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Effects of Economic Factors on Adoption of Robotics and Consequences of Automation for Productivity Growth of Dairy Farms

ABSTRACT

In the long term, productivity and especially productivity growth are necessary conditions for the survival of a farm. In this paper, we focus on the technology choice of a dairy farm, i.e. the choice between a conventional and an automatic milking system. Our aim is to reveal the extent to which economic rationality explains investing in new technology. The adoption of robotics is further linked to farm productivity to show how capital-intensive technology has affected the overall productivity of milk production. In our empirical analysis, we apply a probit model and an extended Cobb-Douglas-type production function to a Finnish farm-level dataset for the years 2000–10. The results show that very few economic factors on a dairy farm or in its economic environment can be identified to affect the switch to automatic milking. Existing machinery capital and investment allowances are among the significant factors. The results also indicate that the probability of investing in robotics responds elastically to a change in investment aids: an increase of 1% in aid would generate an increase of 2% in the probability of investing. Despite the presence of non-economic incentives, the switch to robotic milking is proven to promote productivity development on dairy farms. No productivity growth is observed on farms that keep conventional milking systems, whereas farms with robotic milking have a growth rate of 8.1% per year. The mean rate for farms that switch to robotic milking is 7.0% per year. The results show great progress in productivity growth, with the average of the sector at around 2% per year during the past two decades. In conclusion, investments in new technology as well as investment aids to boost investments are needed in low-productivity areas where investments in new technology still have great potential to increase productivity, and thus profitability and competitiveness, in the long run.

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Contents

List of Figures

List of Tables

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1. Introduction

Average productivity in the agricultural sector may increase as a result of the increased productivity of individual farms or when farms with low productivity exit production (or both). In the long term, productivity and especially productivity growth are necessary conditions for the survival of a farm. To improve productivity development at the farm level, investments in new technology are needed. Thus, farmers' investment behaviour is a very important factor for the productivity growth of the sector.

Over recent years, profound structural change has taken place in the European dairy sector. Structural differences among countries are still significant, however. In the Netherlands, for example, the average herd size is about threefold that in Finland. According to the share of milk produced on farms with more than 50 dairy cows, Austria and Switzerland are in a category of their own. In Finland, the share is clearly greater compared with these mountainous regions but it is much smaller than in most European countries (Table 1).

Traditional and labour-intensive production technology still persists in countries where the average herd size is small. In Finland, for example, many dairy farms were investing in the tied-housing system even at the beginning of the 21st century (Table 2). By 2010, the emphasis of investments had shifted to loose-housing systems and the number of cattle places in those systems equals that of stanchion-tied stables (Tike, 2011). The terms of investment aid are one reason for the annual variation in the number of investments, as very few investments are realised without any subsidy. When investing in new construction with a loose-housing system, about 60% of farms also invest in an automatic milking system or at least in premises for it (Karttunen and Lätti, 2009). As a counterbalance to the decreasing number of investments, the size of facilities has been increasing rapidly in the past ten years (Table 2).

Latvala and Pyykkönen (2008) investigated technology choices and investment plans in Finnish animal husbandry. The data were collected by an survey in 2006. At that time, the most common milking system on dairy farms was a pipeline milking machine, with a share of 75%. The share of modern milking systems, such as milking parlours and automatic milking systems, was about 12%. The rest of the farms still used old technology, such as bucket milking machines. Since then, the number of automatic milking systems has increased rapidly. At the end of 2011, the total number of dairy farms with robotic milking was 641, corresponding to 7% of all dairy farms (Figure 1). De Koning (2010) reported that over 8,000 commercial farms worldwide used one or more milking robots. That number has continued to increase, especially in north-western Europe (Steeneveld et al., 2012).

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Table 1. Structure of dairy farms in selected European countries (2010)

Country	Number of dairy farms (1,000)	Average herd size (number of cows)	Share of milk produced in herds with more than 50 cows (%)
Austria	40	13	7
Belgium	11	44	59
Czech Republic	2	161	98
Denmark	4	140	97
Estonia	3	28	90
Finland	11	26	26
France	77	47	53
Germany	92	46	64
Hungary	12	21	74*
Ireland	18	61	95
Netherlands	20	75	88
Sweden	6	61	74
Switzerland	27	21	10

*2007

Source: IFCN (2011).

