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Analysis of static and dynamic productivity growth in the Spanish meat processing industry

Abstract. This paper estimates static Malmquist and dynamic Luenberger productivity growth measures and decomposes these to identify the contributions of technical change, technical efficiency change and scale efficiency change. The Malmquist and Luenberger productivity growth measures are estimated using Data Envelopment Analysis. The empirical application uses data on Spanish meat processing firms over the period 2000-2010. The dynamic Luenberger indicator and the static Malmquist index show, in the period under investigation, a productivity decrease of, on average, 0.3% and 1% respectively. In both measures, the technical regress is the main driver of change, despite the technical and scale efficiency growth.

Key words: Malmquist TFP, dynamics, Luenberger TFP, meat processing.

Introduction

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… 2012]. Its significance is emphasized by the fact that it is one of the main exporting sectors of Spain. The Spanish meat processing industry is characterized also by a low level of innovations and by the predominance of small and medium-sized enterprises [Study… 2011]. The period analyzed concerns the time of increasing regulation in the European Union (EU) with regard to food safety, consumer information, 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 [The meat… 2004; Wijnands, van der Meulen & Poppe 2006]. Another impact factor is an 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 processing industry. Finally, from 2008 onwards the Spanish meat processing industry is being affected by the economic crisis as reflected by the decrease in the demand for meat. The impact of changes in the policy and the economic environment on the economic performance is an empirical question.

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The Total Factor Productivity (TFP) growth is a frequently used measure of a sector performance over time. The economics literature on efficiency has produced a wide range of productivity growth measures [Balk 2008] with the Malmquist index being prominent among these. The setting of decision environment plays a crucial role in the modelling 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. If the conditions for static models hold, then a static Malmquist index can give a correct representation of productivity growth. However, the business policy relevance for distinguishing between the contributions of variable and fixed capital factors to inefficiency or to productivity growth is clear. For example, when a variable factor use is not meeting its potential, remedies can include better monitoring of the resource use; when an asset use is not meeting its potential, remedies can include training programmes 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 dynamic models of production, where current production decisions constrain or enhance future production possibilities[4].

The characterization of dynamic efficiency can also build on the adjustment cost framework that implicitly measures inefficiency as a temporal concept which accounts for the sluggish adjustment of some factors. In a nonparametric setting, Silva and Stefanou [2007] develop a myriad of efficiency measures associated with a 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 a dynamic shadow price approach to the 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 a powerful advantage of focusing on changes in input and output bundles, in the inefficiency and the technology. Such a productivity measure based on the directional distance function has its origins in work by 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[5]. 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 of technical inefficiency change. Kapelko, Oude Lansink and Stefanou [2012] extended this decomposition to identify the contribution of scale inefficiency change.

This paper nonparametrically estimates the dynamic Luenberger productivity growth measure of Kapelko, Oude Lansink and Stefanou [2012] and decomposes this to identify the contributions of scale efficiency, technical change and technical efficiency change. The results of the Luenberger estimation are then compared with the results of a traditional

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[4] The rationale behind the dynamic characterization of efficiency is described in detail in Stefanou [2009].

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

Malmquist index and its decomposition. The focus of the application is on panel data of Spanish meat processing firms over the period 2000-2010.

The next section presents the measures of static (Malmquist) and dynamic (Luenberger) productivity growth and its decomposition. This is followed by an empirical application to the panel of Spanish meat processing firms showing productivity change and its decomposition. The final section offers concluding comments.

Static and dynamic productivity growth

Malmquist index of static productivity growth

The Malmquist Index is defined through a radial distance functions originally developed by Shephard [1970; 1953]. 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, and $\mathbf{I}_t \in \Re_{+}^{F}$ the vector of gross investments. Computing a Malmquist index of TFP growth requires constant returns to scale (CRS) technology in order to assure feasible solutions to the programming problem. The Malmquist Input-Based TFP Index is defined as [Färe et al. 1994]:

