Assessing productivity growth and technical efficiency in Spain's retail sector: An aggregate sectoral perspective

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Keywords
Retail sector, productivity growth, efficiency changes, technical progress, panel data.

Abstract
This paper analyzes the efficiency and productivity growth of the Spanish retail sector from an aggregate sectoral perspective from 1995 to 2004. The primary interest is on individual comparisons within the Spanish retail sector. For this purpose, DEA methodology is proposed. To test this proposal, a study was carried out using both cross-sectional and panel data. The results obtained in this study confirm that efficiency declined from 1995 to 2004. But, when the role of time is considered, the behavior of the efficiency distribution is different. Productivity growth increased at an average rate of 0.8% per annum over the entire period in the retail sector and, the determinants of the variation in productivity growth will be analyzed here.

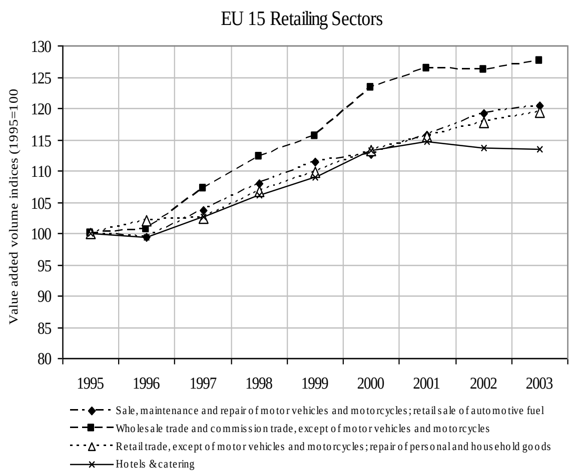
Introduction

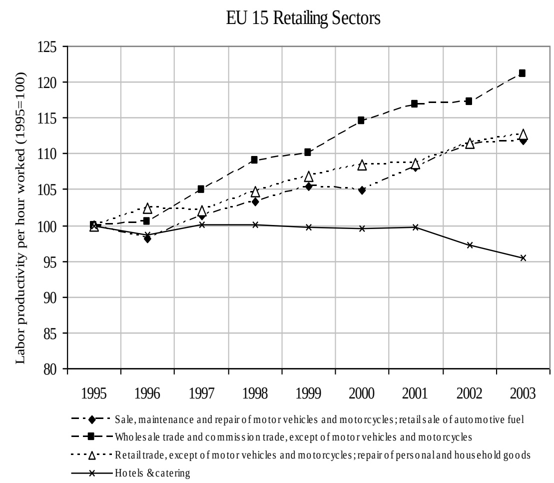
A dynamic transformation has characterized the retail sector over the last few years. Global competition and technological changes are having a significant impact on the market structure. The Spanish retail trade sector is undergoing profound changes, to a certain degree similar to those that are occurring throughout Europe. In Spain this sector has been developing towards higher levels of concentration and has experienced a number of important legislative changes like the Retail Trade Regulation Act (1996) and the Shop Opening Hours Decree-Law (2000), which have impacted retailers' efficiency and productivity (De Jorge, 2006, 2008).

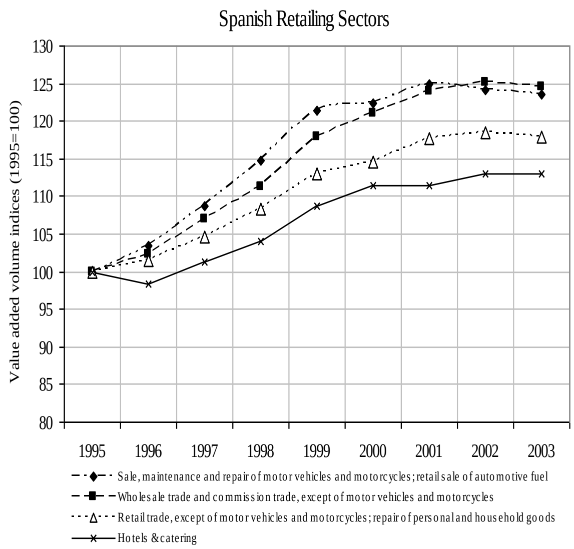
Retail productivity provides vital information for a number of tactical, strategic, and policy-related decisions in this industry. At a tactical level, for a multi-unit firm, a manager's control and expansion strategies begin with an assessment of the stores' relative productivity level (Dubelaar, Bhargava and Ferrarin, 2002). Strategically, retail productivity can be used to differentiate firms and rovides the foundations for developing strategies for growth and diversification (Walters and Laffy, 1996). As Färe, Grosskopf and Lee (2001) mention, productivity is of interest to economists and policymakers, because productivity growth is a major source of economic growth and welfare improvement.

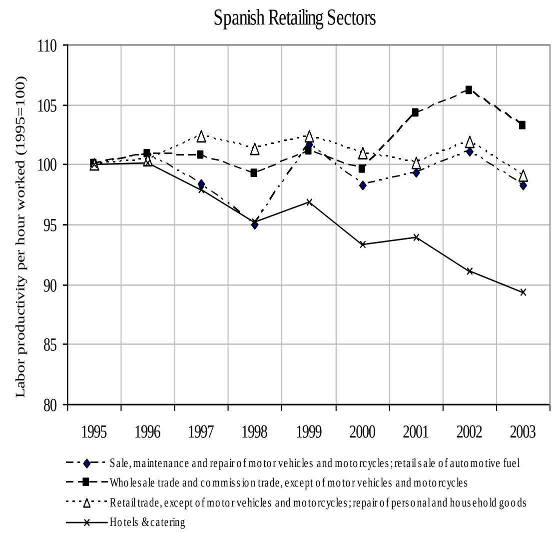
Figure 1 shows the value-added volume indices and labor-productivity-per-hour-worked evolution in the European Union 15 (at the top of the figure) and Spain's retail sector (at the bottom of the figure). As the figure indicates, similar patterns can be seen between the EU 15 and the Spanish sector with respect to value-added volume, but the evolution of labor is falling in the Spanish retail sector in comparison with the European tendency.

Figure 1: Value-added volume indices and labor-productivity-per-hour-worked in the European Union 15 and Spain's retail sector









Source: Groningen database and own elaboration

In recent years, a number of studies that analyze the efficiency and productivity growth in the retail sector have risen sharply. To that effect, Barros (2005) provides a summary of several studies with information on the methodology, the inputs and outputs chosen, and the analysis unit used in them. In connection with these studies, this paper has taken its analysis of the efficiency and productivity among sectors to an added level. The motivation for this paper is twofold: First, to perform a detailed analysis of the efficiency and productivity growth in individual sectors; and, second, to use different analysis methodologies in which time is considered. Due to the heterogeneous nature of the sectors and the unavailability of reliable prices for each sector, Data Envelopment Analysis (DEA) methodology is used.

Since the production function of each sector will not be the same, the DEA-Malmquist TFP Index methodology is appropriate because there is no need to estimate a production function. In this study, the DEAP software developed by Coelli (1996) is used to compute these indices. Summary tables of these indices are presented for the different sectors (for all periods) and for different periods (for all sectors). The rest of the paper is organized as follows. In Section 2, the data, variable selection, and hypotheses are described. In Section 3, different methodologies to measure efficiency are proposed. In

Section 4, technical efficiency, productivity growth, and their determinants are reported and discussed. Finally, Section 5 summarizes the main findings of this paper, limitations, and future research.

DATA, VARIABLE SELECTION, AND HYPOTHESES

Time period and sector coverage

In this paper, productivity growth and technical efficiency in the Spanish retail sector are analyzed from 1995 to 2004, both years included, using the SABI database, which includes all of the sectors in Spain and uses a 4-digit NACE code. This database collects data on more than 180,000 firms registered with the Mercantile Register (BORME) and covers every sector of business activity in Spain. It is highly representative of firms from the 17 Spanish Autonomous Communities (i.e., regions). Firms are included in the SABI database on the condition that their turnover exceeds €6M or they employ a workforce of over 20 employees. Our objective in building the sample was for the companies in each of the sectors analyzed to be present every year, so that a complete panel could be obtained.

