Productivity growth of dairy farms having conventional vs. automatic milking system

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Abstract

The aim of this study was to determine whether the switch from conventional milking systems (CMS) to automatic milking systems (AMS) has positive effects on the productivity growth. Production function analysis was implemented over a rotating panel data of 323 Finnish dairy farms during the period of 2000–2011. The total factor productivity growth was 1.7% per year on farms that stayed in CMS and 3.1% per year on farms that had switched to AMS. The improvement was linked to overall reforms in production technology and an expansion in herd size but the adoption of AMS intensified the positive development.

Key words: milk production, technology, productivity growth

1 Introduction

In the long term, productivity and especially productivity growth are necessary conditions for the survival of a farm. Together with input and output prices, improving productivity is one of the main factors on which profitability at farm level is founded. From farmers point of view productivity growth is actually the most important since input and output prices are out of farmers' possibility to adjust for. Average productivity in the agricultural sector may increase as a result of the increased productivity of individual farms and when farms with low productivity exit production. An investment in new technology is one possible way to improve the productivity development at farm level.

On dairy farms, milking technology forms an essential part of production technology. Automatic milking systems (AMS) have replaced conventional milking systems (CMS) during the past few years. De Koning (2010) reported that over 8,000 commercial dairy farms worldwide used one or more milking robots. That number has continued to increase, especially in north-western Europe (Steeneveld et al., 2012). In Finland, the total number of dairy farms with AMS was 818 at the end of 2013. This number corresponded to about 10% of all Finnish dairy farms.

The pressure to improve productivity on Finnish dairy farms is as evident as the trend to shift from CMS to AMS in new loose-housing systems. However, evidence of the positive effect of the technology switch on productivity development has not yet been documented properly. So far, the impacts of AMS have widely been investigated from technical perspectives (e.g. Castro et al., 2012; Jacobs and Siegford, 2012; Hovinen and Pyörälä, 2011) but economic analysis overall is limited. Bijl et al. (2007) investigated the profitability and Steeneveld et al. (2012) the technical efficiency of AMS farms. These two studies are among the few which investigated the economic performance of AMS farms compared with CMS farms on the basis of empirical data. Rotz et al. (2003) used a farm-simulation model to determine the long-term, whole-farm economic effect of implementing AMS.

Economic rationality does not solely motivate investment in new technologies. Sauer and Zilberman (2012) underscore the importance of risk faced by the operator, the effects of network externalities, and peer-group learning in the adoption of AMS. Moreover, increasing farm size, lack of skilled workers, technical progress, and striving for better quality of life have entailed investments in robotics on dairy farms (Mathijs, 2004; Bijl et al., 2007). Better quality of life includes such components 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 fast structural development. Because access to skilled farm labour has become more and more a restricting factor, development options opened by robotics for expanding the size of dairy operations are crucial.

Several investment allowance programs have been implemented with the objective to improve the structure, productivity and thus competitiveness of the European agricultural sector in the global markets. These programs have been financed partly by the European Union (EU), and in part through national funds. Nevertheless, there are very few quantitative estimates for how the performance of farms has developed as a result of investments realized.

In this study, a comparison of technology-specific differences among Finnish dairy farms was conducted to assess changes in productivity growth caused by the adoption of AMS. The objective of this study was to estimate how the switch from labour-intensive technology to capital-intensive technology affects productivity growth, i.e. whether the ongoing technological change can meet the expectations set for it in improving the productivity and, further, the profitability of dairy farms.

The study analyzes productivity change from the perspective of an average production function. In the approach used in our study, total factor productivity growth can be decomposed into two sub-components, a technological change (TC) component and a component associated with scale (e.g. Kumbhakar et al., 1999). Stochastic frontier analysis (Kumbhakar and Lovell, 2000) provides more extended possibilities for the decomposition of productivity change but, in solving our research problem, we preferred the traditional production function analysis. It generates an answer to our research question by utilizing all observations that were available from the limited number of dairy farms with AMS whereas the parameter estimates of the frontier function are derived from the observations that represent the most efficient farms. This feature of not losing any weight from any observation is important since AMS is a rather new system and the number of these farms in general and particularly in our dataset is just gradually increasing.