$$M_i(\mathbf{y}_{t+1},\mathbf{K}_{t+1},\mathbf{x}_{t+1},\mathbf{y}_t,\mathbf{K}_t,\mathbf{x}_t|CRS)=\left[\frac{D_t^i(\mathbf{y}_t,\mathbf{K}_t,\mathbf{x}_t|CRS)}{D_t^i(\mathbf{y}_{t+1},\mathbf{K}_{t+1},\mathbf{x}_{t+1}|CRS)}\times\frac{D_{t+1}^i(\mathbf{y}_t,\mathbf{K}_t,\mathbf{x}_t|CRS)}{D_{t+1}^i(\mathbf{y}_{t+1},\mathbf{K}_{t+1},\mathbf{x}_{t+1}|CRS)}\right]^{1/2} \quad (1)$$

where $D_t^i(\cdot)$ is an input oriented distance function in period t which is defined as:

$$D_i(\mathbf{y_t},\mathbf{K}_t,\mathbf{x}_t)=\max\gamma\in\Re:(\mathbf{x_t}/\gamma,\mathbf{K}_t/\gamma)\in P(\mathbf{y_t}) \quad (2)$$

and $P(y_t)$ is the input set. $D_t^i(\cdot)$ is the inverse of the Debreu-Farrell input oriented technical efficiency ($F_t^i(\cdot)$) measures [Färe et al. 1994]. The Malmquist input oriented productivity index in equation (1) is written as the product of technical efficiency change and technical change:

$$\frac{F_{t+1}^i(\mathbf{y_{t+1}},\mathbf{K_{t+1}},\mathbf{x_{t+1}}|CRS)}{F_t^i(\mathbf{y_t},\mathbf{K_t},\mathbf{x_t}|CRS)}\times\left[\frac{F_{t+1}^i(\mathbf{y_{t+1}},\mathbf{K_{t+1}},\mathbf{x_{t+1}}|CRS)}{F_t^i(\mathbf{y_{t+1}},\mathbf{K_{t+1}},\mathbf{x_{t+1}}|CRS)}\times\frac{F_{t+1}^i(\mathbf{y_t},\mathbf{K_t},\mathbf{x_t}|CRS)}{F_t^i(\mathbf{y_t},\mathbf{K_t},\mathbf{x_t}|CRS)}\right]^{1/2} \quad (3)$$

The first term in equation (3) reflects the technical efficiency change, measuring the change in technical efficiency in period t+1 compared with period t. The second term (in brackets) reflects the technical change, which is measured as the geometric mean of shift of the frontier relative to the observations in period t+1 (first term) and t (second term). The denominator of the first ratio in the brackets and the numerator of the second ratio in the brackets are so-called mixed-period efficiency measures [Färe et al. 1994]. These efficiency measures are equal to the distance of an observation in a one time period relative to the technology of another time-period. The other efficiency measures equal the Debreu-Farrell efficiency for periods t and t+1.

The first term on the right hand side of equation (3) can be further decomposed into the contributions of technical efficiency change under variable returns to scale (VRS) and scale efficiency change (ΔSE):

$$\frac{F_t^i(\mathbf{y_t},\mathbf{K_t},\mathbf{x_t}|CRS)}{F_{t+1}^i(\mathbf{y_{t+1}},\mathbf{K_{t+1}},\mathbf{x_{t+1}}|CRS)}=\frac{SE_t^i(\mathbf{y_t},\mathbf{K_t},\mathbf{x_t})}{SE_t^i(\mathbf{y_{t+1}},\mathbf{K_{t+1}},\mathbf{x_{t+1}})}\times\frac{F_t^i(\mathbf{y_t},\mathbf{K_t},\mathbf{x_t}|VRS)}{F_{t+1}^i(\mathbf{y_{t+1}},\mathbf{K_{t+1}},\mathbf{x_{t+1}}|VRS)} \quad (4)$$

Hence, the Malmquist index is decomposed into the contributions of technical change (ΔT), technical efficiency change under variable returns to scale (ΔTE) and scale efficiency change:

$$M(\cdot)=\Delta T\times\Delta PTE\times\Delta SE \quad (5)$$

An illustration of the components of Malmquist index in case of one input and one output is shown in Figure 1.