Table 2. Number of dairy farms receiving investment aid for cowshed construction (new, extension and renovation) in Finland (2001–10)

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Total	431	341	329	271	441	389	412	117	217	157
Loose-housing system, warm	109	103	118	103	176	194	222	112	125	95
Loose-housing system, cold	17	24	25	18	44	29	35	13	26	23
Tied-housing system	305	214	186	150	221	166	155	52	60	39
Cows/cowshed	32	36	39	41	43	51	51	63	75	71

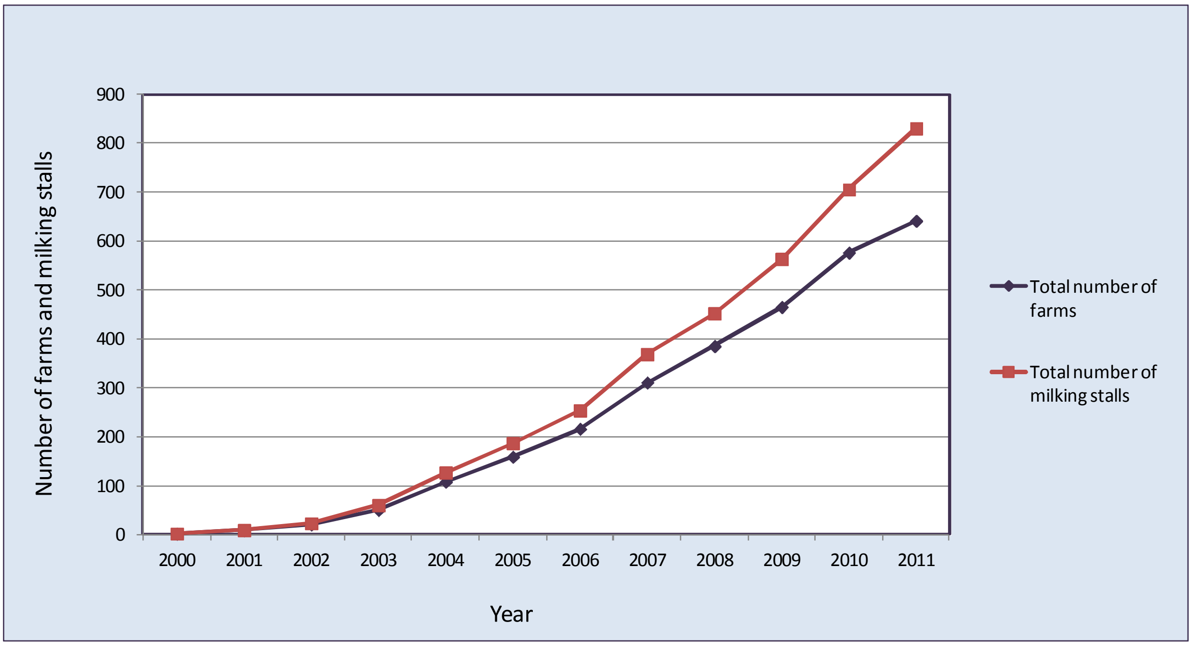
Source: K. Brännes, Ministry of Agriculture and Forestry of Finland, Helsinki.

Economic rationality does not solely motivate investment in new technologies. Increasing farm size, lack of skilled workers, technical progress and striving for a better quality of life have motivated investments in robotics on dairy farms (Mathijs, 2004; Bijl et al., 2007). Better quality of life includes such aspects as less burdensome work and more flexible working hours, but also better economic performance. Investments in automation have been an important strategy for a large number of milk producers to mitigate increasing competition and rapid structural developments, as it has provided an attractive means for substituting scarce farm labour with new technologies and capital. Because access to skilled farm labour has become an ever more restricting factor, the development options opened by robotics for expanding the size of dairy operations are crucial.

Estimations of productivity development in the sector show that the productivity growth of Finnish dairy farms ceased almost completely in the early 1990s, but towards the end of the decade the trend turned positive. The average rise of productivity was 1.9% a year over the period 1987–2007 (Myyrä, 2009). Development in productivity trends followed the investments, which were dominated by uncertainty over Finnish membership in the EU (1995). Yet, neither structural development nor investments encouraged by investment aid have brought the productivity of Finnish agriculture closer to that of Central Europe.

Productivity development has recently been quite stable but not as rapid as it should be to decrease the gap compared with Denmark, for instance, where the level of productivity is 20–30% higher than in Finland (Sipiläinen et al., 2008).

Figure 1. Number of farms with an automatic milking system and number of automatic milking stalls in Finland (2000–11)



Source: E. Manninen, MTT, Helsinki.

The profitability of Finnish dairy farms has also been rather stable compared with the other production lines. During the past ten years, the profitability ratio[1] has been around 0.5, with the minimum being 0.46 and the maximum 0.65. Thus, dairy farmers typically reach only half of the wage and interest claims they aim at through their own work and their own capital (MTT, 2012). Improving productivity is important in terms of the competitiveness of the production, and together with input and output prices it is one of the main factors on which the profitability at farm level is founded.