There are several reasons why this paper focuses on this period. As was mentioned earlier, a number of important legislative changes have occurred within the sector, including the Retail Trade Regulation Act (1996) and the Shop Opening Hours Decree-Law (2000), which have had an impact on retailers' strategies. The changes happened within the market structure. For example, the market shares of different formats have evolved differently. In the case of food, the market share of hypermarkets fell from 33% in 1995 to 25% in 2003. The market share of traditional stores also fell during this same period, from 21% to 11%. Meanwhile, the market share of supermarkets increased from 46% to 64%. In this respect, in 2004 market-leader Mercadona, a supermarket chain, owned 23.3% of all stores, followed by the hypermarket groups Carrefour (11.5%), Eroski (8.4%), El Corte Ingles (6.7%), Aldi (6.2%), and Caprabo (4.3%). This last group was acquired by Eroski in June of 2007.

This study covers each of Spain's service sectors. Table 1 shows the number of firms in each service sector and the number of regions where those firms are present.

Table 1: Sector classification, number of firms and number of regions with presence

No.	Name of sectors[a]	NACE cod.	No. firms	No. Regions
1	r.s. of of systems and equipments	5200	21	5
2	r.s. with predominance of food in non-specialised shops	5211	92	14
3	r.s. of other products in non-specialised shops	5212	19	7
4	r.s. of meat and meat products	5222	9	8
5	r.s. of bread and bakery products, sweets and cakes	5224	16	8
6	r.s. in other shops specialising in food	5227	22	8
7	r.s of medical and orthopaedic products	5232	22	6
8	r.s. of textiles	5241	14	8
9	r.s. of clothing	5242	68	13
10	r.s. of footwear and leather goods	5243	8	8
11	r.s. forniture, lighting and other household goods	5244	55	13
12	r.s. of electrical appliances, radio, TV and sounds systems.	5245	33	10
13	r.s. of ironmongery, paint and glass	5246	36	10
14	r.s. of books, newspapers and stationery	5247	29	10
15	r.s. in other specialised shops	5248	107	15
16	r.s. others reparation	5274	16	7

Note: [a]r.s. retail sector

Output and input series

For the efficiency analysis, that it will be outlined shortly, it would have been desirable for both consumption-of-materials and flow-of-services values to be expressed in physical units. However, the limitations of the information available made it necessary to use accounting variables, expressed in constant monetary units (using the GDP deflator of the Spanish National Institute of Statistics (INE)). The choice of output and input types follows Donthu and Yoo's (1998) recommendations. The inputs are measured by four variables. The measure for labor is personnel costs. The employee variable is more problematic since this value is not available for many companies. This input is a proxy for the quantity of labor. The measure for capital is fixed assets and it is also used as the intermediate consumption input. These three inputs represent the amount of labor, capital, and consumption used in each sector to generate income. The number of firms in each sector is used as a proxy of the size of the retail sector. Finally, output is measured by sales.

Hypotheses

Once the objectives of this paper have been outlined, the literature has been revised, and the variables proposed, tentative hypotheses regarding efficiency and productivity in the retail sector may be formulated.

Hypothesis 1: A significant decline in relative efficiency was experienced in the retail sector between 1995 and 2004. This difference in efficiency will not behave the same behavior when the role of time is factored into the efficiency estimate, which will be explained in the following section on methodology.

Hypothesis 2a: A significant improvement in productivity was experienced, on average, in the retail sector between 1995 and 2004.

Hypothesis 2b: A significant improvement in technical progress took place, on average, in the retail sector between 1995 and 2004.

Hypothesis 2c: A significant decline in the changes in efficiency was experienced, on average, by sectors within the retail sector from 1995 to 2004.

Hypothesis 3: Improvements in productivity growth could be positively related to factors characteristic of the sector; size and concentration, as well as economic factors in terms of GDP and population.

Measuring the efficiency and productivity of the retail sector

Nonparametric frontier techniques are used to measure both the efficiency and the productivity of Decision Making Units (henceforth *DMU*). Firstly, they way efficiency is measured and different approach assessments are presented. Secondly, the way of measuring productivity and the variables that explain the results are examined.

Technical efficiency

The research methodology consists of the following stages. First, a nonparametric methodology is used to measure technical efficiency with data envelopment analysis (Charnes, Cooper and Rhodes, 1978; and Charnes, Clark, Cooper and Golany, 1985). This paper uses an input-oriented model, since commercial distribution is better suited to potential input savings than wasted resources, and because the different formats are subject to demand conditions which lead them to adjust their inputs freely. Consider the existence of n homogeneous decision-making units (DMU_j; $j = 1, n$), whose efficiency is to be evaluated. These units can be characterized by a vector of m inputs $X_j = (x_{1j}, x_{2j}, x_{mj})$, and a vector of s outputs $Y_j = (y_{1j}, y_{2j}, y_{sj})$. For each *DMU*, the following linear programming problem of the BCC (Banker, Charnes and Cooper 1984) model is solved:

$$\min \theta - \varepsilon \sum_{r=1}^{s} s_r^+ - \varepsilon \sum_{i=1}^{m} s_i^-$$

s.a.:

$$\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = y_{r0}$$

$$\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \theta x_{i0}$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

$$\lambda_j , s_r , s_i \geq 0 \qquad (1)$$

where θ is the efficiency obtained for the *DMU* analyzed, and ε is a positive value next to zero. A particular *DMU* is regarded as efficient if θ^*=1 and all of the slack variables s^+ and s^- are zero. In addition, for those non-efficient units, the slack variables indicate either excessive input or reduced output. The previous model assumes implicit variable returns to scale.

To estimate the efficiency scale, the previous problem should be solved eliminating the convexity restriction $\lambda_j = 1$. This is how the CCR model (Charnes, Cooper and Rhodes, 1978) is obtained. The efficiency values obtained with the CCR model (θ_{CCR}) are always less than those obtained with the BCC model (θ_{BCC}), so that the efficiency scale (*SE*) is defined as: $SE_i=(\theta_{CCR}/\theta_{BCC})$. If SE_i=1, the analyzed firm operates at scale efficiency, whereas if $SE_i < 1$, this indicates scale inefficiency.

Since the data are presented in panel form, it is possible to work in different ways. If limited solely to the analysis of cross-sectional data, DEA compares one *DMU* (sector) with all of the other sectors that produced during the same period. The role that time plays is ignored. However, this can be rather misleading since dynamic settings may give rise to a seemingly excessive use of resources which are intended to produce beneficial results. For this reason, panel data prevail over cross-sectional data in that not only do they enable a *DMU* to be compared with its counterparts, but the change in the efficiency of a *DMU* over time can also be deduced. Panel data, therefore, are more likely to show the real efficiency of a *DMU*. Despite the numerous advantages of using panel data over cross-sectional data, only a few attempts have been made at using panel data to apply the non-parametric models above.

According to Cullinane, Ji and Wang (2005: 443), when the role of time is considered, let *t* denote the point in time when the observation is made and *T* stand for the total number of time periods observed. Then, the input and output variables of firm *k* can be rewritten as $(x_{kt}) = (x_{1kt}, x_{2kt}, \ldots x_{Mkt}) \; \varepsilon \; \Re_+^M$ and $(y_{kt}) = (y_{1kt}, y_{2kt}, \ldots y_{Nkt}) \; \varepsilon \; \Re_+^N$, respectively.

Unlike the practice of cross-sectional data analysis, which compares one *DMU* with all of the other units in the feasible data set, the analysis of a set of panel data involves choosing only alternative subsets—termed reference observation subsets (Tulkens and van den Eeckaut, 1995)—rather than the full data set, to evaluate the efficiency of an individual unit. Tulkens and van den Eeckaut (1995) suggest that each observation in a panel can be characterized vis-à-vis efficiency terms into three different kinds of frontiers, labeled (i)-(iii) below. Alternatively, the original approach by Charnes, Clark, Cooper and Golany (1985) is described below (iv):

(i) *Contemporaneous*: involving the construction of a reference observation subset at each point in time, with all of the observations being made at that time only. A different reference

observation subset can be denoted as:
$\{(x_{kt}, y_{kt}) \mid k = 1,2,\ldots\ldots, K\}$ for $t = 1,2,\ldots\ldots, T$. (2)
Throughout the entire observation period, a sequence of *T* reference observation subsets are constructed, one for each time *t*.