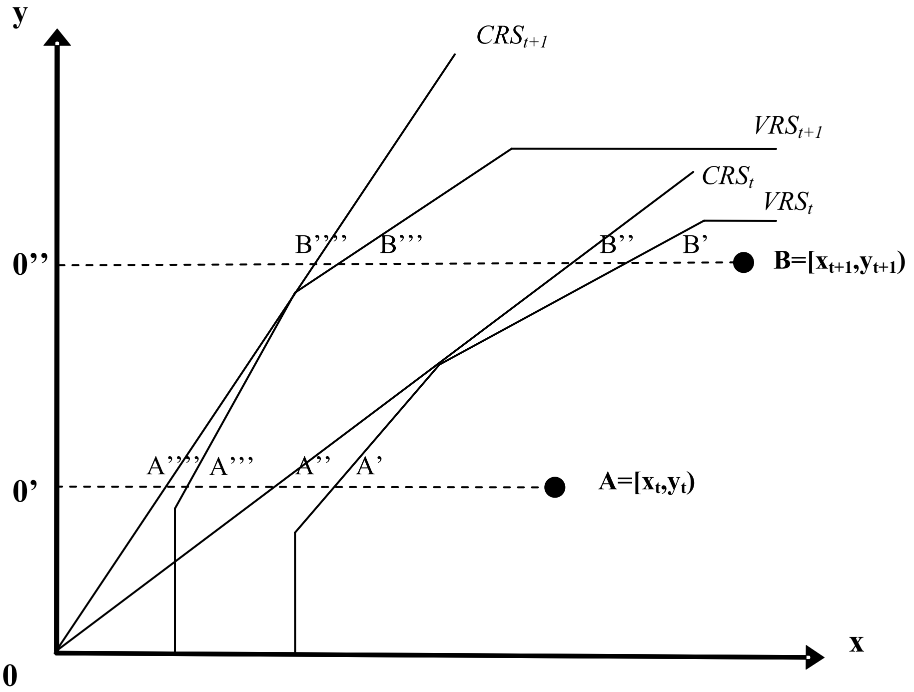

Fig. 1. Malmquist index of productivity change

Source: own elaboration.

The constant returns to scale frontier at the time period t is the line through the origin denoted by CRS_t, while the CRS frontier at t+1 is the line denoted by CRS_{t+1}. The VRS frontiers at t and t+1 are the lines VRS_t and VRS_{t+1}. Technical efficiency in period t relative to the VRS frontier is given by the ratio of the distances O'A'/O'A, whereas in period t+1 this is O''B'''/O''B. Hence, technical efficiency change is given by the ratio of the two technical efficiency measures. Scale efficiency reflects the difference between the VRS and CRS frontier. Scale efficiency in period t is equal to the ratio O'A''/O'A' and in period t+1 this is O''B''''/O''B'''; the ratio of the two scale efficiency measures gives scale efficiency change. Technical change reflects the difference between the CRS_{t+1} frontier and the CRS_t frontier based on the observed values of input and output in period t and period t+1. It is measured as the geometric mean of two ratios of distances, i.e. 0'A''''/0'A'' and 0''B''''/0''B''.

Luenberger dynamic productivity growth

The Luenberger indicator of dynamic productivity growth is defined through a dynamic directional distance function. The production input requirement set can be represented as $V_t(\mathbf{y}_t : \mathbf{K}_t) = \{(\mathbf{x}_t, \mathbf{I}_t)$ can produce $\mathbf{y}_t$, given $\mathbf{K}_t\}$. The input requirement set is defined by Silva and Oude Lansink [2012] and assumed to have the following properties: $V_t(\mathbf{y}_t : \mathbf{K}_t)$ is a closed and nonempty set, has a lower bound, is positive monotonic in variable inputs $\mathbf{x}_t$, negative monotonic in gross investments $\mathbf{I}_t$, 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 with directional vectors for inputs ($\mathbf{g}_x$) and investments ($\mathbf{g}_I$), $\vec{D}_t^i(\mathbf{y}_t, \mathbf{K}_t, \mathbf{x}_t, \mathbf{I}_t; \mathbf{g}_x, \mathbf{g}_I)$ is defined as follows:

$$\vec{D}_t^i(\mathbf{y}_t,\mathbf{K}_t,\mathbf{x}_t,\mathbf{I}_t;\mathbf{g}_x,\mathbf{g}_I)=\max\{\beta\in\Re:(\mathbf{x}_t-\beta\mathbf{g}_x,\mathbf{I}_t+\beta\mathbf{g}_I)\in V_t(\mathbf{y}_t:\mathbf{K}_t)\},$$
$$\mathbf{g}_x\in\Re^N_{++},\mathbf{g}_I\in\Re^F_{++},(\mathbf{g}_x,\mathbf{g}_I)\neq(\mathbf{0}^N,\mathbf{0}^F) \tag{6}$$

