PRODUCTIVITY CHANGE IN POLISH AGRICULTURE: AN APPLICATION OF A BOOTSTRAP PROCEDURE TO MALMQUIST INDICES

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Abstract

This paper employs bootstrapping to correct for bias and to construct confidence intervals for Malmquist TFP indices derived with DEA. It uses these results to investigate the productivity change in Polish agriculture during a crucial period of the country's transition to a market economy, 1996-2000, when Poland was preparing for accession to the European Union.

The bias corrected estimates show regress in productivity at an annual rate of 4 percent. The confidence intervals suggest that between two-thirds and four-fifths of the sample farms (250) in different years might have experienced no change in productivity. The cluster analysis based on confidence bounds reveals three paths of productivity change. Farms which recorded an increase in productivity at least in the last year of the analysed period, are larger, more capital intensive, run by younger farmers, and more integrated in factor and product markets. However, they account for only 19 percent of the sample farms. The most important for Poland now is to unlock the forces that can drive ahead structural reform and thus productivity growth.

Keywords: Malmquist indices, bootstrapping, Poland, farms, productivity change

JEL classification: D24, Q12, C6

Introduction

This study attempts to contribute to the body of literature employing Total Factor Productivity (TFP) indices calculated with non-parametric methods. Although Simar and Wilson (1999) provided a bootstrapping procedure for constructing confidence intervals for Malmquist TFP indices derived with the use of Data Envelopment Analysis (DEA), so far there have only been a few empirical applications (Hoff, 2003; Tortosa-Ausina et al., 2003; Chen, 2002), none of which are to agriculture. This paper employs bootstrapping to construct confidence intervals for the Malmquist TFP indices derived with DEA. It then uses these results to investigate the technological and technical efficiency changes in Polish agriculture during a crucial period of the country's transition to a market economy, 1996-2000, when Poland was preparing for accession to the European Union (EU).

A few recent studies have investigated productivity change in Polish agriculture. They all computed Malmquist indices, measuring changes in productivity and its components technical efficiency and technology changes (Brümmer et al., 2002; Zawalinska, 2003; Latruffe, 2004; Piesse et al., 2004). However, none of the studies using DEA accounted for sampling variability by correcting for sample bias, or constructing confidence intervals for the original Malmquist indices. The present study provides confidence intervals and a correction for the inherent bias in non-parametric distance functions.

The paper is structured as follows. The second section summarises the results of recent studies on Polish productivity developments and technological change, and the third section presents the methodology. The fourth section describes the data set. The fifth section details the results and the sixth section concludes.

Progress or regress in the Polish farm sector: results of previous studies

There are a few recent studies, which have tried to provide insights into the developments of efficiency, productivity and technological changes in the Polish farming sector (Table 1). Piesse et al.

(2004) used FAO aggregate sector level data to estimate the developments of productivity, efficiency and technology over four decades. Both stochastic frontiers and DEA suggested negative trends in productivity, total technical efficiency and technological change.

Other studies provide mixed results. Brümmer et al. (2002), studying a sample of 50 dairy farms located in Poznan region, revealed that between 1991 and 1994 Polish dairy farms experienced a productivity regress of about 5 percent, mainly due to a technological regress of about 7 percent, despite a slight increase in technical efficiency by 0.3 percent. Zawalinska (2003) confirmed Brümmer et al.'s (2002) results with her analysis of 811 farms over the period 1996-2000 using data extracted from the annual survey of a sample of bookkeeping farms carried out by the Polish Institute of Agricultural and Food Economics (IERiGZ). She reports a productivity regress of 1 percent. However, differently to Brümmer et al. (2002), a regress in the pure technical efficiency was also identified, together with technological progress of 1.2 percent. With data provided by the same source as in Zawalinska (2003) and covering the same time period but analysing a larger sample, Latruffe (2004) reports negative productivity and technological changes but increased pure technical efficiency. From this point of view, her results are consistent with those of Brümmer et al. (2002). Dries and Swinnen (2004) used a different approach, to study the effects of Foreign Direct Investment (FDI) on the Polish dairy sector. They argue that FDI did not precipitate structural change but its spillover effect has relaxed some of the financial and investment constraints faced by small dairy farms.

