Dynamic Productivity Growth in the Spanish Meat Industry

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Abstract: This paper develops a dynamic Luenberger productivity growth indicator and decomposes it to identify the contributions of technical change, technical efficiency change and scale change. The Luenberger productivity growth indicator is estimated using Data Envelopment Analysis. The empirical application focuses on panel data of Spanish meat processing firms over the period 2000-2010. The dynamic Luenberger indicator shows productivity decrease of on average -0.003 in the period under investigation, with technical regress being the main driver of change, despite technical and scale efficiency growth.

Key words: directional distance function, dynamics, Luenberger TFP, meat processing.

1 Introduction

The characterization and measurement of economic performance in both theory and practice continues to claim considerable attention in the literature. The major attention of these economic performance measures continues to address the measurement of efficiency and productivity growth. The economics literature on efficiency has produced a wide range of productivity growth measures (see e.g. Balk (2008) for a comprehensive treatment).

The setting of the decision environment plays a crucial role in the modeling framework and the characterization of results. The static models of production are based on the firm's ability to adjust instantaneously and ignore the dynamic linkages of production decisions. The business policy relevance to distinguishing between the contributions of variable and capital factors to inefficiency or productivity growth is clear. For example, when variable factor use is not meeting its potential, remedies can include better monitoring of resource use; when asset use is not meeting potential, remedies can include training programs to enhance performance or even a review of the organization of assets in the production process to take advantage of asset utilization. The weakness underlying the static theory of production in explaining how some inputs are gradually adjusted has led to the development of the dynamic models of production where current production decisions constrain or enhance future production possibilities.

The characterization of dynamic efficiency can also build on the adjustment cost framework that implicitly measures inefficiency as a temporal concept as it accounts for the sluggish adjustment of some factors. In a nonparametric setting, Silva and Stefanou (2007) develop a myriad of efficiency measures associated with the dynamic generalization of the dual-based revealed preference approach to production analysis found in Silva and Stefanou (2003). In a parametric setting, Rungsuriyawiboon and Stefanou (2007) present and estimate the dynamic shadow price approach to dynamic cost minimization.

An intriguing prospect is to incorporate the properties of the dynamic production technology presented in Silva and Stefanou (2003) into the directional distance function framework, which can exploit the Luenberger productivity growth measurement. The directional distance function offers the powerful advantage of focusing on changes in input and output bundles, inefficiency and the technology. Such a productivity measure based on the directional distance function has its origins in Chambers, Chung and Färe (1996) who defined a Luenberger indicator of productivity growth in the static context. A growing

literature employing this approach has emerged more recently[1]. However, in the presence of adjustment costs in quasi-fixed factors of production, the static measures do not correctly reflect productivity growth. Recently, Oude Lansink, Stefanou and Serra (2012) proposed a dynamic Luenberger productivity growth measure based on an econometrically estimated dynamic directional distance function and decomposed this into the contribution of technical change and technical inefficiency change.

This paper extends the dynamic Luenberger productivity growth measure of Oude Lansink, Stefanou and Serra (2012) to make a richer decomposition into the contributions of technical efficiency change, scale efficiency change and technical change. The empirical application uses a nonparametric method (Data Envelopment Analysis) to estimate the dynamic directional distance function. The focus of the application is on panel data of Spanish meat processing firms over the period 2000-2010. The meat processing industry is the most important food sector in Spain, generating approximately 20% of total sales and employment within food industry and 2% of Spanish GDP in 2009 (National Association of Meat Industries of Spain). Its significance is emphasized by the fact that it is one of the main exporting sectors of Spain. The Spanish meat industry is characterized also by a low level of innovations and by the predominance of small and medium-sized enterprises (European Commission, 2011). The period analyzed concerns the time of increasing regulation in the European Union (EU) with regard to food safety, consumer information, the mandatory adoption of environmentally-sustainable practices and the functioning of internal market. In order to cope with the increasing regulation, European firms had to undertake additional investments and deal with more administrative burdens (European Commission, 2004; Wijnands, Van der Meulen and Poppe, 2006). Another impacting event is the increase in production costs of meat producers resulting from the increase in the costs of animal feed in 2007 and 2008. This increase in feed costs decreased the supply of slaughter cattle which serves as an input for the meat industry. Finally, from 2008 onwards the Spanish meat industry is being affected by the economic crisis as reflected by the decrease in the demand for meat.