if $(\mathbf{x}_t-\beta\mathbf{g}_x,\mathbf{I}+\beta\mathbf{g}_I)\in V_t(\mathbf{y}_t:\mathbf{K}_t)$ for some β, then $\vec{D}_t^i(\mathbf{y}_t,\mathbf{K}_t,\mathbf{x}_t,\mathbf{I}_t;\mathbf{g}_x,\mathbf{g}_I)=-\infty$. The directional distance function is a measure of the maximal translation of $(\mathbf{x}_t, \mathbf{I}_t)$ in the direction defined by the vector $(\mathbf{g}_x, \mathbf{g}_I)$ that keeps the translated input combination interior to the set $V_t(\mathbf{y}_t:\mathbf{k}_t)$. 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. Hence, the directional distance function provides a measure of technical inefficiency rather than efficiency. For the case of the static input directional distance function with directional vector gx=x, Färe and Grosskopf [2005] show that $D_t^i(\mathbf{y}_t,\mathbf{K}_t,\mathbf{x}_t;\mathbf{g}_x)=1-1/D_t^i(\mathbf{y}_t,\mathbf{K}_t,\mathbf{x}_t)$. Remind that efficiency is defined as $1/D_t^i(\mathbf{y}_t,\mathbf{K}_t,\mathbf{x}_t)$, so inefficiency is defined as one minus efficiency. As shown by Silva and Oude Lansink [2012], $\vec{D}_t^i(\mathbf{y}_t,\mathbf{K}_t,\mathbf{x}_t,\mathbf{I}_t;\mathbf{g}_x,\mathbf{g}_I)\geq 0$ fully characterizes the input requirement set $V_t(\mathbf{y}_t:\mathbf{K}_t)$, being thus an alternative primal representation of the adjustment cost production technology.

Building in 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:

$$L(\cdot)=\frac{1}{2}\left\{\begin{array}{l}[\vec{D}_{t+1}^i(\mathbf{y}_t,\mathbf{K}_t,\mathbf{x}_t,\mathbf{I}_t;\mathbf{g}_x,\mathbf{g}_I)-\vec{D}_{t+1}^i(\mathbf{y}_{t+1},\mathbf{K}_{t+1},\mathbf{x}_{t+1},\mathbf{I}_{t+1};\mathbf{g}_x,\mathbf{g}_I)]\\+[\vec{D}_t^i(\mathbf{y}_t,\mathbf{K}_t,\mathbf{x}_t,\mathbf{I}_t;\mathbf{g}_x,\mathbf{g}_I)-\vec{D}_t^i(\mathbf{y}_{t+1},\mathbf{K}_{t+1},\mathbf{x}_{t+1},\mathbf{I}_{t+1};\mathbf{g}_x,\mathbf{g}_I)]\end{array}\right\} \tag{7}$$

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 (7)) and the productivity change measured by the technology at time t (i.e., the last two terms in equation (7)).

