Technical and efficiency change in the French food industry

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1 Introduction

The food-processing industry is the largest manufacturing sector in France with a turnover estimated at 147 billion euros (about 193 billion USD). It contributes to 13% of the industry value added and to 1.7% of the Gross Domestic Product in France. Meat processing and dairy products are the two most important activities, gathering about one-third of all firms in the sector and contributing to about one-third of its value added.

In a recent study, Bontemps et al. (2011) applied an index approach to a panel dataset of French firms from the food-processing industry and found that, on average, productivity has decreased by 0.4% per annum between 1996 and 2006, the meat industry experiencing a larger rate of decrease (-0.7%) than the dairy industry (-0.1%). The aim of this paper is to adopt a different approach to provide some further evidence on the dynamics of productivity in this sector using firms data over 1996-2006. Studying this particular period is interesting for at least two reasons. First there has been an increased concentration in the food-processing sector, which is a highly fragmented market with few multinational companies and many small and medium sized enterprizes. Second this period has witnessed a number of food scares following outbreaks of BSE (mad-cow disease), dioxin-contaminated chicken, listeria and salmonella contamination. These raised consumers' concern

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and induced a reinforcement of food safety regulations. In particular the European Union (EU) commission published a white paper on food safety in 2000 and the general food law entered into force two years later.[1]

A standard way to analyze productivity changes over time is to compute a Malmquist Total Factor Productivity (TFP) index and to decompose it into different components accounting for technical change and efficiency change. When firms are followed over a number of periods, one issue is to choose which periods to compare. With annual data for example, one could compare every successive year over the whole period or alternatively one could measure the TFP index between the initial year and the final year. On the one hand, because technical change (and efficiency change) in the industry is a gradual process, we do not find appropriate to calculate a year-by-year TFP index. On the other hand, measuring TFP between the first and the latest year of observations may as well be too restrictive if both technical progress and technical regress have occurred during the period. In the particular case of the French food industry, we argue that more stringent sanitary and environmental regulations may have shrunk the set of firms' production possibilities leading to 'technical regress', at least during some sub-periods. Finally, the computation of the Malmquist TFP index between two dates requires that firms are present in the data at these particular dates, hence a balanced panel is required.

In order to deal with the issues discussed above we propose to analyze technical change over time using a two-stage procedure. In the first stage, we identify sub-periods of technical progress and technical regress, and in the second stage we calculate the Malmquist Index using initial and final years of each sub-period. To identify relevant sub-periods, we develop an iterative testing procedure that is based on the comparison of the distribution of efficiency scores for firms in the latest period of observation, computed (using DEA) from two sets of sequential production possibilities: the Forward Increasing Production Set (or FIPS) and the Backward Increasing Production Set (or BIPS). The FIPS at any time t is constructed from the observations in the base period up until period t, while the BIPS in year t is built from the observations in the latest period of observation back to period t. We construct as many FIPS and BIPS as they are time periods covered by the data. Formal testing of all pairs of distributions is then performed in order to assess whether firms have experienced positive or negative technical change in all sub-periods between 1996 and 2006.

[1]More precisely the European Community Regulation 178/2002 which lays down the general principles and requirements of the food law came into force on 21 February 2002.

Once periods in which technical change occurred have been identified, we calculate the contribution of technical change and efficiency change in TFP by decomposing the Malmquist Index. Because food safety regulations and market restructuring may have had different impacts depending on the type of food product, we perform this productivity analysis at the sub-sectoral level.

This paper adds to the rather scarce literature on the measurement of efficiency and productivity in the food-processing sector. Most of the existing studies on this sector have measured productivity applying parametric approaches to aggregate data. Buccola et al. (2000) estimate a Generalized Leontief cost function to calculate size economies, productivity growth and technical change in the US milling and baking industries over the 1958-94 period. The same approach was used by Morrison and Diewert (1990) on data from the US food and kindred products industry (from 1965 to 1991). Gopinath (2003) estimates a simple parametric model in which value-added per worker is specified as a function of capital per worker, total employment, and a time trend. This model is estimated using country-level data from the food-processing industry for 13 OECD countries from 1975-95. In the case of France this author finds that its TFP level was 55% that of the US TFP over the period (the US was the leading country in the sample in terms of TFP) and that its TFP growth rate was 0.4%. Fischer and Schornberg (2007) use an index approach on data from 13 European countries over the 1995-2002 years. They calculate what they call the industrial competitiveness index, a composite measure of profitability, productivity, and output growth. Their results suggest that overall competitiveness has slightly increased in 1999-2002 compared to the period 1995-1998. As far as we know, Chaaban et al. (2005) was the only published article using firm data from the French food-processing industry. Using DEA, these authors found that the average technical efficiency of cheese manufacturers (from 1985 to 2000) varied from 0.71 to 0.82 depending on the assumption on the technology (constant versus variable returns to scale). In contrast with most of the previous literature our empirical analysis uses non-parametric approaches on a panel data of firms. The results of our study bring new evidence on the recent performance of one of the major manufacturing sectors in Europe.

In Section 2 we present our proposed methodology, a simulation exercise describes basic intuitions. The application on French data is described in Section 3. Section 4 concludes.

2 Description of the methodology

In order to measure the contribution of efficiency and technical change in TFP using panel data, we proceed in two stages. In the first stage, we propose an original methodology to identify periods (without any a priori on their length) during which technical change has occurred. This methodology (which will be described below) allows us to detect both technical progress and technical regress and does not require a balanced panel. In the second stage we measure the change in TFP on the relevant sub-periods identified in stage 1, and we decompose it into interpretable components.

The usual approach to identify the contributions of technical change and efficiency change in the evolution of TFP between a base period b and the current period c, is to compute a Malmquist index (MI). Following Simar and Wilson (1998), we have

$$
\begin{aligned}
MI &= \text{Pure efficiency change} \times \text{Change in the scale efficiency} \\
&\times \text{Pure change in technology} \\
&\times \text{Change in the scale of the technology}
\end{aligned}
$$