(ii) *Intertemporal*: involving the construction of a single production set from the observations made throughout the entire observation period. In this case, the reference observation subset is simply denoted as:
$\{(x_{kt}, y_{kt}) \mid k = 1,2,\ldots\ldots, K; t = 1,2,\ldots\ldots, T\}$. (3)

(iii) *Sequential*: involving the construction of a reference observation subset at each point in time *t*, but using the observations made from points in time h=1 up to *h=t*. The reference observation subsets at each time $t = 1,2,\ldots\ldots, T$ can be denoted as:
$\{(x_{kt}, y_{kt}) \mid k = 1,2,\ldots\ldots, K; h = 1,2,\ldots\ldots, t\}$. (4)
Obviously, this method has the disadvantage of leading to a certain imbalance in the number of observations on which an average efficiency is calculated as *t* moves towards *T*. Because of this problem, this approach has been dropped from the subsequent analysis.

(iv) *Window analysis*: this is a time-dependent version of DEA. A connection should finally be made between the above as initiated by Charnes, Clark, Cooper and Golany (1985). Window analysis is in fact a special case of (ii). The basic idea is to regard each *DMU* as if it were a different *DMU* on each of the reporting dates. Then each *DMU* is not necessarily compared with the whole data set, but instead with only alternative subsets of the panel data. Let *w* be the window width which describes the time period for the reference observation subsets. Then, a single window reference observation subset can be expressed as:
$\{(x_{kt}, y_{kt}) \mid k = 1,2,\ldots\ldots, K; h = 1, t+1,\ldots\ldots, t+w; t \leq T-w$. (5)
Successive windows, defined for $t = 1,2,\ldots\ldots, T-w$, yield a sequence of reference observation subsets.

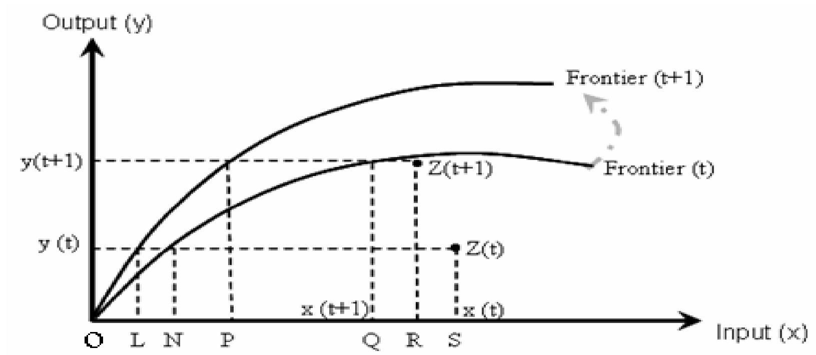
Window analysis is based on the assumption that what was feasible in the past remains feasible forever, and the treatment of time in window analysis is more along the lines of an averaging over the periods of time covered by the window. It is difficult to find more than just an ad hoc justification for the size of the window and, for that matter, for the fact that part of the past is ignored (Tulkens and van den Eeckaut, 1995). In essence, contemporaneous and intertemporal analyses are two extreme cases of window analysis where $w=1$ and $w=T$. This implies that the efficiency of every observation tends to decline as window width (*w*) increases. This can be explained by the fact that a *DMU* in a small sample has fewer counterparts to be compared against and, therefore, has less chance to be dominated, or alternatively, has a greater chance of being classified as more efficient.

The Malmquist productivity index

The efficient frontier approach is adopted using the Malmquist index (1953) based on DEA. The Malmquist productivity index allows changes in productivity to be broken down into changes in efficiency and technical changes. Efficiency change (movement towards or away from the production frontier) and technical change (a shift in the production frontier) are two key factors to productivity growth. Like Barros and Alves (2004) or Sellers and Mas (2006) for the retail sector, to measure productivity this paper adopts the framework set down in papers by Färe, Grossskopf, Yaisawarng, Li and Wang (1990), Hjalmarsson and Veiderpass (1992), and Price and Weyman-Jones (1996). Figure 2 shows two views of the input- *(x)* and output- *(y)* bundles for a retail store at times *t* and *t+1*. The objective is to measure productivity growth between *t* and *t+1* in terms of the change from input-output bundle *z(t)* to input-output bundle *z(t+1).*

This productivity is measured through the potential production frontier that is imposed on the production bundle in Figure 2. The production frontier represents the efficient levels of output *(y)* that can be produced from a given level of input. If the store is technically efficient at *t*, it produces the maximum output attainable along the frontier. Point *z(t)* corresponds to a technically inefficient store, which uses more than the minimal amount of input to produce a given level of output. The bundle *z(t)* can be reduced by the horizontal distance ratio=*ON/OS* to make the production technically efficient.

Figure 2: Production frontier in period *t* and *t+1*



The frontier can shift over time. By analogy, the bundle *z(t+1)* should be multiplied by the horizontal distance ratio=*OR/OQ* to achieve comparable technical efficiency. Since the frontier has shifted in the meantime, *z(t+1)* is technically inefficient at *t+1*; it must be reduced by the horizontal distance=*OP/OQ*. The relative movement of a production observation over time may either be because stores are catching up to their own frontier, or because the frontier is shifting upward over time.

The Malmquist index of productivity growth (*M*) is the ratio of the two distances at *t* and *t+1*. To break the index down into catching up (*MC*) and shifting up (*MF*) effects, *M* is rescaled by multiplying it on the top and bottom by *OP/OQ*:

$$M = \frac{OR \cdot ON}{OQ \cdot OS} = \left[\frac{OP \cdot ON}{OQ \cdot OS}\right] * \frac{OR}{OP} = MC * MF \qquad (6)$$

Formally, the Malmquist index is based on the output distance function defined as:

$S^t=\{(x^t,y^t) : x^t \text{ can produce } y^t\}$

where x^t and y^t are the input and output vectors, respectively.

According to Shephard (1970), the distance function at *t* is defined as:

$$d^T(x^t, y^t) = \min\{\theta : (x^t, y^t/\theta) \in S^t\} \qquad (7)$$

where *x*, *y* denote the input and output vectors, respectively, *S* is the technology set, and superscript *T* denotes the technology reference period, usually *T=t* or *T=t+1*, and *1/θ* defines the amount by which outputs in year *t* could have increased, given the inputs used, if the technology for year *T* had been fully utilized.

Färe, Grosskopf and Lovel (1994) proposed taking the Malmquist index to be the geometric mean of two such indexes calculated for both year *t* and *t*+1 reference technologies as:

$$\mathrm{M}_{\mathrm{i}}(y^{t+1}, x^{t+1}, y^{t}, x^{t}) = \left[\frac{d_i^{t}(x^{t+1}, y^{t+1})}{d_i^{t}(x^{t}, y^{t})} \times \frac{d_i^{t+1}(x^{t+1}, y^{t+1})}{d_i^{t+1}(x^{t}, y^{t})}\right]^{1/2} \tag{8}$$

where M_i *(•)* is the composed geometric mean of two Malmquist productivity indices: the first being evaluated with respect to the technology at time *t*, and the second with respect to the technology at time *t+1*. Färe *et al.* (1994) factor this expression into the product of technical change and efficiency change as follows:

$$\mathrm{M}_{\mathrm{i}}(y^{t+1}, x^{t+1}, y^{t}, x^{t}) = \frac{d_i^{t+1}(x^{t+1}, y^{t+1})}{d_i^{t}(x^{t}, y^{t})}\left[\frac{d_i^{t}(x^{t+1}, y^{t+1})}{d_i^{t+1}(x^{t+1}, y^{t+1})} \times \frac{d_i^{t}(x^{t}, y^{t})}{d_i^{t+1}(x^{t}, y^{t})}\right]^{1/2} \tag{9}$$

where the first ratio represents the change in relative efficiency between *t* and *t+1*, and the geometric mean of the two ratios in the brackets measures the change or the movement of technology between *t* and *t*+1.