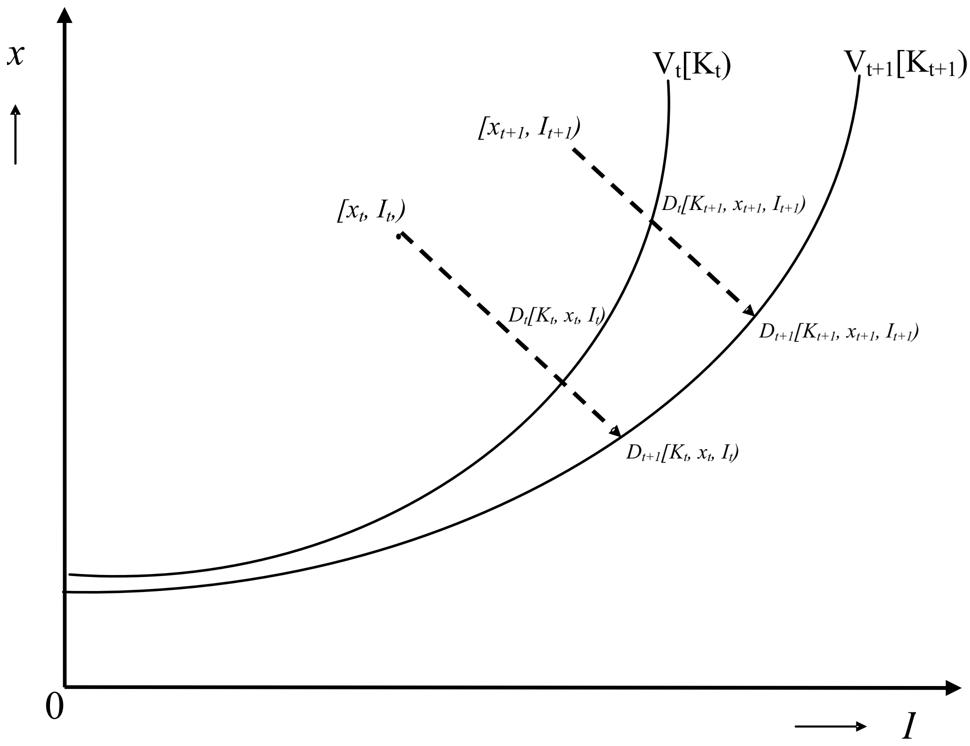

Fig. 2. Luenberger indicator of dynamic productivity growth

Source: own elaboration.

The Luenberger indicator of dynamic productivity growth is illustrated graphically in Figure 2. 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 $\vec{D}^i_{t+1}(\mathbf{y}_t, \mathbf{K}_t, \mathbf{x}_t, \mathbf{I}_t; \mathbf{g}_x, \mathbf{g}_I)$. The Luenberger indicator of dynamic productivity growth can be decomposed into the contributions of technical inefficiency change (ΔTEI) and technical change (ΔT):

$$L(\cdot) = \Delta T + \Delta TEI \tag{8}$$

The decomposition of productivity growth is obtained from equation (7) by adding and subtracting the term $\vec{D}^i_{t+1}(\mathbf{y}_{t+1}, \mathbf{K}_{t+1}, \mathbf{x}_{t+1}, \mathbf{I}_{t+1}; \mathbf{g}_x, \mathbf{g}_I) - \vec{D}^i_t(\mathbf{y}_t, \mathbf{K}_t, \mathbf{x}_t, \mathbf{I}_t; \mathbf{g}_x, \mathbf{g}_I)$. 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 equation (9)) and time t+1 (last two terms in equation (9)):

$$\Delta T = \frac{1}{2}\left\{ \begin{array}{l} [\vec{D}^i_{t+1}(\mathbf{y}_t,\mathbf{K}_t,\mathbf{x}_t,\mathbf{I}_t;\mathbf{g}_x,\mathbf{g}_I) - \vec{D}^i_t(\mathbf{y}_t,\mathbf{K}_t,\mathbf{x}_t,\mathbf{I}_t;\mathbf{g}_x,\mathbf{g}_I)] \\ +[\vec{D}^i_t(\mathbf{y}_{t+1},\mathbf{K}_{t+1},\mathbf{x}_{t+1},\mathbf{I}_{t+1};\mathbf{g}_x,\mathbf{g}_I) - \vec{D}^i_t(\mathbf{y}_{t+1},\mathbf{K}_{t+1},\mathbf{x}_{t+1},\mathbf{I}_{t+1};\mathbf{g}_x,\mathbf{g}_I)] \end{array} \right\} \quad (9)$$

The technical change can be seen in Figure 2 as the average distance between the two isoquants. This involves evaluating the isoquants using quantities at time t, $\vec{D}^i_{t+1}(\mathbf{y}_t,\mathbf{K}_t,\mathbf{x}_t,\mathbf{I}_t;\mathbf{g}_x,\mathbf{g}_I) - \vec{D}^i_t(\mathbf{y}_t,\mathbf{K}_t,\mathbf{x}_t,\mathbf{I}_t;\mathbf{g}_x,\mathbf{g}_I)$ and quantities at time t+1, $\vec{D}^i_{t+1}(\mathbf{y}_{t+1},\mathbf{K}_{t+1},\mathbf{x}_{t+1},\mathbf{I}_{t+1};\mathbf{g}_x,\mathbf{g}_I) - \vec{D}^i_{t+1}(\mathbf{y}_{t+1},\mathbf{K}_{t+1},\mathbf{x}_{t+1},\mathbf{I}_{t+1};\mathbf{g}_x,\mathbf{g}_I)$. Dynamic technical inefficiency change is the difference between the value of the dynamic directional distance function at time t and time t+1:

$$\Delta TEI = \vec{D}^i_t(\mathbf{y}_t,\mathbf{K}_t,\mathbf{x}_t,\mathbf{I}_t;\mathbf{g}_x,\mathbf{g}_I) - \vec{D}^i_{t+1}(\mathbf{y}_{t+1},\mathbf{K}_{t+1},\mathbf{x}_{t+1},\mathbf{I}_{t+1};\mathbf{g}_x,\mathbf{g}_I) \quad (10)$$