The European Commission claims that increasing investment subsidies (and decreasing production subsidies) should solve the problem of low productivity by encouraging farmers to invest in new and more competitive technologies. Hence, several investment aid programmes have been implemented with the objective of improving the structure, productivity and thus competitiveness of the European agricultural sector in the global markets. These programmes have been financed partly by the EU, and partly through national initiatives. Nevertheless, there are very few quantitative estimates of how farmers' technology choices respond to the policy instruments or how the performance of farms has developed as a result of the investments realised.

In this paper, we analyse the technology choice of dairy farms, i.e. the choice between conventional and robotic milking systems. The aim is to reveal the extent to which economic rationality explains the investment. The adoption of robotics is further linked to farm productivity to show how capital-intensive new technology has affected the overall productivity of milk production. The effects of new technology on performance are isolated by comparing samples of farms with different milking systems. The results help in the evaluation of whether the subsidies allocated to investments really improve productivity growth in the sector. The empirical data has been collected from Finland, where both reliable

[1] Ratio between observed and expected compensation for a farmer's own work and capital.

economic data and information concerning milking technology and the timing of switching to new technology are available from the same farms.

2. Materials and methods

2.1 *Analysis of the switch from conventional milking to automatic milking*

We have estimated a probit model to predict the discrete choice between conventional and automatic milking technologies. It has been assumed that the choice between the two introduced technologies is a result of their expected benefits. Boundaries for the choices are determined by differences between the technology-specific value functions and by the difference of corresponding errors. In our application, the differences in the value functions have been approximated in reduced form (e.g. Green et al., 1996; Pietola et al., 2003).

Following the presentation by Maddala (1983), we have assumed that there is a latent response variable Y^* defined by the regression relationship

$$Y_i^* = \beta' Z_i + u_i \quad (1)$$

In practice, Y_i^* is unobservable. What we observe is the dummy variable Y representing the choice of technology, defined as follows:

$$Y_i = 1 \quad \text{if} \quad Y_i^* > 0, \quad \text{else} \quad Y_i = 0 \quad (2)$$

In this formulation, $\beta' Z_i$ is not the expected value of the observable Y given Z, $E(Y_i \mid Z_i)$, as in the linear probability model; it is instead the expected value of the latent variable given Z, $E(Y_i^* \mid Z_i)$. The variable Y that we observe instead of the latent variable Y^* takes on values 0 or 1 depending on the technology chosen. As explanatory variables, we have used farm-specific variables, farmer characteristics and variables describing the general economic environment.

From the relations (1) and (2), we obtain the choice probability relation, written as

$$\Pr\text{ob}(Y_i = 1) = \Pr\text{ob}(u_i > -\beta' Z_i) = 1 - F(-\beta' Z_i) \quad (3)$$

where F is the cumulative distribution function for u. In this case, the observed values of Y are relations of a binomial process with probabilities given by (3). Hence, the likelihood function is

$$L = \prod_{Y_i=0} F(-\beta' Z_i) \prod_{Y_i=1} (1 - F(-\beta' Z_i)) \quad (4)$$

The functional form for F in (4) depends on the assumptions made about u_i in (1). If the cumulative distribution of u_i is assumed to be standardised normal, we have the probit model. Let us denote the density function and the distribution function by $\phi(\cdot)$ and $\Phi(\cdot)$, respectively, of the standard normal. Then, the likelihood function for the probit model is expressed as

$$L = \prod_{i=1}^{n} \left[\Phi(\beta' Z_i)\right]^{Y_i} \left[(1 - \Phi(\beta' Z_i)\right]^{1-Y_i} \quad (5)$$

To find the maximum-likelihood estimate of β coefficients, we have

$$\log L = \sum_{i=1}^{n} Y_i \log \Phi(\beta' Z_i) + \sum_{i=1}^{n} (1 - Y_i) \log \left[1 - \Phi(\beta' Z_i) \right] \qquad (6)$$

After estimating the vector of coefficients, we can obtain estimated values of the probability that the i^{th} observation is equal to 1 (3).

The model has been estimated using LIMDEP software, version 8.0.[2]

2.2 Analysis of productivity growth

Various methods can be applied in productivity analysis. The methods are often divided into non-parametric and parametric (e.g. Färe et al., 1994; Kumbhakar et al., 1999). If price data are available and production technology exhibits constant returns to scale, total factor productivity (TFP) growth can be calculated without econometric estimation. If not, the econometric estimation of a production function or a cost function is necessary (Kumbhakar et al., 1999). The main advantage of the parametric approach over the non-parametric one is the information generated in the form of input elasticities. The disadvantage is the assumptions to be made concerning the functional form of costs or the production function and the distributions of the error term. In parametric analysis, TFP growth can easily be decomposed into a technical change (TC) component and a component associated with scale. A respective decomposition can also be made by non-parametric methods, such as data envelopment analysis. These methods are less restrictive with respect to production technology, but they usually do not account for the stochastic nature of the production process (Kumbhakar et al., 1999; Myyrä, 2009).