The next section develops the measures of dynamic productivity growth and its decomposition. This is followed by the empirical application to the panel of Spanish meat processing firms showing productivity change and its decomposition. The final section offers concluding comments.

2 The Primal Luenberger Indicator of Dynamic Productivity Growth

The primal Luenberger indicator of dynamic productivity growth is defined through a dynamic directional distance function. Let $\mathbf{y}_t \in \Re^M_{++}$ represent a vector of outputs at time *t*, $\mathbf{x}_t \in \Re^N_{+}$ denote a vector of variable inputs, $\mathbf{K}_t \in \Re^F_{++}$ the capital stock vector, $\mathbf{I_t} \in \Re^F_{+}$ the vector of gross investments, and $\mathbf{L}_t \in \Re^C_{++}$ a vector of fixed inputs for which no investments are allowed. The production input requirement set can be represented as $V_t(\mathbf{y}_t : \mathbf{K}_t, \mathbf{L}_t) = \{(\mathbf{x}_t, \mathbf{I}_t) : (\mathbf{x}_t, \mathbf{I}_t) \text{ can produce } \mathbf{y}_t \text{ given } \mathbf{K}_t, \mathbf{L}_t\}$. The input requirement set is defined by Silva and Oude Lansink (2012) and assumed to have the following properties:

[1] See Chambers, Färe and Grosskopf (1996), Boussemart, et al. (2003), Färe and Primont (2003), Briec and Kerstens (2004), Färe and Grosskopf (2005), Balk (2008).

$V_t(\mathbf{y}_t:\mathbf{K}_t,\mathbf{L}_t)$ is a closed and nonempty set, has a lower bound, is positive monotonic in $\mathbf{x}_t$, negative monotonic in $\mathbf{I}_t$, is a strictly convex set, output levels increase with the stock of capital and quasi-fixed inputs and are freely disposable.

The input-oriented dynamic directional distance function $\vec{D}_t^i(\mathbf{y}_t,\mathbf{K}_t,\mathbf{L}_t,\mathbf{x}_t,\mathbf{I}_t;\mathbf{g_x},\mathbf{g_I})$ is defined as follows:

$$\vec{D}_t^i(\mathbf{y}_t,\mathbf{K}_t,\mathbf{L}_t,\mathbf{x}_t,\mathbf{I}_t;\mathbf{g_x},\mathbf{g_I}) = \max\left\{\beta\in\Re:\left(\mathbf{x}_t-\beta\mathbf{g_x},\mathbf{I}_t+\beta\mathbf{g_I}\right)\in V_t(\mathbf{y}_t:\mathbf{K}_t,\mathbf{L}_t)\right\},$$
$$\mathbf{g_x}\in\Re_{++}^N,\ \mathbf{g_I}\in\Re_{++}^F,\left(\mathbf{g_x},\mathbf{g_I}\right)\neq\left(\mathbf{0}^N,\mathbf{0}^F\right) \tag{1}$$

if $\left(\mathbf{x}_t-\beta\mathbf{g_x},\mathbf{I}_t+\beta\mathbf{g_I}\right)\in V_t(\mathbf{y}_t:\mathbf{K}_t,\mathbf{L}_t)$ for some β, $\vec{D}_t^i(\mathbf{y}_t,\mathbf{K}_t,\mathbf{L}_t,\mathbf{x}_t,\mathbf{I}_t;\mathbf{g_x},\mathbf{g_I})=-\infty$, otherwise. The distance function is a measure of the maximal translation of $\left(\mathbf{x}_t,\mathbf{I}_t\right)$ in the direction defined by the vector $\left(\mathbf{g_x},\mathbf{g_I}\right)$, that keeps the translated input combination interior to the set $V_t(\mathbf{y}_t:\mathbf{K}_t,\mathbf{L}_t)$. Since $\beta\mathbf{g_x}$ is subtracted from $\mathbf{x}_t$ and $\beta\mathbf{g_I}$ is added to $\mathbf{I}_t$, the directional distance function is defined by simultaneously contracting variable inputs and expanding gross investments. As shown by Silva and Oude Lansink (2012), $\vec{D}_t^i(\mathbf{y}_t,\mathbf{K}_t,\mathbf{L}_t,\mathbf{x}_t,\mathbf{I}_t;\mathbf{g_x},\mathbf{g_I})\geq 0$ fully characterizes the input requirement set $V_t(\mathbf{y}_t:\mathbf{K}_t,\mathbf{L}_t)$, being thus an alternative primal representation of the adjustment cost production technology.

