Productivity Change Analysis of Polish Dairy Farms After Poland's Accession to the EU – An Output Growth Decomposition Approach

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October 2016

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Abstract

The aim of this study is to assess changes in productivity of Polish dairy farms after Poland's accession to the EU. In order to do so a new decomposition of output growth is proposed in a stochastic frontier framework. We show how changes in economies of scale can be isolated, which leads to redefined components of output growth and a better measure of productivity growth. The productivity component is now disaggregated to its three generic sources: total scale change, real technical change and efficiency change. The analysis of 1,191 Polish dairy farms between 2004-2011 has revealed that production growth (3.91%) is mostly due to inputs accumulation (3.4%) rather than productivity growth (0.51%.) Further decomposition indicates that productivity component is driven by real technical growth (1%) and changes in scale elasticity, which have had a negative effect on productivity (-0.81%). Technical efficiency growth (0.36%) played a rather minor role.

Keywords: productivity analysis, Polish dairy farms, output growth decomposition, stochastic frontier analysis, FADN

Acknowledgements

The first two authors acknowledge the financial support from the Faculty of Management, Cracow University of Economics. The third author gratefully acknowledges the financial support from Polish National Science Centre no. DEC-2013/09/N/HS4/03833. The grant is being carried out at the Department of Econometrics and Operational Research, Faculty of Management, Cracow University of Economics.

1. Introduction

Dairy industry is one of the most important sectors of agriculture in the European Union. In 2012, milk was the single largest agricultural product in terms of value, with a 13% share of total agricultural output in the EU. Poland, who joined the EU on 1 May 2004, was ranked the fourth largest producer in the EU and the world's twelfth largest producer in 2012 (contributing 2.1% to world's milk production). Therefore the need to analyze sources of output and productivity growth of Polish dairy farms is a direct consequence of the country's importance in the joint European agriculture sector.

Bayesian output growth decomposition in a single-output and multi-input setting was first proposed by Koop *et al* (1999). One of the main differences between methodology proposed by these authors and Fuentes *el al* (2001) or Orea, (2002), is that the latter only focus on decomposing productivity change while Koop *et al* (1999) present a full decomposition of output change into three components: input change, technical change and technical efficiency change. Productivity change, however, is made up of only technical efficiency change and technical change. Since there is no component measuring the contribution of economies of scale to productivity, the method lacks a standard three-way decomposition of productivity change (see, e.g., Färe *et al*, 1994, Bertazzoli *et al*, 2014, Theodoridis *et al*, 2014). A key aspect of this paper is to show how the decomposition originally proposed by Koop *et al* (1999) in the context of stochastic frontier analysis (SFA) can be modified in order to include changes in scale economy (returns to scale, RTS) and thus better reflect changes in productivity. Our output change decomposition strategy results in several new components compared with previous works in this field. We derive scale effect change (SEC), scale structural change (SSC), which both amount to the total scale change (TSC), as well as pure input change (PIC) and real technical change (RTC). Moreover, we show how to further decompose real technical change into elasticity structural technical change (ESTC) and neutral technical change components (NTC). Finally, we present the results of an empirical study of 1,191 Polish dairy farms from 2004 to 2011.

2. Productivity of Polish farms in pre-accession period

The first productivity analysis of Polish farms is generally considered to be done by Brümmer *et al* (2002). The authors used a sample of 50 dairy farms from the Poznan region. By employing stochastic output distance functions and their own methodology of decomposition they found a 5% decline in productivity over the period of 1991-1994. Brümmer *et al* (2002) also found that the decrease in total factor productivity (TFP) in the analysed period was mainly caused by technical regress (-9%).

Another study of the Polish agriculture industry was done by Latruffe *et al* (2008) who used a sample of 250 Polish farms (1996-2000) and employed Data Envelopment Analysis (DEA) to derive TFP indices. The authors found a 2% decrease per annum in TFP and that productivity change in the analysed period was dominated by technical change component (-6%). This was consistent with the findings of Brümmer *et al* (2002). However, the studies differ in that, while the former revealed a small progress in technical efficiency, the latter study reported a substantial progress of 4%.

