairy (quota filling), milk yield in kilogram energy corrected milk (ECM), milk quality payment, purchased concentrate in percentage of all feed, and kilogram beef produced per cow per year included fattening of bull calves. A high age at first calving increases total forage consumption, and if we assume that the milk yield does not increase beyond e.g.24 months, this reduces farm efficiency. High insemination costs might indicate problems with detecting cows in heat, and thus reduced efficiency. A low milk yield or bad milk quality payment may indicate e.g. bad forage quality or bad management, which also reduces efficiency. Contrary, a low share of concentrate may signal a good forage quality and good management, which increases efficiency. A high beef production per cow indicates that the farmer utilizes the opportunity to increase revenues by producing beef on male calves. A preliminary analysis showed a low correlation coefficient between kilogram milk per cow and kilogram beef produced per cow (r=0.08). We include dummy variables for farms that had an AMS before 2012, and for those who installed AMS during 2012 or 2013. Similarly, we include dummy variables for the twenty organic farms included and for district subsidy. The subsidy zones F to J include most parts of Northern Norway. Although the climatic conditions for dairy farming and zone subsidy vary within Northern Norway, we decided to merge the farms in these zones to obtain enough farms in each group for the statistical analysis. In a preliminary analysis, we compared the organic farms and the conventional farms using one-way analysis of variance. The analysis showed that the organic farms have significantly larger acreage and milk quota, lower beef production per cow and lower variable forage costs, as compared to the conventional farms. All differences were significant ($p<0.05$). Descriptive statistics of the output variable, the input variables and the efficiency drivers are given in Table 1.

Results

In Table 2 we can see that the average JMLS-estimator $E(u_i|\epsilon_i)$ is estimated to 0.33, with a minimum of 0.09. Similarly, the average revenue efficiency (e^{-JLMS}) is estimated to 0.72, with a minimum of 0.56 and a maximum of 0.91. Approximately five percent of the farms have an index below 64 percent, while approximately five percent of the farms are relatively efficient, with an index above 80 percent. In Table 2 we present the result of the stochastic frontier analysis, and in Table 3 the averages of the efficiency drivers are given.

The variance parameters reported are only used in estimating the efficiency. All output elasticities of the input factors are significantly greater than 0, which means that they are positively correlated with total revenue (Table 2). However, we notice that most elasticities are rather low. The calculated return to scale implies that one percent increase in all input factors increase total revenue by 0.9 percent. A one- sided Wald test rejected the null hypothesis of constant returns to scale. Thus, there is decreasing returns to scale in Norwegian dairy farming. Inspecting the coefficients of the inputs we notice that milk quota has the largest output elasticity, followed by cowshed capacity, variable costs, forage acreage and working hours. Therefore, an increase in milk quota will affect total revenue the most. We also tried to include machinery costs related to forage production as an input in the model, but the coefficient for this variable was not significantly different from zero. In Table 2 we also include the efficiency drivers which have a significant impact on the efficiency indexes. A negative coefficient indicates that an increase in the variable has a positive impact on efficiency, it reduces farm inefficiency. Increasing age at first calving, share of purchased concentrate of all feed and increasing insemination costs reduce efficiency. Contrary, an increase in milk yield, percentage of quota delivered to dairy and quality payment increases efficiency. A similar effect can be observed from increasing beef production per cow. Our results also indicate that farmers who invested in an AMS before 2012 are more efficient than farmers who installed AMS during 2012 or 2013, and farmers with CMS. Further, our findings suggest that organic farms and farms in the district subsidy zones F, G, I and J are more revenue efficient than the others. In addition to the variables mentioned, we also tried other variables which did not have a significant effect on efficiency. These variables were: herd fertility status, forage yield per 0.1 ha, calf mortality, no of veterinary

Table 1: Descriptive statistics of the output variable, the input variables and the efficiency drivers

Variable	Unit	Mean	Std. dev.	Min.	Max
Total farm revenue	NOK[1]	1 996 459	1 074 887	447 122	7 215 143
Labour	Hours	3 242	1 114	1 166	8 683
Cowshed capacity	Cow units	55.4	32.4	10.6	197.4
Forage acreage	Hectares	37.3	23.7	9.6	190.6
Milk quota	Litres	234 949	144 183	43 910	773 000
Variable costs	NOK	660 928	374 753	110 427	2 283 000
Efficiency drivers					
Age at first calving	Months	25.8	2.1	20.8	42.9
Insemination costs	NOK/litre	0.14	0.04	0.01	0.30
Quota filling	%	93.8	10.6	39.1	124.9
ECM per cow	Kg	7 750	880	5 084	10 006
Quality payment	NOK/litre	0.60	0.14	0.19	1.01
Beef produced per cow	Kg	259	123	21	935
Concentrate of total feed	%	41	7	17	63
Dummy variables	No of farms and share of total				
AMS installed before 2012	36 (0.17)				
AMS installed 2012/2013	19 (0.09)				
Organic farming	20 (0.09)				
District subsidy zone					
A and B	80 (0.38)				
C	45 (0.21)				
D	34 (0.16)				
E	27 (0.13)				
F, G, I and J	26 (0.12)				