Building on the Luenberger indicator of productivity growth defined by Chambers, Chung and Färe (1996) to the dynamic setting by using the dynamic directional distance function (assuming CRS) leads to:

$$L(\cdot)=\frac{1}{2}\left\{\begin{array}{l}[\vec{D}_{t+1}^i(\mathbf{y}_t,\mathbf{K}_t,\mathbf{L}_t,\mathbf{x}_t,\mathbf{I}_t;\mathbf{g_x},\mathbf{g_I})-\vec{D}_{t+1}^i(\mathbf{y}_{t+1},\mathbf{K}_{t+1},\mathbf{L}_{t+1},\mathbf{x}_{t+1},\mathbf{I}_{t+1};\mathbf{g_x},\mathbf{g_I})]+\\ [\vec{D}_t^i(\mathbf{y}_t,\mathbf{K}_t,\mathbf{L}_t,\mathbf{x}_t,\mathbf{I}_t;\mathbf{g_x},\mathbf{g_I})-\vec{D}_t^i(\mathbf{y}_{t+1},\mathbf{K}_{t+1},\mathbf{L}_{t+1},\mathbf{x}_{t+1},\mathbf{I}_{t+1};\mathbf{g_x},\mathbf{g_I})]\end{array}\right\} \tag{2}$$

This indicator provides the arithmetic average of productivity change measured by the technology at time t+1 (i.e., the first two terms in equation 2) and the productivity change measured by the technology at time t (i.e., the last two terms in equation 2).

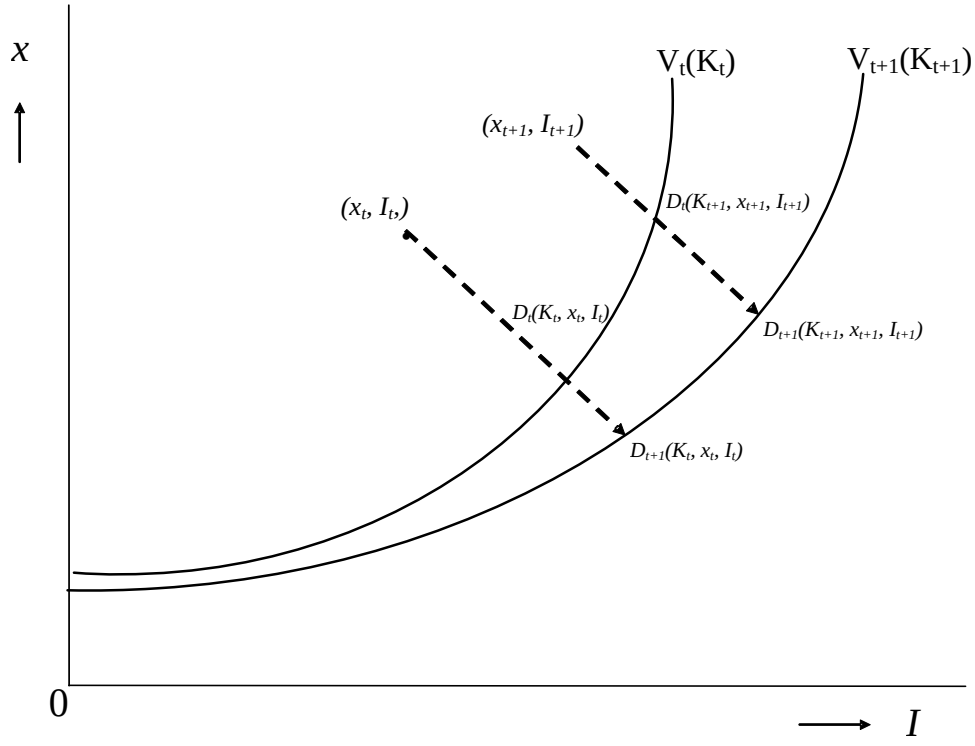

Fig.1. Luenberger indicator of dynamic productivity growth.