A cross-country comparison in the agricultural sector was conducted by Tonini (2012) using FAO data (1993-2006). The author employed Bayesian approach to estimate the extended so-called True Fixed Effects model and the inefficiency model proposed by Cuesta (2000). He found TFP growth in the EU and candidate countries (average annual growth of 0.76%) and the following sources of productivity growth: efficiency change (-0.0457%) technical change (0.9975%) and scale change (-0.0188%). However, these results were based on decomposition approach proposed by Orea (2002)

3. New components of output growth based on stochastic frontier models

To measure farm and time-specific technical efficiency, we use stochastic frontier models, simultaneously introduced by Aigner *et al* (1977) and Meeusen and van den Broeck (1977). Let y_{ti} and x_{ti} be the logs of output and inputs vector respectively for farm i (i=1,…,N) in period t (t=1,…,T). We consider a general stochastic frontier model in a production function framework:

$$y_{ti} = h(x_{ti}; \beta_t) + v_{ti} - u_{ti} \tag{1}$$

where h is a known production function and β_t is its vector of k parameters. We account for two sources of disturbance. The first one, v_{ti}, represents a random disturbance. The second one, u_{ti}, is known as technical inefficiency, which defines a given producer's "distance" from the stochastic production frontier. Its role is to capture decision-making errors, which result in relative differences between "the best practice" outputs and the observed outputs. Technical efficiency is measured as $TE_{ti} = \exp(-u_{ti})$. Under the assumption that the production function has a log-linear form, $h(x_{ti}; \beta_t)$ is then obtained as $\beta_t' x_{ti}$ as in, e.g., translog and Cobb-Douglas models.

The decomposition methodology used in this study builds upon the work of Koop *et al* (1999) who proposed the following components of the output change:

$$\begin{aligned} OC_{t+1,i} = \exp\left(\frac{1}{2}(\beta_{t+1} + \beta_t)'\left(x_{t+1,i} - x_{ti}\right)\right) \exp\left(\frac{1}{2}\left(x_{t+1,i} + x_{ti}\right)' \ \ (\beta_{t+1} - \beta_t)\right) \times \\ \exp\left(\left(u_{t,i} - u_{t+1,i}\right)\right) = IC_{t+1,i} \times TC_{t+1,i} \times EC_{t+1,i}. \end{aligned} \tag{2}$$

Since accounting for efficiency change (EC) is trivial, we focus on the two remaining terms of the above decomposition – IC and TC. First, we turn our attention to input change (IC), which is:

$$IC_{t+1,i} = \exp\left(\frac{1}{2}(\beta_{t+1} + \beta_t)'\left(x_{t+1,i} - x_{ti}\right)\right) = \exp\left(\beta_{av}{}' x_{t+1,i} - \beta_{av}{}' x_{t,i}\right).$$

where β_{av} is the average (fixed) level of technology described by parameters between t and t+1 period. In order to isolate the changes in scale effect from purely input-driven output change, we first express the vector of inputs as the sum of two vectors: $x_{t,i} = a_{t,i} + c_{t,i}$, $x_{t+1,i} = a_{t+1,i} + c_{t+1,i}$, so that $\beta_{av}{}' a$ are returns to scale for inputs given in x (thus $c = x - c$). This rearrangement allows us to write:

$$\begin{aligned} ln\left(\mathrm{IC}_{\mathrm{t+1,i}}\right) &= \beta_{av}{}' x_{t+1,i} - \beta_{av}{}' x_{t,i} = \beta_{av}{}' a_{t+1,i} + \beta_{av}{}' c_{t+1,i} - \beta_{av} a_{t,i} - \beta_{av} c_{t,i} \\ &= \beta_{av}{}' a_{t+1,i} - \beta_{av} a_{t,i} + \beta_{av}{}' c_{t+1,i} - \beta_{av} c_{t,i} \\ &= RTS.\,\mathrm{ct}_{t+1,i} - RTS.\,\mathrm{ct}_{t,i} + \beta_{av}{}'(c_{t+1,i} - c_{t,i}) \end{aligned}$$

where $RTS.\mathrm{ct}_{t,i}$ ($RTS.\mathrm{ct}_{t+1,i}$) are returns to scale measured at the constant, "fixed" technology; that is the average between t and t+1 periods, and i-th producer's input in period t (t+1). This yields the following decomposition of input change:

$$\begin{aligned} IC_{t+1,i} &= \exp(RTS.\mathrm{ct}_{t+1,i} - RTS.\mathrm{ct}_{t,i}) \times \exp(\beta_{av}{}'(c_{t+1,i} - c_{t,i})) \\ &= SEC_{t+1,i} \times PIC_{t+1,i} \end{aligned} \tag{3}$$

where the first component measures changes to i-th producer's scale effect under current, fixed technology (scale effect change – SEC) and the second one is the pure input change (PIC). The term "scale effect change" is used because this component shows the share of returns to scale increase/decrease solely based on changes in the input mix between periods t and t+1 (under fixed, average technology frontier between the two periods). It should be noted that the IC component can further be decomposed in order to assess each factor's contribution to input change; see Makieła (2014). Since PIC is IC under CRS restrictions (constant returns to scale), it can be shown that PIC decomposition is proportional to IC decomposition.

Obtaining SEC from IC is especially important because this term affects productivity and as such it should be added to productivity change component giving a more accurate measure than the one in Koop et al. (1999). Thus, we have:

$$TPC_{t+1,i} = SEC_{t+1,i} \times TC_{t+1,i} \times EC_{t+1,i}$$

where TPC is here referred to as the "total" productivity change to distinguish it from the PC component in Koop *et al* (1999). Under the assumption of constant technology as well as technical efficiency, SEC component indicates how a given producer becomes more or less productive due to input-driven changes in the scale of operation. Moreover, as there can be no additional productivity gain/loss due to changes in the scale of operation under the CRS restriction, the SEC ratio equals 1 by default then.

Now we move to the second part of the decomposition in (2) and redefine the technical change component from Koop *et al* (1999):

$$TC_{t+1,i} = \exp\left(\frac{1}{2}(x_{t+1,i} + x_{ti})'(\beta_{t+1} - \beta_t)\right) = \exp(x_{av,i}{}'\beta_{t+1} - x_{av,i}{}'\beta_t)$$

where $x_{av,i}$ is the vector of inputs averaged between the t and t+1 periods. Again, we define the input vector $x_{av,i}$ as the sum of two vectors $x_{av,i} = a_{av,i} + b_{av,i}$, so that $a_{av,i}{}'\beta_t$ is i-th producer's returns to scale ratio given technology in period t and the average input level between t and t+1. Furthermore, $a_{av,i}{}'\beta_{t+1}$ are returns to scale given technology in period t+1 and average input level between t and t+1. We then have that:

$$\begin{aligned} \ln(TC_{t+1,i}) &= a_{av,i}{}'\beta_{t+1} - a_{av,i}{}'\beta_t + b_{av,i}{}'\beta_{t+1} - b_{av,i}{}'\beta_t \\ &= RTS.\mathrm{ci}_{t+1,i} - RTS.\mathrm{ci}_{t,i} + b_{av,i}{}'(\beta_{t+1} - \beta_\mathrm{t}) \end{aligned}$$

where $RTS.\mathrm{ci}_{t,i}$ are returns to scale for constant inputs (average between t and t+1) in period t and $RTS.\mathrm{ci}_{t+1,i}$ are returns to scale for constant inputs given technology in period t+1. This allows us to rewrite technical change component:

$$\begin{aligned} TC_{t+1,i} &= \exp\left(RTS.\mathrm{ci}_{t+1,i} - RTS.\mathrm{ci}_{t,i}\right) \times \exp\left(b_{av,i}{}'(\beta_{t+1} - \beta_{\mathrm{t}})\right) \\ &= SSC_{t+1,i} \times RTC_{t+1,i} \end{aligned} \tag{4}$$

where SSC is the scale structural change component, i.e. the share of returns to scale change that is due to changing frontier parameters (frontier shift between t and t+1); RTC can be referred to as the real technical change, i.e. the part of technical change which is not due to changes in scale elasticity. Hence, RTC expresses changes in technology that are either due to changes in the factors' elasticity structure or due to neutral technical change:

$$RTC_{t+1,i} = ESTC_{t+1,i} \times NTC_{t+1,i} \tag{5}$$

where the $ESTC$ is the elasticity structure technical change component and NTC is neutral technical change component, which can be directly calculated based on the production function parameters.