The technical inefficiency change is easily seen from Figure 2 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 inefficiency 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 equation (10) can be decomposed as follows:

$$\begin{array}{l} \Delta PEI = \vec{D}^i_t(\mathbf{y}_t,\mathbf{K}_t,\mathbf{x}_t,\mathbf{I}_t;\mathbf{g}_x,\mathbf{g}_I \mid VRS) - \vec{D}^i_{t+1}(\mathbf{y}_{t+1},\mathbf{K}_{t+1},\mathbf{x}_{t+1},\mathbf{I}_{t+1};\mathbf{g}_x,\mathbf{g}_I \mid VRS) \\ \Delta SEI = \vec{D}^i_t(\mathbf{y}_t,\mathbf{K}_t,\mathbf{x}_t,\mathbf{I}_t;\mathbf{g}_x,\mathbf{g}_I \mid CRS) - \vec{D}^i_t(\mathbf{y}_t,\mathbf{K}_t,\mathbf{x}_t,\mathbf{I}_t;\mathbf{g}_x,\mathbf{g}_I \mid VRS) \\ -\left[\vec{D}^i_{t+1}(\mathbf{y}_{t+1},\mathbf{K}_{t+1},\mathbf{x}_{t+1},\mathbf{I}_{t+1};\mathbf{g}_x,\mathbf{g}_I \mid CRS) - \vec{D}^i_{t+1}(\mathbf{y}_{t+1},\mathbf{K}_{t+1},\mathbf{x}_{t+1},\mathbf{I}_{t+1};\mathbf{g}_x,\mathbf{g}_I \mid VRS)\right] \end{array} \quad (11)$$

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

Data

The data used in this study come from the SABI (System for the Analysis of Iberian Balance Sheets or Iberian Balance Sheet Analysis System) 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 involved in processing and preserving of meat and production of meat products (NACE Rev. 2 code 101). In what follows, we refer to our sample as the meat processing industry. Initially, 3000 firms were obtained from the database. After filtering out companies with missing information and after removing the outliers[6], 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

[6] 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.

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 (production) was defined as total sales plus the change in the value of stock at current prices and was deflated using the industrial price index (1999=100%) for output in the 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 at 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 price indices used to deflate output and inputs are obtained from the Spanish Statistical Office (various years). Additionally, to estimate the dynamic Luenberger indicator, gross investments were used. Gross investments in fixed assets in year t are computed as the deflated beginning value of fixed assets in year t+1 minus the deflated value of fixed assets in year t plus the deflated 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.

Table 1. Descriptive statistics of input-output data of the Spanish meat processing industry, 2000/2001-2009/2010, constant 1999 prices, EUR thousand

Variable	Mean	Standard deviation	Minimum	Maximum
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

Source: SABI database.

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 EUR million. 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.

Results and discussion

Table 2 summarizes the geometric means of static Malmquist productivity index and its decomposition for the pairs of consecutive years and Table 3 summarizes the arithmetic means of dynamic Luenberger productivity indicator and its decomposition for the pairs of consecutive years. Some of the mixed directional distance functions used to compute Malmquist and dynamic Luenberger indicators do not have a feasible solution. Literature mentions two possible solutions to this problem: (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, 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 Tables 2 and 3. Out of 13103 observations, 19 observations are found to be infeasible for the static Malmquist estimations and 204 observations are found to be infeasible in case of the dynamic Luenberger estimations.

The results of the Malmquist index in Table 2 show that productivity growth was, on average -1% per year in the period 2000-2010, with technical change making, on average, a negative contribution to TFP growth. Technical efficiency change slightly increases in the period under investigation, to make a positive contribution to TFP growth; scale efficiency changes also contributed positively. Results of individual years show that TFP growth is negative in all years, except the period 2001/2002 and 2009/2010. The technical change shows very large fluctuations, from a 34.2% decrease in 2005/2006 to a 3.5% increase in 2001/2002.