In this study, we prefer to estimate a production function and derive TFP growth from it. In the case of logarithmic production function, following Denny et al. (1981) and Bauer (1990), TFP growth can be defined as follows:

$$\dot{\text{TFP}} = \dot{y} - \dot{X} \text{ when } \dot{X} = \sum_{j=1} \frac{w_j x_j}{C} \dot{x}_j \qquad (7)$$

where $\frac{w_j x_j}{C}$ is the observed cost share on the input j (w is the price of the input x). The dot indicates the rate of change (log derivative with respect to time). Taking the total differential of logarithmic $y = f(x,t;\alpha)$ and adding it into (7), we obtain

$$\begin{aligned} \dot{TFP} &= \partial \ln y / \partial t + \sum_j (\varepsilon_j - \frac{w_j x_j}{C}) \dot{x}_j \\ &= \partial \ln y / \partial t + (\sum_j \varepsilon_j - 1) \sum_j \left(\frac{\varepsilon_j}{\sum_j \varepsilon_j} \right) \dot{x}_j + \sum_j \left[\left(\frac{\varepsilon_j}{\sum_j \varepsilon_j} \right) - \frac{w_j x_j}{C} \right] \dot{x}_j \end{aligned} \qquad (8)$$

After testing different flexible function forms, an extended Cobb-Douglas-type production function with a time trend variable and variables controlling for farm-specific effects is chosen for the productivity analysis. The model can be presented as follows:

$$lny_{it} = \beta_0 + \sum_{j=1} \beta_j \, lnx_{jit} + \beta_t t + \sum_{jj=1} \beta_{jj} lnx_{jit}^2 + \beta_{tt} t^2 + \sum_{q=1} \beta_q z_{qit} + v_{it} \qquad (9)$$

where i (i = 1, ..., N) and t (t = 1, ..., T) indicate the farm and the time periods, y is the output, x is the vector of input variables, z the vector of farm-specific variables, and t the time trend

[2] Econometric Software, Inc., Plainview, NY.

variable. The constant term β_0, the slope coefficients β_j, β_{jj}, β_t , β_{tt} and β_q are unknown parameters to be estimated. The random error term v_{it} is assumed to have zero mean and constant variance.

As TC is the derivative of the production function with respect to time, it is defined in the following way:

$$TC = \beta_t + \beta_{tt} t \tag{10}$$

When we assume allocative efficiency of production, we may omit the last part of equation (8) because the elasticity share and the cost share must coincide (Myyrä, 2009). Consequently, TFP growth is the sum of TC and the scale effect, both of which can be derived from the production function:

$$\dot{TFP} = TC + (RTS - 1)\sum_j \frac{\varepsilon_j}{RTS}\dot{x}_j \, , \tag{11}$$

$$\text{where } \varepsilon_j = \frac{\partial \ln y}{\partial \ln x_j} = \beta_j + \beta_{jj} \ln x_j$$

$$\text{and } RTS = \sum_j \varepsilon_j$$

The production function has been estimated using SAS software, version 9.2.[3]

2.3 Empirical data

Our empirical analysis is based on data from Finnish dairy farms gathered by the EU Farm Accountancy Data Network (FADN) over the years 2000–10. The first year of the research period is the year when the first Finnish dairy farms switched to robotic milking. All farms in the category of 'dairy farms' have been included in the research sample. As farms in the FADN are rotating, the sample forms unbalanced panel data. Nevertheless, nearly 25% of the farms are in the sample from beginning to end.

The total number of individual farms in the sample is 608. Among them, 551 farms had a conventional milking system (CMS) and 15 farms an automatic milking system (AMS) throughout the period for which they were included in the sample. The rest, 42 farms (TRANS), switched from a CMS to an AMS during the research period. In the sample, there were no switches from an AMS back to a CMS, but within the entire population, there are some examples of returning to a CMS. Therefore, we have not considered the switch irreversible while modelling the technology choice.

Farm size is measured as hectares, as the number of dairy cows and milk production increased in all farm categories. The herd size of TRANS farms more than doubled during the research period. The intensity of production measured as the number of cows per hectare also increased most rapidly in this category of farms. Total milk production was the highest on TRANS farms at the end of the research period. Milk production per cow varied annually depending, for example, on the yield of grass silage, but the mean over the whole research period was the highest in the category of AMS farms (Table 3).