The new output decomposition can be expressed as:

$$OC_{t+1,i} = PIC_{t+1,i} \times (SEC \times SSC \times ESTC \times NTC \times EC)_{t+1,i} = PIC_{t+1,i} \times TPC_{t+1,i} \tag{6}$$

where the productivity change component (TPC) is now made up of five, not two, sub-components

$$TPC_{t+1,i} = SEC_{t+1,i} \times SSC_{t+1,i} \times ESTC_{t+1,i} \times NTC_{t+1,i} \times EC_{t+1,i}. \tag{7}$$

The new "total" productivity change component is equal to the PC component from Koop *et al* (1999), augmented by the scale effect change, i.e. $TPC = SEC \times PC$. It can be shown that if the new components (SEC and SSC) are combined together they are equal to the total returns to the scale change:

$$\begin{aligned} TSC_{t+1,i} &= SEC_{t+1,i} \times SSC_{t+1,i} \\ &= \exp\left(RTS.av_{t+1,i} - RTS.av_{t,i}\right) \times \exp\left(av.RTS_{t+1,i} - av.RTS_{t,i}\right) \\ &= \exp(RTS_{t+1,i} - RTS_{t,i}) \end{aligned} \tag{8}$$

where TSC is the total scale change component of the total productivity change, $RTS_{t,i}$ are returns to scale in period t (for inputs and technology in t) and $RTS_{t+1,i}$ are returns to scale in period t+1 for producer i. Thus, we can express the productivity change in (7) as:

$$\begin{aligned} TPC_{t+1,i} &= (SEC \times SSC)_{t+1,i} \times (ESTC \times NTC)_{t+1,i} \times EC_{t+1,i} \\ &= TSC_{t+1,i} \times RTC_{t+1,i} \times EC_{t+1,i}, \end{aligned} \tag{9}$$

which brings us the desired three-way decomposition of productivity change into changes in scale, technology (frontier shift) and technical efficiency. Moreover, based on (5) and (8), RTC and TSC components can be further decomposed to provide more insight into sources of productivity growth. The results of the empirical analysis are expressed as average annual percentage growth rates. For example, for technical change component we use $ATG = 100 \times (ATC - 1)$, where ATC is the geometric mean of annual changes given in (4).

4. The econometric model

In this study we employ the following translog form of the model given in (1):

$$h_t(x_{ti}, \beta_t) = \beta_0^{(t)} + \sum_{j=1}^{J} \beta_j^{(t)} \ln x_{ti,j} + \sum_{j}^{J} \sum_{g \geq j}^{J} \beta_{j,g}^{(t)} \ln x_{it,j} \ln x_{it,g}$$
$$\beta_0^{(t)} = \dot{\beta}_0 + \ddot{\beta}_0 t, \quad \beta_j^{(t)} = \dot{\beta}_j + \ddot{\beta}_j t, \quad \beta_{j,g}^{(t)} = \dot{\beta}_{j,g} + \ddot{\beta}_{j,g} t \quad \text{for} \quad j = 1, \ldots, J \tag{10}$$

where inputs are aggregated into five categories (J=5).

It should be noted that the trend has been introduced into all frontier parameters, which yields a significantly more dynamic structure in comparison to a standard translog model. This allows us to better reflect the influence of technical progress on productivity change over time only at the expense of additional $J+1$ parameters in the frontier function. Specifically, factors' elasticities and returns to scale can now change over time – even when inputs are constant – and the technical change component can vary across objects.

We use the Bayesian approach to stochastic frontier analysis, which allows us to derive full posterior distribution of any quantity of interest. This is especially important when analysing the components of output growth because Bayesian inferences allows us to relatively easily assess their measurement uncertainty. If we were to use the classic approach to SFA based on the maximum likelihood estimator then the reader should note that, due to *latent* variables in the model, acquiring even the simplest dispersion measures for the components discussed in Section 3 would be extremely problematic in practice (i.e. although theoretically possible, it would require a significant numerical effort with little or no knowledge about the possible error of such simulation-based procedure). The reader should also note that in general the presented decomposition strategy does not require us to use SFA, nor Bayesian inference. However, tracing efficiency variation over time, as well as uncertainty measurement, are important factors to consider when analysing productivity and sources of output growth (Makieła, 2009, 2014).