or

$$
\begin{aligned}
MI &= \left(\frac{D_{\mathbf{c}}^{VRS}(x_{\mathbf{c}}, y_{\mathbf{c}})}{D_{\mathbf{b}}^{VRS}(x_{\mathbf{b}}, y_{\mathbf{b}})}\right) \times \left(\frac{D_{\mathbf{c}}^{CRS}(x_{\mathbf{c}}, y_{\mathbf{c}}) \;/\; D_{\mathbf{c}}^{VRS}(x_{\mathbf{c}}, y_{\mathbf{c}})}{D_{\mathbf{b}}^{CRS}(x_{\mathbf{b}}, y_{\mathbf{b}}) \;/\; D_{\mathbf{b}}^{VRS}(x_{\mathbf{b}}, y_{\mathbf{b}})}\right) \\
&\times \left(\frac{D_{\mathbf{b}}^{VRS}(x_{\mathbf{c}}, y_{\mathbf{c}})}{D_{\mathbf{c}}^{VRS}(x_{\mathbf{c}}, y_{\mathbf{c}})} \times \frac{D_{\mathbf{b}}^{VRS}(x_{\mathbf{b}}, y_{\mathbf{b}})}{D_{\mathbf{c}}^{VRS}(x_{\mathbf{b}}, y_{\mathbf{b}})}\right)^{0.5} \\
&\times \left(\frac{D_{\mathbf{b}}^{CRS}(x_{\mathbf{c}}, y_{\mathbf{c}}) \;/\; D_{\mathbf{b}}^{VRS}(x_{\mathbf{c}}, y_{\mathbf{c}})}{D_{\mathbf{c}}^{CRS}(x_{\mathbf{c}}, y_{\mathbf{c}}) \;/\; D_{\mathbf{c}}^{VRS}(x_{\mathbf{c}}, y_{\mathbf{c}})} \times \frac{D_{\mathbf{b}}^{CRS}(x_{\mathbf{b}}, y_{\mathbf{b}}) \;/\; D_{\mathbf{b}}^{VRS}(x_{\mathbf{b}}, y_{\mathbf{b}})}{D_{\mathbf{c}}^{CRS}(x_{\mathbf{b}}, y_{\mathbf{b}}) \;/\; D_{\mathbf{c}}^{VRS}(x_{\mathbf{b}}, y_{\mathbf{b}})}\right)^{0.5} \qquad (1)
\end{aligned}
$$

where

$$
D_t^s(x, y) = \min\left\{\theta |\ (x, y/\theta) \in \text{Production set}\right\}, \qquad (2)
$$

with $x \in R_+^p$ (inputs) and $y \in R_+^q$ (outputs), is the distance function at time t. Superscript s either stands for constant returns to scale (CRS) or variable returns to scale (VRS). The distance functions are usually calculated using Data Envelopment Analysis (DEA) (Cooper et al., 2007).

The Malmquist index is decomposed into a (pure) efficiency effect, a (pure) technical effect and scale effects. The efficiency effect measures the change in the (output-oriented) measure of technical efficiency between periods b and c without imposing a constraint on the shape of the technology, the technical effect captures the shift in technology between the two periods, evaluated at x_b and x_c, and the scale effects take into account possible changes in the shape of the technology (Simar and Wilson, 1998).[2]

A contentious issue when computing the distance function in equation (2) is the choice of the production set or reference technology. For example, one could consider contemporaneous production sets, i.e., production sets that are constructed at each point in time, from the observations at that time only. In this case production sets at different points in time are assumed to be completely unrelated. They can expand or contract from one year to another and technical progress as well as technical regress can occur whatever the base time period is. If one consider sequential production sets instead, i.e., production sets which, at each point in time, are constructed from the observations made from the base period up until the contemporaneous period, the production possibilities frontier will expand as we move from period t to period $t+1$. The underlying assumption on the technology is that there is technical progress over time, i.e. 'what was possible in the past remains always possible in the future', see Tulkens and Van den Eeckaut (1995) for related discussions. In what follows, we develop an iterative procedure for detecting technical regress and technical progress on a panel data of firms using sequential production sets.

2.1 Construction of Forward and Backward Increasing Production Sets

We consider the following two sets of sequential production possibilities:

1. The Forward Increasing Production Set (FIPS):[3]

$$P_t^{FIPS} = \left\{ (x,y) \mid y \leq \sum_{\tau=1}^{t} \sum_{i} z_{i\tau} Y_{i\tau},\ x \geq \sum_{\tau=1}^{t} \sum_{i} z_{i\tau} X_{i\tau},\ \text{all } z_{i\tau} \geq 0 \right\}.$$

   The FIPS in year t is constructed from the observations in the first period ($\tau = 1$) up until period t.

[2]The distances can be either output-orientated or input-orientated. The Malmquist TFP indices will differ according to the orientation used except when the technology in periods b and c exhibit global constant returns to scale.

[3]In the following, we omit the constraints describing the nature of returns to scale for ease of presentation.

2. And the Backward Increasing Production Set (BIPS):

$$P_t^{BIPS} = \left\{ (x, y) \mid \; y \leq \sum_{\tau=t}^{T} \sum_i z_{i\tau} Y_{i\tau}, \; x \geq \sum_{\tau=t}^{T} \sum_i z_{i\tau} X_{i\tau}, \text{ all } z_{i\tau} \geq 0 \right\}. \tag{3}$$

The BIPS in year t is constructed from the observations in the latest period of observation (T) back to period t.

The FIPS and BIPS have the following properties:

- If technical progress occurs between t and $t+1$, then $P_t^{FIPS} \subset P_{t+1}^{FIPS}$ and $P_t^{BIPS} \equiv P_{t+1}^{BIPS}$.
- If technical regress occurs between t and $t+1$, then $P_t^{FIPS} \equiv P_{t+1}^{FIPS}$ and $P_{t+1}^{BIPS} \subset P_t^{BIPS}$.

We propose the following methodology: we estimate non-parametrically (using DEA) T frontiers based on sequential FIPS (from P_1^{FIPS} to P_T^{FIPS}) and T frontiers based on sequential BIPS (from P_T^{BIPS} to P_1^{BIPS}). We then calculate the efficiency scores for firms present in T using each of these frontiers (note that we could have chosen any subset of firms).[4] The test of no technical change versus technical progress between periods t and t' ($t < t'$, consecutive periods or not) corresponds to the test of equality of the distributions of efficiency scores computed from the FIPS in t and the FIPS in t'. Symmetrically, the test of no technical change versus technical regress between periods t and t' is based on the test of equality of the distributions of efficiency scores for firms in the latest period of observation, computed from the BIPS in t and the BIPS in t'. If the equality between two distributions is rejected, then there is evidence of technical change.

The intuition underlying these tests is illustrated through various graphics using simulated data in the next section. More formally, we propose to implement the test developed by Li (1996) and studied by Fan and Ullah (1999) to test the null hypothesis of the equality of two distributions of efficiency scores for the firms in the latest period computed using FIPS and BIPS (see Appendix A1 for greater details on this test). This test is commonly used, for example, when testing whether income distribution across regions, groups, or time periods are the same. It works with either independent or dependent variables, and its finite sample properties when testing equalities

[4] Because we calculate efficiency scores for firms present in the data in the latest year of observation T, efficiency scores calculated based on sequential FIPS can be greater than 1.

of distributions of efficiency scores have been recently investigated by Simar and Zelenyuk (2006). These authors raise the issue that the random variables (here, the efficiency scores) whose distributions are compared, are unobserved. Because the efficiency scores are estimated, it may cause a form of dependence between these estimates, which can damage the finite sample properties of the test. Due to high sampling variation or noise from the estimation, researchers may then run into the type-I error (incorrectly reject the true null hypothesis) and type-II error (failing to reject the incorrect null hypothesis) more often than they would under the (unrealistic) situation that the true efficiency scores are known. Simar and Zelenyuk (2006) have developed approaches to adapt the test to various contexts. Such adaptations have not yet been proposed in the context of the testing methodology implemented in this article. For this reason, it will be necessary to interpret test results cautiously when they lead to the conclusion that the null hypothesis is rejected with a probability close to the usual thresholds at which rejection occurs.