[1] 1 NOK corresponds to 0.11 €.

treatments per calf, veterinary costs, amount spent on advisory services and joint farming operations.

In Table 3 we compare the estimated average values of the efficiency drivers for each of the three groups of farms ranked after efficiency. In group L, the efficiency index is below 68 percent, in group M between 68 and 75 percent, and in group H beyond 75 percent. In Table 3 one can see that quota filling, kg ECM per cow and beef produced per cow are significantly higher in the H group, as compared to the two other groups. For an average farm in the sample, the difference in quota filling between the H group and the L group amounts to 84370 NOK per year, given the mean milk revenue minus feed costs in the sample. Similarly, the difference in kg beef produced per herd between the two groups amounts to 3131 kg per year on an average farm. Given the sample mean of beef revenue minus variable feed costs this difference amounts to 77 962 NOK per year.

The average age at first calving is significantly lower in the H group as compared to the L group. Group H also tends to have lower age at first calving as compared to the M group, but the difference is smaller. Further, the H group has lower insemination costs as compared to the L group. The farms in the L group achieve significantly lower quality payment as compared to the two other groups. For an average farm the differences between the L group and the H group amounts to 12 032 NOK per year. However, the average share of concentrate of total feed does not differ significantly between the groups. The frequency of automatic milking systems (AMS) installed prior to 2012, and the frequency of organic farms are higher in the H group, as compared to the two other groups. Finally, there are more farms in the district zones E, F, G, I and J in the H group, than in the L group.

Discussion

The findings reported here indicate that there are diminishing returns to scale in Norwegian combined milk and beef production, and the return to scale in our study is in line with the findings in Haga and Lindblad (2018). In our sample, total subsidies received is negatively correlated with no of cows per farm, and this can explain why our study differs from studies reporting constant returns to scale (Lawson *et al*., 2004; Kompas and Che, 2006, and Cabrera *et al*., 2010). Our finding is as expected since subsidies are included in the revenue and some of the rates in the subsidy scheme decrease with increasing number of cows and acreage. The relationship between the sizes of the output elasticities reported in this study is comparable to the findings in Lawson *et al*. (2004). On average, each farm in our sample can increase the total revenue by 28 percentage points, given the input factors. Thus, many farms have a potential to increase their revenue efficiency. However, to become 100 percent efficient, the farmer must apply best practice on all the efficiency drivers, which is demanding. Further, we agree with Lawson *et al*. (2004) that an average efficiency index in one study cannot easily be compared to other studies. Our finding that the output elasticity for milk quota is the highest relates to that since 2012/2013 many farms have increased their milk production by buying or renting milk quota. Much of the increased production needed to expand milk production has been possible due to increased milk yield per cow, from 7 509 kilogram to 8 374 kilogram per cow (Tine, 2018). In the same period the number of cows has increased by 4.2 (ibid.).

Table 2: Results from the stochastic frontier analysis

	Coefficients		Std. error
Input factors[1,2]			
ln(working hours)	0.029**		0.012
ln(cowshed capacity)	0.240***		0.028
ln(forage acreage)	0.073***		0.011
ln(milk quota)	0.353***		0.032
ln(variable costs)	0.209***		0.022
Efficiency drivers			
Age at first calving	0.007***		0.002
Insemination costs	0.256***		0.077
Quota filling	-0.005***		0.001
Kg ECM per cow (in 1000)	-0.009*		0.005
Quality payment	-0.089***		0.026
Kg beef produced per cow (in 100)	-0.026***		0.005
Concentrate, share of total feed	0.158**		0.062
AMS before 2012	-0.030***		0.011
Organic farming	-0.132***		0.011
District zones A and B	0.126***		0.011
District zone C	0.102***		0.011
District zone D	0.068***		0.011
District zone E	0.064***		0.012
Log- likelihood value[3]	675.3		
Variance parameters			
ln σ_u^2	-7.233***		0.263
ln σ_v^2	-6.317***		0.100
	Mean	**Max.**	**Min.**
JMLS- estimator ($E(u_i \mid \varepsilon_i)$)	0.33		
Income efficiency (e^{-JLMS})	0.72	0.91	0.56

*p ⩽ 0.10, **p ⩽ 0.05, ***p ⩽ 0.01.