Table 2. Evolution of static Malmquist productivity change (growth rate)

Period	Number of firms	Malmquist productivity change	Technical change	Technical efficiency change	Scale efficiency change
2000/2001	1000	-0.070	0.027	-0.151	0.044
2001/2002	1157	0.045	0.035	0.043	-0.033
2002/2003	1340	-0.010	-0.054	0.037	0.004
2003/2004	1418	-0.018	-0.018	0.037	-0.038
2004/2005	1465	-0.004	-0.184	0.112	0.046
2005/2006	1499	-0.013	-0.342	0.120	0.142
2006/2007	1527	-0.003	0.005	-0.010	0.002
2007/2008	1412	-0.032	-0.228	0.126	0.039
2008/2009	1357	-0.008	-0.088	0.074	0.001
2009/2010	928	0.006	-0.061	0.048	0.015
Total or geometric mean 2000/2001-2009/2010	13103	-0.010	-0.093	0.052	0.025

Note: out of 13103 observations, 19 (0.15%) were found to be infeasible.

Source: own calculations.

The results of the dynamic Luenberger indicator in Table 3 also show a decline in dynamic productivity in the Spanish meat processing industry. However, there is a productivity growth from 2001 to 2002 and an upward trend of productivity growth from 2009 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 a mean value of 0.004. From the three components of dynamic Luenberger productivity change we can observe that the negative productivity growth is mainly due to technological regress in most years. Especially the period from 2005 to 2009 is characterized by a technological regress (with an exception of 2008/2009 when technical stagnation is observed).

Comparing the results of the Malmquist and the Luenberger analyses shows that the Malmquist estimation reports a higher productivity decline than the Luenberger (-1% versus -0.3%). Also, technological change is lower for the Malmquist than for the Luenberger estimations. Technical efficiency and scale efficiency make a larger contribution to productivity growth in case of the Malmquist than in case of the Luenberger analysis.

Table 3. Evolution of dynamic Luenberger productivity change (growth rate)

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
Total or 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.

Source: own calculations.

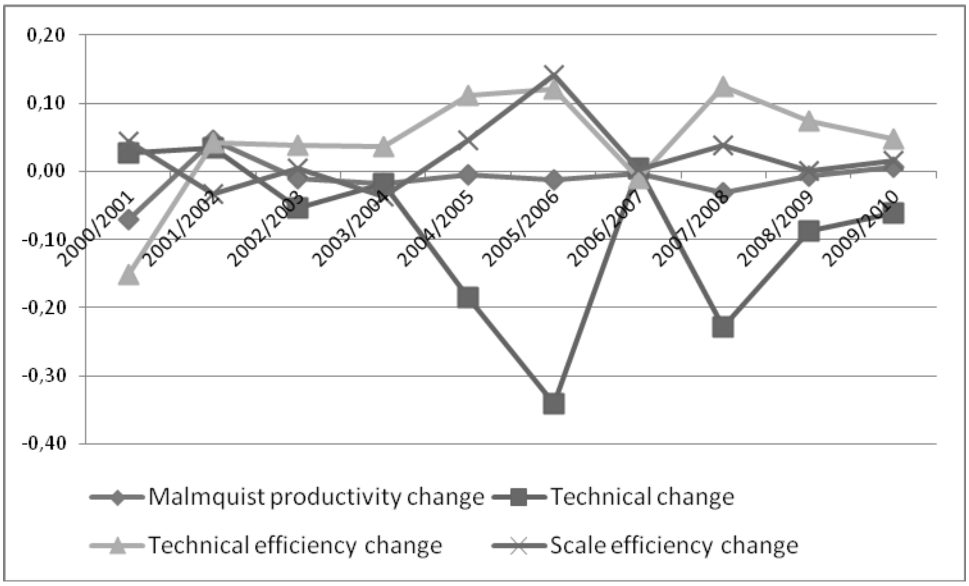

Fig. 3. Evolution of the Malmquist productivity change and its components

Source: own elaboration.