In order to estimate the component distance functions of the Malmquist index, this paper uses the non-parametric data envelopment analysis (DEA) technique, based on linear programming. By assuming variable returns to scale and by exploiting the fact that distance functions can be estimated as the reciprocals of Farrell efficiency measures, the specific problem to calculate $d^T(y^t,x^t)$ can be expressed as:

$$[d_0^{t}(x_i^{t}, y_i^{t})]^{-1} = \max_{\lambda} \Phi_i^{t,t} \tag{10}$$

s.t. $\sum_{k=1}^{K} \lambda_k^t y_{sk}^t \geq \Phi_i^{t,t} y_{si}^t$ *s=1,…,S*

$\sum_{k=1}^{K} \lambda_k^t x_{mk}^t \leq x_{mi}^t$ *m=1,…,M*

$\lambda_k^t = 1$ *k,i=1,…,K*

Where *K* represents the number of cross-sectional units for each time period within the panel data, *S* and *M* indicate outputs and inputs, respectively, and λ_k^t measures the weight of each cross-sectional *DMU* within the peer group against which any particular observation is compared to determine the distance to the efficiency frontier.

ESTIMATION RESULTS

Estimation of technical efficiency

When cross-sectional data is used in DEA approaches, in the absence of categorical empirical proof for the production function in the retail sector at an aggregate level, the *DMU* has either constant or variable returns to scale. The DEA-CCR and DEA-BCC models were chosen from among several DEA models to analyze the retail sector. Alternative DEA panel data analyses including contemporaneous, intertemporal, and window (3 years) models were chosen in order to determine the efficiency of the retail sector. Tables 2-5 report the results of intertemporal and contemporaneous analyses using the DEA-CCR and DEA-BCC models (the results of the window analysis are not included to save space). The column and row totals represent, respectively, the year-by-year average efficiency for all of the sectors and the average efficiency for every single sector over the study period.

Table 2: DEA-CCR contemporaneus analysis of sectors efficiency (1= efficient)

sectors denomination	NACE cod.	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	Average
r.s. of of systems and equipments	5200	1.000	0.989	0.963	0.972	0.971	0.990	0.961	0.958	0.920	0.896	0.962
r.s. with predominance of food in non-specialised shops	5211	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
r.s. of other products in non-specialised shops	5212	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
r.s. of meat and meat products	5222	0.935	0.939	0.907	0.906	0.910	0.927	0.914	0.909	0.891	0.865	0.910
r.s. of bread and bakery products, sweets and cakes	5224	0.960	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.996
r.s. in other shops specialising in food	5227	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
r.s of medical and orthopaedic products	5232	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
r.s. of textiles	5241	0.891	0.876	0.851	0.845	0.881	0.898	0.852	0.821	0.811	0.869	0.860
r.s. of clothing	5242	0.942	0.934	0.912	0.901	0.895	0.921	0.887	0.898	0.867	0.871	0.903
r.s. of footwear and leather goods	5243	0.957	0.965	0.909	0.969	0.901	0.906	0.885	0.878	0.851	0.907	0.913
r.s. forniture, lighting and other household goods	5244	0.994	0.966	0.931	0.937	0.934	0.939	0.941	0.933	0.905	0.865	0.935
r.s. of electrical appliances, radio, TV and sounds systems.	5245	0.982	0.956	0.925	0.958	0.923	0.921	0.897	0.886	0.868	0.851	0.917
r.s. of ironmongery, paint and glass	5246	0.951	0.942	0.926	0.933	0.945	0.976	0.940	0.943	0.912	0.910	0.938
r.s. of books, newspapers and stationery	5247	1.000	1.000	1.000	0.849	0.884	0.880	0.892	0.856	0.842	0.858	0.906
r.s. in other specialised shops	5248	1.000										

Table 3: DEA-BCC contemporaneus analysis of sectors efficiency (1= efficient)

sectors denomination	NACE cod.	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	Average
r.s. of of systems and equipments	5200	1.000	1.000	0.999	0.996	1.000	1.000	0.995	0.996	0.972	0.965	0.992
r.s. with predominance of food in non-specialised shops	5211	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
r.s. of other products in non-specialised shops	5212	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
r.s. of meat and meat products	5222	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
r.s. of bread and bakery products, sweets and cakes	5224	0.982	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.998
r.s. in other shops specialising in food	5227	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
r.s of medical and orthopaedic products	5232	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
r.s. of textiles	5241	0.956	1.000	0.974	0.995	0.981	0.993	0.990	1.000	1.000	1.000	0.989
r.s. of clothing	5242	0.988	0.983	0.912	0.901	0.896	0.924	0.891	0.903	0.874	0.872	0.914
r.s. of footwear and leather goods	5243	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
r.s. forniture, lighting and other household goods	5244	0.997	0.979	0.947	0.943	0.942	0.942	0.952	0.945	0.920	0.886	0.945
r.s. of electrical appliances, radio, TV and sounds systems.	5245	0.988	0.967	0.957	0.981	0.948	0.931	0.926	0.918	0.909	0.903	0.943
r.s. of ironmongery, paint and glass	5246	0.959	0.946	0.938	0.950	0.954	0.987	0.954	0.955	0.924	0.922	0.949
r.s. of books, newspapers and stationery	5247	1.000	1.000	1.000	0.874	1.000	0.904	1.000	0.890	0.862	0.880	0.941
r.s. in other specialised shops	5248	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
r.s. others reparation	5274	1.000	1.000	1.000	1.000	1.000	0.968	1.000	1.000	1.000	1.000	0.997
Average		0.992	0.992	0.983	0.978	0.983	0.978	0.982	0.975	0.966	0.964	0.979
Number of efficient sectors		10	12	10	9	11	9	10	10	10	10	

Table 4: DEA-CCR intertemporal analysis of sectors efficiency (1= efficient)

sectors denomination	NACE cod.	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	Average
r.s. of of systems and equipments	5200	0.923	0.923	0.927	0.937	0.935	0.937	0.916	0.916	0.900	0.896	0.921
r.s. with predominance of food in non-specialised shops	5211	0.981	0.981	1.000	0.997	1.000	1.000	0.998	1.000	1.000	1.000	0.996
r.s. of other products in non-specialised shops	5212	0.971	0.977	0.985	0.984	1.000	0.985	0.987	0.992	1.000	1.000	0.988
r.s. of meat and meat products	5222	0.875	0.883	0.877	0.873	0.876	0.876	0.870	0.866	0.869	0.865	0.873
r.s. of bread and bakery products, sweets and cakes	5224	0.929	0.950	0.932	0.930	0.934	0.939	0.953	0.969	0.972	1.000	0.951
r.s. in other shops specialising in food	5227	1.000	1.000	1.000	1.000	1.000	0.984	0.984	1.000	1.000	1.000	0.997
r.s of medical and orthopaedic products	5232	0.937	0.967	0.949	0.982	1.000	0.965	1.000	0.999	1.000	1.000	0.980
r.s. of textiles	5241	0.796	0.803	0.806	0.824	0.831	0.819	0.824	0.806	0.807	0.815	0.813
r.s. of clothing	5242	0.846	0.856	0.863	0.873	0.863	0.872	0.853	0.868	0.856	0.850	0.860
r.s. of footwear and leather goods	5243	0.867	0.886	0.861	0.937	0.869	0.864	0.848	0.850	0.847	0.850	0.868
r.s. forniture, lighting and other household goods	5244	0.893	0.891	0.893	0.904	0.905	0.892	0.899	0.893	0.886	0.865	0.892
r.s. of electrical appliances, radio, TV and sounds systems.	5245	0.913	0.894	0.888	0.924	0.889	0.873	0.856	0.848	0.849	0.851	0.879
r.s. of ironmongery, paint and glass	5246	0.890	0.885	0.896	0.902	0.915	0.922	0.895	0.897	0.890	0.910	0.900
r.s. of books, newspapers and stationery	5247	0.833	0.859	0.828	0.823	0.869	0.831	0.836	0.818	0.825	0.858	0.838
r.s. in other specialised shops	5248	0.936	0.958	0.995	0.975	0.997	0.948	0.954	0.952	0.975	1.000	0.969
r.s. others reparation	5274	1.000	0.870	0.880	0.822	0.858	0.816	0.833	0.821	0.849	0.894	0.864
Average		0.912	0.911	0.911	0.918	0.921	0.908	0.907	0.906	0.908	0.916	0.912
Number of efficient sectors		2	1	2	1	4	1	1	2	4	6	