[1] Interpretation of the constant term is not meaningful when we estimate the efficiency drivers in the same model, and therefore we do not show it. As a robustness check, we also estimated the model without an intercept. The results of this check is not reported as the coefficients are at the same order of magnitude as the ones reported in Table 2. The results are however, available from the authors on request.

[2] The model also includes a time dummy variable to capture changing climate conditions and other factors which affects each farm equally. The time dummy is significantly greater than one (p⩽0.05).

[3] The log- likelihood value and number of parameters are used in BIC-tests to find the optimal model.

The drivers identified and the figures for the H- group can be interpreted as the best practice in dairy farming (Table 3). High age at first calving implies a high feed consumption during the rearing period, and postponed milk revenue, which reduces farm efficiency. Our finding that the H group has lower age at first calving is in line with the findings of Lawson *et al.* (2004), Hansen *et al.* (2005) and Allendorf and Wettemann (2015). High insemination costs reduce revenue efficiency, in line with the findings of Hansen *et al.* (2005). This can indicate bad reproductive performance in the herd, leading to e.g. involuntary culling of cows, long calving intervals and fewer calves for beef production. The findings reported here support the findings of Hansen *et al.* (2005) and Allendorf and Wettemann (2015).

The milk yield in group H is approximately 600 kg lower as compared to the L group. Given a fixed milk quota, a high milk yield requires fewer cows, and thus fewer hours of work and less space needed in the cowshed. Our finding is in line with the findings of Hansen *et al.* (2005), Hansson (2007), Sipiläinen *et al.* (2009) and Allendorf and Wettemann (2015). However, when interpreting the positive effect of milk yield on efficiency, one should keep in mind that the coefficient for milk yield in Table 2 is significant at the ten percent level only.

The H- group achieves 0.055 NOK lower quality payment per liter milk as compared to the L- group. Under the Norwegian milk payment scheme farmers get extra paid for low bacteria and somatic cell counts, and for contents of protein and fat above average. Thus, it is important for farmers to adapt to the payment scheme to be revenue efficient. Our finding is in line with the finding of Hansen *et al.* (2005). A high quota filling also increases revenue efficiency. The quota filling in the L group is remarkably low. The low quota filling relates to the low milk yield in the L group as compared to the H group.

Farms in group H have significantly higher revenue from beef production than farms in the L group. Beef production requires relatively few hours of labour and little forage as compared to milk production, and the farmer can use the same cowshed and the same forage machinery as for the dairy cows. Our findings are in line with the findings of Hansen *et al.* (2005), and studies reporting negative effects on efficiency from specialization in dairy (Brümmer, 2001; Hadley, 2006; Hansson, 2007a).

Table 3: Average values of the farm efficiency drivers in each efficiency group

Efficiency drivers	Unit	Efficiency index group			Significant differences		
		Low (L) < 68 %	Medium (M) 68-75 %	High (H) > 75 %	L-M	L-H	M-H
Age at first calving	Months	26.6	25.7	25.4	***	***	*
Insemination costs	NOK/l	0.149	0.145	0.139	-	*	-
Quota filling	%	86.3	95.5	97.7	***	***	**
ECM per cow	Kg	7394	7802	8003	***	***	**
Quality payment	NOK/l	0.568	0.608	0.623	***	***	-
Beef produced per cow	Kg	205	261	306	***	***	***
Concentrate of total feed	%	40.3	40.9	40.2	-	-	-
AMS before 2012	%	15.1	13.2	26.4	-	***	***
Organic farming	%	1.9	5.7	24.5	*	***	***
District zones A and B	%	52.8	35.8	26.4	***	***	**
District zone C	%	20.8	26.4	11.3	-	**	***
District zone D	%	11.3	17.9	17.0	*	-	-
District zone E	%	11.3	10.4	18.9	-	*	**
District zones F, G, I, J	%	3.8	9.4	26.4	**	***	***

*p ⩽ 0.10, **p ⩽ 0.05, ***p ⩽ 0.01.