2 Materials and methods

2.1 Empirical data

Our empirical analysis was based on data from Finnish dairy farms in the EU Farm Accountancy Data Network (FADN) over the years 2000–2011. The research period begins from the year when the first Finnish dairy farms switched to AMS. All farms in the category of ‘dairy farms’ were primarily included in the research sample (European Commission, 2009). To form more homogenous samples for the comparison of the farms with different milking systems, the smallest farms were excluded from the data. To keep all farms with AMS in the data, the herd size of 25 dairy cows was set the minimum requirement for the farms included in the data.

As farms in the FADN are rotating, the sample formed an unbalanced panel data. The total number of individual farms in the sample was 323. Out of them, 261 farms had CMS throughout the period for which they attended the sample. 47 farms switched from CMS to AMS during the research period and 15 farms had AMS already when they were included in the sample and stayed in the same system as long as they attended the sample.

The total number of observations in the panel data was 1,966 of which 1,677 belonged to farms with CMS and 289 to farms with AMS. The farms that changed the milking system during the research period were also the target of our interest. As adopters where classified for the estimation by the prevailing technology status, results were classified after the estimation by the stability of the milking technology (having stable milking system, changing milking system). The results were also classified by herd size (≤ 65 dairy cows, > 65 dairy cows) to evaluate the size effect on the results.

Table 1. Development of farm size and average milk yield in the sample by milking system category

Year	Arable area, ha		Number of dairy cows		Total milk production, L		Milk yield per cow, L	
	Farms CMS[1]	Farms AMS[2,3]	Farms CMS[1]	Farms AMS[2,3]	Farms CMS[1]	Farms AMS[2,3]	Farms CMS[1]	Farms AMS[2,3]
2000	60		34		238,580		7,431	
2001	63		35		226,306		7,518	
2002	67		37		239,362		7,691	
2003	67		37		234,131		7,887	
2004	68		39		254,628		8,038	
2005	72	92	41	58	268,871	478,476	7,929	8,197
2006	74	93	43	64	247,192	533,404	8,068	8,347
2007	76	95	45	64	302,346	539,289	8,230	8,476
2008	79	100	47	66	322,704	548,744	8,119	8,346
2009	80	107	48	71	318,276	601,306	8,101	8,531
2010	79	111	49	73	317,306	607,762	8,189	8,405
2011	85	115	51	76	334,447	628,661	8,304	8,380
Mean	75	103	43	68	347,001	571,803	8,006	8,390

[1] Conventional milking system

[2] Automatic milking system

[3] The means are not presented in 2000–2004 because of the small number of farms in the category

Farm size, herd size and milk production increased in both farm categories (Table 1). As the arable area did not increase as fast as the herd size, intensity of production measured as the number of cows per hectare increased slightly towards the end of the research period in both farm categories. Total milk production, i.e. milk delivered to a dairy, rose with growing herd sizes and average milk yields. Milk production per cow varied annually depending e.g. on the yield of grass silage but the trend was upward sloping.

Descriptive statistics of the output variable and the input variables of the production function are presented in Table 2. The output variable was the market return of the farm. It includes all farm products but milk return constitutes the main part of the return. Considering only milk return as an output would have led to difficult problems of input allocation. Therefore, in the case of specialized dairy farms, we preferred taking into account the whole market return and, correspondingly, all the inputs used for producing it. By measuring the output in monetary terms, we can cater for possible quality differences of milk between the different milking systems.

The input variables of the model were capital, labour and materials. Capital is the sum of the value of animals, land, buildings, machines and drains. The labour variable includes the labour input which was needed for day-to-day tasks. Both paid labour and family work were taken into consideration. The materials variable includes the variable costs of purchasing materials and supplies.

All monetary values in this study are presented in the fixed prices of 2010. The market return was corrected by using the producer price index of milk and the material costs with the input price index of agriculture. The capital values were deflated by the consumer price index. Annual price indices were obtained from Statistics Finland (2012).