2.2 Examples

The goal of this section is to illustrate the methodology described above using simulations. We simulate single-input single-output technologies since they allow us to visualize the plot of the true technology as well as the spread of the observed realizations of input and output combinations for each firm, along with the estimated FIPS and BIPS.

Case 1

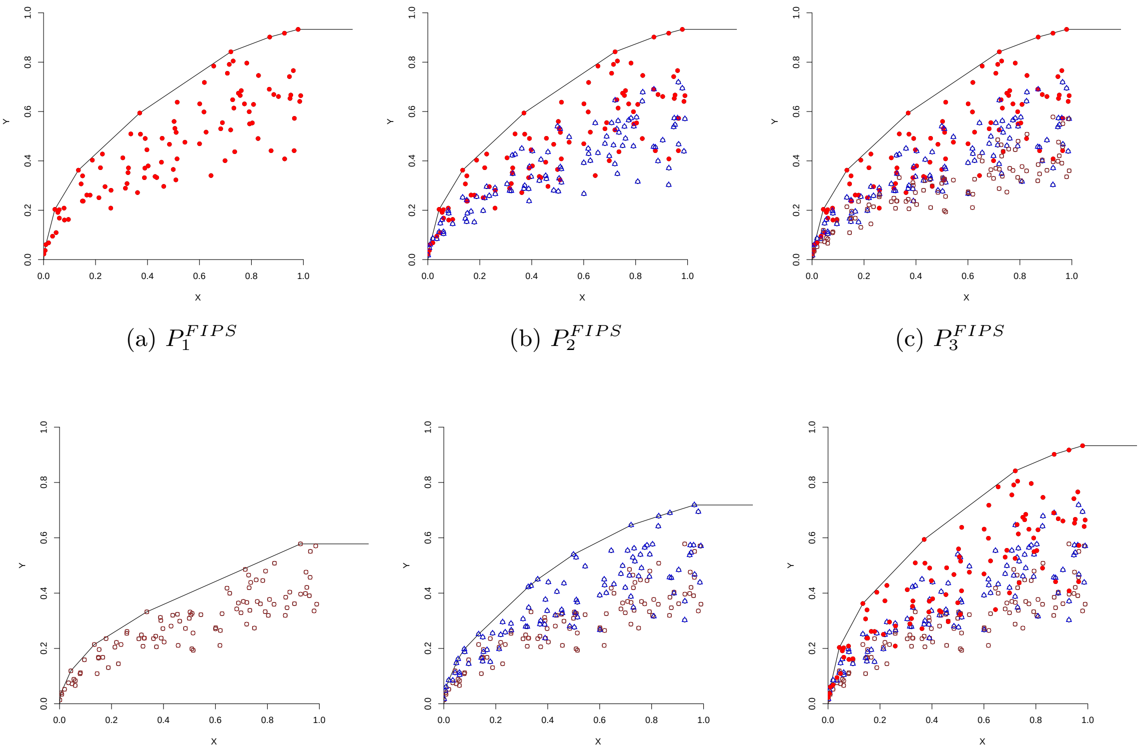
We start by generating a dataset of $N = 100$ single-input single-output firms over three years from the following equation:

$$y_t = x_t^{0.5} \times \exp\{-0.25 \times (t-1)\} / \, (1 + u_t) \tag{4}$$

with $x_t \sim U[0, 1]$ and $u_t \sim \mathcal{N}^{+}(0.2, 0.25)$. This procedure generates input-output pairs for year 1, year 2, and year 3, and incorporates an assumption of technical regress. For each year, the corresponding frontier has been obtained using DEA as shown on Figure 1. As explained above, and as confirmed on the graphs, only the BIPS frontier does move over time under technical regress.

The basis of our testing procedure is the comparison of the distribution of DEA-based efficiency scores (Figure 2) when (1) efficiency scores of firms in year 3 are computed on the basis of FIPS

Figure 1: **DEA estimates of frontiers using FIPS and BIPS, case 1**

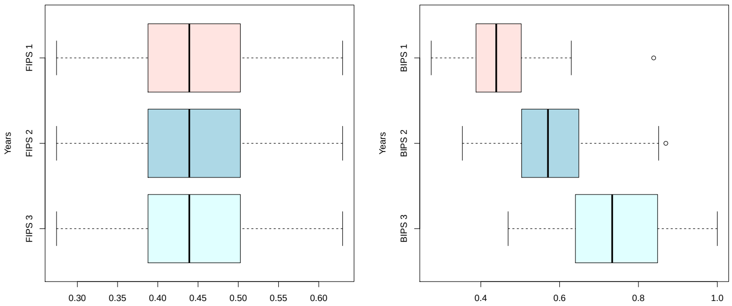


(a) P_1^{FIPS} (b) P_2^{FIPS} (c) P_3^{FIPS}

(d) P_3^{BIPS} (e) P_2^{BIPS} (f) P_1^{BIPS}

frontiers (Figure 2a) and (2) efficiency scores of firms in year 3 are computed on the basis of BIPS frontiers (Figure 2b). The time pattern of the distributions of efficiency scores is very different in the two cases. When considering frontiers based on sequential FIPS, the distribution of efficiency scores does not change over time which indicates that there was no technical progress between year 1 and year 3. On the contrary, the graph showing distributions of efficiency scores computed from BIPS provides evidence for technical regress between year 1 and year 3. A similar simulation exercise with technical progress would lead to a reverse pattern of distributions of efficiency scores for both BIPS and FIPS.