3 SAS Institute Inc., Cary, NC.

Table 3. Development of farm size in the sample by milking system category

Year	Arable area (ha)			Number of dairy cows			Milk production (l)		
	CMS	AMS*)	TRANS	CMS	AMS*)	TRANS	CMS	AMS*)	TRANS
2000	39	–	64	20	–	34	147,184	–	261,203
2001	42	–	67	21	–	38	159,016	–	298,411
2002	42	–	74	22	–	39	164,829	–	304,413
2003	44	–	76	23	–	38	172,599	–	309,068
2004	46	–	76	24	–	41	188,019	–	342,190
2005	50	88	85	27	49	47	209,452	420,086	386,058
2006	52	88	91	28	60	52	224,280	515,393	438,038
2007	54	97	93	30	62	57	244,022	510,263	475,252
2008	58	99	101	32	66	63	257,737	556,517	519,357
2009	62	109	106	34	70	69	276,751	590,616	580,329
2010	62	108	112	36	68	74	289,693	575,236	618,869

*) The means are not presented in 2000–04 because of the small number of farms in the category.

The dependent variable of the probit model is the binary choice between the milking systems (CMS=0, AMS=1). A CMS is defined as bucket milking machines, a pipeline system or a parlour system, and an AMS as robotic milking. The independent variables describe both farm-specific characteristics and the economic environment. The descriptive statistics of the model variables are presented in Table 4. Milk production includes the delivery to a dairy and the farm's own consumption. The capital stock of machines solely comprises machines used in animal husbandry. Similarly, the labour input includes only those working hours needed in animal husbandry. The working hours per cow have been calculated by dividing the total number of hours by the average herd size (Table 4).

The maximum rate of investment allowances varied between 45% and 70%, an average being about half of the total investment outlays (Table 4). The allowances were paid as aid or as subsidised loans. From 2000 to 2006, the allowances were differentiated by the farmer's age, with the younger ones being eligible for a higher level of aid. Since 2007, the allowances have also been graded regionally. The allowance paid as an interest subsidy was higher in northern parts of Finland and the allowance paid as a straight aid in the southern parts of the country.

Table 4. Descriptive statistics of model variables

Variable	Description	N	Mean	Standard deviation
Output	Market return (€)	3,815	108,721	78,957
Capital	Total capital stock (€)	3,815	376,872	339,416
Labour	Labour input (h)	3,815	5,118	1,896
Materials	Costs of materials and supplies (€)	3,815	68,734	52,704
Milk	Milk production (l)	3,815	239,753	175,650
Machines	Machines of animal husbandry (€)	3,815	21,736	40,273
Labour/cow	Labour in animal husbandry per cow (h)	3,815	157	78
Investment aid	Maximum rate of investment allowance (%)	3,815	53.4	9.37

The output variable of the estimated production function is the market return of the farm. It includes all the products of farms, but milk return constitutes the main part of the return. Considering only milk return as an output would have led to difficult allocation problems of inputs. Therefore, in the case of specialised farms, we prefer to take into account the entire market return, and correspondingly all the inputs used for producing it.

There are three input variables in the production function: capital, labour and materials. Capital is the sum of the value of land, buildings, machines, drains and the milk quota. The labour variable includes the labour input that is needed for day-to-day tasks. Both paid labour and family work have been taken into consideration. The materials variable includes the variable costs of purchasing materials and supplies (Table 4).

The fixed effects have been modelled with the help of group-specific effects, not as farm-specific effects. In the production function, there are three herd-size dummy variables. The size ‘small’ (1–24 dairy cows) represents herds that are smaller than the sample mean, size ‘medium’ (25–70 dairy cows) are herds up to the maximum size for one robot, and size ‘large’ (71– dairy cows) are herds that would need more than one robot unit in the case of automatic milking. Moreover, there are seven regional dummy variables (A, B, C1, C2, C2P, C3, C4) that represent the agricultural support areas, the order being from south to north. Milk production is concentrated in C areas. The same regional dummy variables are included in the probit model.

All monetary values in the study are presented in fixed prices of 2010. The capital values have been deflated by the consumer price index. The market return has been corrected for inflation by using the producer price index of milk, and the material costs with the input price index of agriculture. Annual price indices (2005=100) have been obtained from Statistics Finland (2012) and the producer price of standard milk (quality class I) from the Information Centre of the Ministry of Agriculture and Forestry (Tike, 2012). For a given year, the milk price was the same for all farms in the sample. The production aid for milk, which varied by support area, was tested as a separate variable in the probit model. Either it or the milk price was not included in the final model, however.

We tested several other variables in the probit model but either their coefficients were not statistically significant or their presence did not improve the rate of correct predictions. The indices of farm buildings and farm machinery for animal husbandry have been used to indicate the price of buildings and purchasing of machines. An index of the wage and salary earnings of agricultural workers represents the price of paid work. The equity ratio measures the solvency of agricultural holdings, i.e. the ability to withstand losses and to fulfil financial commitments in the long run. The mean of the equity ratio is 75.4% (st. dev. 22.56%). The interest rate paid for agricultural debt was not available in the data but has been calculated with the help of the interest paid and the amount of liabilities. The mean rate for long-term loans was 4.0% (st. dev. 2.15%). There was a significant variation in interest rates, however, both among farms and over time. The average age of the principal farmer was 44.9 years (st. dev. 9.1 years). Although the quota claim for investment subsidies and the milk yield per dairy cow were among the variables tested in the probit model, they were excluded from the final version of the model.