The Luenberger indicator of dynamic productivity growth is illustrated graphically in Figure 1. The quantities of inputs and investments at time t and time t+1 are denoted as $(\mathbf{x}_t, \mathbf{I}_t)$ and $(\mathbf{x}_{t+1}, \mathbf{I}_{t+1})$, respectively. The dynamic directional distance function measures the distance to the isoquants at time t and time t+1, which is denoted as $\vec{D}^i_{t+1}(\mathbf{y}_t, \mathbf{K}_t, \mathbf{L}_t, \mathbf{x}_t, \mathbf{I}_t; \mathbf{g_x}, \mathbf{g_I})$. The Luenberger indicator of dynamic productivity growth can be decomposed into the contributions of technical inefficiency change (ΔTEI) and technical change (ΔT):

$$L(\cdot) = \Delta T + \Delta TEI \tag{3}$$

The decomposition of productivity growth is obtained from (2) by adding and subtracting the term $\left[\vec{D}^i_{t+1}(\mathbf{y}_{t+1}, \mathbf{K}_{t+1}, \mathbf{L}_{t+1}, \mathbf{x}_{t+1}, \mathbf{I}_{t+1}; \mathbf{g_x}, \mathbf{g_I}) - \vec{D}^i_t(\mathbf{y}_t, \mathbf{K}_t, \mathbf{L}_t, \mathbf{x}_t, \mathbf{I}_t; \mathbf{g_x}, \mathbf{g_I})\right]$. Technical change is computed as the arithmetic average of the difference between the technology (represented by the frontier) at time t and time t+1, evaluated using quantities at time t (first two terms in (4)) and time t+1 (last two terms in (4)):

$$\Delta T = \frac{1}{2}\left\{\begin{array}{l}[\vec{D}^i_{t+1}(\mathbf{y}_t, \mathbf{K}_t, \mathbf{L}_t, \mathbf{x}_t, \mathbf{I}_t; \mathbf{g_x}, \mathbf{g_I}) - \vec{D}^i_t(\mathbf{y}_t, \mathbf{K}_t, \mathbf{L}_t, \mathbf{x}_t, \mathbf{I}_t; \mathbf{g_x}, \mathbf{g_I})] \\ +[\vec{D}^i_{t+1}(\mathbf{y}_{t+1}, \mathbf{K}_{t+1}, \mathbf{L}_{t+1}, \mathbf{x}_{t+1}, \mathbf{I}_{t+1}; \mathbf{g_x}, \mathbf{g_I}) - \vec{D}^i_t(\mathbf{y}_{t+1}, \mathbf{K}_{t+1}, \mathbf{L}_{t+1}, \mathbf{x}_{t+1}, \mathbf{I}_{t+1}; \mathbf{g_x}, \mathbf{g_I})]\end{array}\right\} \tag{4}$$

Technical change can be seen in Figure 1 as the average distance between the two isoquants. This involves evaluating the isoquants using quantities at time t, $\vec{D}^i_{t+1}(\mathbf{y}_t, \mathbf{K}_t, \mathbf{L}_t, \mathbf{x}_t, \mathbf{I}_t; \mathbf{g}_x, \mathbf{g}_I) - \vec{D}^i_t(\mathbf{y}_t, \mathbf{K}_t, \mathbf{L}_t, \mathbf{x}_t, \mathbf{I}_t; \mathbf{g_x}, \mathbf{g_I})$ and quantities at time t+1,

$\vec{D}^i_{t+1}(\mathbf{y}_{t+1},\mathbf{K}_{t+1},\mathbf{L}_{t+1},\mathbf{x}_{t+1},\mathbf{I}_{t+1};\mathbf{g_x},\mathbf{g_I}) - \vec{D}^i_t(\mathbf{y}_{t+1},\mathbf{K}_{t+1},\mathbf{L}_{t+1},\mathbf{x}_{t+1},\mathbf{I}_{t+1};\mathbf{g_x},\mathbf{g_I})$. Dynamic technical inefficiency change is the difference between the value of the dynamic directional distance function at time *t* and time *t*+1:

$$\Delta TEI = \vec{D}^i_t(\mathbf{y}_t,\mathbf{K}_t,\mathbf{L}_t,\mathbf{x}_t,\mathbf{I}_t;\mathbf{g_x},\mathbf{g_I}) - \vec{D}^i_{t+1}(\mathbf{y}_{t+1},\mathbf{K}_{t+1},\mathbf{L}_{t+1},\mathbf{x}_{t+1},\mathbf{I}_{t+1};\mathbf{g_x},\mathbf{g_I}) \quad \textbf{(5)}$$

