Food Safety Regulation and Firm Productivity: Evidence from the French Food Industry

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Abstract

The purpose of this article is to assess whether food safety regulations imposed by the European Union in the 2000s may have induced a slow-down in the productivity of firms in the food processing sector. The impact of regulations on costs and productivity has seldom been studied. This article contributes to the literature by measuring productivity change using a panel of French food processing firms for the years 1996 to 2006. To do so, we develop an original iterative testing procedure based on the comparison of the distribution of efficiency scores of a set of firms. Our results confirm that productivity decreased in two major food processing sectors (poultry and cheese) at the time when safety regulation was reinforced.

1 Introduction

A number of food scares following outbreaks of BSE (mad-cow disease), dioxin-contaminated chicken, listeria and salmonella contamination have raised consumers' concern and induced a reinforcement

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of food safety regulations. For instance, the United States (US) put into force in the 1990s new quality control regulations that included the use of Hazard Analysis Critical Control Points (HACCP) methods as well as tests for pathogens. In Europe, the European Commission published a white paper on food safety in 2000 and the general food law entered into force two years later.[1] This law introduced traceability (from farm to fork) requirements as well as generalized risk assessment based on the principles of HACCP, and emphasized the responsibility of food producers.[2] To implement this new policy, norms dealing with quality management and food safety were put in place.[3] In addition, most firms 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).[4] As shown by Antle (2000), safety regulations induced significant additional costs for the industry which in turn affected its productive efficiency. In the meat industry, according to Antle's study, these costs might be in the range of 1 to 10% of the final price depending on the plant's size and initial level of safety.

The impact of various new regulations on productive efficiency has been extensively discussed in the literature on environmental regulation (for a recent overview of this literature, see Ambec et al., 2010). From an empirical point of view, while most papers in the 1990s found that environmental regulation had a negative impact on firms' performance, some recent papers suggest that more stringent regulation is not always detrimental to productivity (e.g., Lanoie et al., 2008). Changes in productivity are generally measured as ratios of Total Factor Productivity (TFP) indices and these ratios are regressed on regulation indicators. A further step should involve the decomposition of these ratios into different interpretable components, including measures of technical change and efficiency change.

Technical change can be analyzed in terms of the movements of the production possibilities frontier. If one agrees with the idea that "what was possible yesterday should be possible today",

[1]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.

[2]The preamble to the European Union'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).

[3]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.

[4]For example the BRC (British Retail Consortium) global standard was put in place in 1998, the IFS (International Food Standard) standard in early 2000s and the EUREP-GAP standard on fresh products was developed in the late 1990s (Valceschini and Saulais, 2005).

then there is no reason to expect the frontier to shift inward over time. However, if regulation becomes more stringent, an inward shift of the frontier can no longer be excluded since "what was authorized yesterday is no longer authorized today". So the observed shift of the frontier may be the result of an upward shift due to technical progress combined with an inward shift due to regulation. Depending on the relative size of these two effects one can observe "apparent" technical regress (if the inward shift dominates) or "apparent" technical progress (if the outward shift dominates). In the particular case of the French food industry, we argue that the sanitary regulations imposed by the European Union (EU) in the early 2000s may have shrunk the set of firms' production possibilities and hence may have induced some "apparent" technical regress.

In a recent study, Bontemps et al. (2011) applied an index approach to aggregate data on the French food processing industry and found that, on average, TFP decreased by 0.4% per year between 1996 and 2006, with the meat industry experiencing a larger rate of decrease (0.7%) than the dairy industry (0.1%). In this paper, TFP is measured as the ratio of an output quantity index to an input quantity index where the output quantity index is obtained by dividing the (observed) value of output by the corresponding price index. According to price index theory, this index should be built in such a way that it takes into account changes in output quality. However, as the French food industry faced more stringent safety regulations, the consequent change in food quality is likely to be omitted when measuring the corresponding food price index. Therefore, when costly regulations are put in place, one could detect a slow-down, or even a negative change, in the rate of TFP if the change in food quality/safety were not properly accounted for in the corresponding price index.

We provide further evidence on the dynamics of productivity in the food industry using firm data. More precisely, we analyze technical change over time using a two-stage procedure. In the first stage we identify time spans (covering one or more years) when "apparent" technical regress or conversely "apparent" technical progress occurred, and in the second stage we calculate an index of TFP change, the Färe-Primont index, between the initial and final years of each period identified in stage one (O'Donnell, 2011). To identify relevant periods, we develop an original iterative testing procedure based on the comparison of the distribution of efficiency scores of a set of observations, computed from two sets of sequential production possibilities. The first set is called the Forward Increasing Production Set (or FIPS). For a given year, it is constructed from the observations from the first year up until that year. This set is used to detect periods of "apparent" technical progress. The second set is named the Backward Increasing Production Set (or BIPS). For a given year, it is constructed from the observations in the latest year of observation back to the given year. This set is used to detect periods of "apparent" technical regress. Once periods in which the technical change occurred in the same direction have been identified, we calculate the contribution of technical change and efficiency change in TFP by decomposing the Färe-Primont index. Because food safety regulations may have had different impacts depending on the type of food product, we perform this productivity analysis at the sectoral level. In the empirical application we present our findings for two important sectors: poultry and cheese. In contrast with most of the previous literature our empirical analysis uses non-parametric approaches on a panel data of firms. Our results suggest that "apparent" technical progress occurred during the first years of the 1996-2006 period, whereas some "apparent" technical regress is observed in the more recent years at the time when safety regulation was being reinforced in the EU.

Section 2 reviews the related literature. In section 3 we discuss some issues in productivity measurement with panel data. In section 4 we present our methodology, including a simulation exercise describing the basic intuitions. The application using panel data from France is developed in section 5 and section 6 concludes.

2 Related literature

Most studies on the food industry have measured productivity by applying parametric approaches to aggregate data. Buccola et al. (2000) estimated a Generalized Leontief cost function to calculate size economies, productivity growth and technical change in the US milling and baking industries from 1958 to 1994. 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) estimated a simple parametric model in which value-added per worker was specified as a function of capital per worker, total employment, and a time trend. This model was estimated using country-level data from the food processing industry for 13 OECD (Organisation for Economic Co-operation and Development) countries from 1975 to 1995. According to his results, TFP in France was 55% that of the US TFP over the period (the US was the leading country in the sample in terms of TFP).

Moreover, the TFP growth rate in France was 0.4% per year. Fischer and Schornberg (2007) used an index approach on data from 13 European countries. They calculated an industrial competitiveness index; a composite measure of profitability, productivity, and output growth. Their results suggest that overall competitiveness was slightly higher in the 1999-2002 period compared to the 1995-1998 period. As far as we know, Chaaban et al. (2005) is the only published article using firm data from the French food processing industry. Using Data Envelopment Analysis (DEA), the authors found that the average technical efficiency of cheese manufacturers (from 1985 to 2000) varied from 0.71 to 0.82 (a technical efficiency score of 1 indicates that a firm is fully efficient) depending on the assumption made about the technology (that is, either constant or variable returns to scale).