3. Results

3.1 Factors affecting the switch to an automatic milking system

The probit model has been estimated to find factors affecting the choice between a CMS and an AMS. Various estimation methods and independent variables were tested while modelling the binary choice. Pooled estimation produced reasonable signs of parameters and the highest share of correct predictions. The estimation results are presented in Table 5.

Besides the trend, the existing machinery capital in animal husbandry has very significant and positive effects on switching from a CMS to an AMS. This result gives an idea about strategy differentiation among farms. Some farms have clearly decided to go for more automatic and mechanised production technologies in animal husbandry. This is not limited to milking systems, but is also present in other activities in a cowshed. Meanwhile, other farmers have decided to take a more conservative investment strategy, whereby all machinery investments are postponed. The results from the productivity analysis reveal whether the bold investment strategy is rewarded by a rapid development of productivity.

The rate of maximum investment aid also has a positive effect on the switch. This confirms that investment aids are useful tools in agricultural policy when the goal is to boost investments in new technologies. This is especially important in areas with low productivity levels.

The coefficient of total milk production is positive but not statistically significant. The result is in line with the current structural development in Finnish agriculture. Small farms are exiting the agribusiness and it is obvious that farms leaving the industry are not those investing in new technology. Still, the connection between the amount of milk and the probability of choosing an AMS is not very distinct. The result is reasonable, as an AMS is not the only modern milking system available for large farms.

The parameter estimate of labour input in animal husbandry per cow is negative and very significant ($p < 0.0001$). This result is connected with overall mechanisation in the cowshed, including feeding and manure removal. Farms, which most probably switch to an AMS, will have already organised their production in a way that decreases the labour demand per cow before exchanging the milking system. Thus, an AMS is not adopted by the most labour-intensive farms but those that have been orienting themselves towards continuous development in their milk production. Similar conclusions can be drawn from the fact that existing machinery capital has a positive effect on the switch to an AMS.

Table 5. Parameter estimates of probit model and elasticity estimates of response probabilities

Model variable	Parameter estimate	Standard error	t-value	p	Elasticity estimate
Intercept	-12.409	1.8066	-6.869	<0.0001	
ln (milk)	0.178	0.1440	1.239	0.2155	7.75
ln (machines)	0.794	0.0655	12.124	<0.0001	25.23*
Labour/cow	-0.009	0.0018	-4.843	<0.0001	-4.90*
Investment aid	0.012	0.0058	1.985	0.0471	2.19
Trend	0.104	0.0225	4.628	<0.0001	2.26*
Region B	-0.104	0.2478	-0.419	0.6751	
Region C1	-0.260	0.2098	-1.238	0.2157	
Region C2	-0.003	0.2009	-0.014	0.9886	
Region C2P	0.274	0.3112	0.881	0.3784	
Region C3	0.208	0.2486	0.837	0.4028	
Region C4	0.908	0.4851	1.871	0.0613	
NT	3,815				
logL	-395.8376				
Chi squared	978.9267				

*p<0.05

Regional dummy variables are jointly significant and their presence improves the overall performance of the model, although parameter estimates of single dummy variables are not found to be statistically significant. The coefficients for regional dummies indicate the probability of investing in an AMS in reference region A. The results show first a decrease and then an increase when moving towards the northern regions of Finland (Table 5). Increased probability in sparsely populated northern Finland may be an indicator of the poor availability of agricultural workers.

Around the sample means, the probability of choosing a CMS is 95.2% and the probability of choosing an AMS correspondingly 4.8%. The share of correct predictions is as high as 96.9% in the whole sample but the success is much greater when predicting actual 0s (99.1%) than when predicting actual 1s (63.1%). In a dataset with unbalanced shares of binary groups, it is typical that the model minimises the error term by expecting all observations to go to the larger group, here to the group of non-investors. Yet our model has succeeded in predicting 63.1% of actual investors correctly.

The elasticity estimates in Table 5 represent the percentage change in the probability of a switch to an AMS when the model variable is changed (*ceteris paribus*) given average values of other model variables. The switch responds very elastically to the current, predetermined machinery capital in animal husbandry. The elasticity estimates suggest that the likelihood of the switch increases with the scale of milk production and investment allowances. The estimated elasticity of investment allowances of about two implies elastic behaviour; an increase of 1% in the maximum rate of investment allowance will provide 2% more investment in an AMS. The estimation results build up to a possibility to calculate the profitability of investment aid schemes when linked to the result from productivity development analysis.