To define a statistical model, we make a usual assumption that v_{ti}, is normally distributed, i.e. i.i.d. $N(0, \sigma_v^2)$. This study employs a standard Bayesian normal-exponential SFA model with Constant Efficiency Distribution (CED) proposed by Koop *et al* (1997). Unlike in traditional SFA, the model allows us to specify *prior* median efficiency, which makes it more practical in use. It uses the concept of the hierarchical priors. Here, inefficiency follows an exponential distribution with mean (and standard deviation) λ_{ti}. For the coefficients in the production frontier (β) and the inverse of the variance of the random disturbance $(\sigma_v^2)^{-1}$, we use a standard normal-gamma prior. For vector β we initially assume that the production function takes a Cobb-Douglas form (C-D) with elasticities of all five inputs equal to 1/5, and that there is a constant return to scale. Thus, the elasticity at the geometric mean of the data (for a typical farm) with respect to each input draws from a normal distribution, $N(0.2, 0.2^2)$. It follows that RTS is $N(1, 0.45^2)$. Note that the prior for λ_{ti}^{-1} is exponential with mean $\left(-\ln(r_{med})\right)^{-1}$, where

$r_{med} \in (0, 1)$. In the normal-exponential CED model r_{med} denotes a median of the prior distribution of TE_{ti} (van den Broeck *et al.*, 1994). Since the above setting implies very weak prior information, this hyperparameter plays an important role because it represents the researcher's initial knowledge about the efficiency of units. We set r_{med} = 0.8, which is a reasonable value for the Polish farm sector due to historical reasons and previous comparisons with the old EU Member States (Brümmer *et al*, 2002). Summarising, the above setting provides a reasonable assumption regarding the parameters. Also, we find that information in such a large dataset as the one used in this study is so strong that the results are robust to any changes in the prior distribution.

The complexity of the stochastic frontiers model requires advanced numerical methods to estimate posterior distributions. In the empirical application we use Gibbs sampling, which amounts to repetitive drawing from the full conditional posterior distributions – these are provided, e.g. in Koop *et al* (1999), or Osiewalski and Steel (1998). We ran 200,000 cycles in order to approximate the posterior characteristics of the model (discarding initial 100,000; sampler's burn-in stage).

5. Data on Polish Dairy Farms

The dataset used for the analysis is taken from Polish FADN. It covers farms, which main source of revenue in the analysed period was milk production. The analysis is based on a balanced panel data from 1,191 Polish dairy farms over the period between 2004 and 2011. Construction of the variables is based on other studies on dairy farms, in which FADN data have been used (see. Emvalomatis *et al*, 2011; Reinhard *et al*, 1999). The output (Q) is specified as the deflated total net farm revenues from sales excluding the value of feed, seeds and plants produced within the farm. Five categories of input are used in the model:

1. Buildings and machinery (K) is measured in terms of deflated book value. It includes fixed capital such as buildings and fixed equipment, as well as machines and irrigation equipment.
2. Total labour (L) is measured in hours. Both hired and family labour declared by the farmer during the interview is included in this measure.
3. Total utilized agricultural area (A, in hectares) refers to owned and rented land.
4. Materials and services (M) is measured in terms of deflated values. This category consists of several other subcategories: purchased feed, seeds and plants, fertilizers, crop protection, crop and livestock specific costs and energy. In order to deflate the total reported expenditure on materials and services, we used price indices provided by Central Statistical Office for each subcategory. Moreover, we excluded the value of feed produced within the farm from this category to avoid double measuring these costs.
5. Dairy cows (S) is expressed in standardized livestock units (LU).

All variables have been mean-corrected prior to estimation. Therefore, the first-order parameters in (10) are interpreted as the elasticities at the sample means.

6. Empirical Analysis of Productivity Change in the Polish Dairy Sector

Table 1 shows posterior characteristics of the model parameters based on the data from 1,191 Polish dairy farms in 2004-2011. Note that the C-D production function is rejected by the data and that the basic regularity conditions implied by economic theory (i.e. the production function to be non-decreasing in inputs) are almost always accepted in the sample. Our analysis indicates that almost all dairy farms have experienced increasing returns to scale of about 1.14 (±0.02) for a typical farm. Livestock (S) and materials (M) have had the highest output elasticity while elasticities of capital (K) and labour (L) have been just slightly higher than area (A), which has been the lowest. Also, we report an average technical efficiency score equal 0.85 with an error of ±0.01.