The impact of regulations on costs and productivity has seldom been studied. Antle (2000) showed that US sanitary regulations (HACCP and tests for pathogen) increased production costs in the meat industry. Among other reasons, costs increased because of the necessary process modifications induced by the HACCP plan, additional requirements on the slaughter lines, and loss in operating efficiency. 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's total sales. In France, Magdelaine and Chesnel (2005) analyzed the cost induced by regulatory constraints in the poultry industry since the 1990s, including the ban of meat and bone flour in 2000, the progressive ban of some antibiotics, the requirement of full traceability along the chain (in 2002, with full implementation in 2005), and the regulation aimed at decreasing the risk of salmonella and other food-borne diseases. Their findings indicate that the cost of these sanitary regulations represents about 6% of the value of chicken meat, with 40% of the costs occurring at the processing level. However, as pointed out by Antle (2000) it is likely that the accounting costs are only a part of the overall costs of adaptation.

3 Issues in productivity measurement

In order to measure productivity change and the subsequent contribution of efficiency and technical change using panel data, we proceed in two stages. In the first stage, we propose an original methodology to identify time spans without any assumption on their length when the production possibilities frontier has shifted. This methodology allows us to detect both inward and outward movements of the frontier and does not require a balanced panel. In the second stage, we measure the change in TFP in the periods identified in stage one, and decompose it into interpretable components. Before describing the methodology, we discuss some related issues in productivity measurement.

3.1 The unobservability of output quality

There is evidence that sanitary regulations have increased production costs in the meat and poultry industry (Antle, 2000; Goodwin and Shiptsova, 2000; Magdelaine and Chesnel, 2005). It is quite straightforward to understand that, if the change in product safety or quality is not taken into account in the measurement of the quantity of output that is produced by a firm, then the firm might be described as being less productive after the sanitary regulations have been put into force.

To illustrate this issue, consider a technically-efficient firm producing a product Y whose level of safety K can vary. Figure 1 illustrates the production frontier in the $\{Y, K\}$ space for a given amount of input (X). We assume that this efficient firm is producing $\{Y_1, K_1\}$ at time t_1 and $\{Y_2, K_2\}$ at time t_2 with $\{Y_1 > Y_2\}$ and $\{K_1 < K_2\}$ using the same level of input X. We assume that there is no technical change between t_1 and t_2. However, the level of safety has increased from K_1 to K_2. The apparent productivity of the firm at time t_1, i.e. Y_1/X, is larger than its apparent productivity at time t_2, i.e. Y_2/X. Generalizing this to the whole space of observations, that is for different levels of input, one would conclude erroneously that the production possibilities frontier had shifted inward between t_1 and t_2. Hence, if the calculation of the quantity of output produced by the firm does not account properly for the change in output quality, then producing a safer product could be mistakenly interpreted as an inward shift in the production frontier.

Figure 1 about here

Sanitary regulations may also lead food processing firms to buy more quality-certified raw products, which are more costly than non-certified products. If the price index that is used to recover the quantity of raw product used in the production process does not account for a change in quality, then the input price index will underestimate the true price of the raw product and the derived input quantity index will be overestimated. If the same applies to most firms in an industry, then the calculation of TFP may again indicate some "apparent" technical regress. Since sanitary regulations were implemented in the French food sector in the early 2000s, “apparent” technical regress could show in our data if the corresponding price indexes do not properly account for any change in safety. It is thus important that the approach used to measure TFP allows for both outward and inward shifts of the production possibilities frontier.

3.2 Technical change versus efficiency change

The usual approach to identifying the contribution of technical change and efficiency change in the evolution of TFP between two periods is to compute and decompose an index of TFP change. For example, Simar and Wilson (1998) decompose the Malmquist index into a (pure) efficiency effect, a (pure) technical effect and scale effects. The efficiency effect measures the change in technical efficiency between periods t_1 and t_2, the technical effect captures the shift in technology, and the scale effects take into account possible changes in the shape of the technology. However, as pointed out by O’Donnell (2008), when the technology does not exhibit constant returns to scale (CRS), the Malmquist index is not “multiplicatively complete” meaning that it may be an unreliable measure of TFP change.

More recently, O’Donnell (2010) proposed a method of decomposing the change in TFP into three multiplicative terms: technical change; the change in firm efficiency; and a residual term which encompasses both change in scale and mix efficiency. However, in the proposed decomposition, technical change is defined as the ratio of the maximum TFP that can be achieved at each time period, and hence is common to all firms. In our case, we would like to have a more local measure of technical change, i.e., to be able to measure technical change for given levels of inputs.

Following O’Donnell (2010), let $Y_{n,t}$ and $X_{n,t}$ denote the observed output and inputs of firm n at time t, respectively. $\overline{Y}^{s}_{n,t}$ denotes the maximum output feasible at time s, that is with the technology available at time s when using $X_{n,t}$. We thus write:

$$\frac{Y_{n,t_2}/X_{n,t_2}}{Y_{n,t_1}/X_{n,t_1}} = \frac{\frac{Y_{n,t_2}}{\overline{Y}^{t_2}_{n,t_2}}}{\frac{Y_{n,t_1}}{\overline{Y}^{t_1}_{n,t_1}}} \times \left(\frac{\frac{Y_{n,t_2}}{\overline{Y}^{t_1}_{n,t_2}}}{\frac{Y_{n,t_2}}{\overline{Y}^{t_2}_{n,t_2}}} \times \frac{\frac{Y_{n,t_1}}{\overline{Y}^{t1}_{n,t_1}}}{\frac{Y_{n,t_1}}{\overline{Y}^{t_2}_{n,t_1}}} \right)^{0.5} \times \left(\frac{\frac{\overline{Y}^{t_2}_{n,t_2}}{X_{n,t_2}}}{\frac{\overline{Y}^{t_2}_{n,t_1}}{X_{n,t_1}}} \times \frac{\frac{\overline{Y}^{t_1}_{n,t_2}}{X_{n,t_2}}}{\frac{\overline{Y}^{t^1}_{n,t_1}}{X_{n,t_1}}} \right)^{0.5} \tag{1}$$

The left-hand-side (LHS) of equation (1) is the change in TFP. The right-hand-side (RHS) is composed of three terms: the change in (pure) efficiency; the (firm specific) technical change; and a residual term integrating mix and scale efficiency. The first term of the RHS is the ratio of the technical efficiencies of firm n measured at period t_2 and at period t_1. The second term is the geometric mean of technical changes measured between period t_1 and t_2 when using X_{n,t_1} and X_{n,t_2} as inputs, respectively. Thus $Y_{n,t_2}/\overline{Y}^{t_1}_{n,t_2}$ is the efficiency of firm n evaluated at the level of input X_{n,t_2} with respect to the technology available at period t_1. Similarly $Y_{n,t_2}/\overline{Y}^{t_2}_{n,t_2}$ is the efficiency of firm n evaluated at the level of input X_{n,t_2} with respect to the technology available at period t_2.