Table 5: DEA-BCC intertemporal analysis of sectors efficiency (1= efficient)

sectors denomination	NACE cod.	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	Average
r.s. of of systems and equipments	5200	0.977	0.969	0.968	0.972	0.968	0.967	0.943	0.942	0.925	0.920	0.955
r.s. with predominance of food in non-specialised shops	5211	0.982	0.981	1.000	0.997	1.000	1.000	0.998	1.000	1.000	1.000	0.996
r.s. of other products in non-specialised shops	5212	0.972	0.977	0.986	0.985	1.000	0.985	0.987	0.992	1.000	1.000	0.988
r.s. of meat and meat products	5222	1.000	1.000	1.000	1.000	1.000	0.996	0.975	0.956	0.973	0.984	0.988
r.s. of bread and bakery products, sweets and cakes	5224	0.968	0.972	0.961	0.958	0.960	0.962	0.969	0.981	0.983	1.000	0.971
r.s. in other shops specialising in food	5227	1.000	1.000	1.000	1.000	1.000	0.986	0.985	1.000	1.000	1.000	0.997
r.s of medical and orthopaedic products	5232	0.954	0.976	0.972	0.996	1.000	0.971	1.000	0.999	1.000	1.000	0.987
r.s. of textiles	5241	0.943	0.937	0.920	0.923	0.918	0.900	0.898	0.885	0.882	0.889	0.910
r.s. of clothing	5242	0.860	0.866	0.871	0.880	0.869	0.876	0.858	0.873	0.860	0.853	0.867
r.s. of footwear and leather goods	5243	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
r.s. forniture, lighting and other household goods	5244	0.924	0.917	0.911	0.917	0.927	0.902	0.908	0.901	0.893	0.872	0.907
r.s. of electrical appliances, radio, TV and sounds systems.	5245	0.961	0.935	0.926	0.958	0.918	0.899	0.880	0.870	0.869	0.871	0.909
r.s. of ironmongery, paint and glass	5246	0.909	0.903	0.912	0.916	0.935	0.931	0.904	0.904	0.896	0.914	0.912
r.s. of books, newspapers and stationery	5247	0.986	1.000	0.939	0.855	1.000	0.851	0.858	0.829	0.834	0.867	0.902
r.s. in other specialised shops	5248	0.942	0.960	1.000	0.975	1.000	0.948	0.955	0.952	0.975	1.000	0.971
r.s. others reparation	5274	1.000	0.946	0.922	0.895	0.923	0.865	0.873	0.869	0.902	0.929	0.912
Average		0.961	0.959	0.956	0.952	0.964	0.940	0.937	0.935	0.937	0.944	0.948
Number of efficient sectors		4	4	5	3	8	2	2	3	5	7	

Figure 3 depicts the development of the year-by-year average efficiency for the entire sector in the sample using contemporaneous, intertemporal, and window DEA-CCR and DEA-BCC analyses. Figure 3 shows that the general trend in average efficiency for intertemporal analysis during the study period increased compared to the observed average efficiency derived from contemporaneous analyses.

Figure 3: Year by year average efficiency for all sectors

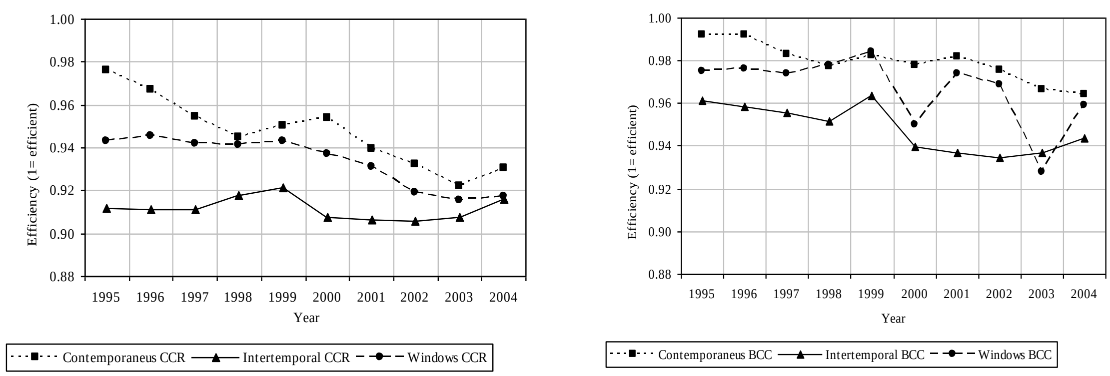


Figure 3 also shows that there is a downward trend in average efficiency in contemporaneous and intertemporal analyses. To that effect, it is necessary to consider that each sector is compared with 15 other counterparts in the same set in a contemporaneous analysis. However, each sector is compared with 159 other counterparts in an intertemporal analysis. A large sample is obviously more likely to make a sector appear inefficient (see the last row at the bottom of Tables 2-5 for CCR and BCC).

Figures 4 and 5 present an individual look at contemporaneous, intertemporal, and window analyses at a cross-sectional level. These figures show that there are remarkable differences among the three indices. In both DEA-CCR and BCC, average efficiency is higher in a contemporaneous than in an intertemporal analysis. In the window analysis over a three-year period, the behavior has its fluctuations.