Technical inefficiency change is easily seen from Figure 1 as the difference between the distance functions evaluated using quantities and technologies in period *t* and period *t+1*.
We can decompose the Luenberger measure further to allow for scale efficiency change (ΔSEI). With the Luenberger measure historically being developed in the context of constant returns to scale, this further decomposition relaxes the technology assumptions of constant returns to scale to permit variable returns to scale.
From a primal perspective, the technical inefficiency change component in (5) can be decomposed as follows**:**

$$\begin{aligned}
\Delta PEI &= \vec{D}^i_t(\mathbf{x}_t,\mathbf{I}_t,\mathbf{k}_t\mathbf{y}_t;\mathbf{g}_x,\mathbf{g}_I \,|\, VRS) - \vec{D}^i_{t+1}(\mathbf{x}_{t+1},\mathbf{I}_{t+1},\mathbf{k}_{t+1},\mathbf{y}_{t+1};\mathbf{g}_x,\mathbf{g}_I \,|\, VRS) \\
\Delta SEI &= \vec{D}^i_t(\mathbf{x}_t,\mathbf{I}_t,\mathbf{k}_t\mathbf{y}_t;\mathbf{g}_x,\mathbf{g}_I \,|\, CRS) - \vec{D}^i_t(\mathbf{x}_t,\mathbf{I}_t,\mathbf{k}_t\mathbf{y}_t;\mathbf{g}_x,\mathbf{g}_I \,|\, VRS) \\
&- \left[\vec{D}^i_{t+1}(\mathbf{x}_{t+1},\mathbf{I}_{t+1},\mathbf{k}_{t+1},\mathbf{y}_{t+1};\mathbf{g}_x,\mathbf{g}_I \,|\, CRS) - \vec{D}^i_{t+1}(\mathbf{x}_{t+1},\mathbf{I}_{t+1},\mathbf{k}_{t+1},\mathbf{y}_{t+1};\mathbf{g}_x,\mathbf{g}_I \,|\, VRS)\right]
\end{aligned} \quad \textbf{(6)}$$

Where ΔPEI is technical inefficiency change under variable returns to scale and ΔSEI is scale inefficiency change.

3 Data

The data used in this study come from the SABI database, managed by Bureau van Dijk, which contains the financial accounts of Spanish companies. The study sample includes the firms belonging to the category of firms in processing and preserving of meat and production of meat products (NACE Rev. 2 code 101). This study focuses on firms of all size categories: micro, small, medium-sized and large. After filtering out companies with missing information and after removing the outliers[2], the final data set consists of between 928 and 1527 firms that operated in Spain at least two consecutive years during the period from 2000 to 2010. The dataset is unbalanced and it sums up to 13103 observations (in total 26206 observations if we consider that each observation is repeated two times in two consecutive years).

One output and three inputs (material costs, labour costs and fixed assets) are distinguished. Output was defined as total sales plus the change in the value of the stock and was deflated using the industrial price index for output in meat processing industry. Material costs and labour costs were directly taken from the SABI database and were deflated using the industrial price index for consumer non-durables and labour cost index in manufacturing, respectively. Fixed assets are measured as the beginning value of fixed assets from the balance sheet (i.e. the end value of the previous year) and are deflated using the industrial price index for capital goods. All prices used to deflate output and inputs are obtained from the Spanish Statistical Office (various years). Gross investments in fixed assets in year *t* are computed as the beginning value of fixed assets in year *t+1* minus the value of fixed assets in year *t* plus the value of depreciation in year *t*. Table 1 provides the descriptive statistics of the data used in this study, for the whole period 2000/2001-2009/2010.

[2] Outliers were determined using ratios of output to input. An observation was defined as an outlier if the ratio of output over any of the three inputs was outside the interval of the median plus and minus two standard deviations.

Table 1. Descriptive statistics of input-output data, 2000/2001-2009/2010.

Variable	Mean	Std. dev.	Min	Max
Fixed assets	2066.131	15233.260	0.134	896472.800
Employee cost	671.038	3465.618	1.420	87188.160
Material cost	5064.267	23834.010	0.333	737417.900
Investments	375.900	4609.822	-41366.180	400870.600
Production	6465.920	30897.880	0.490	859756.100

Note: the values of variables are presented in thousands of euros, constant prices from 1999.

The data in Table 1 shows that the average meat processing company in our sample is relatively small in terms of the EU size classification, with a mean turnover of approximately 6 million euros. On the other hand, the standard deviations relative to their respective means are relatively high showing that the firms in our sample differ considerably in size.