Table 2. Descriptive statistics of model variables

Variable	Description	N	Mean	Standard deviation
Production function, Farms CMS[1]				
Output	Market return €	1,677	157,167	80,102
Capital	Total capital stock, €	1,677	550,306	350,440
Labour	Labour input in agriculture, h	1,677	6,026	2,063
Materials	Costs of materials and supplies, €	1,677	123,203	64,361
Production function, Farms AMS[2]				
Output	Market return €	289	252,622	85,347
Capital	Total capital stock, €	289	1,053,320	388,459
Labour	Labour input in agriculture, h	289	5,999	1,856
Materials	Costs of materials and supplies, €	289	204,822	73,920

[1] Conventional milking system

[2] Automatic milking system

2.2 Productivity change

Total factor productivity (TFP) growth is one of the most widely employed measures of an overall productivity change. It can be defined as the growth in the scalar output which cannot be explained by the growth in the input vector over time (e.g. Denny et al., 1981; Bauer, 1990). To produce estimates for TFP growth and its components, a production function was built in this study (e.g. Kumbhakar et al., 1999). Both translog and Cobb- Douglas type of production functions have been applied for milk production. Out of them, the translog function is more flexible allowing non-constant output elasticities with respect to inputs. However, we had to discard estimating the translog function due to serious monotonicity violations (e.g. Chambers, 1988). Thus, the Cobb-Douglas production function extended with the time trend variable was chosen. The final model can be presented as follows:

$$\ln y_{it} = \beta_0 + \sum_j \beta_j \ln x_{jit} + \beta_k T + \frac{1}{2}\beta_{kk} T^2 + \sum_j \beta_{jk} \ln x_{jit} T + \sum_i \beta_i D_i + v_{it} \tag{1}$$

where y is the scalar output, x is the vector of j (j = 1,…,J) input variables, T the time trend variable, D the farm-specific dummy variable. i (i= 1,…,I) indicates a farm, t a year and v the random error term. The farm-specific dummy variables are present in the model to control for the farm- and farmer-specific effects. The constant term β_0, the slope coefficients β_j, β_k, β_{kk}, β_{jk} and β_i are unknown parameters to be estimated.

When allocative efficiency of production is assumed, TFP growth is the sum of technological change (TC) and the scale effect which both can be derived from the production function (Denny et al., 1981; Bauer, 1990). In the case of the model presented in equation (1), the definition is as follows:

$$\dot{TFP}_{it} = TC_{it} + (RTS - 1)\sum_j \frac{\varepsilon_j}{RTS} \ln \dot{x}_{jit} \,, \tag{2}$$

$$\text{where } TC_{it} = \beta_k + \beta_{kk} T + \sum_j \beta_{jk} \ln x_{jit} \,,$$

$$\varepsilon_j = \frac{\partial \ln y_{it}}{\partial \ln x_{jit}} = \beta_j + \beta_{jk} T \,,$$

$$\text{and} \quad RTS = \sum_j \varepsilon_j \,.$$

The dot in equation (2) indicates the rate of change (log derivative with respect to time). TC, the derivative of the production function with respect to time, means a shift of the production function over a period of years. Such a shift is the result of introducing new and more productive technology. ε_j is the elasticity of the output with respect to input j . It is the measurement of how the change in input *j* affects the output. The sum of output elasticities of inputs indicates returns to scale (RTS). It refers to the change in output resulting from a proportional change in all inputs. A sum of 1 indicates constant RTS (i.e. the proportional change in output equals the change in inputs). When the sum is larger than 1, RTS are increasing. A sum of less than 1 suggests that RTS are decreasing.

The production function was estimated separately for farms with CMS and for farms with AMS because the farms with AMS and CMS represent clearly different production technologies. To verify that the regression coefficients of the production function differ across the milking systems, a single production function was estimated using a pooled estimation method. With that preliminary estimation, the null hypothesis that the coefficients are equal was tested (Clogg et al., 1995; UCLA, 2014). Among the predictors of that model there were a dummy variable indicating one of the milking systems and interaction terms of that milking system and each input variable of the production function. These interaction terms represent the difference in the coefficients between the reference group and the comparison group. The coefficient of the milking system dummy variable and all the coefficients of the interaction terms between the milking system and the input variables of the model were significant: milking system ($p = 0.0005$), milking system × capital ($p < 0.0001$), milking system × labour ($p = 0.0002$), and milking system × materials ($p < 0.0001$). This means that the regression coefficients do indeed differ across the milking systems and, thus, two separate models are justified.