[Table 1 here]

In order to provide more insight into the structure of productivity change of Polish dairy farms we have summarised the results into three categories according to the number of dairy cows in a farm; these are: small (up to 10 cows), medium (10 – 20 cows) and large (20 – 30 cows).

The results based on the new decomposition are in Table 2. Production in the Polish dairy sector has increased by nearly 4%. This growth has been mostly driven by pure input change at an average rate of 3.40%. Productivity growth, of about 0.51%, has been dominated by real technical change and total scale change. Efficiency growth has played a rather minor, yet positive role. Furthermore, although technical progress has been positively contributing to productivity growth, changes in scale elasticity (TSC) have had a negative effect. Further decomposition of these components have revealed that real technical growth is mainly driven by elasticity structural technical change; thus little impact of neutral technical progress. The TSC component has been dominated by changes in the structure of scale elasticity over time (SSC).

Analysis of the three herd size categories indicates that although the main component of output growth has been pure input growth, its contribution varies quite significantly across farm categories, from 5.03% in large dairy farms to 1.03% in small dairy farms. Decomposition of productivity growth reveals that its sources are different between the categories. Small farms have experienced efficiency and technical growth accompanied by a strong decrease in scale elasticity. Similarly, productivity growth of medium farms has been due to developments in efficiency and technical progress with a simultaneous decline in scale elasticity. However, output decomposition for large farms indicates that all three components have positively contributed to productivity growth there.

[Table 2 here]

Table 3 shows what happens to decomposition results if we do not account for scale elasticity change. Output growth in the dairy sector is still driven by input growth, but at an average annual rate of 3.13% and productivity growth at an average rate of 0.77%. Productivity growth is here decomposed only into technical efficiency and technical change, which are now almost equal; the former amounts to 0.36%, whilst the latter is 0.41%. Hence, not accounting for scale elasticity change gives a biased view about the sources of productivity growth.

Large dairy farms have experienced the highest production growth; for the small ones, it is quite the opposite. In medium and large farms production has grown mainly due to the accumulation of inputs, while in small farms it is the growth of productivity that has had the biggest impact. Further decomposition of input growth reveals that in small and medium farms livestock growth has contributed the most to the overall inputs growth. In large farms, it is the accumulation of materials that has been the most significant. Capital component, on average, has had a negative impact on growth in the Polish dairy industry. Since the estimated capital elasticity is positive, this outcome is due to decreasing capital inputs in the analysed period. We also report different sources of productivity growth among the distinguished categories. Productivity growth of small and large farms has been mainly due to technical progress, whilst medium farms have grown due to technical efficiency growth.

[Table 3 here]

7. Conclusions

The proposed methodology of output growth decomposition leads to different results in comparison to its predecessor, which does not account for scale change. Although in both cases input growth is the main driver of increasing production, there are differences in terms of the exact shares of input and productivity components. Hence, distinguishing scale elasticity change is important as it provides a more appropriate measure of sources of production and productivity growth. In this particular study, the lack of the scale elasticity component in output growth decomposition has resulted in an undervalued contribution of inputs accumulation on output growth and a misrepresented impact of technical and efficiency growth on productivity change.

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Tables and Figures

Table 1. Posterior moments (means and standard deviations) of parameters in the CED translog model