3.2 Returns to scale, technical change and growth of total factor productivity

The extended Cobb-Douglas-type production function (9) has been estimated in the study. The estimation results are presented in Table 6. The signs of the parameter estimates are as expected. Most of the coefficients of input variables are statistically significant, the labour input being an exception. The trend variable has a positive effect on output. Among dummy variables, small herd size has a negative effect and, correspondingly, large herd size a positive effect on the total output compared with medium-size farms. Regional dummy variables indicate a shift of the production function downwards when the farm is located north of reference region A.

Due to the form of our production function, output elasticities with respect to variable inputs vary across farms but not over time. Thus, the minor differences among the means by year result from the changes in the sample (Table 7). The output elasticity of capital is the highest with a sample mean of 0.68 and the output elasticity of labour the lowest with a sample mean of 0.29. As expected, the output elasticities of all inputs decrease when increasing herd size. The size effect may also be the reason for the differences between the milking systems (Table 7).

Returns to scale (RTS) are defined as the sum of output elasticities of inputs and are thus farm-specific following differences in the farm-specific levels of input use. The sample mean of RTS is above one (1.514), indicating increasing returns to scale at the average level (Table 7). This means that productivity can be improved by increasing the scale of production. Based on earlier studies, RTS has stayed constant over a long time. Sipiläinen (2007) observed that in the 1990s RTS averaged 1.527 in a similar dairy-farm group as studied here.

Table 6. Parameter estimates (farm level) of the extended Cobb-Douglas production function

Model variable	**Parameter estimate**	**Standard error**	**t-value**	**p**
Intercept	-5.4420	1.0881	-5.001	< 0.0001
ln (capital)	1.1740	0.1316	8.921	< 0.0001
ln (labour)	0.4300	0.2399	1.793	0.0731
ln (materials)	0.5801	0.1520	3.816	0.0001
ln $(\text{capital})^2$	-0.0395	0.0052	-7.532	< 0.0001
ln $(\text{labour})^2$	-0.0163	0.0143	-1.138	0.2546
ln $(\text{materials})^2$	-0.0035	0.0071	-0.489	0.6222
Trend	0.0115	0.0045	2.560	0.0110
Trend^2	0.0003	0.0004	0.750	0.4129
Herd size small	-0.1863	0.0101	-18.441	< 0.0001
Herd size large	0.2547	0.0218	11.682	< 0.0001
Region B	-0.0606	0.0166	-3.649	0.0003
Region C1	-0.0239	0.0154	-1.550	0.1220
Region C2	-0.0443	0.0148	-2.995	0.0028
Region C2P	-0.0821	0.0200	-4.103	< 0.0001
Region C3	-0.0727	0.0177	-4.106	< 0.0001
Region C4	-0.2199	0.0253	-8.692	< 0.0001

NT	Root MSE	F value	R-Squared	Adj. R-Squared
3,815	0.1996	2,267 ($p < 0.0001$)	0.9052	0.9048

The sample mean of TC was 1.3% per year (Table 7). TC means a shift of the production function over a period of years (10). Such a shift is the result of introducing new and more productive technology. We did not have cross-term parameters between time and input variables in our production function. Such a function does not allow TC to be farm-specific. Furthermore, TC is described as a trend variable along with the input variables. With this specification, it is not possible to capture the erratic changes over time, but the trend is revealed. This dataset indicates a slight acceleration in TC from 2000 to 2010.

TFP (11) increased by 0.9% per year. For the period 1990–2000, Sipiläinen (2007) estimated a rate of 1.09% per year. The annual variation is from a negative rate to 3.6% per year. Large farms have higher TFP growth than small farms.

No productivity growth is observed for CMS farms using conventional milking systems for the whole research period. AMS farms, using robotic milking every year in the sample, show the highest rate of TFP growth. TRANS farms that changed the milking system to robotic milking have almost as high a rate of TFP growth as the AMS farms. Steeneveld et al. (2012) found that farms with an AMS and a CMS were not different in their ability to use inputs to produce outputs. We have not studied the level of productivity, but at the least productivity growth has been observed to be better on farms using an AMS compared with farms using a CMS.

Table 7. Means of input elasticities, returns to scale, technical change and growth of total factor productivity