Table 1. Average rate of change in productivity, technology and efficiency in Polish agriculture documented in recent studies (%)

Study	Data set	Years	Methodology	Results
Piesse et al. (2004)	FAO Agrostat database (sector level)	1961-2001	Malmquist TFP with stochastic frontier	Efficiency (-)0.59 Techn. Change (-)0.61 TFP (-)1.19
			Malmquist TFP with DEA	*Efficiency (-)0.52 Techn. Change (-)0.99 TFP (-)1.50
Latruffe (2004)	IERiGZ farm level data – 914 farms	1996-2000	Malmquist TFP with DEA	**Efficiency (+)2.0 Techn. Change (-)5.0 TFP (-)2.0
Zawalinska (2003)	IERiGZ farm level data – 811 farms	1996-2000	Malmquist TFP with DEA	**Efficiency (-)2.0 Techn. Change (+)1.2 TFP (-)1.0
Brümmer et al. (2002)	50 dairy farms located in Poznan region	1991-1994	Malmquist TFP with translog distance frontier	Efficiency (+)0.3 Techn. Change (-)7.3 TFP (-)5.2

* Total technical efficiency
** Pure technical efficiency

All of the above studies, which focused on productivity, suggest some negative trends in the Polish farming sector. However, first, none of them provided bias corrected estimates, and second, their results have not been consistently indicating technological, productivity and efficiency progress or regress. This paper aims at contributing to these issues by providing, analysing and interpreting bias corrected estimates and confidence intervals of Malmquist indices.

Methodology

Malmquist indices

Malmquist productivity indices, pioneered by Caves et al. (1982) and developed further by Färe et al. (1992) provide a decomposition of firms' productivity change into efficiency change and technological change. The input-orientation Malmquist productivity indices are used in this study as it has been assumed that under the transition conditions farmers had more control over the reduction of their inputs than over the expansion of their outputs. The input-based Malmquist indices are based on the concept of distance function within the production set, $S(X,Y)$, which is assumed to be convex and where inputs (X) and outputs (Y) are assumed to be strongly disposable. The input distance function is formulated as:

$$d = \max\{\theta : (X/\theta) \in L\} \tag{1}$$

where
$L(Y)$ is the input set;
θ is a scalar.

Farrell's (1957) input efficiency measure is the inverse of this distance function:

$$TE = \min\{\theta : (\theta X) \in L\} = d^{-1}. \tag{2}$$

Using the input distance function defined by equation (1), Malmquist productivity indices can be defined taking as a benchmark period t or period t+1. As the choice of the benchmark is arbitrary, it is conventional to take the geometric mean of indices in adjacent periods. For each farm, the input-orientation Malmquist productivity index is therefore defined by:

$$M = \left[\frac{d^t\left(X_{t+1}, Y_{t+1}\right)}{d^t\left(X_t, Y_t\right)} \frac{d^{t+1}\left(X_{t+1}, Y_{t+1}\right)}{d^{t+1}\left(X_t, Y_t\right)} \right]^{\frac{1}{2}} \tag{3}$$

where
$d^t\left(X_{t+1}, Y_{t+1}\right)$ is the input distance from observations of the t+1 period to the technology frontier of the t-th period;
$\left(X_t, Y_t\right)$ is the input-output vector in the t-th period.

Malmquist productivity indices represent the move from output in period t to output in period t+1 and therefore indicate the TFP change. They also allow identify which share of the movement is due to better practice with the available technology, that is to say technical efficiency change, and which share is due to technological change. The decomposition of the Malmquist productivity index is as follows:

$$M = \frac{d^{t+1}\left(X_{t+1}, Y_{t+1}\right)}{d^t\left(X_t, Y_t\right)} \left[\frac{d^t\left(X_{t+1}, Y_{t+1}\right)}{d^{t+1}\left(X_{t+1}, Y_{t+1}\right)} \frac{d^t\left(X_t, Y_t\right)}{d^{t+1}\left(X_t, Y_t\right)} \right]^{\frac{1}{2}} \tag{4}$$

where the ratio outside the brackets on the right hand side measures the index of change in technical efficiency, whilst inside the brackets is the technological change index between period t and period t+1.