The above-mentioned method requiring the use of technology-specific dummy variable is not applicable with functions including farm-specific dummy variables. The coefficients of the final technology-specific functions were compared utilizing the following statistical test suggested by Clogg et al. (1995) and Brame et al. (1998):

$$z = \frac{\beta_1 - \beta_2}{\sqrt{SE_{\beta 1}{}^2 + SE_{\beta 2}{}^2}} \tag{3}$$

where β_1 and β_2 are the coefficients of the same predictor in two models and $SE_{\beta 1}$ and $SE_{\beta 2}$ their standard errors. Significance of the differences across the coefficients was defined by *z*-values similarly to the examples of Paternoster et al. (1998).

3 Results

The estimated production functions (1) are presented in Table 3. Input variables had a positive effect on production with the exception of capital input of the farms with AMS. The effects were also statistically significant except the weight of capital input on the farms with CMS and labour input on the farms with AMS. The time trend variable and its square term had a significant coefficient on the farms with CMS but an insignificant coefficient on the farms with AMS. The cross terms of the capital and materials variables and the time trend variable were significant in both farm categories (Table 3).

In the model, 169 out of 304 dummy variables for farms with CMS had a significant coefficient ($p < 0.05$). The respective share for farms with AMS was 14 out of 61 dummy variables. The significant parameter estimates varied between the values of -0.6098 and 0.3238 with a mean of - 0.1703 on farms with CMS. On farms with AMS, the mean of significant coefficients was - 0.2637 and the range from -0.9888 to 0.2150.

Table 3. Estimated production functions and the results of z-test

Model variable	Farms CMS[1] Parameter estimate	Farms CMS[1] Standard error	Farms AMS[2] Parameter estimate	Farms AMS[2] Standard error	*z*
Intercept	6.0857	0.4632	4.8443	1.9465	
ln (capital)	0.0538	0.0298	-0.6349	0.1381	4.874***
ln (labour)	0.1487	0.0360	0.1179	0.1068	0.273
ln (materials)	0.3107	0.0332	1.2162	0.1134	7.664***
Time trend	-0.2137	0.0375	-0.2978	0.1721	0.478
ln (capital)×time trend	0.0071	0.0030	0.0689	0.0133	4.531***
ln (labour)×time trend	-0.0066	0.0041	-0.0026	0.0108	0.351
ln (materials)×time trend	0.0194	0.0036	-0.0465	0.0123	5.143***
Squared time trend	-0.0013	0.0003	-0.0013	0.0011	0.060
$D_2 - D_{305}$	Not presented				
$D_2 - D_{62}$			Not presented		
Observations	1,677		289		
Adjusted R^2	0.93		0.91		

[1] Conventional milking system

[2] Automatic milking system

*** $p < 0.001$

In the production function of farms with CMS, the coefficient of capital input was bigger and the coefficient of materials smaller than in the function of farms with AMS. There was no significant difference in the coefficients of labour input. The coefficients of the cross terms between capital and time trend and between materials and time trend were also significantly different across the milking sytems (Table 3).

The TFP growth and its components (2) derived from the production functions are presented in Table 4. Due to the form of our production function, output elasticities with respect to variable inputs varied over time but not across farms. The output elasticity of materials was the highest in both farm categories. Labour input had the lowest elasticity on farms with CMS and capital input on farms with AMS. The mean of RTS was less than one on both farm categories indicating decreasing RTS at the average level. As we included cross-term parameters between time and input variables in our production function, the function allowed TC to be farm-specific. In the model for farms with AMS, the mean rate of TC was higher than the mean rate derived from the model for farms with CMS. The average TFP growth of the research period was 1.7% per year for farms with CMS and 3.1% per year for farms with AMS.

The results of the technology-specific models are also presented by herd size (Table 4). There was no difference in the rate of TFP growth between the farm size categories on farms with AMS but, on farms with CMS, the rate was higher for farms having more than 65 dairy cows compared with farms having less than 65 dairy cows. The difference was mainly due to the higher rate of TC on bigger farms.

The results were finally categorized by the stability status of the farms, i.e. whether they adopted AMS during the research period or whether they had either CMS or AMS for the whole period (Table 4). The results show that the farms with a stable system had slightly higher rate of TFP growth than the farms without technology changes. The effect was more evident after the change than before it (0.033 vs. 0.030 and 0.017 vs. 0.016). However, the change from CMS to AMS clearly improved the productivity growth of the adopters (0.030 vs. 0.016).