The finding of technological regress from the results of the estimation of the Malmquist and the Luenberger suggests 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. The highest technical regresses occur in the period from 2005 to 2006, 2006 to 2007 and 2007 to 2008. In these years, an increase in animal feed costs occurred and also the financial crisis added its negative effects to the Spanish meat processing sector. On the other hand, most years of the period under investigation are characterized by efficiency improvement. The improvement of technical efficiency shows that the firms in the sample moved towards the frontier.

Figures 3 and 4 show the evolution of the static Malmquist and dynamic Luenberger productivity growth and their decomposition into technical change, technical (in)efficiency and scale (in)efficiency change.

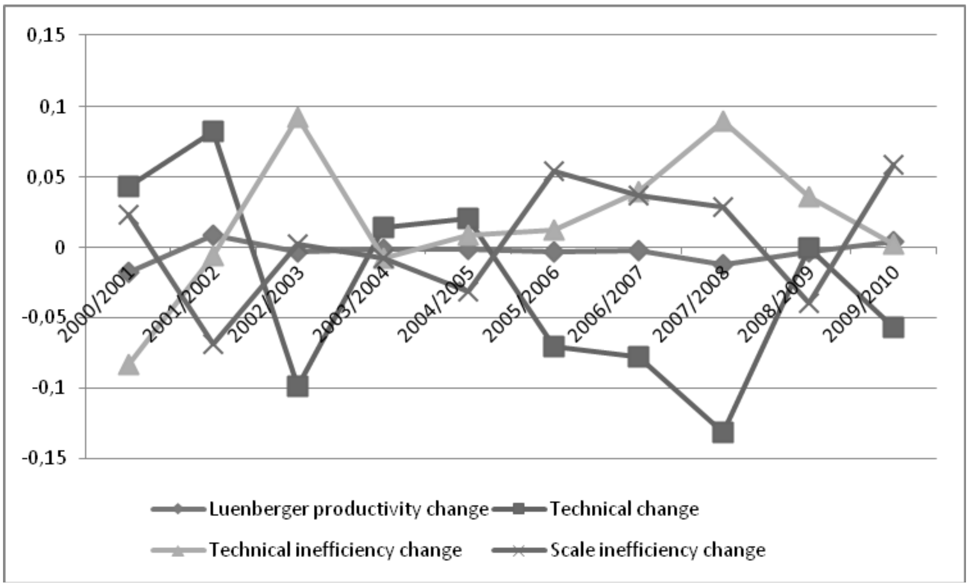

Fig. 4. Evolution of the Luenberger productivity change and its components

Source: own elaboration.

Figures 3 and 4 indicate that fluctuations of TFP growth are slightly higher for the static Malmquist index than for the dynamic Luenberger productivity. The biggest changes are associated with technical change and technical efficiency change for both productivity measures. The technical efficiency growth clearly dominates the analyzed period with high increases observed between 2007 and 2008 in both TFP measures. On the other hand, a technical regress is observed in most periods with highest decline in 2007/2008.

Confronting our results with these reported in other studies, first of all we should notice that the literature on productivity change in the European meat processing sector (or food industry in general) is rather limited. Bontemps et al. [2012] studied the impact of regulations on productivity in French food processing industry (poultry and cheese) from 1996 to 2006. They show that these industries experienced a period of technical progress, followed by a period of technical regress, which might be a consequence of constraints imposed by stricter sanitary regulations. Therefore, our conclusions are similar to those reported in their study.

Conclusion

This paper uses DEA to estimate a static Malmquist index and a dynamic Luenberger productivity growth indicator. Both productivity measures are decomposed to identify the contributions of technical (in)efficiency change, scale (in)efficiency change and technical change. The empirical application focuses on panel data of firms in the Spanish meat processing industry over the period 2000-2010.

The results show that the static and dynamic productivity measures report, on average, a negative productivity growth over the period under investigation. The Malmquist index results suggest a higher productivity decline than the dynamic Luenberger productivity growth indicator. In both productivity measures, technical change made a large (on average 9% for the Malmquist and 3% for the Luenberger indicator) negative contribution to TFP growth, particularly in the years after the beginning of financial crisis. For both productivity measures, technical efficiency and scale efficiency improved on average in the period under investigation, to make a positive contribution to TFP growth.

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 the on-going regulation. The results also suggest that the financial crisis had a large negative impact on the productivity of the meat processing sector.

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