Both stochastic frontier (Nishimizu and Page, 1982) and DEA (Färe et al., 1992) can be used to compute the indices and to provide their decomposition. The stochastic frontier approach requires a specification of a functional form, whilst DEA uses linear programming to construct a piece-wise frontier that envelops all data points, so that the observations lie on or below the frontier. DEA method has been chosen in this study as it avoids misspecification errors and allows to investigate a multi-output multi-input case simultaneously. Additionally, DEA allows decomposing the index of technical efficiency change into pure technical efficiency change and scale efficiency change, by running separate linear programmings under constant returns to scale and variable returns to scale.

A multi-output multi-input model is used here. Three outputs are included in value terms, crop, livestock and other (non-agricultural) output. Four inputs are used: land, labour, capital and intermediate consumption. Land is defined as the utilised agricultural area (UAA) in hectares, labour is calculated in annual work units (AWU)[1], capital is proxied by the value of depreciation of fixed assets plus interest paid on loans, and the intermediate consumption includes the aggregate value of seeds, fertilisers, chemicals, feed and fuel. The monetary values for the period 1997-2000 have been deflated using indices based on 1996 and published by the Polish Central Statistical Office (GUS, 2001).

Bootstrapping Malmquist indices

One of the main drawbacks of DEA is that its results may be affected by sampling variation, implying that distances to the frontier are likely to be underestimated. Such bias arises when the most efficient firms within the population are not contained in the sample at hand. As a consequence, inefficient firms form the envelopment frontier. The distance of all other firms is then measured relative to the sample frontier instead of the true population frontier, and therefore might be biased. The issue of sampling variation in DEA models is now receiving increasing attention, following the method introduced by Simar and Wilson (1998, 2000) allowing the construction of confidence intervals for DEA efficiency scores. Their method, relying on resampling the efficiency scores with the help of bootstrapping, has been adapted to the case of Malmquist index derived with DEA (Simar and Wilson, 1999). The rationale behind bootstrapping is to simulate a true sampling distribution by mimicking a data generating process, here the outputs from DEA. The procedure relies on constructing a pseudo-data set and re-estimating the DEA model with this new data set. Repeating the process many times allows getting a good approximation of the true distribution of the sampling (Brümmer, 2001).

Simar and Wilson (1998) noted that the bounded nature of the distance functions renders the naive bootstrap, that relies on drawing randomly with replacement a bootstrap sample from the input-output data set, inconsistent. The authors proposed a smoothed bootstrap procedure in order to avoid the inconsistency of the naive bootstrap. The smoothed bootstrap performs the repeated sampling not from the empirical distribution itself, but from a smooth version of it. A smooth consistent estimator of the distribution is provided by a kernel density estimate, which introduces smoothing via a bandwidth parameter, h. Simar and Wilson (1999) adapted their efficiency bootstrapping procedure to the Malmquist index case in order to account for possible temporal correlation arising from the panel data characteristic. They provided a consistent method using a bivariate kernel density estimate, that accounts for the temporal correlation via the covariance matrix of data from adjacent years.

The final procedure for constructing confidence intervals consists of two main stages. First, a set of bootstrap Malmquist indices is provided. This allows calculating the bias in the results. Second, the confidence intervals are constructed based on the bootstrap sample. In this study, 95 percent confidence intervals were constructed using the smoothed homogenous bootstrap algorithm. The choice of the number of bootstrapping iterations B was constrained by computer power and was set to 2000. The bandwidth parameter (h) was chosen as in Simar and Wilson (1999), using the following rule, appropriate for bivariate data:

$$h = \left(\frac{4}{5}n\right)^{1/6}. \tag{5}$$

where n is the number of farms in the sample.

Data set

The data set consists of 250 farms extracted randomly from the farm level IERiGZ sample. Data cover a large range of resource, output, management of farms, and social variables of principal farmers, drawn from all 16 administrative regions in Poland (voivodships). This sample of 250 is the largest employed in studies estimating bias corrected Malmquist indices so far. Other studies used

[1] One AWU corresponds to 2,200 labour hours per year.

between 40 and 50 observations (Hoff, 2003; Tortosa-Ausina et al., 2003; Chen, 2002; Simar and Wilson, 1999).