Figure 2: Distribution of efficiency scores



(a) on FIPS frontiers (b) on BIPS frontiers

Case 2

In practice, technical change is likely not to be homogeneous across all firms, even in a specific sector. We thus consider a second single-input single-output example in which the true technology at time t is assumed to be defined as follows:

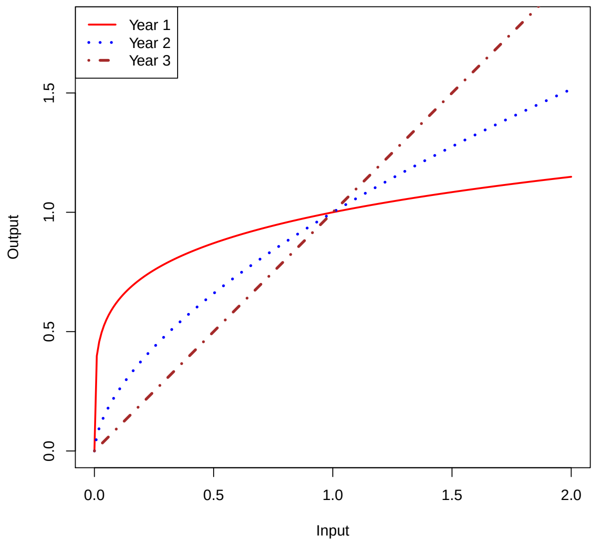
$$y_t = x_t^{\alpha_t} / (1 + u_t), \ t = 1, 2, 3 \tag{5}$$

where $\alpha_1 = 0.2$, $\alpha_2 = 0.6$, and $\alpha_3 = 1$. Input quantities and true technical efficiency scores are simulated in the same way as in the first example but, as shown in Figure 3, the chosen technology exhibits technical progress for large firms and technical regress for small firms.[5]

The distributions of efficiency scores calculated using sequential FIPS and BIPS are shown in Figure 4. When based on sequential FIPS, the distribution of efficiency scores changes over time which is evidence for technical progress occurring between year 1 and year 3 (Figure 4a). Similarly, the graph showing distributions of efficiency scores computed from BIPS provides evidence for technical regress between year 1 and year 3 (Figure 4b). Our testing procedure thus allows us to detect both technical progress and technical regress occurring over the same period.

[5]This might be the result of an improvement in the conversion rate of raw material to final product which shifts the frontier upward, and an increase in fixed costs (e.g., investment) which shifts the frontier downward. For large firms the former effect would dominate while the reverse would be observed for small firms.

Figure 3: True frontiers, case 2



3 Application to French Food Industries (1996-2006)

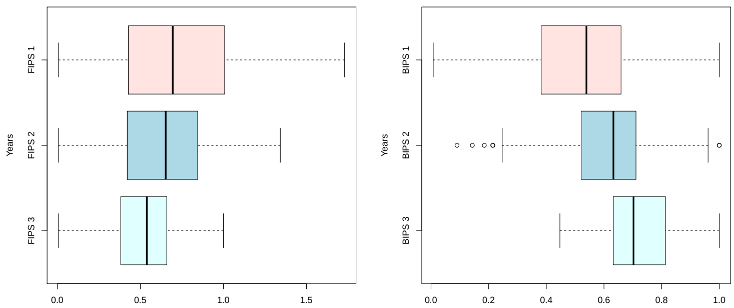
We use data from a national accounting survey (Enquête Annuelle d'Entreprise, source: INSEE, French Statistical Institute) which gathers information at the firm level for 41 sub-sectors of the food-processing industry. For each firm and each year over the 1996-2006 period we have the following variables: production in value (Y), stock of capital (K), labor (L) both in volume and value, and raw materials expenditure (M) in value. Values have been converted into quantity indices using appropriate price indices obtained from the French Statistical Institute (INSEE).[6]

We propose an in-depth analysis of two sub-sectors: the poultry industry and the cheese industry. These sub-sectors were chosen for two main reasons: the number of firms in our sample is large enough to produce meaningful results (about 200 firms in each industry) and these two sub-sectors have a significant economic importance (respectively 5 and 8% of total food industry production). We first apply procedures to detect outliers in each sub-sector.[7] We then use DEA to estimate

[6] Appendix A2 provides some additional information.

[7] We identify outliers on the basis of firms' average productivity Y/X with X an aggregate quantity index of inputs. Ouliers are firms with an average productivity larger than the productivity of the third quartile ($p75$) plus 1.5 times the difference between third and first quartile ($p75 - p25$). More formal outlier detection techniques, such as the one proposed by Wilson (1993), would have induced exclusion of almost all large firms. The input quantity index was built using price indices obtained from the French Statistical Institute (INSEE).

Figure 4: Distribution of efficiency scores (case 2)



(a) on FIPS frontiers (b) on BIPS frontiers

production frontiers based on FIPS and BIPS from 1996 to 2006 and the corresponding efficiency scores for firms present in the data in 2006. We thus obtain 11 distributions of efficiency scores under FIPS and 11 distributions of efficiency scores under BIPS. We then test the null of no technical change between all time periods by testing the equality of the distribution of efficiency scores using a bootstrapped version of the Li (1996) test of equality of densities.[8]

3.1 Poultry industry

This industry represents about 5% of the food industry (based on total sales).[9] In 2006, 151 firms (which are very heterogenous in size) were present in the data (Table 1). The ratio of production over raw materials (Y/M) is rather homogenous as this ratio is in the range [1.19 - 1.37] for 50% of the firms. This might be due to the fact that the conversion rate of raw material to the final product is strongly constrained by the technology. On the contrary partial productivity of labor (Y/L) and capital (Y/K) is more variable as labor and capital might be more substitutable and can therefore be used in different proportions leading to more variable partial productivity.

The average efficiency score in 2006 is 0.93 and half of the firms have an efficiency score in the range 0.89-0.98 (these scores were calculated based on the contemporaneous frontier), indicating that the performances are not too heterogenous even when the small subset of firms with very high

[8]DEA and the Li-test have been implemented using R-packages *Benchmarking* (Bogetoft and Otto (2010)) and *np* (Hayfield and Racine (2008)), respectively.

[9]The original sample was composed of 1,960 observations from 282 distinct firms. We apply the procedure to detect outliers every year independently. When a firm is classified as an 'outlier' in a given year, we remove all the observations for this firm. Using this procedure induced the removal of 118 observations (from 49 different firms).

Table 1: Poultry industry in 2006

Variable	Mean	Std dev	Min	1st quart.	3rd quart.	Max	N
Y	33,854.25	66,401.60	1,190	5,660	33,710	486,890	151
Y/K	8.28	31.28	0.35	1.89	5.13	342.03	151
Y/L	239.82	436.42	41.03	118.22	201.76	4,585.55	151
Y/M	1.38	0.37	0.96	1.19	1.37	2.90	151

level of partial productivity of labor or capital is included.