Figure 4: Cross section average efficiency by sectors for the analysis CCR

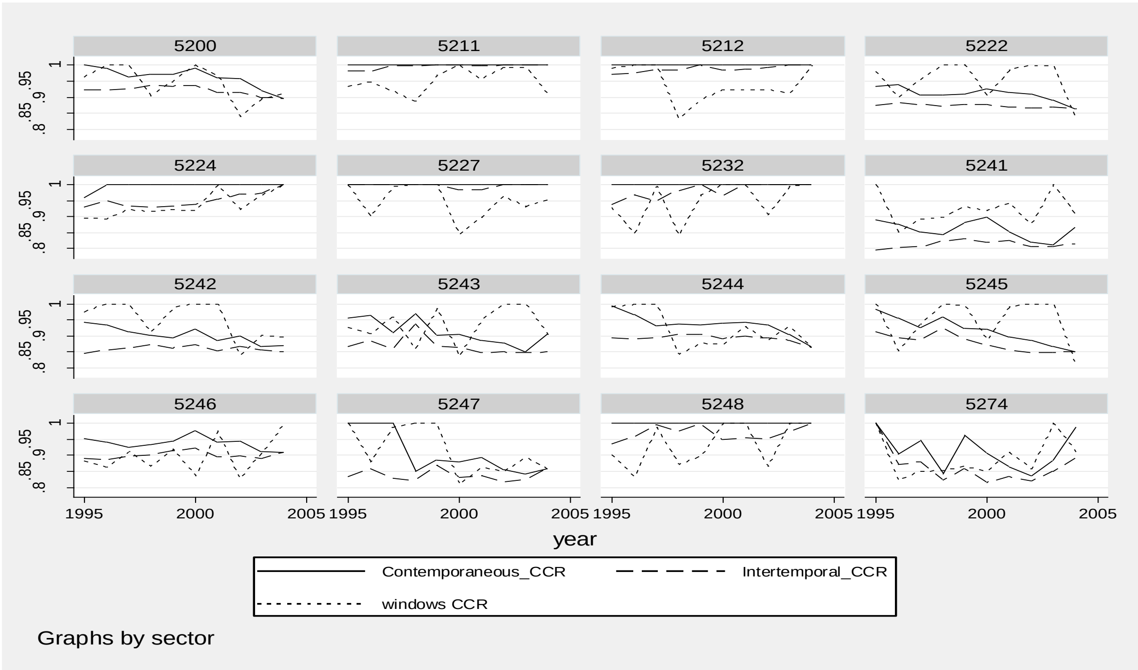
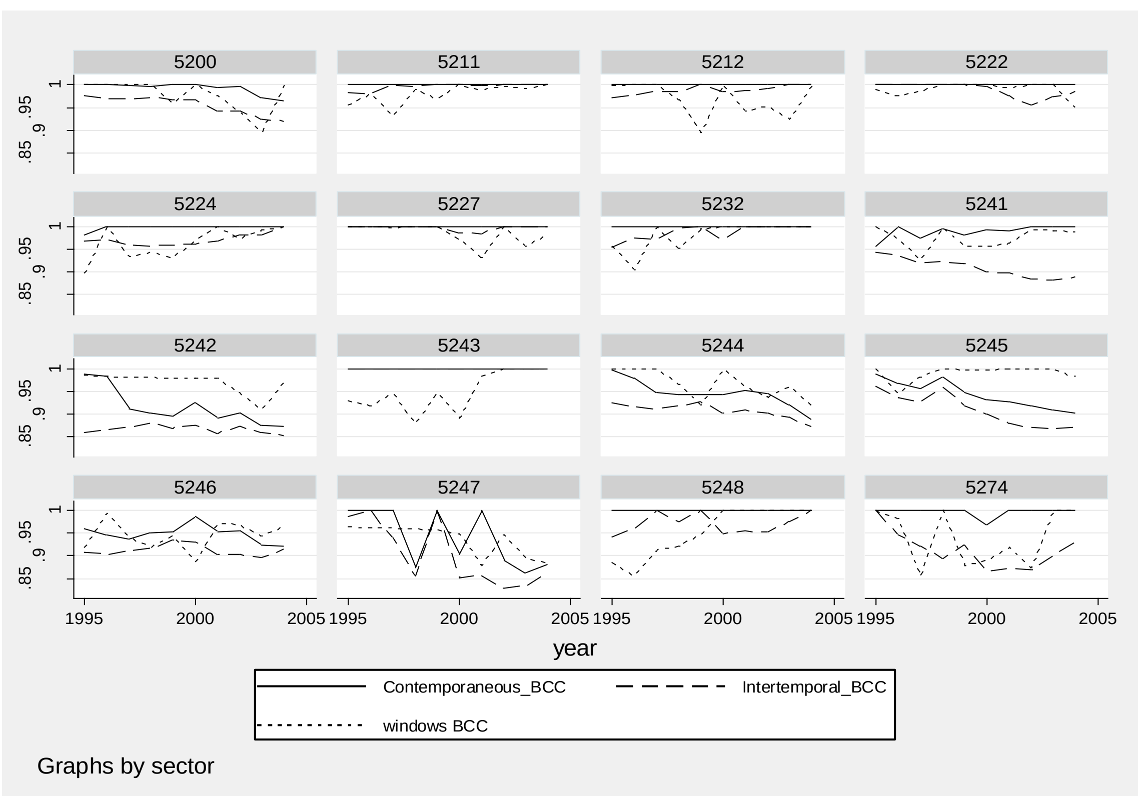


Figure 5: Cross section average efficiency by sectors for the analysis BCC



A Kruskal-Wallis test for the average efficiency of each sector over time for contemporaneous and intertemporal analyses (KW=31.00 and 57.00, which correspond to DEA-CCR and DEA-BCC analyses, respectively) indicates that the average efficiency values calculated using these two different approaches are significantly different at the 1% level (these differences have the same significant difference using ANOVA analysis at the means level, but the efficiency score is not distributed normally). The Spearman rank order correlation coefficients between the efficiency derived from the two approaches are showed in Table 6.

Table 6: Spearman's rank order correlation

	DEA-CCR			DEA-BCC		
	Contemporaneous	Intertemporal	Window	Contemporaneous	Intertemporal	Window
Contemporaneous	1			1		
Intertemporal	0.88***	1		0.71***	1	
Window	0.16**	0.16**	1	0.194***	0.30***	1

***, ** p<0.01 and p<0.05 respectively

The high value of the Spearman rank order coefficients of the contemporaneous and intertemporal approaches indicates that both of them yield similar efficiency ranks for production sector. However, the low coefficients of the window approach indicate range differences.

This section concludes with an efficiency analysis showing the kernel density distribution for the contemporaneous and intertemporal approaches. The implications of this analysis are clear: If the probability mass tends to be more markedly concentrated around a certain value, for example close to unity, the outcome will be a process of convergence towards a high efficiency value. Although the opposite outcome (divergence) would imply that the probability mass is increasingly spread across a wider range, there is a broad spectrum of additional outcomes, such as different emerging or vanishing modes, phenomena with strong economic implications. There are a variety of techniques to estimate density functions non-parametrically. This paper uses kernel smoothing (Silverman, 1986; Wand and Jones, 1994), a technique that allows the data structure to be uncovered without imposing parametric structures.

The results can be seen in Figure 6. The graphs on the top left show the density functions for the CRS contemporaneous approach, while those on the right correspond to the VRS. Both graphs show the time evolution of the cross-sectional distribution of efficiency scores for the years 1995-2000-2004. The efficiency distributions show two similar divergence patterns (stratification processes in 1995, and the appearance of two modes in 2000 and 2004). The graphs at the bottom of Figure 6 show the time evolution of the cross-sectional distribution of efficiency scores for the intertemporal approach in 1995, 2000, and 2004. In the graph in the bottom right-hand corner of the figure, a clearer divergence in the efficiency distribution of VRS can be seen when compared with the kernel density distribution (CRS). In the latter, the formation of two modes with high and medium-high levels of efficiency between 1995 and 2004 are clear.

Figure 6: Non parametric kernel estimates of technical efficiency scores in selected years by approach

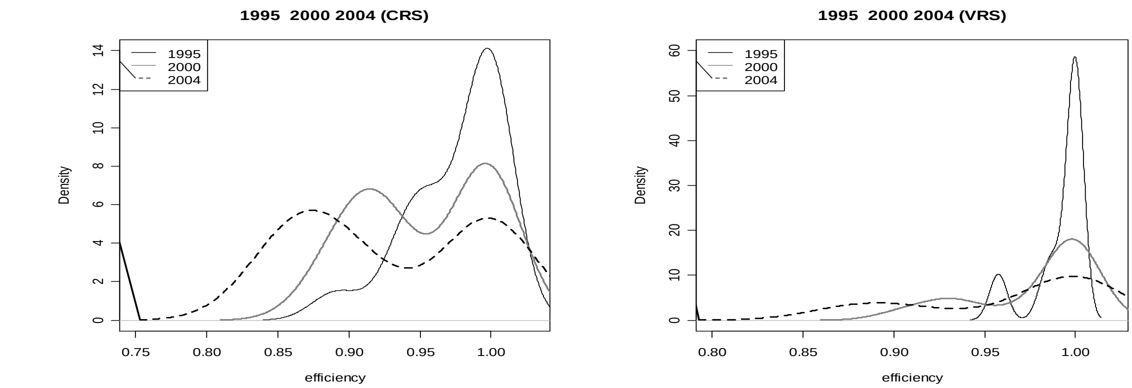


Figure 6a: Contemporaneous approach

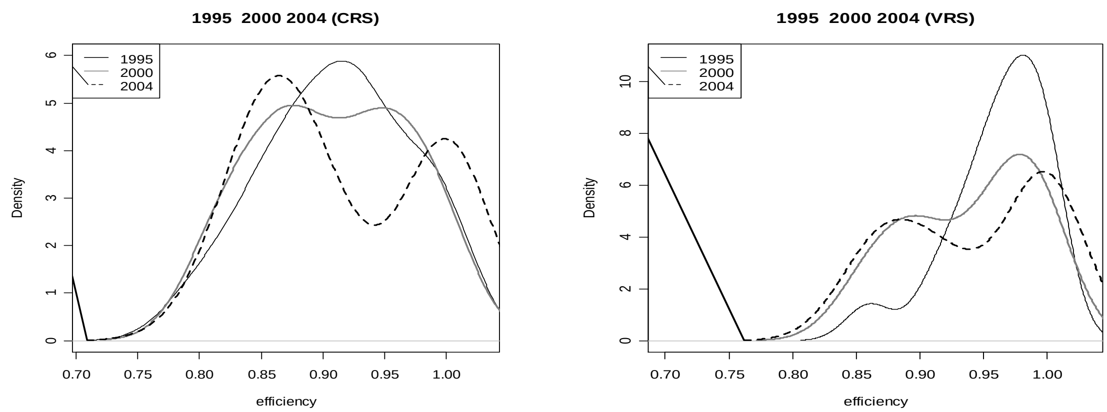


Figure 6b: Intertemporal approach

The results reached in this section allow hypothesis 1 to be accepted. Thus, it is possible to confirm a decline in efficiency from 1995 to 2004. On the other hand, when the role of time considered, the behavior of the efficiency distribution is different. As was mentioned earlier, panel data prevail over cross-sectional data in that not only do they enable a *DMU* to be compared against its counterparts, but the change in the efficiency of a *DMU* over a certain time period can also be deduced. In this sense, the different behavior can be explained by the fact that long-term technological advances and managerial developments provide an important impetus for improving productivity and efficiency. Within a shorter time period, different *DMUs* (the same sector at different times is treated as different sectors) are more likely to use the same, or similar, technological and managerial systems. As a result, efficiency results were not greatly influenced by the technological and managerial systems utilized.