Corresponding variable	Mean	Std. Dev.	Variable	Mean	Std. Dev.
1	0.1014	0.0089	t	0.0012	0.0016
lnK	0.1369	0.0122	t·lnK	-0.0043	0.0024
lnL	0.1254	0.0236	t·lnL	-0.0042	0.0045
lnM	0.3349	0.0112	t·lnM	0.0041	0.0022
lnA	0.1169	0.0148	t·lnA	-0.0002	0.0029
lnH	0.4278	0.0207	t·lnH	0.0002	0.0040
lnK·lnL	0.0648	0.0479	t·lnK·lnL	0.0028	0.0088
lnK·lnM	-0.0397	0.0220	t·lnK·lnM	0.0012	0.0042
lnK·lnA	0.0852	0.0309	t·lnK·lnA	-0.0148	0.0055
lnK·lnH	-0.0404	0.0368	t·lnK·lnH	0.0039	0.0064
lnL·lnM	-0.0497	0.0386	t·lnL·lnM	-0.0014	0.0075
lnL·lnA	0.0099	0.0561	t·lnL·lnA	-0.0135	0.0106
lnL·lnH	-0.1822	0.0661	t·lnL·lnH	0.0144	0.0120
lnM·lnA	0.0329	0.0238	t·lnM·lnA	-0.0021	0.0047
lnM·lnH	-0.0930	0.0317	t·lnM·lnH	-0.0021	0.0056
lnA·lnH	-0.1624	0.0486	t·lnA·lnH	0.0153	0.0088
$\ln^2K$	0.0084	0.0159	$t\cdot\ln^2K$	0.0023	0.0029
$\ln^2L$	0.1901	0.0546	$t\cdot\ln^2L$	-0.0059	0.0099
$\ln^2M$	0.0625	0.0100	$t\cdot\ln^2M$	0.0009	0.0021
$\ln^2A$	0.0199	0.0234	$t\cdot\ln^2A$	-0.0017	0.0044
$\ln^2H$	0.1430	0.0325	$t\cdot\ln^2H$	0.0024	0.0050

Table 2. Decomposition of Output Growth accounting for scale change – herd size profiles

Component	Overall	Cows		
		<10 cows	10-20 cows	>20 cows
Average Output Growth	3.91 (±2.22)	1.37 (±0.19)	3.61 (±0.13)	5.90 (±0.15)
Average Pure Input Growth	3.40 (±0.29)	1.03 (±0.13)	3.32 (±0.08)	5.03 (±0.07)
Average Total Productivity Growth:	0.51 (±2.16)	0.38 (±0.23)	0.30 (±0.15)	0.84 (±0.16)
Average Efficiency Growth	0.36 (±2.12)	0.21 (±0.16)	0.43 (±0.11)	0.37 (±0.11)
Average Real Technical Growth:	1.00 (±0.86)	2.83 (±0.74)	0.76 (±0.43)	0.11 (±0.45)
Neutral Technical Change	0.12 (±0.16)	0.12 (±0.16)	0.12 (±0.16)	0.12 (±0.16)
Average Elasticity Structural Technical Growth	0.88 (±0.85)	2.71 (±0.75)	0.65 (±0.41)	-0.01 (±0.44)
Average Total Scale Growth:	-0.81 (±0.8)	-2.55 (±0.61)	-0.87 (±0.41)	0.38 (±0.46)
Average Scale Efficiency Growth	-0.25 (±0.24)	-0.58 (±0.11)	-0.27 (±0.08)	-0.02 (±0.07)
Average Structural Scale Growth	-0.56 (±0.77)	-1.98 (±0.62)	-0.60 (±0.41)	0.40 (±0.47)

Table 3. Decomposition of output growth without accounting for scale change – herd size profiles

Component	Overall	Cows		
		<10 cows	10-20 cows	>20 cows
Average Output Growth	3.91 (±2.22)	1.37 (±0.19)	3.61 (±0.13)	5.90 (±0.15)
Average Productivity Growth:	0.77 (±2.15)	0.97 (±0.2)	0.58 (±0.13)	0.87 (±0.15)
Average Efficiency Growth	0.36 (±2.12)	0.21 (±0.16)	0.43 (±0.11)	0.37 (±0.11)
Average Technical Growth	0.41 (±0.37)	0.76 (±0.2)	0.14 (±0.12)	0.50 (±0.15)
Average Input Growth (total)	3.13 (±0.16)	0.42 (±0.06)	3.03 (±0.03)	4.99 (±0.04)
Average Input Growth of Capital	-0.12 (±0.07)	-0.68 (±0.05)	-0.12 (±0.01)	0.24 (±0.02)
Average Input Growth of Labour	0.1 (±0.07)	0.01 (±0.01)	0.13 (±0.01)	0.13 (±0.03)
Average Input Growth of Materials	1.34 (±0.08)	0.29 (±0.01)	1.17 (±0.02)	2.21 (±0.04)
Average Input Growth of Area	0.22 (±0.04)	0.17 (±0.01)	0.23 (±0.01)	0.24 (±0.02)
Average Input Growth of Dairy Herd	1.5 (±0.1)	0.59 (±0.03)	1.54 (±0.04)	2.04 (±0.07)