Figure 2 about here

In figure 2, A and B are observations of the performance of a firm at periods t_1 and t_2 respectively. The ratio B_0B/B_0B_2 is the efficiency of the firm at period t_2. Similarly, the ratio A_0A/A_0A_1 is the efficiency of the firm at period t_1. The ratio of these two is the change in pure efficiency. At a given level of input, technical change is measured by the increase in output between period t_1 and t_2. It is measured by A_0A_2/A_0A_1 for the firm at period t_1 and B_0B_2/B_0B_1 for the firm at period t_2. The geometrical mean of these two terms is the measure of firm-specific technical change. We implement this approach using the Färe-Primont index as the index of TFP change.[5]

3.3 Choice of production sets

The measurement of efficiency depends on 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 "apparent" technical progress as well as "apparent" technical regress can occur whatever the base time period is. If one considers 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 always remains possible in the future" (for related discussions, see Tulkens and Van den Eeckaut, 1995). In the following, we

[5]We use DPIN and R to calculate the first and second terms of the decomposition. DPIN Version 3.0 is software for Decomposing Productivity Index Numbers into measures of technical change and various measures of efficiency change. It is available at the following address: http://www.uq.edu.au/economics/cepa/dpin.htm

develop an iterative procedure for detecting both inward and outward shifts of the frontier using sequential production sets.

4 Methodology

The sequential production sets used to implement our iterative procedure are defined as follows:

1. The Forward Increasing Production Set (FIPS):[6]

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

   where $S(\tau)$ is the set of firms operating at time τ and $z_{i\tau}$ is a constant. The FIPS in year t is constructed from the observations from the first year ($\tau = 1$) up until year t.

2. The Backward Increasing Production Set (BIPS):

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

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

These sequential production sets have the following useful properties:

- If an outward shift of the frontier, i.e. "apparent" 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 an inward shift of the frontier, i.e. "apparent" 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 use these properties to detect "apparent" technical changes over time. We implement the following methodology. First, using the DEA technique, we estimate T frontiers based on sequential

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

FIPS (from P_1^{FIPS} to P_T^{FIPS}) and T frontiers based on sequential BIPS (from P_T^{BIPS} to P_1^{BIPS}). Then, we calculate the efficiency scores for a set of observations that are randomly chosen from the whole population of firms.[7] The test of no technical change versus "apparent" technical progress between periods t_1 and t_2 ($t_1 < t_2$) corresponds to the test of equality of the distributions of efficiency scores computed using the FIPS in t_1 and the FIPS in t_2. Similarly, the test of no technical change versus ("apparent") technical regress between periods t_1 and t_2 is based on the test of equality of the distributions of efficiency scores computed using the BIPS in t_1 and the BIPS in t_2. If the equality between the two distributions is rejected, then there is evidence of technical change. In the empirical application, we 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 computed using FIPS and BIPS (see appendix A1 for additional details of this test).

The intuition underlying the methodology is illustrated below using simulated data. 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. Two cases are considered:

Case 1

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

$$y_t = x_t^{0.5} \times \exp\{-0.25 \times (t-1)\} / (1 + u_t) \tag{2}$$

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 "apparent" technical regress through the term $(\exp\{-0.25 \times (t-1)\})$. In line with the above discussion, this example could illustrate a situation where no technical change has occurred but product safety has improved over time due to changes in the production process or the purchase of more costly inputs. Each year, the FIPS and BIPS frontiers are obtained using DEA as shown in figure 3. In figure 3(a) (P_1^{FIPS}) the frontier is calculated from the observations of year 1; in figure 3(b) (P_2^{FIPS}) the frontier is calculated from

[7] Because we calculate efficiency scores of a sample of observations drawn from the whole sample which is composed with the observations of every firm at every date, efficiency scores are not bounded by 1.

the observations of year 1 and year 2; in figure 3(c) (P_3^{FIPS}) the frontier is calculated from the observations of year 1, year 2 and year 3. Given the assumption of technical regress, the FIPS frontier does not move over time. Conversely, in figure 3(d)(P_3^{BIPS}) the frontier is calculated from the observations of year 3; in figure 3(e) (P_2^{BIPS}) the frontier is calculated from the observations of year 3 and year 2; in figure 3(f)(P_1^{BIPS}) the frontier is calculated from the observations of year 3, year 2 and year 1. Given the assumption of technical regress, the BIPS frontier does move over time.

Figure 3 about here

The basis of our testing procedure is the comparison of the distribution of efficiency scores (figure 4) when (1) the efficiency scores of a set of observations are computed on the basis of FIPS frontiers (figure 4(a)) and (2) efficiency scores of the same set of observations are computed on the basis of BIPS frontiers (figure 4(b)). 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 remains constant over time which indicates that there was no "apparent" technical progress between year 1 and year 3. On the contrary, the graph showing distributions of efficiency scores computed from BIPS provides evidence for (apparent) 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 4 about here

Case 2

In practice, technical change (as well as the unobserved change in quality) is likely not to be homogeneous across all firms, even in a specific sector. This might be the result of either an improvement in the conversion rate of raw material to final product which shifts the frontier outward or an increase in fixed costs (e.g., investment) to deal with additional safety which (apparently) shifts the frontier inward. For large firms the former effect would dominate while the reverse would be observed for small firms. 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:

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

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 case but, as shown in figure 5, the chosen technology exhibits "apparent" technical progress for large firms and ("apparent") technical regress for small firms.

Figure 5 about here

The distributions of efficiency scores calculated using sequential FIPS and BIPS are shown in figure 6. When based on sequential FIPS, the distribution of efficiency scores changes over time which is evidence of an outward shift of the frontier (or "apparent" technical progress) occurring between year 1 and year 3 (figure 6(a)). Similarly, the graph showing distributions of efficiency scores computed from BIPS provides evidence of an inward shift of the frontier or "apparent" technical regress between year 1 and year 3 (figure 6(b)). Our testing procedure thus allows us to detect both "apparent" technical progress and "apparent" technical regress occurring over the same period.

Figure 6 about here

To summarize, "apparent" technical progress is detected through a change in the distribution of efficiency scores using FIPS while "apparent" technical regress is detected through a change in the distribution of efficiency scores using BIPS.

5 Application to French Food Industries

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 food processing industries. For each firm and each year from 1996 to 2006 we have information on 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).[8]

[8] Appendix A2 provides some additional information.

In the following, we focus on the poultry and cheese sectors for two main reasons: first, the number of firms in our sample, approximately 200 in each sector, is large enough to produce meaningful results; second, these sectors are economically important as they represent 5% and 8% of the total production in the food industry, respectively. First, we use DEA to estimate production frontiers based on FIPS and BIPS from 1996 to 2006 and the corresponding efficiency scores for a randomly-drawn sample of 200 observations.[9] Throughout we assume that all firms in a given sector operate under the same technology. We thus obtain 11 distributions of efficiency scores under FIPS and 11 under BIPS. We then test the null hypothesis of no technical change between all (consecutive and non-consecutive) 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.[10] 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 Färe-Primont index.