The descriptive statistics of the outputs and inputs used in DEA for the sample farms are presented in Table 2. The value of other output is not presented, as it is negligible, between 0.3 and 50 euros per farm.

Table 2. Descriptive statistics for the sample farms (250 farms)

	Mean	Standard deviation	Minimum	Maximum
Crop output (000 euros)	10.9	1.2	0.6	217.9
Livestock output (000 euros)	8.2	0.8	0	137.6
UAA (ha)	26.2	46.1	1.4	587.1
Labour (AWU)	1.96	0.07	0.21	12.3
Depreciation plus interest (000 euros)	2.5	0.2	0.08	35.4
Intermediate consumption (000 euros)	11.3	1.1	1.0	15.5

Table 3. Distribution of farms in Poland and in the sample used in the study according to land size in 2000

	1-2 ha	2-5 ha	5-10 ha	10-15 ha	> 15 ha
Poland [a] (%)	23.8	32.6	23.8	9.9	9.9
Sample used [b] (%)	1.2	10.0	25.2	15.2	48.4

[a] Source: GUS (2001).
[b] 250 farms extracted from IERiGZ survey.

The distribution of sample farms according to the land area is presented in Table 3. Compared to the overall farm population in Poland, the sample used is biased towards larger farms.

Discussion of results

The extent of productivity change

The point estimates of Malmquist indices indicate that over the period 1996-2000 TFP in Polish agriculture decreased by 2 percent. This unfavourable trend in productivity has been a result of a negative technological change (-6 percent) accompanied by an improvement in technical efficiency (+4 percent), particularly due to an increase in the pure technical efficiency (Table 4). Therefore, there have been simultaneous negative developments in technology and positive changes in efficiency. Such a pattern is not surprising. With technological regress, more farmers are able to adopt the prevailing technology and hence lie on average closer to the efficiency frontier. Thus, the disparities in terms of efficiency decrease and the observations, on average, are more clustered near the frontier. The beginning of the analysed period was marked by the deepest deterioration in technology, which was toned down during the transition. The last year even showed technological progress (of 7 percent). This seems to suggest that the greater exposure to international competition during the transition period allowed progressively Polish farmers to improve their technology. Dries and Swinnen (2004) FDI spillover effect is one of the possible factors facilitating this switch from technological regress to progress.

The comparison of original Malmquist indices with the bias corrected estimates shows the same directions of change in productivity, efficiency and technology. However, on average, the regress in productivity appears to be deeper (2 percent annual rate indicated by the original Malmquist indices and 4 percent by the bias corrected estimates), whilst the positive rate of efficiency change appears to be greater (4 and 6 percent respectively) (Table 5). This suggests that the lack of correction for sampling variability might understate both regress and progress, although in this particular analysis the difference is relatively modest.

Table 4. Changes in productivity, technology and efficiency, consecutive years and 1996-2000 average: non-bias corrected Malmquist indices (%)

	1996/97	1997/98	1998/99	1999/2000	1996-2000
Malmquist TFP change	0	-7	-8	+8	-2
Technological change	-19	-7	-3	+7	-6
Efficiency change	+22	0	-5	+1	+4
Pure efficiency change	+17	0	-4	0	+3
Scale efficiency change	+4	-1	-1	0	+1

Table 5. Changes in productivity, technology and efficiency, consecutive years and 1996-2000 average: bias corrected Malmquist indices (%)

	1996/97	1997/98	1998/99	1999/2000	1996-2000
Malmquist TFP change	+3	-13	-3	-2	-4
Technological change	-16	-9	+7	+1	-5
Efficiency change	+30	0	-6	+2	+6
Pure efficiency change	+26	-1	-5	+1	+5
Scale efficiency change	+3	0	-1	0	0

The confidence intervals of the Malmquist indices are wide. This, we believe, gives additional justification for bootstrapping. Very little can be revealed by the productivity change indicated by the original Malmquist indices of -2 percent over 1996-2000, since the upper bound is +18 percent and lower bound -31 percent (Table 6). Identically, it is not very informative to claim that between 1996 and 2000 there was an average technological regress by 6 percent per annum, if the upper bound of the confidence intervals is +40 percent and the lower bound -22 percent (Table 7). The confidence intervals for the efficiency change are the narrowest out of the three sets of indicators, with a width of 26 percent on average (Table 8).