4 Results and Discussion

Table 2 summarizes the arithmetic means of dynamic Luenberger productivity indicator and its decomposition for the pairs of consecutive years. It should be noted that the mixed directional distance functions used to compute dynamic Luenberger indicator might not have a bounded solution. Literature mentions two possible solutions to this problem in the context of static Luenberger, which can be adapted to the dynamic context: (1) to omit the infeasible observations in the computation of averages or (2) to assign to the indices the value equal to no change in indicator (in our case the value equal to 0), which is the strategy we have followed. In general, Briec and Kerstens (2009) recommend reporting the infeasibilities that occurred in the empirical application as shown in Table 2. Out of 13103 observations, only 204 observations are found to be infeasible (that is 1.6% of the entire sample).

Table 2. Evolution of dynamic Luenberger productivity change.

Period	Number of firms	Luenberger productivity change	Technical change	Technical inefficiency change	Scale inefficiency change
2000/2001	1000	-0.018	0.043	-0.083	0.023
2001/2002	1157	0.009	0.083	-0.006	-0.069
2002/2003	1340	-0.003	-0.099	0.093	0.002
2003/2004	1418	-0.001	0.014	-0.008	-0.008
2004/2005	1465	-0.001	0.021	0.009	-0.031
2005/2006	1499	-0.003	-0.070	0.012	0.054
2006/2007	1527	-0.002	-0.078	0.040	0.037
2007/2008	1412	-0.012	-0.131	0.090	0.029
2008/2009	1357	-0.003	0.000	0.036	-0.039
2009/2010	928	0.004	-0.057	0.002	0.059
Arithmetic mean 2000/2001-2009/2010	**13103**	-0.003	-0.031	0.022	0.005

Note: Out of 13103 observations, 204 (1.6%) were found to be infeasible.

The results show consistently a decline in dynamic productivity in Spanish meat processing industry. However, there is a productivity growth from 2001 to 2002 and an upward trend of productivity growth from 2008 to 2010. From 2007 to 2008 the dynamic productivity decline has a mean value of -0.012, from 2008 to 2009 of only -0.003, but from 2009 to 2010 there is a productivity growth with mean value of 0.004. From the three components of dynamic Luenberger productivity change we can observe that the negative growth of productivity is mainly due to technological regress observed in most years. Especially the period from 2005/2006 to 2009/2010 is characterized by a consistent technological regress (with an exception of 2008/2009 when technical stagnation is observed). This finding might be interpreted that in these periods the technology eliminates some productive options that were previously available for the firms in the Spanish meat processing industry. Under the regulatory environment of EU with regard to food safety, the firms are forced to adapt to new standards by undertaking additional investments and absorbing additional costs without a productive impact. As a result some production practices could not be undertaken anymore after the new regulation and consequently the situations of technical regress are produced. In the period from 2006 to 2007 and from 2007 to 2008, especially high technical regress is observed. In these years, the increase in animal feed costs occurred and also the financial crisis added its negative effects on the Spanish meat processing sector. These two factors may also explain the highest decline occurring from 2007 to 2008. On the other hand, the period under investigation is characterized by inefficiency decline, with exception of 2000/2001, 2001/2002 and 2003/2004. The decrease in technical inefficiency might reflect the reaction of the firms in the meat processing industry to the new regulations. Therefore, summarizing, although the best practice frontier moved back, the firms in the sample moved towards the frontier.

Overall, Table 2 indicates a decline in productivity over the 2000-2010 time-period (the Luenberger productivity indicator has a mean value of -0.003), which can be attributed to

technological regress (the technical change indicator with a mean value equal to -0.031), not being fully compensated by a positive technical inefficiency change (mean value of 0.022) and a positive scale inefficiency change (mean value equal to 0.005).

Figure 2 shows the evolution of dynamic Luenberger productivity growth and its decomposition into technical change, technical inefficiency and scale inefficiency change.