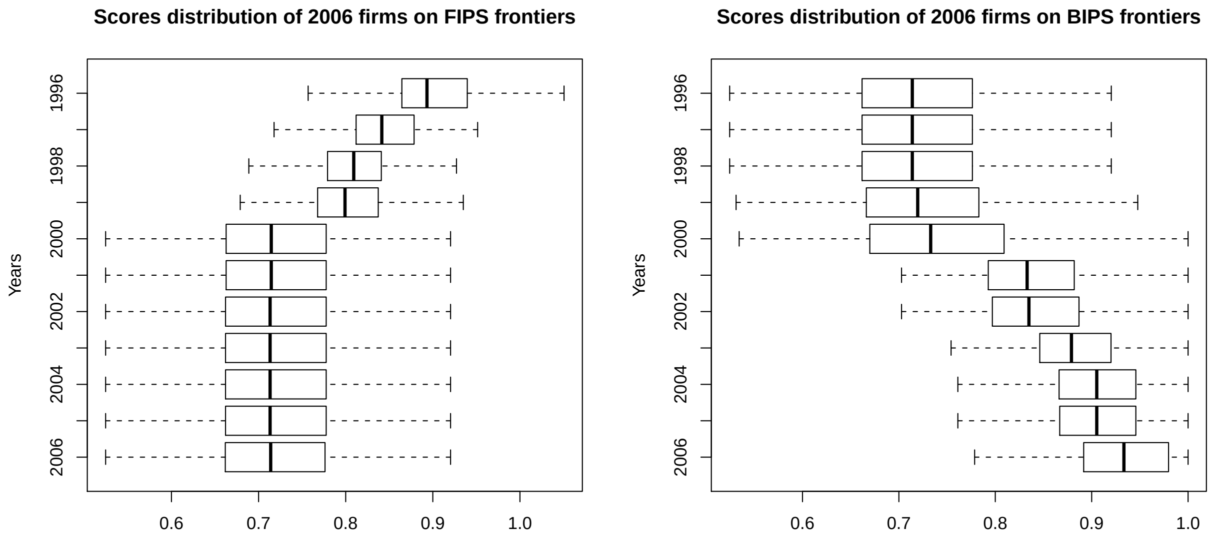
Technical change can be analyzed from the graphs showing the distribution of efficiency scores based on the sequential FIPS and BIPS (Figure 5) but formal testing is needed to assess significant technical progress or technical regress. The graphs and tests comparing all pairs of distributions indicate that, over the 1996-2006 period, this industry has experienced a period of technical progress (from 1996 to 2000) followed by a period of technical regress (2000-2006). Results from the tests (cf. Table 5 in Appendix A3) clearly reveals that from 1996 to 2000 frontiers based on FIPS significantly changed from t to $t+1$ (except from 1998 to 1999) while frontiers calculated from BIPS did not change significantly over the period (BIPS 2000 is not different from BIPS 1996). Conversely, from 2000 to 2006 frontiers based on BIPS have significantly moved (from t to $t+1$, except in 2001-2002 and 2004-2005) while frontiers calculated from FIPS did not change over time (2000 not significantly different from 2006).

According to these results, the poultry industry experienced two very different periods. The first one, from 1996 to 2000, was a period of significant technical progress while the second one is characterized by significant technical regress. To get more precise view on these two periods we compute the Malmquist index over 1996-2000 and 2000-2006 as well as over the whole period for comparison. The Malmquist index is decomposed in four terms: change in pure efficiency (Δ Pure Eff.), change in scale efficiency (Δ Scale Eff.), a pure change in technology (Δ Tech.), and change in the scale of the technology (Δ Scale Tech.), see Table 2. Note that the Malmquist index is computed using only the subset of firms which are observed over the 11 years.[10]

The calculated Malmquist index (MI) indicates that productivity has slightly increased over the 1996-2000 period, while it has decreased over the 2000-2006 years. More interestingly, there is evidence of (pure) technical change (Δ Tech. $= 1.25$) from 1996 to 2000, while negative technical

[10] The Malmquist index was calculated using 137 firms for the period 1996-2000, 119 firms for the period 2000-2006 and 110 firms for the period 1996-2006.

Figure 5: Evolution of efficiency scores in the poultry industry



(a) Firms in 2006 on FIPS frontiers

(b) Firms in 2006 on BIPS frontiers

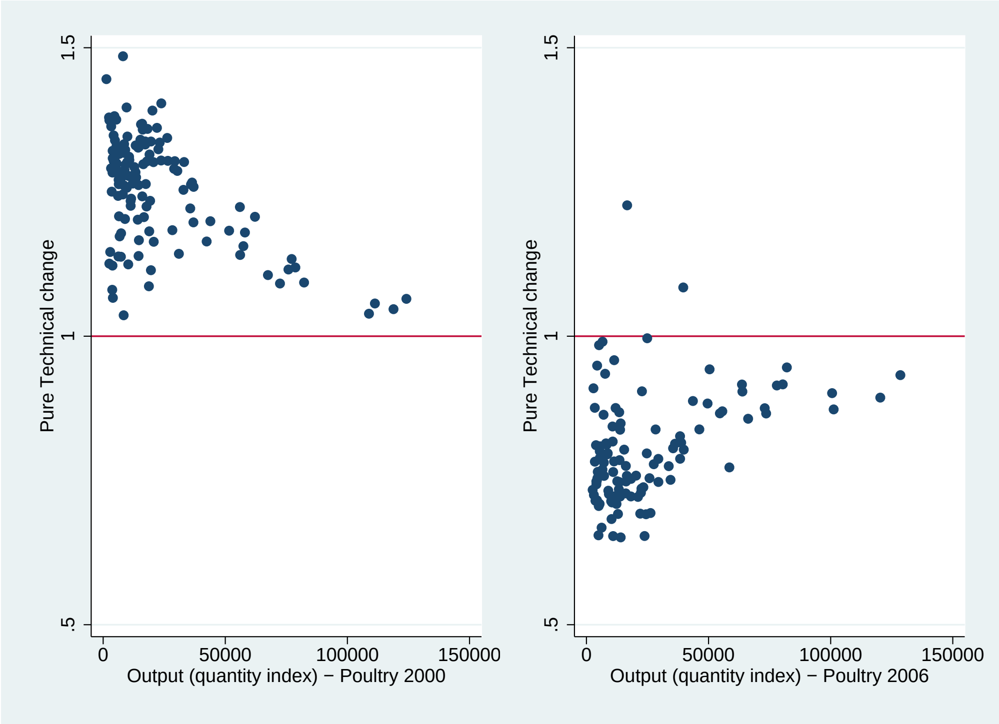
change (Δ Tech. = 0.81) is confirmed between 2000 and 2006. Those results are in line with the analysis using FIPS and BIPS which revealed that there was technical progress during the first sub-period and technical regress during the second one. Thus during the first period, the frontier moves upward while during the second period, it moves downward. The scores of pure efficiency change (that is the change in the distance to the frontier) exhibits inverse results: during the first period there is evidence of negative (pure) efficiency change (Δ Eff. = 0.83) and inversely during the second period there is evidence of positive efficiency change (Δ Eff. = 1.23). On the whole period (1996-2006) such changes are no longer apparent. The overall decrease in productivity is thus mainly explained by technical regress.