Table 6. Inference results for productivity change, consecutive years and 1996-2000 average (%)

	1996/97	1997/98	1998/99	1999/2000	1996-2000
Malmquist change	0	-7	-8	+8	-2
Bias corrected Malmquist change	+3	-13	-3	-2	-4
Confidence intervals					
Upper bound	+31	+11	+15	+24	+18
Lower bound	-23	-36	-21	-29	-31
Width	53	48	37	53	48

Table 7. Inference results for technological change, consecutive years and 1996-2000 average (%)

	1996/97	1997/98	1998/99	1999/2000	1996-2000
Technological change	-19	-7	-3	+7	-6
Bias corrected technological change	-16	-9	+7	+1	-5
Confidence intervals					
Upper bound	+67	+18	+49	+30	+40
Lower bound	-33	-24	-13	-15	-22
Width	73	39	56	40	51

Table 8. Inference results for efficiency change, consecutive years and 1996-2000 average (%)

	1996/97	1997/98	1998/99	1999/2000	1996-2000
Efficiency change	+22	0	-5	+1	+4
Bias corrected efficiency change	+30	0	-6	+2	+6
Confidence intervals					
Upper bound	+64	+15	+9	+21	+26
Lower bound	+13	-9	-16	-10	-6
Width	41	20	21	25	26

Based on the point estimates of Malmquist indices, farms that have experienced productivity progress (that is to say whose Malmquist index is strictly greater than 1) were 128 in 1996/97 (51 percent of the sample), 82 in 1997/98 (33 percent), 76 1998/99 (30 percent) and 176 in 1999/2000 (70 percent). Only between 0 and 3 farms in different years recorded a lack of change in productivity (index equal to 1). The remaining farms recorded productivity regress. The picture is not different if the bias corrected point estimates are considered. By contrast, if farms are analysed based on their interval bounds, out of the total sample of 250, 205 farms in 1996/97 (82 percent), 158 in 1997/98 (63 percent), 169 in 1998/99 (68 percent) and 206 in 1999/2000 (82 percent) might have experienced no change in productivity[2]. This result shows that there is a large uncertainty about the extent of productivity change in Polish farming and strongly supports Simar and Wilson's (1999: 471) argument that "it is not enough to know whether the Malmquist index estimator indicates increases or decreases in productivity, but whether the indicated changes are significant in a statistical sense; i.e., whether the result indicates a real change in productivity, or is an artifact of sampling noise".

The patterns of productivity change

The above analysis emphasised the usefulness of confidence intervals for assessing productivity change. Although the extent of the change cannot be assessed for certain, confidence intervals can help identifying patterns of change, that is to say whether some groups of farms perform better than others and have a better potential for productivity increases. From a policy point of view, it is also important to know the characteristics of such farms. For this reason, a cluster analysis has been performed to investigate homogenous farm groups, using confidence intervals as well as the original Malmquist estimates as a comparison.

Clusters were created with a two-step clustering method based on log-likelihood distance that places a probability distribution on the variables used for clustering. In contrast to non-hierarchical clustering, stepwise clustering used here involves starting with all farms in a single cluster and then dividing them into clusters between which farms are most dissimilar (Hair et al., 1998). Clusters were firstly created based on the four original Malmquist point estimates (one per period for each farm). The point estimates were used in order to underline the difference whilst using the interval bounds for

[2] A farm is said to have experienced significant progress if its confidence interval's lower bound is greater than 1, significant regress if its upper bound is less than 1, and no significant change if 1 is included in its confidence interval.