5.1 Poultry industry

This industry represents about 5% of the food industry's total sales. In 2006, our sample contains 151 firms of varying size.[11] The partial productivity of raw materials (Y/M) is relatively 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. In contrast, the partial productivity of labor (Y/L) and capital (Y/K) is much more variable since labor and capital might be more substitutable and can therefore be used in different proportions (table 1). Even if constrained by technology, firms can use different combinations of inputs to produce a given quantity of output. For this reason, efficiency scores calculated with respect to a production frontier provide a more general measure of firms' performance than simple partial productivity ratios. The average (output-oriented) efficiency score in 2006 is 0.93 and half the firms

[9] The same conclusions are reached when using a larger number of observations to estimate the production frontiers.

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

[11] The original sample was composed of 1,960 observations from 282 distinct firms. As DEA is known to be sensitive to outliers, we apply a procedure to detect outliers every year independently. We identify outliers on the basis of firms' average productivity Y/X where X is an aggregate quantity index of inputs. Outliers 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 the exclusion of almost all large firms. The input quantity index was built using price indices obtained from the French Statistical Institute (INSEE). Using this procedure induced the removal of 118 observations (from 49 different firms).

have an efficiency score in the range 0.89-0.98, indicating that performance is relatively homogenous even if some firms have a very high level of partial productivity of labor or capital.[12]

Table 1 about here

The distributions of efficiency scores calculated using sequential FIPS and BIPS indicate that the poultry industry experienced a period of "apparent" technical progress from 1996 to 2000, followed by a period of "apparent" technical regress from 2000 to 2006 (figure 7). These findings are confirmed by the formal tests of equality of distributions (see table 8 in appendix A3).[13]

Figure 7 about here

To better understand what occurred during these two periods, we compute the Färe-Primont TFP index over 1996-2000 and 2000-2006 as well as over the whole period for comparison. The Färe-Primont TFP index is decomposed into three terms: the change in technology (dTech); the change in efficiency (dOTE); and a residual term (dRES) that takes into account changes in scale and input mix. Note that, by definition, the Färe-Primont index can only be computed using a balanced panel, hence using firms which are present both at the beginning and at the end of the period.[14]

Results indicate that productivity increased slightly over the 1996-2000 period, while it decreased over 2000-2006 (table 2). There is evidence of technical progress (dTech = 1.16) from 1996 to 2000, followed by technical regress (dTech = 0.87) between 2000 and 2006. These results are in line with the findings from the FIPS and BIPS analysis.

The decomposition of the Färe-Primont index shows a negative change in pure efficiency (dOTE lower than one) between 1996 and 2000, which may indicate that firms did not manage, on average, to catch up with the improved technology. Between 2000 and 2006, the (pure) technical efficiency of the observed firms remained almost constant (dOTE = 0.99). The TFP index calculated over

[12] Efficiency scores were calculated using the contemporaneous frontier. Note that we get similar results for the initial year (1996). Efficiency scores are not shown here but are available upon request.

[13] The formal tests show, on the one hand, that FIPS-based frontiers significantly moved from one year to another between 1996 and 2000 (except between 1998 and 1999). On the other hand BIPS-based frontiers did not change significantly over the period.

[14] The Färe-Primont 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. Because the sets of firms used for calculating the TFP index for the different periods are not identical, the Färe-Primont index for 1996-2006 is not equal to the product of the two indices calculated over 1996-2000 and 2000-2006.

the entire period (1996 to 2006) shows a decrease in TFP, mainly explained by an inward shift of the technological frontier.

Table 2 about here

Table 3 provides greater details on the distribution of technological change across the population of firms: between 1996 and 2000 all firms in our sample experienced technical progress while almost all firms (98%) experienced "apparent" technical regress between 2000 and 2006. When looking at the whole period (1996 to 2006), most firms (82%) experienced "apparent" technical regress meaning that the inward shift that occurred between 2000 and 2006 was more pronounced than the outward shift that occurred between 1996 and 2000.

Table 3 about here

These results are consistent with the reinforcement of the EU food safety regulation in the poultry industry. As reported by Magdelaine and Chesnel (2005), food safety regulations were gradually put in place and came into force in the early 2000s (table 4). These policy measures had an impact on the whole chain. Some of them, such as the ban on antibiotics, had a direct impact on the cost of production of chicken, while others, such as the need to develop traceability of the whole production process, affected different levels of the production chain. All in all, the ban of the use of meat and bone flour for animal feeding had the largest impact at the processing stage (Magdelaine and Chesnel, 2005): before 2001, processors were selling slaughtering co-products to producers. This was no longer possible after the ban and processors now have to pay for the removal of these co-products. Our results thus suggest that, even if there were some technical progress over time in the poultry industry, the upward shift of the frontier was more than annihilated by the impact of additional requirements which led to an (apparent) inward shift of the frontier from 2000 to 2006.

Table 4 about here

5.2 Cheese industry

This industry represents about 8% of the food industry's total sales. The 182 firms observed in 2006 are heterogeneous in size (table 5).[15] As for the poultry industry, the ratio of output over raw materials (Y/M) is relatively homogeneous since 50% of the values are in the range 1.15 to 1.32. The partial productivity of labor and capital is more variable than in the poultry industry.[16] Similarly to the poultry sector, the distribution of efficiency scores in 2006 indicates that the performance of firms is relatively homogeneous even if some of them have a very high level of partial productivity of labor or capital (the average efficiency score is 0.92 and three-quarters of the sampled firms have an efficiency score larger than 0.87).

Table 5 about here

As can be seen in figure 8 and confirmed by the formal testing of the equality of distributions (see table 9 in appendix A3), the pattern of technical change is more complex than that detected in the poultry industry: there is evidence of both "apparent" technical progress and technical regress from 1996 to 1998 while there is no technical progress but some periods of "apparent" technical regress from 1998 to 2006. To quantify these changes, we compute the Färe-Primont index of TFP change for the following periods: 1996-1998, 1998-2006, and 1996-2006 for comparison purposes (table 6).

Figure 8 about here

Table 6 about here

The index of TFP exhibits only slight variations. Between 1996 and 1998, the average TFP index remained roughly constant (0.99) as was the case for technical change (dTech), change in technical efficiency (dOTE) and change in residual efficiency (dRES). There was some technical progress on average (dTech = 1.01) even if a majority of firms (64%) experienced some "apparent" technical regress (table 7). Between 1998 and 2006, the TFP index is 0.97 on average. This decrease in TFP is mainly explained by an inward shift of the frontier (dTech=0.98). Most firms (88%) exhibit apparent technical regress which confirms the analysis based on BIPS and FIPS. The decomposition

[15] 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).

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

of the TFP index over the whole period (1996 to 2006) indicates that the global performance of firms decreased (TFP = 0.95), the main reason being that most firms (82%) experienced some "apparent" technical regress.