Table 2: Decomposition of the Malmquist index (MI) (poultry industry)

Year 1	Year 2	MI	Δ Pure Eff.	Δ Scale Eff.	Δ Tech.	Δ Scale Tech.
1996	2000	1.02	0.83	0.96	1.25	1.04
2000	2006	0.97	1.23	1.05	0.81	0.96
1996	2006	0.96	1	0.98	0.97	1.01

As shown on Figure 6 the largest changes in pure technical change are experienced by small

Figure 6: Pure technical change for the 1996-2000 and 2000-2006 periods - Poultry.



firms. During the first period a large number of small firms exhibit a positive technical change larger than 20% while during the second period a large number of small firms experience negative technical change larger than 20% (that is a score lower than 0.8).

3.2 Cheese industry

This industry represents about 8% of the food industry (based on total sales).[11] The 182 firms observed in 2006 are heterogenous in size (Table 3). As for the poultry industry, the ratio of output over raw materials (Y/M) is rather homogeneous as 50% of the values are in the range 1.15 to 1.32. Partial productivity of labor and capital is more variable than in the poultry industry.[12] The average efficiency score of firms in 2006 is 0.92 and three-fourth of these firms have an efficiency score larger than 0.87. The average efficiency score is lower on average than the average efficiency score measured in the poultry industry.

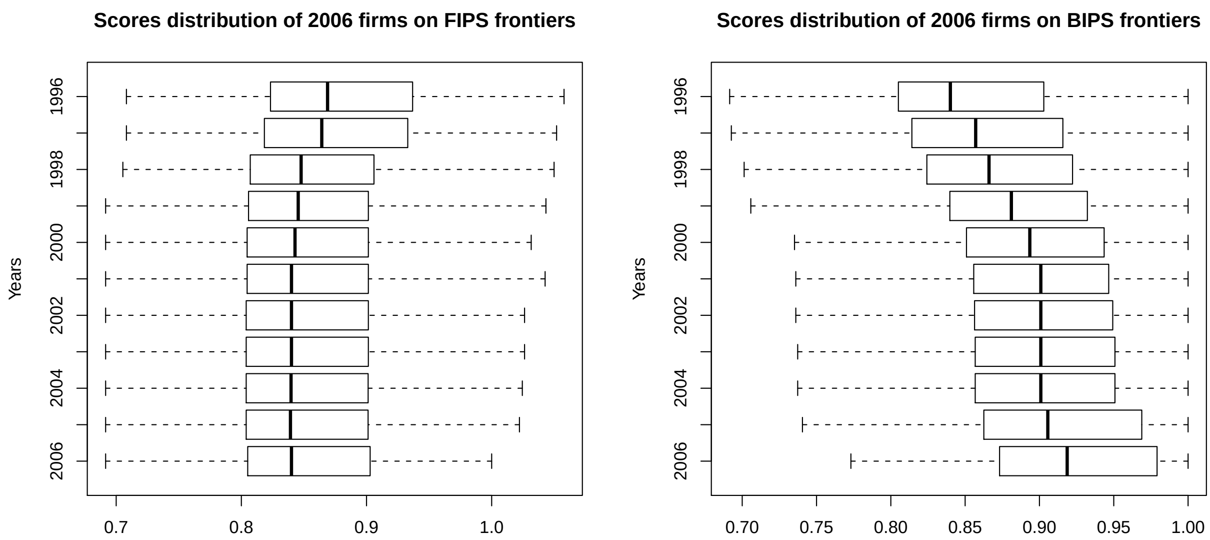
[11]The original sample was composed of 2,193 observations from 300 distinct firms. The procedure to detect outliers led to the removal of 77 observations (from 31 different firms).

[12]Note that 26 firms report having no capital. Most of these firms are affiliated to the same company.

Table 3: Cheese industry in 2006

Variable	Mean	Std dev	Min	1st quart.	3rd quart.	Max	N
Y	50,135.36	112,714.41	223	6,599	47,402	1e+06	182
Y/K	157.96	1,916.66	0.07	1.33	4.56	23,943.33	156
Y/L	463.83	1,426.40	9.29	177.42	357.88	18,051	182
Y/M	1.26	0.23	0.57	1.15	1.32	2.88	182

Figure 7: Evolution of efficiency scores in the cheese industry



(a) Firms in 2006 on FIPS frontiers

(b) Firms in 2006 on BIPS frontiers

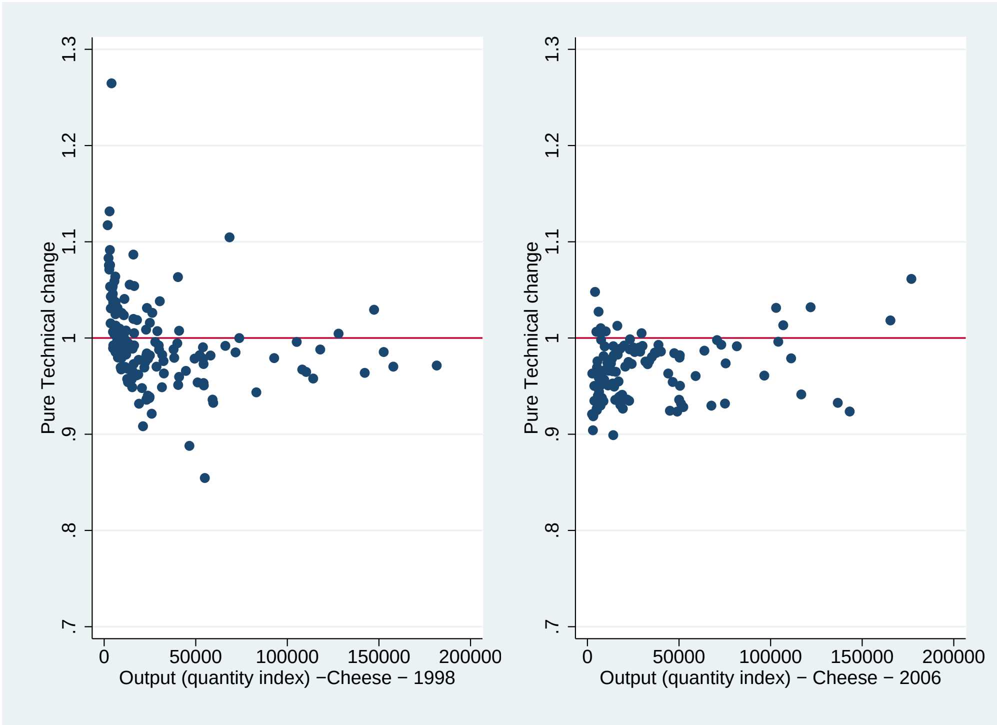
As apparent on Figure 7 and confirmed by testing the equality of distributions (see Table 6 in Appendix A3), the pattern of technical change is more complex than the one detected for poultry industry. Indeed, from 1996 to 1998, there is evidence of both technical progress (based on the analysis of FIPS) and technical regress (based on the analysis of BIPS). Then from 1998 to 2006 there is no technical progress while there are some sub-periods of technical regress. Thus we compute the Malmquist index for the following periods: 1996-1998 and 1998-2006 as well as for the entire period (Table 4).