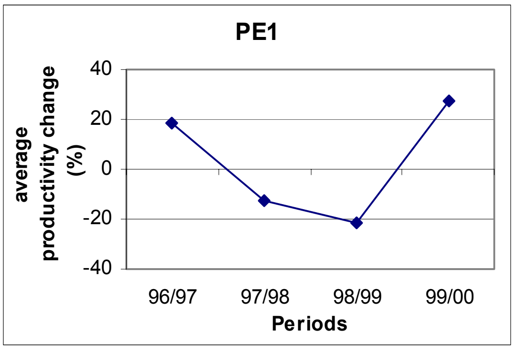
the clustering process. A three-cluster solution was accepted identifying homogenous groups of farms with respect to their path of productivity change over the whole period. This path is depicted on the left hand side column in Chart 1. The first cluster (PE1) shows a U-shape change in productivity with two consecutive declines and a substantial increase in 2000. So, this cluster appears to have bottomed out. The second cluster (PE2), switches year on year from increase to decrease and back to increase. The third cluster (PE3) records very little changes in productivity.

New clusters based on the upper and lower confidence interval bounds were then created in order to reassess the findings when accounting for sampling noise. The cluster solution again indicated three clusters. The three clusters, denoted, CI1, CI2 and CI3 are presented on the right hand side of Chart 1. The first cluster CI1, similarly to PE1, has a U-shape of productivity change, however both the decreasing part of the graph and increasing one are less steep than in PE1. CI2 shows a slightly different pattern than its counterpart from the point estimates. Productivity decreased for two consecutive years but then increased steeply. CI3 indicates an identical productivity path as the cluster PE3. Broadly speaking, it seems that assessing levels of confidence does not modify the different productivity paths in homogeneous farms groups. However, the membership of clusters varies depending on the clustering process. A large share of farms that were originally in cluster PE1 did not remain in Path 1 when clustering over confidence bounds. Similar observations were made for Path 2 and Path 3. Table 9 shows the number of farms in each path based on Malmquist indices and on confidence bounds.

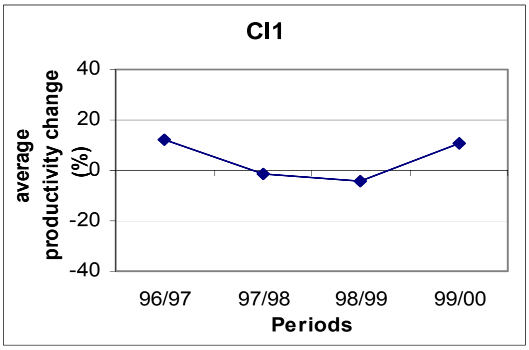
Table 9. Number of farms in each path with respect to clustering based on original Malmquist indices and on confidence bounds of original Malmquist indices

	Path 1	Path 2	Path 3
Clustering based on Malmquist point estimates	47	67	135
Clustering based on confidence bounds of Malmquist indices	48	98	103

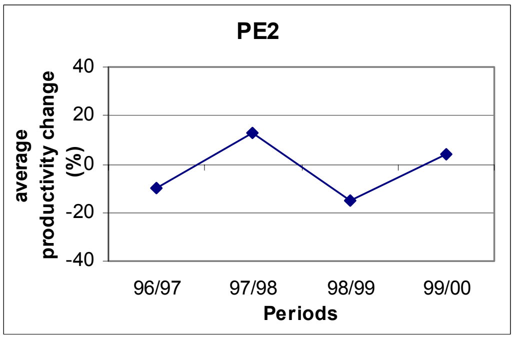
Point estimates Path 1 (PE1)



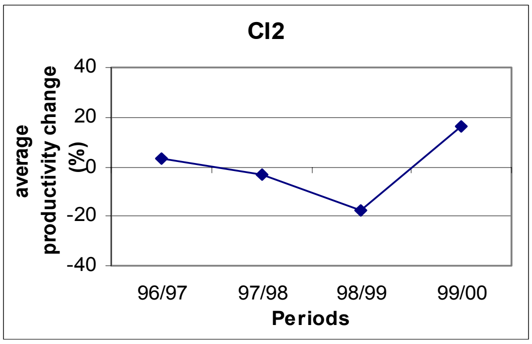
Confidence intervals Path 1 (CI1)