Table 4. Means of elasticities, returns to scale, technological change, and total factor productivity growth by milking system category, herd size, and stability status

Model	Output elasticity with respect to inputs			Returns to scale	Technological change	Total factor productivity growth
	Capital	Labour	Materials			
Farms CMS[1]						
Mean	0.105	0.101	0.449	0.655	0.028	0.017
25–65 dairy cows	0.103	0.103	0.445	0.650	0.027	0.016
> 65 dairy cows	0.120	0.087	0.491	0.698	0.041	0.024
Stable farms[3]	0.106	0.100	0.455	0.661	0.027	0.017
Adopters[4]	0.091	0.114	0.412	0.617	0.036	0.016
Farms AMS[2]						
Mean	0.012	0.094	0.780	0.886	0.042	0.031
25–65 dairy cows	-0.018	0.095	0.800	0.877	0.044	0.031
> 65 dairy cows	0.052	0.092	0.753	0.897	0.040	0.031
Stable farms[3]	0.032	0.093	0.766	0.891	0.043	0.033
Adopters[4]	0.005	0.094	0.785	0.884	0.042	0.030

[1] Conventional milking system

[2] Automatic milking system

[3] Farms having stable milking system (CMS vs. AMS) during the research period

[4] Farms changing the milking system (change from CMS to AMS) during the research period

4 Discussion

Previous estimations of productivity development in the Finnish dairy sector show that productivity growth ceased almost completely in the early 1990s but, towards the end of the decade, the trend turned positive. Development in productivity trends followed the trend of investments which was dominated by the uncertainty over Finnish membership in the EU (1995). For the period 1990–2000, Sipiläinen (2007) estimated a rate of growth of 1.09% per year from an input distance function and from a similar sample of dairy farms to the one in this study. Our production function analysis gave slightly higher rates in the period from 2000 to 2011, 1.7% per year for farms with CMS and 3.1% for farms with AMS. Divisia indices estimated by Myyrä (2009) showed that the average rise of productivity was 1.9% a year in 1987–2007. This rate was estimated for the whole sector taking into account the exits from production.

In this study, the rate of TFP growth improved along with the switch to AMS. It was shown by the comparison of farms with CMS and farms with AMS and by the comparison of the results of the adopters of AMS before and after the switch of milking technology. However, the comparison by herd size categories indicated that the improvement was also related to the enlargement of the farms, not only to milking technology. Farms with CMS could improve their productivity growth by enlarging their herd size but their rate did not reached the rate of adopters of AMS. On farms with AMS, the rate of the TFP growth was equal in both herd size categories investigated in the study (Table 4). The maximum number of dairy cows on farms with AMS was 145 whereas on farms with CMS the maximum was 169 dairy cows.

The lower TFP growth for the adopters of AMS compared with farms without a change in their milking technology may result from the preparation for enlargement and investment e.g. by raring extra heifers who need labour and other inputs but do not produce any output yet. After the adaption of AMS, the rate of productivity growth was higher than the rate on farms with CMS but lower than the rate of stable farms with AMS. Among farms with CMS, there were also farms that developed and enlarged their milk production but also farms that were exiting production. Probably, there were no farms with AMS exiting production which might affect the results along with the adoption of AMS.

Elasticities estimated from the production functions indicated that all farms would get the highest increase in output by increasing material input. Elasticities of capital and labour input reflected the current level of those inputs, i.e. the higher the level, the lower the elasticity. Thus, an increase in labour input is more beneficial for farms with AMS than for farms with CMS. Correspondingly, increasing capital input generates a higher increase in the output on farms with CMS than on farms with AMS. On farms with AMS, the effect was even negative which violates the monotonicity condition of the production function (e.g. Chambers, 1988). However, the unexpected result was originated from the farms having AMS and less than 65 dairy cows (Table 4). These farms were obviously recent adopters of AMS having high capital costs and a herd where the whole capacity of the robot was not utilized.