Productivity growth

Changes in productivity, technology, and efficiency are reported in Tables 8, 9, and 10, respectively, for both pairs of consecutive years and the sub-periods 1995-1999 and 2000-2004, and the whole sample period 1995-2004. The last row in each table provides the mean for each selected pair of years. Note that if the value of the Malmquist index (henceforth MALM) or any of its components (technical change or efficiency change, henceforth TECH and EFFCH respectively) is less than 1, this value denotes a regression or deterioration in the performance for any two adjacent years, whereas values greater than 1 denote improvements in the relevant performance. Also note that these measurements capture performance in terms of the best practice in the sample.

Table 8: Malmquist Productivity Index, consecutive years and sub-periods

sectors	1995/96	1996/97	1997/98	1998/99	1999/00	2000/01	2001/02	2002/03	2003/04	1995/99	2000/04	1995/04
5200	0.997	1.002	1.011	0.998	1.001	0.977	0.998	0.981	0.995	1.002	0.988	0.996
5211	1.003	1.045	1.027	1.091	0.968	0.996	1.017	1.006	0.993	1.041	1.003	1.016
5212	0.996	1.061	1.066	1.128	0.973	1.048	1.065	1.062	1.052	1.062	1.057	1.049
5222	1.010	0.993	0.994	1.004	0.998	0.994	0.993	1.004	0.995	1.000	0.997	0.998
5224	1.019	0.978	0.994	1.000	1.001	1.026	1.021	1.006	1.027	0.998	1.020	1.008
5227	1.053	1.026	1.068	1.019	0.925	1.038	1.064	0.992	1.023	1.041	1.029	1.022
5232	1.072	1.122	1.092	1.213	0.820	1.030	1.063	1.085	0.989	1.123	1.041	1.049
5241	1.008	1.004	1.025	1.008	0.996	1.008	0.970	0.996	1.013	1.011	0.996	1.003
5242	1.011	1.008	1.012	0.989	1.013	0.988	1.018	0.984	0.995	1.005	0.996	1.002
5243	1.031	0.978	1.084	0.927	0.994	0.987	0.997	0.986	1.012	1.003	0.996	0.999
5244	0.999	0.997	1.011	1.004	0.987	1.007	0.993	0.991	0.976	1.003	0.992	0.996
5245	0.980	0.995	1.040	0.961	0.982	0.980	0.988	1.002	1.002	0.994	0.993	0.992
5246	0.999	1.010	1.003	1.018	1.005	0.964	0.998	0.990	1.022	1.008	0.994	1.001
5247	1.116	0.973	0.874	1.254	0.838	1.023	0.970	1.006	1.041	1.045	1.010	1.004
5248	1.014	1.027	0.987	1.020	0.947	1.012	0.976	1.038	1.040	1.012	1.016	1.006
5274	0.842	1.022	0.903	1.101	0.911	1.014	0.981	1.112	1.066	0.962	1.042	0.991
mean	1.008	1.014	1.010	1.043	0.958	1.005	1.007	1.014	1.015	1.019	1.010	1.008

Table 9: Changes in technology, consecutive years and sub-periods

sectors	1995/96	1996/97	1997/98	1998/99	1999/00	2000/01	2001/02	2002/03	2003/04	1995/99	2000/04	1995/04
5200	1.009	1.029	1.002	0.998	0.983	1.007	1.001	1.022	1.022	1.009	1.013	1.008
5211	1.003	1.045	1.027	1.091	0.968	0.996	1.017	1.006	0.993	1.041	1.003	1.016
5212	0.996	1.061	1.066	1.128	0.973	1.048	1.065	1.062	1.052	1.062	1.057	1.049
5222	1.005	1.027	0.996	0.999	0.981	1.008	0.997	1.025	1.025	1.007	1.014	1.007
5224	0.979	0.978	0.994	1.000	1.001	1.026	1.021	1.006	1.027	0.988	1.020	1.003
5227	1.053	1.026	1.068	1.019	0.925	1.038	1.064	0.992	1.023	1.041	1.029	1.022
5232	1.072	1.122	1.092	1.213	0.820	1.030	1.063	1.085	0.989	1.123	1.041	1.049
5241	1.025	1.033	1.032	0.967	0.977	1.062	1.007	1.008	0.945	1.014	1.005	1.006
5242	1.019	1.032	1.025	0.995	0.985	1.026	1.005	1.019	0.990	1.018	1.010	1.011
5243	1.023	1.038	1.016	0.996	0.989	1.011	1.005	1.018	0.950	1.018	0.995	1.005
5244	1.028	1.034	1.005	1.007	0.981	1.005	1.001	1.022	1.021	1.019	1.012	1.012
5245	1.007	1.029	1.004	0.998	0.984	1.006	1.001	1.022	1.023	1.009	1.013	1.008
5246	1.009	1.028	0.996	1.005	0.973	1.002	0.995	1.024	1.024	1.009	1.011	1.006
5247	1.116	0.973	1.030	1.204	0.841	1.010	1.011	1.022	1.022	1.077	1.016	1.021
5248	1.014	1.027	0.987	1.020	0.947	1.012	0.976	1.038	1.040	1.012	1.016	1.006
5274	0.932	0.975	1.014	0.965	0.967	1.065	1.012	1.051	0.954	0.971	1.020	0.992
mean	1.017	1.028	1.022	1.035	0.955	1.022	1.015	1.026	1.006	1.026	1.017	1.014

Table 10: Changes in efficiency, consecutive years and sub-periods

sectors	1995/96	1996/97	1997/98	1998/99	1999/00	2000/01	2001/02	2002/03	2003/04	1995/99	2000/04	1995/04
5200	0.989	0.974	1.009	0.999	1.019	0.971	0.997	0.960	0.974	0.993	0.975	0.988
5211	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
5212	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
5222	1.004	0.967	0.998	1.005	1.018	0.986	0.995	0.980	0.971	0.993	0.983	0.991
5224	1.042	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.010	1.000	1.005
5227	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
5232	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
5241	0.983	0.972	0.993	1.042	1.020	0.949	0.963	0.988	1.071	0.997	0.992	0.997
5242	0.992	0.977	0.988	0.994	1.029	0.963	1.012	0.966	1.004	0.987	0.986	0.991
5243	1.008	0.942	1.066	0.930	1.005	0.977	0.992	0.969	1.066	0.985	1.000	0.994
5244	0.972	0.964	1.006	0.997	1.006	1.002	0.991	0.970	0.956	0.984	0.980	0.985
5245	0.973	0.967	1.037	0.963	0.998	0.975	0.987	0.980	0.980	0.985	0.981	0.984
5246	0.990	0.983	1.008	1.013	1.033	0.963	1.003	0.967	0.998	0.998	0.983	0.995
5247	1.000	1.000	0.849	1.041	0.996	1.013	0.960	0.984	1.019	0.970	0.994	0.983
5248	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
5274	0.903	1.048	0.891	1.141	0.942	0.953	0.970	1.058	1.117	0.990	1.022	0.999
mean	0.991	0.987	0.989	1.007	1.004	0.984	0.992	0.989	1.009	0.993	0.993	0.995

Looking first at the bottom of Table 8, MALM (thirteenth column) increased at an average rate of 0.8% per annum over the entire 1995-2004 period for the retail sector.