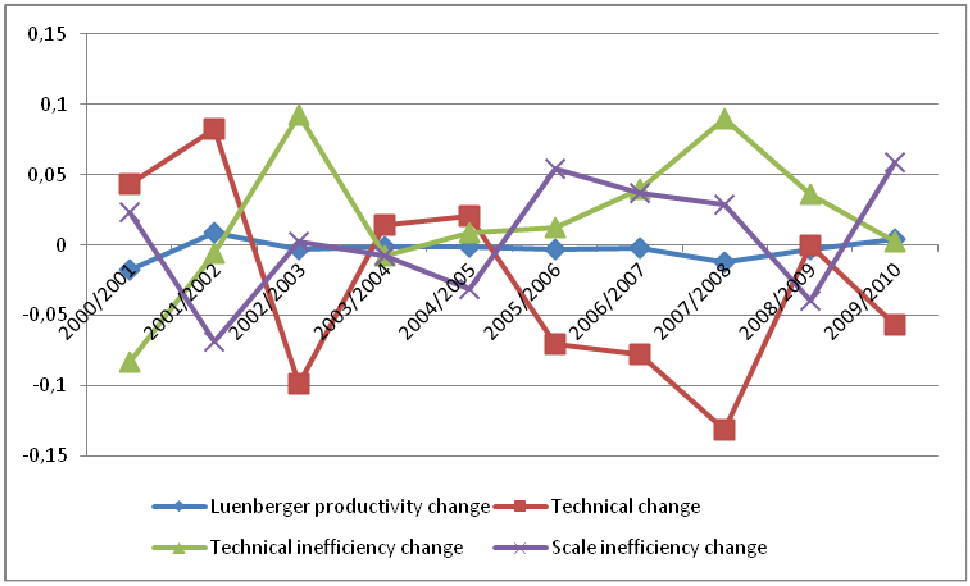

Fig. 2. Evolution of Luenberger and decomposition.

Figure indicates that dynamic Luenberger productivity indicator varies only slightly between pairs of years. The biggest changes are associated with technical inefficiency and technical inefficiency change. Efficiency growth clearly dominates the analyzed period with the highest increase between 2002 and 2003. On the other hand, the technical regress is observed in most periods with highest decline in 2007/2008.

Dynamic productivity change and its decomposition by firm size is analyzed next and reported in Table 3. The comparison is made across four firms' size intervals: micro, small, medium-sized and large. Following EU definition, the category of micro/small/medium firms in made up of enterprises which employ less than 10/50/250 employees and which have an annual turnover not exceeding 2/10/50 million euros, respectively. The firms with more than 250 employees and an annual turnover exceeding 50 million euros are defined as large. Differences in the components of Luenberger productivity growth between these groups are assessed using the test proposed by Simar and Zelenyuk (2006)[3].

[3] Simar and Zelenyuk (2006) adapt the nonparametric test of the equality of two densities developed by Li (1996). In particular, they propose two algorithms and among them they found the Algorithm 2 to be more robust, hence we apply it here. In essence, the algorithm is based on computation and bootstrapping the Li statistic using DEA estimates, where values equal to unity are smoothed by adding a small noise. As productivity change and its decomposition indices are not truncated, we omit the step of smoothing in the algorithm. The implementation of this algorithm is done in R using 1000 bootstrap replications.

Table 3. Dynamic Luenberger productivity growth by firms' sizes (2000/2001-2009/2010).

Size class	Number of firms	Luenberger productivity change	Technical change	Technical inefficiency change	Scale inefficiency change
Large	378	0.005[a]	-0.026[a,b]	-0.003[a]	0.033[a]
Medium	1499	-0.003[b]	-0.030[a]	0.000[b]	0.026[b]
Small	5932	-0.003[b]	-0.031[c,b]	0.020[c]	0.009[c]
Micro	5294	-0.004[c]	-0.031[c]	0.034[d]	-0.006[d]

[a,b,c,d]) difference between a,b,c and d significant at 5% level.

The results reveal that during 2000/2001-2009/2010 large firms experience productivity growth, while medium, small and micro firms experienced a productivity decline. Productivity growth decreased more for micro rather than for small and medium-sized firms. With regard to technical change, although all groups of firms experience technical regress, the difference between size classes is not always significant. Finally, both technical inefficiency change and scale inefficiency change differ significantly across size groups. Technical inefficiency change decreases with size: micro firms experience the highest contribution of technical inefficiency change, while large companies had a negative contribution of technical inefficiency change. The opposite pattern is observed with respect to the change in scale inefficiency as micro firms undergo scale inefficiency increase and large firms have the highest scale inefficiency decline. We also note that technical regress observed in the entire sample is driven mainly by medium, small and micro firms, while technical efficiency growth in the sample is due to micro and small firms.