RTS indicated decreasing RTS in both farm categories. It means that productivity cannot be improved by increasing the use of all inputs in the same proportion because long-run production changes are smaller than the proportional change in inputs. This problem was earlier recognized by Sipiläinen (2008) who widely investigated the productivity of Finnish dairy farms. He concluded that the utilization of scale economies seems to face special constraints in Finnish conditions. Our results indicate that the constraints, which Sipiläinen (2008) connected to the structure of Finnish dairy farms, have not yet disappeared. Although, the smallest dairy farms were not included to our research sample which for its part may affect the low rate of RTS. However, the results indicate that the adoption of new technology is necessary for creating possibilities to improve productivity development in the sector. The results of this study indicate that the adoption of AMS generates TC that enables the positive development of productivity despite the unfavourable scale effects.

Decreasing RTS estimated in this study may also be affected by the applied estimation method and the form of the production function. Sipiläinen (2007) found that, in the 1990s, RTS averaged 1.527 when the estimate was derived from a translog input distance function whereas, in this study, a Cobb-Douglas production function was estimated. The translog function allows non-constant output elasticities with respect to inputs and, thus, RTS to be farm-specific. Our unbalanced panel data did not support estimation of the more flexible function.

The properties of the panel data were utilized in this study to estimate the farm-specific effects on the productivity growth. In the model for farms with CMS, 56% of the coefficients of the farm-specific dummy variables were significant. In the model for farms with AMS, the share was 23%. The result indicates that these effects contribute to the variation in the productivity, especially on farms with CMS. These dummy variables also controlled for e.g. the regional effects, not only the effects of an individual farm or a farmer.

Steeneveld et al. (2012) found no difference in the technical efficiency between recent and non-recent adopters of AMS. Thus, we cannot expect that improvement in technical efficiency will improve the productivity development of the adopters of AMS after the transition period has passed and an established stage of production has been reached. However, we may expect that the TFP growth of Finnish dairy farms with AMS will further improve when the recent adopters reach the herd size and milk production level that match the milking capacity of AMS. Rotz et al. (2003) estimated that a single-stall AMS provides the greatest potential benefit, measured as net return, on a farm size of 60 cows at a moderate milk production level (8,600 kg/cow). Castro et al. (2012) suggested 68 to 69 cows/stall at the milk production level around 8,000 kg/cow. In our data, milk yield per cow was at a moderate level but many farms having AMS were still on their way to the desired herd size. 166 out of the 289 observations from the farms with AMS belonged to the category of farms having less than 65 dairy cows.

5 Conclusions

Dairy farmers' investment behaviour is an important factor for the productivity growth of the sector. The adoption of new milking technology improves the productivity development of dairy farms although the switch to a new production system may cause a temporary drop in the development. The result underscores proper timing of the technology change; old farmers may not ever have a possibility to benefit the positive impacts of their investments. To ensure a favourable development, investment allowance programmes should promote farm successions to young generations who have incentives to invest in novel technology.

The increased productivity growth of dairy farms is linked to the overall organization and mechanization of milk production in large herds. Positive productivity change accelerates with the herd size also on farms staying in CMS. Still, AMS generates TC that results in even better productivity development on farms having AMS compared with farms having CMS. However, further research is needed to compare the productivity development between the farms having invested in AMS and the farms having invested in CMS. Having only investing farms in the sample we could eliminate the possible impact of the farms that exit or plan to exit milk production.

The direct effect of AMS was linked to beneficial technological change but AMS may also contribute to improved productivity growth by solving problems related to the availability of skilled labour force. AMS may open access to larger herd size which is a premise for improving productivity growth of the Finnish dairy sector in the long run.

References

Bauer, P.W. 1990. Decomposing TFP growth in the presence of cost inefficiency, non-constant returns to scale, and technological progress. *Journal of Productivity Analysis* 1, 287–299. doi: 10.1007/BF00160047.

Bijl, R., Kooistra, S.R. and Hogeveen, H. 2007. The profitability of automatic milking on Dutch dairy farms. *Journal of Dairy Science* 90, 239–248. doi:10.3168/jds.S0022-0302(07)72625-5.

Brame, R., Paternoster, R., MazeroIIe, P. and Piquero, A. 1998. Testing for the Equality of Maximum-Likelihood Regression Coefficients between Two Independent Equations. *Journal of Quantitative Criminology* 14, 245-261.