Table 7 about here

6 Conclusion

This paper contributes to the literature on food safety regulation and its impact on firms' productivity. We argue that food safety regulation may induce "apparent" technical regress by constraining "what is possible to produce today" compared to "what was possible yesterday". If food quality and/or safety are not observable, then not taking food safety regulation into account could lead to the counterintuitive conclusion of technical regress. In this paper, we develop a methodology to analyze the dynamics of productivity when food safety regulation is implemented but food quality is not observed.

Our methodology lies in a two-stage data-driven procedure. In the first stage, we compare the distributions of efficiency scores of a sample of randomly-drawn observations calculated using Forward Increasing Production Sets (FIPS) and Backward Increasing Production Sets (BIPS). A formal testing procedure allows us to identify periods of "apparent" technical progress and "apparent" technical regress. In the second stage, Färe-Primont TFP indices are computed over the identified sub-periods and are decomposed into technical change and efficiency change.

Using panel data of firms from the French food processing industry, we show that the poultry industry experienced a period of technical progress from 1996 to 2000 followed by a period of "apparent" technical regress from 2000 to 2006. We argue that this "apparent" technical regress might be a consequence of the higher constraints exerted on the industry such as those imposed by the more stringent sanitary regulations. Our results could thus confirm that the sanitary regulations which came into force in the 2000s induced additional costs for this industry. In the cheese sector, our analysis also reveals two distinct sub-periods even though the findings are less clear-cut. Between 1996 and 1998 some firms benefited from "apparent" technical progress and others did not while, between 1998 and 2006, most firms experienced "apparent" technical regress. Evidence of technical regress over the period might also have been induced by the stricter sanitary regulations enforced in the 2000s.

One caveat of our analysis is the use of DEA to estimate production frontiers and efficiency scores. More robust techniques such as m-frontiers or alpha-frontiers might be worth considering for future research. To investigate further the contribution of technical change, it could be useful to gather data on polluting outputs at the level of the firm in order to take these directly into account when estimating firms' efficiency scores (e.g. Cuesta et al., 2009, in the US electricity generating sector). With respect to sanitary regulations, it seems much more challenging to gather data at the firm level to control for the sanitary/quality characteristics of the products. Finally, a possible extension of our work would be the analysis of the efficiency of firms that enter and exit the industry. Our analysis of technical change takes into account all firms whatever their age. However when quantifying and decomposing TFP change, we use a balanced panel and thus exclude firms which entered or exited during the period.

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Figure 1: Quantity-quality frontier

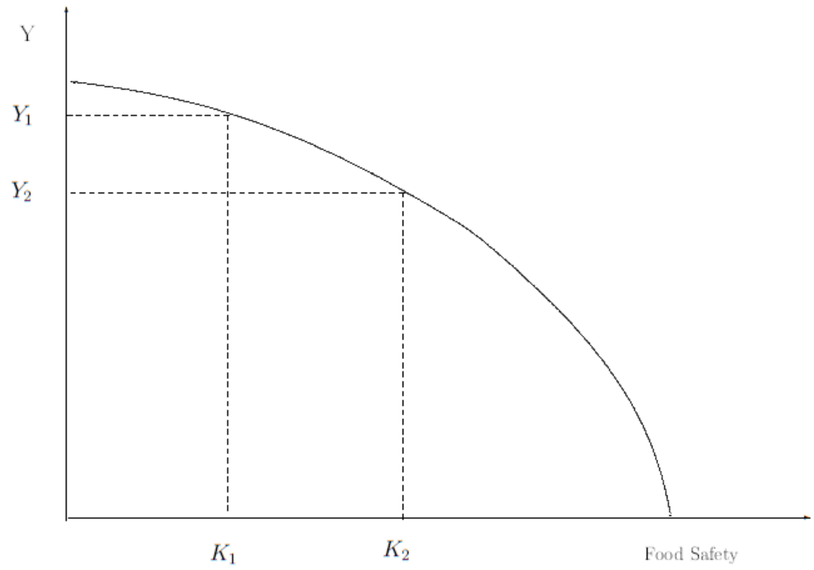


Figure 2: Decomposition of the TFP index

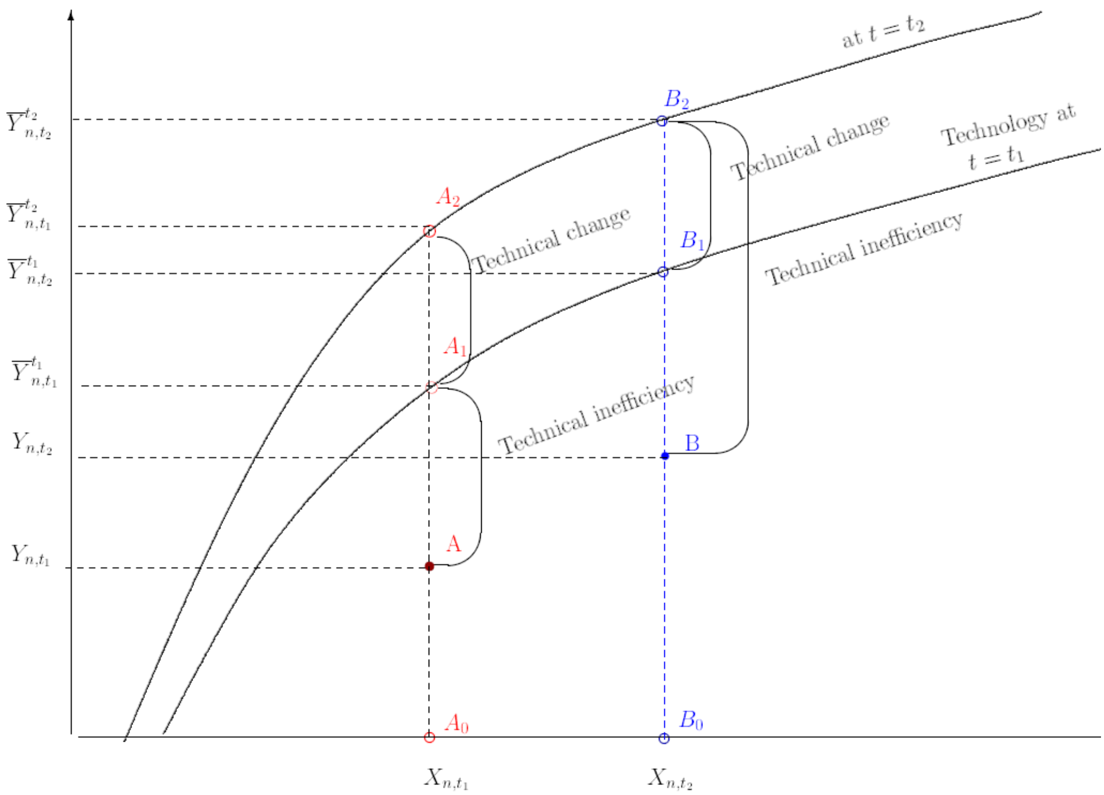
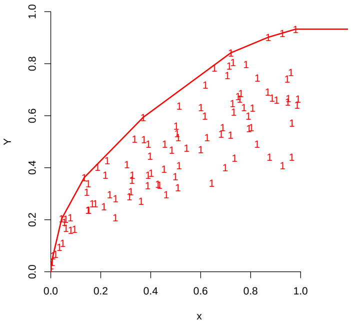
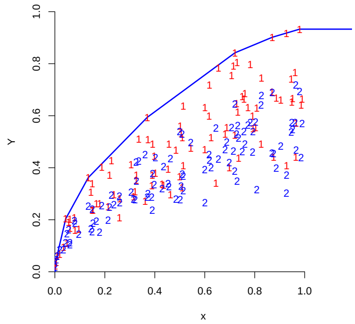