The figures indicate a negative technical change (0.93), a 5% increase in pure efficiency, and an overall decrease in productivity (4%) between 1996 and 2006. It thus seems that the downward shift of the frontier, which might be explained by a gradual change in regulations (sanitary,

Table 4: Decomposition of the Malmquist index (MI) (cheese industry)

Year 1	Year 2	MI	Δ Pure Eff.	Δ Scale Eff.	Δ Tech.	Δ Scale Tech.
1996	1998	0.99	0.99	0.99	1.00	1.01
1998	2006	0.99	1.01	0.99	0.98	1.01
1996	2006	0.96	1.00	0.97	0.97	1.02

Figure 8: Pure technical change for the 1996-1998 and 1998-2006 periods - Cheese.



environmental), has been accompanied by a reduction in the inefficiency of firms.

The Malmquist index exhibits only slight variations. During the first period (1996-1998) the MI and its components almost did not change, at least on average. A closer look (Figure 8) reveals that some firms exhibit (pure) technical progress while some others exhibit (pure) technical regress. This is in line with the analysis using FIPS and BIPS which revealed that during the first sub-period both technical progress and technical regress were present. Moreover, firms which benefit from technical progress are small while those exhibiting technical regress are of any size. During the 1998-2006 period, changes are very small on average even if there is heterogeneity among firms in particular with respect to (pure) efficiency. Very few firms (less than 10%) exhibit (pure) technical progress and the period is thus characterized by technical regress which confirmed the analysis using BIPS and FIPS. Finally on the whole period the global performance of firms decreases as MI is lower than one. This is mainly due to technical regress over the whole period.

3.3 How to explain technical regress?

In the industry, there is no reason a priori to observe technical regress over time as technologies that were available in the past should still be available today. However this might be the case if the regulatory environment changes. A recent example is the ban regarding use of meat and bone flour for feeding cattle after BSE (mad-cow disease). As a consequence the industry had to use less efficient inputs, which might have reduced the productivity of cattle production. In the EU a number of food scares following outbreaks of BSE, dioxin-contaminated chicken, listeria and salmonella contamination, have raised consumers' concern and led to a progressive reinforcement of food safety regulations. As mentioned in introduction, the EU commission published a white paper on food safety in 2000 and the general food law entered into force two years later. This law introduced traceability (from farm to fork) requirements as well as generalized risk assessment based on the principles of Hazard Analysis Critical Control Points (HACCP). More importantly, this law emphasized the responsibility of food producers. For example, the preamble to the EU's General Food Law legislation states that: "A food business operator is best placed to devise a safe system for supplying food and ensuring that the food it supplies is safe; thus, it should have primary legal responsibility for ensuring food safety." (CEC (2002)) To implement this new policy, norms dealing with quality management and food safety were put in place.[13] In addition, most firms have developed their own quality control systems. In particular food retailers have set private standards which frequently go beyond the requirements of public standards (Henson and Humphrey (2009)).[14]

All these private and public regulations have increased costs of processing food products which in the present context are interpreted as technical regress. For example, in the specific case of poultry, Goodwin and Shiptsova (2000) estimated that the cost of implementing HACCP control in the US broiler industry amounted to about 0.7% of the industry total sales. In the French case, Magdelaine

[13]The norm ISO 15161 extended the norm ISO 9000 to the food sector in 2001 and the norm ISO 22000 is now specifically devoted to food safety issues.

[14]For example the BRC (British Retail Consortium) global standard was put in place in 1998, the IFS (International Food Standard) standard in early 2000's and the EUREP-GAP standard on fresh products was developed in the late nineties (Valceschini and Saulais (2005)).

and Chesnel (2005) analyzed the cost effects of regulatory constraints in the chicken industry. According to their results, sanitary regulations are more costly than environmental regulations. They report different changes in the regulation over the last 15 years: ban of meat and bone flour in 2000, progressive ban of some antibiotic, full traceability along the chain (2002 with a full implementation in 2005), regulation in order to decrease the risk of salmonella and other food-borne diseases (sanitary charter in the nineties, French law in 1998, European law in 2003). According to their estimates the costs of these sanitary regulations is about 6% of the value of chicken. About 40% of the additional costs are linked to slaughterhouses. They did not evaluate the impact on the other processing activities. Those results suggest that sanitary regulations have had a negative impact on the productivity of the sector. They also indicate that most of the new regulations were put in place in the sub-period 2000-2006 which is consistent with our results.

4 Conclusion

Using panel data of firms from the French food-processing industry, we provide some new evidence on the dynamics of productivity in this sector. We propose an original methodology to test for technical change (technical progress and technical regress) using panel data. The testing procedure is based on the comparison of the distribution of efficiency scores of the firms in the most recent period of observation (2006 in our sample) calculated using different production sets. More precisely, we calculate the distribution of efficiency scores for firms in 2006 using sequential 'Forward Increasing' Production Sets (FIPS) and sequential 'Backward Increasing' Production Sets (BIPS).

This approach has proven useful to identify periods of technical progress and technical regress in a number of sectors. Time patterns of technical change over the 1996-2006 years are found to be sector-specific and call for analyzes to be performed at a disaggregated level. Two sectors were analyzed in greater details: the poultry industry and the cheese industry. We show that the poultry industry has experienced a period of technical progress from 1996 to 2000 followed by a period of technical regress from 2000 to 2006. Technical regress might be a consequence of higher constraints exerted on the industry such as sanitary regulations and, to a lower extent, environmental regulations. Our results are consistent with analysis of the additional costs of sanitary regulations which came into forces in the 2000's. In the cheese industry, we find evidence of limited technical regress over the period, which again might have been induced by stricter environmental and/or sanitary regulations. We did not find any industry study supporting this point, though. However, the cheese industry also had to comply with the more stringent food safety regulation progressively put in place in the years 2000's.

In the poultry industry, there were clearly two subperiods with respect to technical change: one characterized by technical progress (almost all firms exhibited technical progress) and one characterized by technical regress (all firms exhibited technical regress). In the cheese industry, we also distinguish two subperiods. However, during the first period (1996-1998) some small firms benefited from technical progress while others did not. In the second period most firms experienced (pure) technical regress.

One caveat of our analysis is the use of DEA to estimate production frontiers and efficiency scores. More robust techniques such as Free Disposal Hull (FDH) or alpha-frontiers may be considered. Also, in order to test if stricter environmental regulations played a role in technical regress in some sectors, we plan in future research to take into account polluting outputs when estimating firms' efficiency scores.