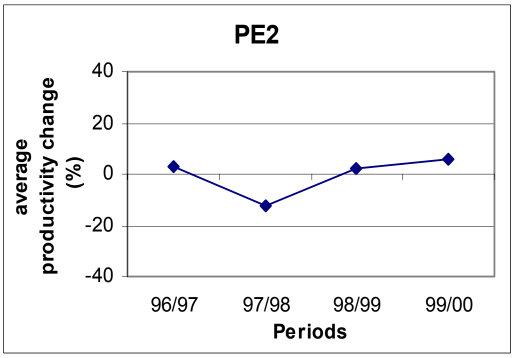
Point estimates Path 2 (PE2)



Confidence intervals Path 2 (CI2)



Point estimates Path 3 (PE3)



Confidence intervals Path 3 (CI3)

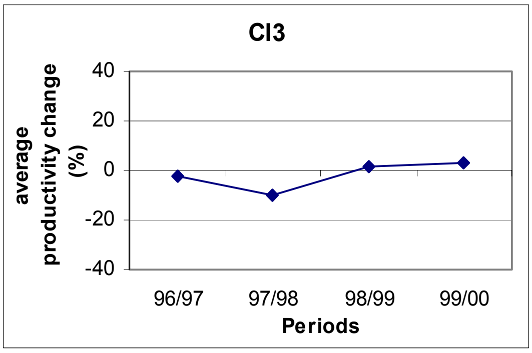


Chart 1. Average productivity path for clusters based on original Malmquist point estimates and on confidence intervals

From a policy point of view, it is useful to investigate whether there are statistically significant differences between the farm characteristics in different clusters and what is the typology of farms that recorded an increase in productivity at the end of the analysed period (clusters CI1 and CI2), as opposed to farms in cluster CI3. Only the results of clustering over confidence bounds are discussed below as they indicate a real change in productivity. Several groups of variables have been used in order to investigate farm characteristics in different clusters. The choice of variables has been based, to a great extent, on the study of technical efficiency of Polish farms by Latruffe et al. (2004). Farm size is represented by UAA in hectares. One of the typical characteristics of Polish farms is that although they are small, they are additionally fragmented into several plots. In order to account for this fragmentation, the number of plots has been included. Another typical characteristic of the Polish farms is that the small ones, in particular, are not well integrated in upstream and downstream markets. This lack of market integration is a clear indicator of the peasant character of Polish agriculture (Davidova et al., 2005). Integration in the factor markets is included with the shares of hired labour in total labour input and of rented land in UAA. The ratio of marketed output in total output is used as an indicator of integration into agricultural product markets. The ratios of capital to labour and land to labour are used as proxies for technology (capital is measured as the quantity of depreciation and interest on loans). The degree of diversification in activities other than agricultural production is measured as a share of other income in total income. Two financial indicators are also included, the debt to asset ratio showing the long-term capital position, and the financial stress calculated as rents plus interest paid as a share of revenue from marketed output, which is indicative of the financial stress of the farm caused by rents and repayments of loans. The crop or livestock specialisation is represented by the share of crop output in total output. Finally, two socio-economic characteristics of the farmer have been included, age and agricultural education. The latter consists of six categories, from a lack of agricultural education to an agricultural university degree.

The means for each cluster are presented in Table 10. All variable means are statistically different amongst the clusters, most of them at 1 percent level. The results reveal that cluster CI1, which appears to have bottomed out (although this is speculative due to the short analysed period), incorporates the largest farms, on average 49.5 ha, with predominantly arable crop output, which are run by the youngest and most educated farmers amongst the three clusters. These farms use more hired labour and rented land than farms in the other two clusters and are, thus, less dependent on the family initial endowment of resources and familial human capital. They employed the most capital-intensive technology which most probably brought about the highest debt to asset ratio and financial stress (although both are not of a high enough magnitude in which they could undermine the future farm viability). Cluster CI3, which recorded very little productivity growth, is on the other extreme with the smallest (16.7 ha on average) and the least integrated in factor and product markets farms. According to the mean of all variables, cluster CI2 is between the two extremes, often closer to the worst performing cluster, CI3.