Figure 3: DEA estimates of frontiers using FIPS and BIPS (case 1)

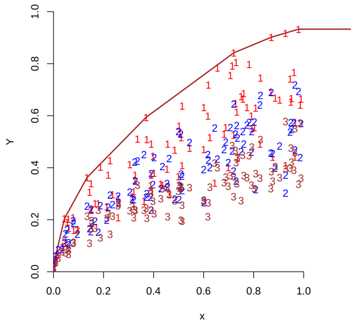
(a) P_1^{FIPS}



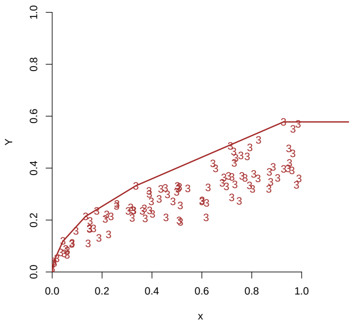
(b) P_2^{FIPS}



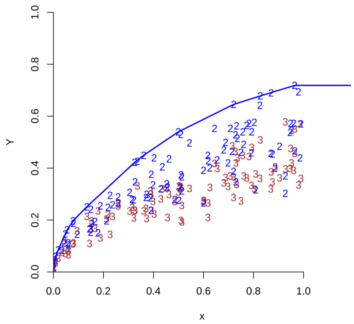
(c) P_3^{FIPS}



(d) P_3^{BIPS}



(e) P_2^{BIPS}



(f) P_1^{BIPS}

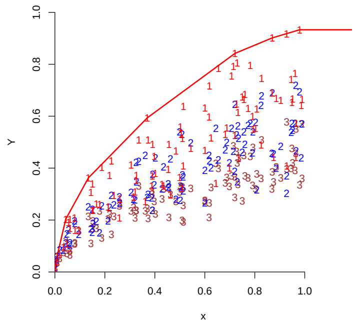


Figure 4: Distribution of efficiency scores (case 1)

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

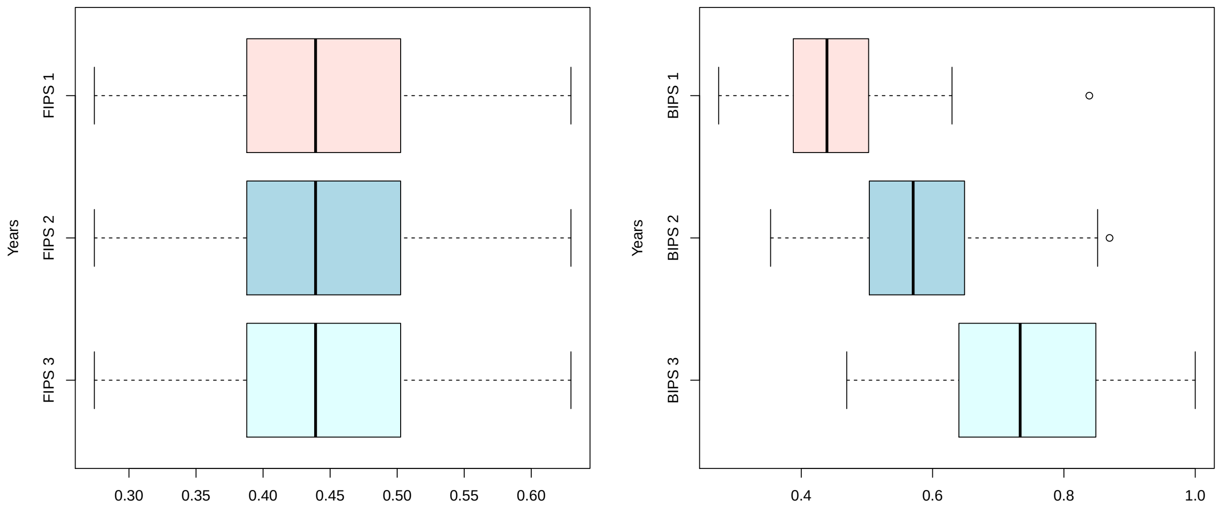


Figure 5: True frontiers (case 2)

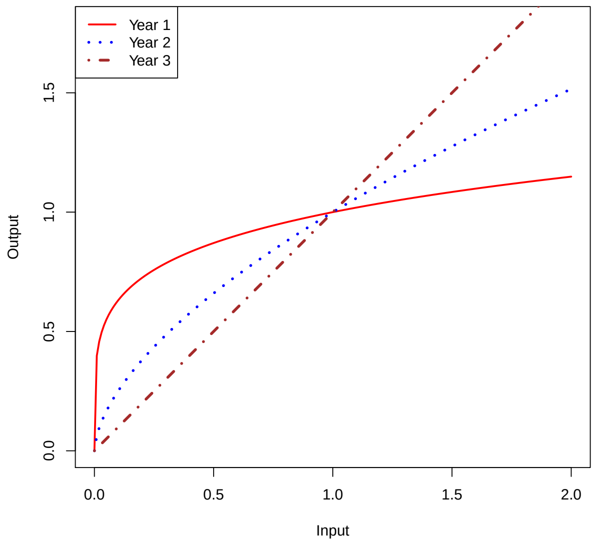
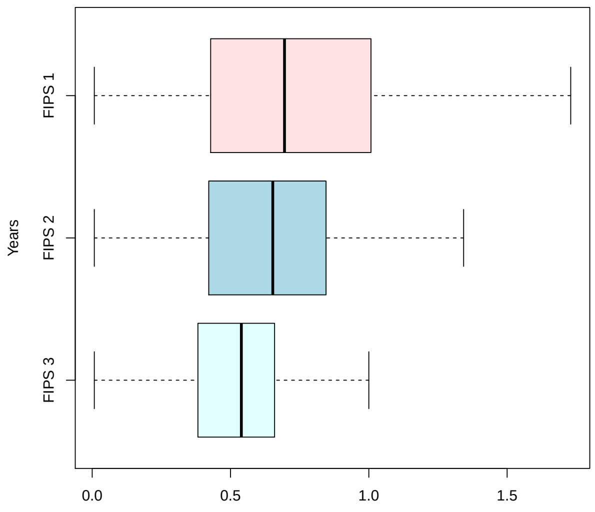