Year/ herd size/ technology	Elasticity of capital	Elasticity of labour	Elasticity of materials	Returns to scale	Technical change	Total factor productivity growth
Mean by year						
2000	0.695	0.292	0.543	1.530	0.012	.
2001	0.693	0.292	0.543	1.528	0.012	-0.093
2002	0.692	0.293	0.543	1.527	0.012	0.025
2003	0.689	0.292	0.543	1.524	0.013	0.008
2004	0.685	0.292	0.543	1.519	0.013	0.031
2005	0.679	0.292	0.542	1.513	0.013	0.012
2006	0.675	0.292	0.542	1.509	0.014	0.022
2007	0.671	0.292	0.542	1.505	0.014	0.025
2008	0.667	0.292	0.542	1.501	0.014	0.013
2009	0.666	0.292	0.541	1.499	0.015	0.036
2010	0.665	0.292	0.541	1.498	0.015	0.006
Mean by herd size						
Small	0.700	0.295	0.544	1.539	0.013	-0.032
Medium	0.661	0.290	0.541	1.491	0.014	0.047
Large	0.621	0.283	0.537	1.442	0.014	0.074
Mean by milking system						
CMS	0.684	0.293	0.543	1.519	0.013	0.000
TRANS	0.647	0.289	0.540	1.475	0.013	0.070
AMS	0.631	0.289	0.539	1.458	0.014	0.081
Sample mean	0.679	0.292	0.542	1.514	0.013	0.009

4. Concluding remarks

Based on economic theory, investments are viable if they can pay back investment costs. Investments are also needed to increase productivity. This is a well-established goal in the common agricultural policy of the EU. Yet, there are large differences in productivity levels among the member states. Our results show that low-productivity areas like Finland could catch up in the productivity difference through investments in new technology. Our results highlight that productivity development is heavily concentrated on those front-line farms switching to the latest technologies like an AMS. Those farms that kept conventional milking systems did not improve their productivity in average terms at all during the years 2000–10.

The next question is whether there are means to affect the investment decisions of farmers. Our results show that very few economic factors on a dairy farm or in its economic environment could be identified to affect the switch to new technology. Both input and output prices proved to be non-significant factors in the limits that were observed in the research period. The interest rate on agricultural debt and the equity ratio of the farm behaved similarly, and did not have any significant effect on investments in an AMS. These results confirm the previous findings that the welfare of the farm family is a very dominating factor in the switch to an AMS. In Finland, where almost all dairy farms are operated by a farm family, the influence of the welfare factor may be especially strong. Despite the non-economic incentives, the switch seems to promote productivity development, and thus better economic performance.

Olsen and Lund (2011) concluded their study with the policy implication that improved knowledge about farmers' socio-economic factors and investment behaviour might reduce the deadweight losses associated with many governmental investment programmes. Our results indicate that investment behaviour can be affected by investment allowances, at least to some extent. It is probable that the role of a particular investment aid would be more evident in relation to a building investment than an investment in an AMS. As the existing machinery capital and existing milk production proved to positively affect the switch to an AMS, we may derive that the investment subsidies are an essential factor in forming the basis for investments in modern technology. Our results are in line with the results of Pietola and Heikkilä (2005), who found that existing building capital encourages investing even more in capital-intensive technologies. Significant investment aids are thus needed to support farms that currently have too little capacity in their operations to have access to and obtain full benefits from large-scale modern technologies.

EU agriculture appears to be characterised by overcapitalisation rather than by credit constraints (Petrick and Kloss, 2012). Therefore, Petrick and Kloss (2012) have suggested that future policy reforms of the EU should aim at downsizing the capital subsidies. Our results, however, show that investments as well as the investment aids to boost them are needed in low-productivity areas, where investments in new technology still have great potential to increase productivity and thus profitability in the long run.

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FACTOR MARKETS

Comparative Analysis of Factor Markets for Agriculture across the Member States

245123-FP7-KBBE-2009-3

The Factor Markets project in a nutshell

Title	Comparative Analysis of Factor Markets for Agriculture across the Member States
Funding scheme	Collaborative Project (CP) / Small or medium scale focused research project
Coordinator	CEPS, Prof. Johan F.M. Swinnen
Duration	01/09/2010 – 31/08/2013 (36 months)
Short description	Well functioning factor markets are a crucial condition for the competitiveness and growth of agriculture and for rural development. At the same time, the functioning of the factor markets themselves are influenced by changes in agriculture and the rural economy, and in EU policies. Member state regulations and institutions affecting land, labour, and capital markets may cause important heterogeneity in the factor markets, which may have important effects on the functioning of the factor markets and on the interactions between factor markets and EU policies. The general objective of the FACTOR MARKETS project is to analyse the functioning of factor markets for agriculture in the EU-27, including the Candidate Countries. The FACTOR MARKETS project will compare the different markets, their institutional framework and their impact on agricultural development and structural change, as well as their impact on rural economies, for the Member States, Candidate Countries and the EU as a whole. The FACTOR MARKETS project will focus on capital, labour and land markets. The results of this study will contribute to a better understanding of the fundamental economic factors affecting EU agriculture, thus allowing better targeting of policies to improve the competitiveness of the sector.
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Website	www.factormarkets.eu
Partners	17 (13 countries)
EU funding	1,979,023 €
EC Scientific officer	Dr. Hans-Jörg Lutzeyer

SEVENTH FRAMEWORK PROGRAMME