5 Conclusion

This paper extends the dynamic Luenberger productivity growth indicator to decompose it into the contributions of technical efficiency change, scale efficiency change and technical change. The empirical application focuses on panel data of Spanish meat processing firms over the period 2000-2010. The results show that dynamic Lueberger productivity growth was overall small but negative in the period 2000-2010. Technical change made a large (on average 3%) negative contribution to TFP growth, particularly in the years after the beginning of the financial crisis. Technical inefficiency reduced on average in the period under investigation, to make 2% positive contribution to TFP growth. The analysis of results for firms in different size classes showed that productivity growth has been more favorable on large firms than small firms. Large firms benefitted from a positive contribution of scale inefficiency change yielding an overall productivity improvement of 0.5% over analyzed period; medium, small and micro firms all had productivity decreases ranging from -0.3% to -0.4% on average over analyzed period.

The results suggest that the introduction of hygiene regulations in the slaughter industry have caused a negative technical change in the period under investigation. Hence, policy makers should be aware of the negative impacts on competitiveness of on-going regulation. The results also suggest that the financial crisis had a large negative impact on the productivity of the meat processing sector.

References

National Association of Meat Industries of Spain (Asociación Nacional de Industrias de la Carne de España ANICE), http://www.anice.es

Balk, B. (2008) *Price and quantity index numb*ers, Cambridge: Cambridge University Press.

Boussemart, J., Briec, W., Kerstens, K. and Poutineau, J. (2003) 'Luenberger and Malmquist productivity indices: Theoretical comparisons and empirical illustration', *Bulletin of Economic Research*, vol. 55, no. 4, pp. 391-405.

Briec, W. and Kerstens, K. (2004) 'A Luenberger-Hicks-Moorsteen productivity indicator: Its relation to the Hicks-Moorsteen productivity index and the Luenberger productivity indicator', *Economic Theory*, vol. 23, no. 4, pp. 925-939.

Briec, W. and Kerstens, K. (2009) 'Infeasibility and directional distance functions with application to the determinateness of the Luenberger productivity indicator', *Journal of Optimization Theory and Application*, vol. 141, no. 1, pp. 55-73.

Chambers, R.G., Chung, Y. and Färe, R. (1996) 'Benefit and distance functions', *Journal of Economic Theory*, vol. 70, no. 2, pp. 407-419.

Chambers, R. G., Färe, R. and Grosskopf, S. (1996) 'Productivity growth in APEC countries', *Pacific Economic Review*, vol. 1, no. 3, pp. 181–190.

European Commission (2004) 'The meat sector in the European Union'.

European Commission (2011) 'Study on the competitiveness of the European meat processing industry'.

Färe, R. and Primont, D. (1995) *Multi-output production and duality: Theory and applications*, Boston: Kluwer Academic Publishers.

Färe, R. and Grosskopf, S. (2005) 'Essay 1: Efficiency Indicators and Indexes' In *New Directions: Efficiency and Productivity*, by Färe, R., Grosskopf, S. Boston: Kluwer Academic Publishers.

Li, Q. (1996) 'Nonparametric testing of closeness between two unknown distribution functions', *Econometric Reviews*, vol. 15, no. 3, pp. 261–274.

Oude Lansink, A.G.J.M., Stefanou, S.E. and Serra, S. (2012) 'Primal and dual dynamic Luenberger productivity indicators', Wageningen University, working paper.

Rungsuriyawiboon, S. and Stefanou, S.E. (2007) 'Dynamic efficiency estimation: An application to U.S. electric utilities', *Journal of Business & Economic Statistics*, vol. 25, no. 2, pp. 226-238.

Silva, E. and Stefanou, S.E. (2003) 'Nonparametric dynamic production analysis and the theory of cost', *Journal of Productivity Analysis*, vol. 19, no.1, pp. 5-32.

Silva, E. and Stefanou, S.E. (2007) 'Nonparametric dynamic efficiency measurement: Theory and application', *American Journal of Agricultural Economics*, vol. 89, no. 2, pp. 398-419.

Silva, E. and Oude Lansink, A.G.J.M. (2012), 'Dynamic efficiency measurement: A directional distance function approach', Wageningen University, working paper.

Simar, L. and Zelenyuk, V. (2006) 'On testing equality of distributions of technical efficiency scores', *Econometric Reviews*, vol. 25, no. 4, pp. 497-522.

Wijnands, J.H.M., Van der Meulen, B.M.J. and Poppe, K.J. (2006) 'Competitiveness of the European food industry. An economic and legal assessment', European Commission.