Figure 6: Distribution of efficiency scores (case 2)

(a) on FIPS frontiers



(b) on BIPS frontiers

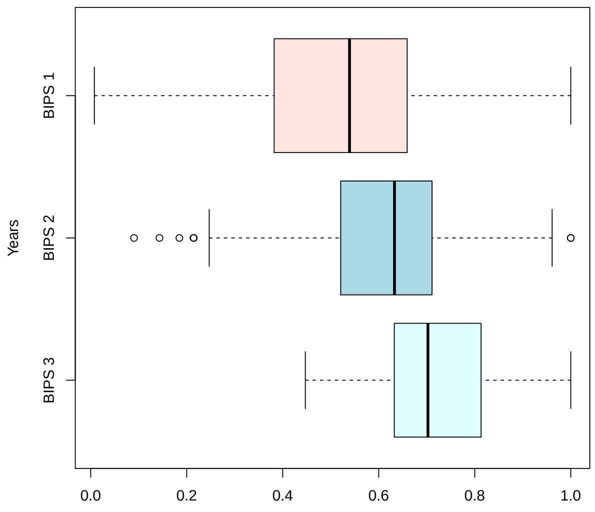


Figure 7: Distributions of efficiency scores in the poultry industry

(a) Efficiency scores based on FIPS frontiers (b) Efficiency scores based on BIPS frontiers

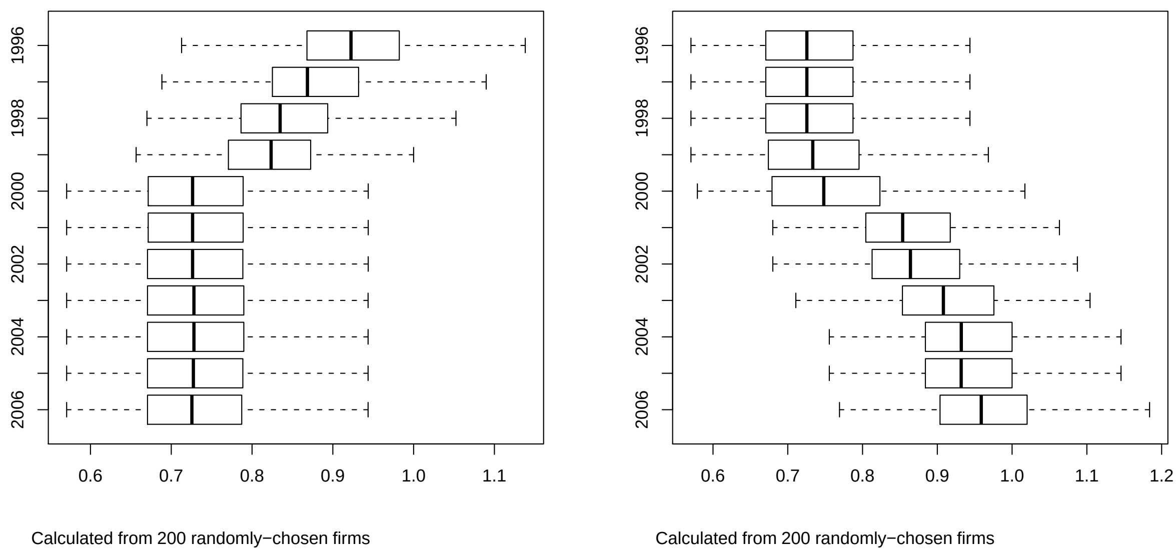
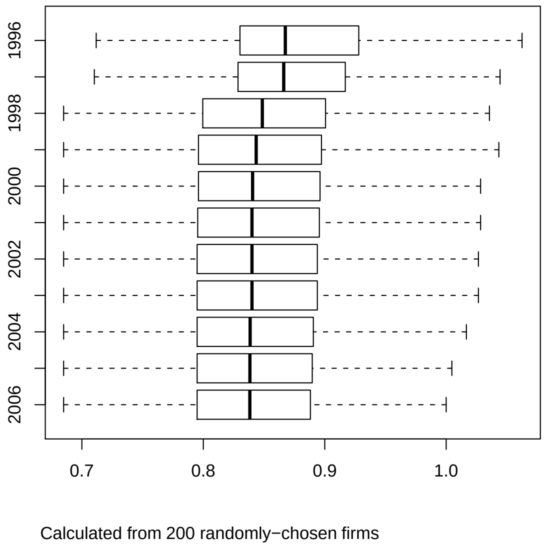


Figure 8: Distributions of efficiency scores in the cheese industry

(a) Efficiency scores based on FIPS frontiers



(b) Efficiency scores based on BIPS frontiers

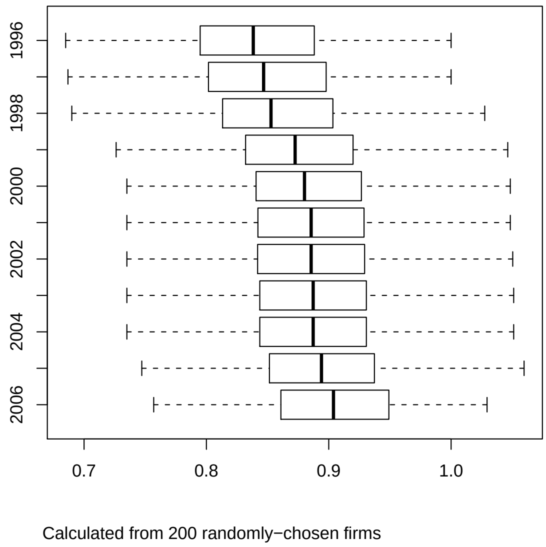


Table 1: Poultry industry

	1996, (N=180)			2006, (N=151)		
Variable	Mean	Std dev	Max	Mean	Std dev	Max
Y	26,153	57,616	405,249	33,854	66,402	486,890
Y/K	6.63	6.56	53.95	8.27	31.28	342.03
Y/L	334.39	1,673.36	19,524.89	239.82	436.42	4,585.55
Y/M	1.41	0.34	3.14	1.38	0.37	2.90

Table 2: Decomposition of the Färe-Primont index of TFP (poultry industry)

Year 1	Year 2	No. observations	TFP	dTech	dOTE	dRES
1996	2000	137	1.04	1.16	0.94	0.97
2000	2006	119	0.95	0.87	0.99	1.12
1996	2006	106	0.95	0.97	1.00	0.99

Table 3: Distribution of the technological change per firm (poultry industry)

Year 1	Year 2	Min	First Quartile	Median	Third Quartile	Max
1996	2000	1.02	1.18	1.27	1.32	1.49
2000	2006	0.65	0.74	0.79	0.87	1.23
1996	2006	0.88	0.94	0.97	0.99	1.23

Table 4: Main changes in the safety regulation from 1996 to 2006 (poultry industry)