Comparing sub-periods (before and after the Shop Opening Hours Decree-Law 2000), productivity growth was greater in 1995/99 than in 2000/04, with improvements of 1.9% and 1%, respectively. With the exception of the drop in productivity for the 1999/00 period (-4.2%), the rest of the periods showed improvements.

With respect to the 1995/99 period, the trend for productivity growth fluctuated, but with an especially high productivity ratio for the 1998/99 period (4.3%). In the initial post-deregulation years, productivity growth improved gradually, but at a more modest rate. Suitable explanations for these trends come from the decomposition of the Malmquist productivity index. The last row of Table 9 reveals that productivity growth is attributable to an improvement in "best practice" or, in other words, in production possibilities (with the single exception of the 1999/00 period in which technical return took place, 4.5%). An accurate examination of the last row of both Tables 9 and 10 reveals that the behavior of productivity growth is the result of two antagonistic forces: TECH and EFFCH gains and losses, respectively. Comparing the last rows of Tables 9 and 10 and columns 11 and 12, TECH is superior in the 1995/99 period (2.6%), but EFFCH is the same for both sub-periods (-0.7%).

However, individual scrutiny shows that there are remarkable differences when the three indices are compared. For instance, sectors 5211, 5227, and 5232 have larger unit values in both MALM and TECH and EFFCH for the 1995/99 period. These same improvements can also be seen in sectors 5224 and 5212 for the 2000/04 period. The rest of the sectors have more irregular patterns. Therefore, the results reached in this section allow hypotheses 2a, 2b, and 2c to be accepted.

Determinants of productivity growth

Having analyzed productivity growth and its components in each of the sectors, the next step is to study the factors that determine this growth. In our panel regression framework, the dependent variable is the MALM index and the explanatory variables are real GDP per capita (GDP). The square of GDP per capita is included to capture any quadratic relationships between the MALM index and these variables. In order to represent the importance of competition on productivity growth, a market concentration variable (CONC) was built that is defined as the percentage of total sales of the three largest sectors. The size of the sectors (SIZE) is quantified by the fixed asset value. The average sample size of the log is used to classify sectors into small or large (dummy variable). Sectors with a log size below the sample average are classified as small, with the large sectors being above average. This paper has also included the number of regions where the sector operates (REGIONS). This variable captures the influence of geographical diversification on productivity growth. Finally, population was also included as a way of seeing the influence of demand on productivity (POPULATION).

The results of the regression estimated for the period from 1995/96 to 2003/04 are shown in Table 11. The Breusch-Pagan test indicates that random effects specification is preferred to OLS regression (statistically significant at the 10% level). Nevertheless the results are practically the same ones for both regressions. The comparison between fixed effects and OLS shows that the latter is preferable (F=0.43, Prob=0.9683).

Table 11: Results of the estimation for Productivity Growth index

	Random effects		
	Coef.	**Std. Err.**	
Constant	0.894	(0.225)	***
GDP	-0.156	(0.068)	**
GDP2	0.022	(0.008)	***
SIZE[a]	0.023	(0.010)	**
REGIONS	-0.003	(0.001)	**
CONC	0.033	(0.025)	
POPUL	9.3e-09	(4.3e-09)	**
Breusch and Pagan test	3.27		*
χ^2	27.84		***
Number of observations	144		

***, ** ,* $p<0.01$, $p<0.05$ and $p<0.10$ respectively. [a] Omitted small size sector.

All of the parameters are statistically significant except for the variable market concentration (CONC). The quadratic relationship between the MALM index and GDP is U-type, with a turning point at an annual rate of approximately 3.4 (the range oscillates between 2.7 and 5 for the whole period). The statistically significant coefficient at 5% of the SIZE variable shows the existence of a positive association between size and productivity. These sectors are made up of large-sized companies, for example the non-specialized sector retailer 5211. This may be the consequence of a higher level of quality in the making of internal decisions or in the organization of the production process due to their larger size. On the other hand, a negative correlation is obtained between regions and productivity growth. This indicates that a larger geographical expansion of activity could be linked to larger coordination difficulties and risk. This is especially significant given the legislative complexity existent in the Spanish commercial sector, as was discussed earlier.

Finally, a positive and significant effect of the population variable is observed. In this respect, higher rates of demand are associated with improvements in productivity. The results obtained in this section allow hypothesis 3 to be partially accepted. Productivity growth is positively associated with the GDP, size, and population variables. However, its connection with geographical diversification is negative, though this relationship does not exist in the market concentration.

Conclusions and Recommendation

This paper analyzes sectoral efficiency and productivity growth. The primary interest is on individual comparisons within the Spanish retail sector. Thus, the DEA methodology is proposed and both cross-sectional and panel data are used. This methodology was chosen because the role of time was considered. The results reached in this study confirm that efficiency declined in the period from 1995 to 2004. However, when time is taken into consideration, the behavior of the efficiency distribution is different. To that effect, the different behavior can be explained by the fact that long-term technological advances and managerial developments provide an important impetus for improving productivity and efficiency.

As for productivity growth, this paper found that productivity growth increased at an average rate of 0.8% per annum over the entire period for the retail sector. Productivity growth (MALM) is the result of two antagonistic forces, gains and losses in technical changes (TECH) and efficiency changes (EFFCH), respectively. Comparing sub-periods (before and after the Shop Opening Hours Decree-Law 2000), productivity growth increased, but the growth ratio is bigger for the 1995/99 period than for the 2000/04 period (1.9% vs. 1%, respectively).

The individualized analysis of productivity growth reveals that the sectors which achieve the largest growth rations are: r.s. of other products in non-specialized shops (5212), r.s. of medical and orthopedic products (5232) and r.s. in other shops specializing in food (5227) with a rate of 4.9% for the first two and 2.2% for the last one, respectively. These three sectors are devoted to specialized trade activities. In these types of sectors, companies derive more than 50% of their sales from one product with a total range of five products. The fourth sector in earnings for productivity is r.s., with a predominance of food in non-specialized shops (5211), whose ratio is 1.6%. The activity of the non-specialized sector is characterized by companies that have more than five types of products with no single product brining in more than 50% of the total earnings. The differences in the productivity of these sectors, considering specialized and non-specialized activities, could be due to the fact that these firms can operate with larger commercial margins in markets that have little elastic demand.

Finally, the variations in the determinants of productivity growth are analyzed. It was found that the dummy variable representing the large-sized sector has a significant positive effect on the MALM. On the other hand, a larger geographic expansion of activities could lead to more coordination difficulties and risk. This is especially significant given the legislative complexity existent in the Spanish commercial sector, and which was discussed earlier. However, demand is positively related to productivity growth. Furthermore, threshold levels of GDP were established for the retail sectors above in which productivity growth trended upward.

The limitations of this study include the generalization of the conclusions due to the lack of comparative sectoral studies carried out in Spain. Another of the limitations to keep in mind refers to sectoral heterogeneity when comparing sectors within it. However, this problem is smaller than if the comparison had been carried out among sectors belonging to industry and commerce in which heterogeneity is much larger. Nevertheless, it seems to be a logical way of performing an analysis when sectoral comparisons are carried out.

Despite working with panel data over an extensive period of time, it would have been desirable to work with larger samples that could back up the results more robustly. The choice of non-parametric DEA methodology imposed certain constraints. The DEA model does not impose any functional form on the data, or make distributional assumptions for the inefficient term. This efficiency measurement assumes that the production function of the fully efficient outlet is known. In practice, this is not the case, and the efficient isoquant must be estimated from the sample data. Under these conditions, the frontier is relative to the sample considered in the analysis. Moreover, without statistical distribution hypotheses, DEA does not allow for random errors in the data. Nevertheless, DEA estimators have been applied in more than 1,800 articles published in more than 490 refereed journals (Gattoufi *et al.*, 2004). This paper could allow sectoral comparisons and their evolution over time to be studied. Although one of the greatest difficulties is the readiness of data allowing the type of commercial format to be controlled, this possibility could inspire interesting reflections.

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