Castro, A., Pereira, J.M., Amiama C. and Bueno, J. 2012. Estimating efficiency in automatic milking systems. *Journal of Dairy Science* 95,929–936. doi: 10.3168/jds.2010-3912.

Chambers, R.G. 1988. Applied production analysis. A dual approach. Cambridge University Press. New York, NY.

Clogg, C.C., Petkova, E. and Haritou, A. 1995. Statistical Methods for Comparing Regression Coefficients between Models. *American Journal of Sociology* 100, 1261-1293.

De Koning, C.J.A.M. 2010. Automatic milking–Common practice on dairy farms. Pp. 52–67 in Proceedings of the First North American Conference on Precision Dairy Management. *Progressive Dairy Operators*, Toronto, ON, Canada.

Denny, M., Fuss, M. and Wawerman, L. 1981. The measurement and interpretation of total factor productivity in regulated industries with an application to Canadian telecommunications, in T. G. Cowing and R. E. Stevenson (eds.) *Productivity measurement in regulated industries*. Academic Press, New York, NY.

European Commission. 2009. Typology Handbook. Directorate-general for agriculture and rural development. Community committee for the farm accountancy data network. 74 p.

Hovinen, M. and Pyörälä, S. 2011. Udder health of dairy cows in automatic milking. *Journal of Dairy Science* 94, 547–562. doi:10.3168/jds.2010-3556.

Jacobs, J. A. and Siegford, J.M. 2012. The impact of automatic milking systems on dairy cow management, behavior, health, and welfare. *Journal of Dairy Science* 95, 2227–2247. doi:10.3168/jds.2011-4943.

Kumbhakar, S. and Lovell C. A. K. 2000. Stochastic Frontier Analysis. Cambridge University Press, Cambridge, UK.

Kumbhakar, S. C. and Heshmati, A., Hjalmarsson, L. 1999. Parametric approaches to productivity measurement: A comparison among alternative models. *Scandinavian Journal of Econ*omics 101, 405–424. doi:10.1111/1467-9442.00163.

Mathijs, E. 2004. Socio-economic aspects of automatic milking, in A. Meijering, H. Hogeveen, and C.J.A.M. de Koning (eds.) *Automatic Milking: A better understanding*. Wageningen Academic Publishers, Wageningen, The Netherlands.

Myyrä, S. 2009. Productivity development in agriculture, in J. Niemi, and J. Ahlsted (eds.) *Finnish Agriculture and Rural Industries 2009*. Agrifood Research Finland, Publications 109a.

Paternoster, R., Brame, R., Mazerolle, P. and Piquero, A. 1998. Using the correct statistical test for the equality of regression coefficients. *Criminology* 36, 859-866.

Rotz, C.A., Coiner, C.U. and Soder, K.J. 2003. Automatic milking systems, farm size, and milk production. *Journal of Dairy Science* 86, 4167-4177. doi:10.3168/jds.S0022-0302(03)74032-6.

Sauer, J. and Zilberman, D. 2012. Sequential technology implementation, network externalities, and risk; the case of automatic milking systems. *Agricultural Economics* 43:233-251.

Sipiläinen, T. 2007. Sources of productivity growth on Finnish dairy farms: application of an input distance function. *Food Economics – Acta Agriculturae Scandinavica, Section* C, 4, 65–76.

Sipiläinen, T. 2008. *Components of Productivity Growth in Finnish Agriculture*. Doctoral Dissertation. Agrifood Research Finland, Agrifood Research Reports 116, 1-153, 5 appendices. Available at: http://www.mtt.fi/met/pdf/met116.pdf.

Statistics Finland. 2012. *Official Statistics of Finland*. Statistics Finland, Helsinki. Assessed December 2013, available at: http://www.stat.fi/til/hin_en.html.

Steeneveld, W., Tauer, L.W., Hogeveen H. and Oude Lansink, A. G. J. M. 2012. Comparing technical efficiency of farms with an automatic milking system and a conventional milking system. *Journal of Dairy Science* 95,1–8. doi: 10.3168/jds.2012-5482.

UCLA, 2014. Introduction to SAS. UCLA: Statistical Consulting Group. Assessed June 26, 2014, available at http://www.ats.ucla.edu/stat/sas/notes2/.