Similar to the findings of Mishra and Lovell (2007) and Hansen *et al*. (2005) we find that a low share of concentrate improves farm efficiency. The H group produces approximately 600 kilogram more milk per cow on the same share of concentrate. This indicates a better management and a significantly better forage quality in the H group as compared to the L group. Under Norwegian conditions, variable roughage costs per energy unit feed are significant lower than the concentrate costs. Normally substitution is therefore profitable, but the degree of substitution depends on the roughage quality. Thus, good quality roughage in sufficient amounts appears to be an important strategy to maintain efficient dairy farm production, in line with the findings of Charbonneau *et al*. (2011).

Our findings show that farmers who invested in AMS before 2012 are more efficient than others. It might take some time before farmers with AMS utilize the efficiency potential. Thus, our finding indicates that there are learning costs involved, similar to the findings reported by Sauer and Latacz- Lohmann (2015), Hansen (2015), Hansen and Jervell (2014) and Hansen *et al*. (2019). However, neither the specific capital costs, nor the operating costs related to the AMS was available in this study. Therefore, one cannot conclude that farms with AMS are more revenue efficient as compared to farms with CMS based on this study only. The study of economic efficiency of AMS merits careful consideration and is a topic for a special study, see e.g. Hansen *et al*. (2019) for an example.

Almost one quarter of the farms in the H group are run organic. Our finding relates to the findings reported by NIBIO (2013), that organic farms achieve a higher return to labour as compared to conventional farms due to higher milk price, higher subsidies and lower costs. In 2012 and 2013 the organic farms were paid 0.75 NOK extra per litre milk. Low variable forage costs also contribute to efficiency. They also received slightly more subsidies, although this difference alone cannot explain the difference in efficiency. On the other hand, the organic concentrate is more expensive than the conventional. The findings reported here support the finding of Lansink *et al.* (2002), but are contrary to those reported by Kumbhakar *et al*. (2009), Sipiläinen and Oude Lansink (2005) and Mayen *et al*. (2009). The reason might be that these studies focus on technical efficiency, and do not take revenue efficiency into account. Future studies could also consider other possible explanatory variables such as differences in education (Koesling *et al*., 2008; Latruffe and Nauges, 2013) and intrinsic motivation (Rigby *et al*., 2001) between organic and conventional farmers.

The findings in this study indicate that farms in less favorable areas (district zones F, G, I and J) are more revenue efficient. District subsidy is intended to even out differences in climatic conditions and higher prices of input factors due to e.g. transportation costs. Our analysis does not cover all costs the subsidy scheme is supposed to compensate for, thus one cannot conclude whether farms in these zones are over- compensated for their disadvantages or not.

One can draw some policy implications based on our results. First, our results indicate that for dairy farmers it is profitable to combine production of milk and beef. The bull calves are already in place and feeding them requires relatively little extra work. Further, little extra equipment and machinery is needed, neither in the cowshed nor on the fields. In recent years, the number of dairy cows in Norway has decreased, and this decline has not been compensated by an equivalent increase in the number of suckler cows (Hegrenes *et al*., 2009). Manevska-Tasevska *et al*. (2013) describe similar challenges with keeping up beef production in Sweden, thus our results are relevant also for other Nordic countries. Taken together our findings suggest that the government should consider a policy which better facilitates farm expansion for production of both milk and beef together. Further, our results indicate that organic farmers are more efficient than conventional ones, a topic more thoroughly treated in Haga and Lindblad (2018). Their findings also suggest that organic farmers are more revenue efficient than conventional farmers.

The data in this study are from 2012 and 2013. Meanwhile the differentiation of headage and acreage payment has been changed, and this might have influenced how revenue varies with inputs as measured in this paper. For example, the headage payment for youngstock is no longer limited to the first 250 animals, and the rate for acreage payment for forage is no longer differentiated by the number of 0.1 ha. These changes may have influenced the results of this study, in favor of larger farms. Finally, a new headage payment favoring small and medium sized farms was introduced from 2019 on, and this may somewhat dampen this effect.

Conclusion

Norwegian dairy farms above average size can increase their total revenue by 28 percentage points, given their input factors. There are diminishing returns to scale in Norwegian dairy farming due to the structure of the subsidy scheme. The most important efficiency drivers are: A low age at first calving, low insemination costs, a low share of concentrate out of total feed, a high quota filling and beef production per cow, a high milk yield and quality payment, and organic farming. The comparison of different milking systems suggests that farms with AMS are more efficient than farms with CMS, and that there are learning costs involved in the transition from CMS to AMS. Our findings that combined milk and beef production, and organic farming increases revenue efficiency have implications for policy makers.

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