Policy Decision	Date	Reference
Ban of the use of meat and bone flour for animal feed	Nov 2000	Ordinance on animal feed 14 Nov 2000
Progressive ban of antibiotics	Dec 1998	Council regulation (EC) No 2821/98
General principles and requirements of food law and procedures in matters of food safety	Jan 2002	Regulation (EC) No 178/2002
Measures for protection against zoonoses to prevent outbreaks of food borne infections	1992 - 2003	Directive 92/117/EEC Regulation CE 2160/2003 Directive 2003/99/CE

Table 5: Cheese industry

	1996, (N=196)			2006, (N=182)		
Variable	Mean	Std dev	Max	Mean	Std dev	Max
Y	40,535	93,583	804,976	50,135	112,714	1,000,530
Y/K	16.49	165.28	2,132.41	157.96	1,916.66	23,943.33
Y/L	279.23	200.94	1,474.07	463.83	1426.4	18,051
Y/M	1.35	0.24	3.00	1.26	0.23	2.88

Table 6: Decomposition of the Färe-Primont index of TFP (cheese industry)

Year 1	Year 2	No. observations	TFP	dTech	dOTE	dRES
1996	1998	171	0.99	1.01	1.02	0.97
1998	2006	125	0.97	0.98	1.01	0.99
1996	2006	116	0.95	0.98	1.01	0.97

Table 7: Distribution of technological change per firm (cheese industry)

Year 1	Year 2	Min	First Quartile	Median	Third Quartile	Max
1996	1998	0.85	0.97	0.99	1.01	1.26
1998	2006	0.85	0.94	0.97	0.99	2.16
1996	2006	0.70	0.93	0.95	0.98	2.33

Appendix A1: Li (1996)'s test

This test has frequently been implemented to test equality between income distributions across regions, groups, or time periods. It works with either independent or dependent variables, and its finite sample properties when testing equalities of distributions of efficiency scores have recently been 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 type-I errors (incorrectly reject the true null hypothesis) and type-II errors (failing to reject the incorrect null hypothesis) more often than they would under the (unrealistic) situation that the true efficiency scores were 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 is 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.

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:

$$I = \int (f_A(u) - f_Z(u))^2 \, du \tag{4}$$

which can be written as

$$I = \int f_A(u)dF_A(u) + \int f_Z(u)dF_Z(u) - \int f_A(u)dF_Z(u) - \int f_Z(u)dF_A(u) \tag{5}$$

The Li's test statistic is obtained by replacing the unknown distribution functions $F_A(.)$ and $F_Z(.)$ in equation (5) with their corresponding empirical distribution functions, and the unknown densities with their nonparametric (leave-one-out) kernel estimators. We have:

$$\begin{aligned}\widehat{I}_{n_A,n_Z,h} = \quad & \tfrac{1}{hn_A(n_A-1)} \textstyle\sum_{j=1}^{n_A} \sum_{k\neq j,k=1}^{n_A} K\left(\tfrac{u_j^A - u_k^A}{h}\right) \\ & + \tfrac{1}{hn_Z(n_Z-1)} \textstyle\sum_{j=1}^{n_Z} \sum_{k\neq j,k=1}^{n_Z} K\left(\tfrac{u_j^Z - u_k^Z}{h}\right) \\ & - \tfrac{1}{hn_A(n_Z-1)} \textstyle\sum_{j=1}^{n_Z} \sum_{k\neq j,k=1}^{n_A} K\left(\tfrac{u_j^Z - u_k^A}{h}\right) \\ & - \tfrac{1}{hn_Z(n_A-1)} \textstyle\sum_{j=1}^{n_A} \sum_{k\neq j,k=1}^{n_Z} K\left(\tfrac{u_j^A - u_k^Z}{h}\right) \end{aligned} \tag{6}$$

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 (6) 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 provide 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 (refer to **?**, for more details on how we built the series). Labor (L) is the yearly average 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 8: Nonparametric test for equality of distributions, Li (1996)

(The upper diagonal reports the P-values associated with 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	.	.	.	0.52	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	1.00	1.00	1.00	1.00	1.00
2001	.	.	.	.	.	.	1.00	1.00	1.00	1.00	1.00
2002	.	.	.	.	.	.	.	1.00	1.00	1.00	1.00
2003	.	.	.	.	.	.	.	.	1.00	1.00	1.00
2004	.	.	.	.	.	.	.	.	.	1.00	1.00
2005	.	.	.	.	.	.	.	.	.	.	1.00

Using **BIPS** frontiers

	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
1996	.	1.00	1.00	1.00	0.68	0.00	0.00	0.00	0.00	0.00	0.00
1997	.	.	1.00	1.00	0.68	0.00	0.00	0.00	0.00	0.00	0.00
1998	.	.	.	1.00	0.69	0.00	0.00	0.00	0.00	0.00	0.00
1999	.	.	.	.	0.96	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	.	.	.	.	.	.	0.13	0.02	0.00	0.00	0.00
2002	.	.	.	.	.	.	.	0.80	0.06	0.03	0.66
2003	.	.	.	.	.	.	.	.	0.06	0.04	0.95
2004	.	.	.	.	.	.	.	.	.	0.96	0.92
2005	.	.	.	.	.	.	.	.	.	.	0.90

Cheese industry

Table 9: Nonparametric test for equality of distributions, Li (1996)

(The upper diagonal reports the P-values associated with 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	.	0.95	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1997	.	.	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1998	.	.	.	0.95	0.91	0.84	0.79	0.79	0.60	0.55	0.45
1999	.	.	.	.	1.00	1.00	1.00	1.00	0.98	0.95	0.89
2000	.	.	.	.	.	1.00	1.00	1.00	1.00	0.99	0.96
2001	.	.	.	.	.	.	1.00	1.00	1.00	0.99	0.97
2002	.	.	.	.	.	.	.	1.00	1.00	1.00	0.99
2003	.	.	.	.	.	.	.	.	1.00	1.00	0.99
2004	.	.	.	.	.	.	.	.	.	1.00	1.00
2005	.	.	.	.	.	.	.	.	.	.	1.00

Using **BIPS** frontiers

	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
1996	.	0.42	0.05	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1997	.	.	0.70	0.25	0.04	0.02	0.01	0.01	0.01	0.00	0.00
1998	.	.	.	0.53	0.18	0.10	0.10	0.09	0.09	0.01	0.00
1999	.	.	.	.	0.22	0.07	0.07	0.05	0.05	0.00	0.00
2000	.	.	.	.	.	0.87	0.59	0.52	0.49	0.19	0.00
2001	.	.	.	.	.	.	0.81	0.80	0.77	0.44	0.00
2002	.	.	.	.	.	.	.	0.99	0.99	0.48	0.01
2003	.	.	.	.	.	.	.	.	0.99	0.58	0.03
2004	.	.	.	.	.	.	.	.	.	0.59	0.03
2005	.	.	.	.	.	.	.	.	.	.	0.29