This analysis, not surprisingly, suggests that the smallest farms exhibit the worst path in productivity change. It also provides important insights into heterogeneity of farms and farmer's characteristics that may help indicate which farm group might become a driver of productivity growth in future.

Table 10. Cluster means based on confidence bounds and F-statistics for equality of means, based on data for 1996

	Cluster 1 (48 farms)	Cluster 2 (98 farms)	Cluster 3 (103 farms)	F-test and significance
Mean across farms in each cluster				
UAA (ha)	49.5	19.2	16.7	11.02 ***
Number of plots	7.6	5.3	5.7	3.31 **
Share of hired labour (%)	14.1	4.9	2.8	17.27 ***
Share of rented land (%)	27.5	15.5	12.7	17.12 ***
Share of marketed output in total output (%)	67.0	60.0	55.3	9.31 ***
Capital to labour ratio (euro/AWU)	1,206.0	798.7	768.7	9.48 ***
Land to labour (ha/AWU)	15.7	8.86	8.29	18.59 ***
Share of other income in total income (%)	47.1	54.2	56.2	3.94 **
Debt to asset ratio	0.052	0.019	0.020	9.26 ***
Financial stress	0.043	0.019	0.021	6.90 ***
Share of crop output in total output (%)	62.6	53.4	48.9	9.84 ***
Age	42.2	44.5	46.1	2.40 *
Agricultural education [a]	3.21	2.48	2.42	5.42 ***

[a] This variable consists of six categories. Category 1 represents a lack of agricultural education, while category 6 represents an agricultural university degree.

Conclusions

This study underlines the uncertainty surrounding the findings regarding productivity change measured through Malmquist DEA method and the need to use bootstrapping to estimate confidence intervals when the size of the sample makes it technically feasible.

The analysis of productivity change in Polish agriculture between 1996 and 2000 based on Malmquist DEA point estimates revealed a gloomy picture. The use of bias corrected indices confirmed this finding as it indicated an average productivity regress of 4 percent. Thus, during this crucial period of the preparations for EU membership, the Polish agriculture was not closing the large productivity gap with the EU. According to Pouliquen (2001), in 1998 labour productivity was estimated to be only 8.4 percent of the EU average. This has created important implications for the international competitiveness of Polish agriculture. A recent study (Davidova and Gorton, 2004), employing Domestic Resource Costs (DRCs), indicates that if the productivity rates are maintained at historic levels, due to price effects stemming principally from increases in land and labour prices, overall, accession will impact negatively on the international competitiveness. Without dynamic changes in productivity and convergence towards the EU, rye, sugar beets and most livestock products in Poland will be uncompetitive in the mid-term. The authors indicate a consistently inverse relationship between DRCs and farm size. Therefore, the most important for Poland is to unlock the forces that can drive ahead structural reform and productivity growth.

Although the construction of confidence intervals for Malmquist point estimates did not allow assessing with certainty the extent of productivity change, the cluster analysis based on these intervals supported the above conclusion. It suggests that farms, which recorded an increase in productivity at least in the last year of the analysed period, are larger, more capital intensive, run by younger farmers, and more integrated in land, labour and product markets. However, the best performing cluster based on confidence intervals, CI1, includes 48 farms, thus only 19 percent of the sample farms. Most of the farms, 41 per cent, are in the worst performing cluster CI3, which shows almost no productivity change. Thus, the removal of the impediments to structural change appears to be central to the productivity growth.

Pre-accession, one of the main impediments to structural change, discussed in literature, has been the subsidisation of the farmers' pension (Latruffe et al., 2005). Post-accession, the introduction of the Common Agricultural Policy (CAP) support may create disincentives to change. According to preliminary estimates, during the first year of EU membership the farm sector in Poland produced excellent results. On the backdrop of an average, for the EU-25, rise in the real agricultural income per worker by 3.3 percent in 2004, the increase in Poland was 74 percent (Eurostat, 2004). However, this boost in farmers' income was not induced by technological change but by the introduction of the CAP support. This support may continue locking unproductive small farmers in agriculture and impede productivity increases.

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