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Appendix A1: Li (1996)'s test

The test proposed by (Li, 1996) aims at comparing the densities of two random variables that we denote U^A and U^Z (which, in our case, belong to R^1). Assume that two random samples, $\{u_k^A\}_{k=1}^{n_A}$ and $\{u_k^Z\}_{k=1}^{n_Z}$ representing the two groups A and Z in the population, are available. Let $f_l(.)$ denote the density of the random variable U^l, $l = A, Z$. The null and alternative hypotheses are: $H_0 : f_A(u) = f_B(u)$ and $H_1 : f_A(u) \neq f_B(u)$, on a set of positive measures, respectively. To test such an hypothesis, Li (1996) considers the integrated distance criterion:

$$I = \int (f_A(u) - f_Z(u))^2 \, du \tag{6}$$

which can be written as

$$I = \int f_A(u) dF_A(u) + \int f_Z(u) dF_Z(u) - \int f_A(u) dF_Z(u) - \int f_Z(u) dF_A(u) \tag{7}$$

The Li's test statistics is obtained by replacing the unknown distribution functions $F_A(.)$ and $F_Z(.)$ in equation (7) with their corresponding empirical distribution functions, and the unknown densities with their nonparametric (leave-one-out) kernel estimators. We have:

$$\begin{aligned}
\widehat{I}_{n_A,n_Z,h} = \quad & \tfrac{1}{hn_A(n_A-1)} \textstyle\sum_{j=1}^{n_A} \sum_{k\neq j,k=1}^{n_A} K\left(\frac{u_j^A - u_k^A}{h}\right) \\
& + \tfrac{1}{hn_Z(n_Z-1)} \textstyle\sum_{j=1}^{n_Z} \sum_{k\neq j,k=1}^{n_Z} K\left(\frac{u_j^Z - u_k^Z}{h}\right) \\
& - \tfrac{1}{hn_A(n_Z-1)} \textstyle\sum_{j=1}^{n_Z} \sum_{k\neq j,k=1}^{n_A} K\left(\frac{u_j^Z - u_k^A}{h}\right) \\
& - \tfrac{1}{hn_Z(n_A-1)} \textstyle\sum_{j=1}^{n_A} \sum_{k\neq j,k=1}^{n_Z} K\left(\frac{u_j^A - u_k^Z}{h}\right)
\end{aligned} \tag{8}$$

where h and $K(.)$ are the bandwidth and the kernel involved in the kernel estimators of the unknown density functions, respectively. After appropriate standardization, the limiting distribution of equation (8) is standard normal.

Appendix A2: Description of the input and output variables

Production (Y) is the annual value of production excluding trade activities. The stock of capital (K) is estimated at constant prices rather than historical prices. The original data provides the stock of capital at historical prices (which is a non-deflated sum of the different investments). In order to build the stock of capital at constant prices we used the permanent inventory method (OCDE (2001) and Bontemps et al. (2011) for greater details on how we built the series). Labor (L) is the average (over the year) number of employees including non-permanent employees but net of employees working for other firms. Material (M) corresponds to intermediate consumptions and are evaluated net of stock variation.

Appendix A3: Equality tests and distributions of efficiency scores

Poultry industry

Table 5: Nonparametric test for equality of distributions Li (1996)

(The upper diagonal reports the P-values associated to the test of $H_0 : \{ScoreYear_i(row) = ScoreYear_j(col)\}$)

Using **FIPS** frontiers

	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
1996	.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1997	.	.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1998	.	.	.	0.42	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1999	.	.	.	.	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2000	.	.	.	.	.	1.00	0.98	0.98	0.98	0.97	0.85
2001	.	.	.	.	.	.	0.98	0.98	0.98	0.97	0.85
2002	.	.	.	.	.	.	.	1.00	1.00	1.00	0.91
2003	.	.	.	.	.	.	.	.	1.00	1.00	0.91
2004	.	.	.	.	.	.	.	.	.	1.00	0.91
2005	.	.	.	.	.	.	.	.	.	.	0.93

Using **BIPS** frontiers

	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
1996	.	1.00	1.00	1.00	0.56	0.00	0.00	0.00	0.00	0.00	0.00
1997	.	.	1.00	1.00	0.56	0.00	0.00	0.00	0.00	0.00	0.00
1998	.	.	.	1.00	0.56	0.00	0.00	0.00	0.00	0.00	0.00
1999	.	.	.	.	0.66	0.00	0.00	0.00	0.00	0.00	0.00
2000	.	.	.	.	.	0.00	0.00	0.00	0.00	0.00	0.00
2001	.	.	.	.	.	.	0.96	0.00	0.00	0.00	0.00
2002	.	.	.	.	.	.	.	0.00	0.00	0.00	0.00
2003	.	.	.	.	.	.	.	.	0.00	0.00	0.00
2004	.	.	.	.	.	.	.	.	.	1.00	0.00
2005	.	.	.	.	.	.	.	.	.	.	0.00

Cheese industry

Table 6: Nonparametric test for equality of distributions Li (1996)
(The upper diagonal reports the P-values associated to the test of $H_0 : \{ScoreYear_i(row) = ScoreYear_j(col)\}$)

Using **FIPS** frontiers

	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
1996	.	0.89	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1997	.	.	0.11	0.11	0.11	0.11	0.00	0.00	0.00	0.00	0.00
1998	.	.	.	0.56	0.56	0.44	0.22	0.22	0.11	0.11	0.22
1999	.	.	.	.	1.00	1.00	1.00	1.00	1.00	0.89	0.67
2000	.	.	.	.	.	1.00	1.00	1.00	1.00	0.78	0.78
2001	.	.	.	.	.	.	1.00	1.00	1.00	1.00	0.67
2002	.	.	.	.	.	.	.	1.00	1.00	1.00	0.67
2003	.	.	.	.	.	.	.	.	1.00	1.00	0.67
2004	.	.	.	.	.	.	.	.	.	1.00	0.78
2005	.	.	.	.	.	.	.	.	.	.	0.78

Using **BIPS** frontiers

	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
1996	.	0.22	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1997	.	.	0.56	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1998	.	.	.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1999	.	.	.	.	0.11	0.00	0.11	0.00	0.00	0.00	0.00
2000	.	.	.	.	.	1.00	1.00	0.89	0.89	0.00	0.00
2001	.	.	.	.	.	.	1.00	1.00	1.00	0.56	0.00
2002	.	.	.	.	.	.	.	1.00	1.00	0.44	0.00
2003	.	.	.	.	.	.	.	.	1.00	0.44	0.00
2004	.	.	.	.	.	.	.	.	.	0.44	0.00
2005	.	.	.	.	.	.	.	.	.	.	0.11