Technical Change *vs* Efficiency Change: How do Food Industries Evolve Over Time?

Christophe Bontemps[(1)], Céline Nauges[(2)], Vincent Réquillart[(3)] & Michel Simioni[(3)]

(1) Toulouse School of Economics, INRA-GREMAQ
(2) Toulouse School of Economics, INRA-LERNA
(3) Toulouse School of Economics, INRA-GREMAQ and IDEI

21, Allées de Brienne, 31000 Toulouse, France

Paper prepared for presentation at the EAAE 2011 Congress
Change and Uncertainty
Challenges for Agriculture,
Food and Natural Resources

August 30 to September 2, 2011
ETH Zurich, Zurich, Switzerland

Technical Change vs Efficiency Change:
How do Food Industries Evolve Over Time?

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 value added in the French industry and 1.7% of the Gross Domestic Product (GDP). 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 panel data of French firms from the food-processing industry and found that productivity has decreased over the last two decades. 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 the 1996-2006 period. 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 enterprises. Second this period has witnessed a number of food scares following outbreaks of BSE (mad-cow disease), dioxin-contaminated chicken, listeria and salmonella contamination, etc. These raised consumers' concern and induced a reinforcement of food safety regulations.

Because more stringent regulations may have, in some cases, shrunk the set of firms' production possibilities, we propose an original methodology in order to identify technical change using panel data and allowing for both technical progress and technical regress. 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 technical change in all sub-periods between 1996 and 2006. Once periods in which technical change occurred have been identified, we calculate the contribution of technical change and efficiency change in total factor productivity. 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 find 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 discuss the role of production possibilities set in the measurement of technical change using panel data. We also 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

2.1 Production possibilities set

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

$$\begin{aligned}
MI &= \text{Pure efficiency change} \times \text{Change in the scale efficiency} \\
&\times \ \text{Pure change in technology} \\
&\times \ \text{Change in the scale of the technology} \\
&= \left(\frac{D_{\mathbf{c}}^{VRS}(x_{\mathbf{c}},y_{\mathbf{c}})}{D_{\mathbf{b}}^{VRS}(x_{\mathbf{b}},y_{\mathbf{b}})}\right) \times \left(\frac{D_{\mathbf{c}}^{CRS}(x_{\mathbf{c}},y_{\mathbf{c}}) \;/\; D_{\mathbf{c}}^{VRS}(x_{\mathbf{c}},y_{\mathbf{c}})}{D_{\mathbf{b}}^{CRS}(x_{\mathbf{b}},y_{\mathbf{b}}) \;/\; D_{\mathbf{b}}^{VRS}(x_{\mathbf{b}},y_{\mathbf{b}})}\right) \\
&\times \left(\frac{D_{\mathbf{b}}^{VRS}(x_{\mathbf{c}},y_{\mathbf{c}})}{D_{\mathbf{c}}^{VRS}(x_{\mathbf{c}},y_{\mathbf{c}})} \times \frac{D_{\mathbf{b}}^{VRS}(x_{\mathbf{b}},y_{\mathbf{b}})}{D_{\mathbf{c}}^{VRS}(x_{\mathbf{b}},y_{\mathbf{b}})}\right)^{0.5} \\
&\times \left(\frac{D_{\mathbf{b}}^{CRS}(x_{\mathbf{c}},y_{\mathbf{c}}) \;/\; D_{\mathbf{b}}^{VRS}(x_{\mathbf{c}},y_{\mathbf{c}})}{D_{\mathbf{c}}^{CRS}(x_{\mathbf{c}},y_{\mathbf{c}}) \;/\; D_{\mathbf{c}}^{VRS}(x_{\mathbf{c}},y_{\mathbf{c}})} \times \frac{D_{\mathbf{b}}^{CRS}(x_{\mathbf{b}},y_{\mathbf{b}}) \;/\; D_{\mathbf{b}}^{VRS}(x_{\mathbf{b}},y_{\mathbf{b}})}{D_{\mathbf{c}}^{CRS}(x_{\mathbf{b}},y_{\mathbf{b}}) \;/\; D_{\mathbf{c}}^{VRS}(x_{\mathbf{b}},y_{\mathbf{b}})}\right)^{0.5}
\end{aligned}$$

where $D_t^s(x,y) = \min\{\theta |\ (x, y/\theta) \in \mathbf{Production\ set}\}$, with $x \in R_+^p$ (inputs) and $y \in R_+^q$ (outputs), is the distance function at time t. Superscrit 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-orientated 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).[1]

A contentious issue is the choice of the production set or reference technology. Three main types of production sets can be considered (Tulkens and Van den Eeckaut, 1995):

1. Contemporaneous production set:

$$\left\{(x, y) \mid y \leq \sum_i z_{ic} Y_{ic},\ x \geq \sum_i z_{ic} X_{ic},\ \text{all } z_{ic} \geq 0\right\}.$$

   Contemporaneous production sets are production sets that are constructed at each point in time, from the observations at that time only. There are as many production sets as there are periods of observations, and contemporaneous production sets are not related one to each other.

2. Sequential production set *à la* Diewert (Diewert, 1980):

$$\left\{(x, y) \mid y \leq \sum_{\tau=b}^{c} \sum_i z_{i\tau} Y_{i\tau},\ x \geq \sum_{\tau=b}^{c} \sum_i z_{i\tau} X_{i\tau},\ \text{all } z_{i\tau} \geq 0\right\}.$$

   A sequential production set at each point in time is constructed from the observations made from the base period (usually the first period of observation) up until the contemporaneous period. In this case, successive sequential production sets are nested into one another.

The measurement of firms' performance (efficiency, technical change) depends crucially on the choice of the production set. By considering contemporaneous production sets, production sets at different points in time are assumed to be completely unrelated. Production sets 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. Under sequential production sets, the production possibilities frontier expands 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'.

Because the choice of the production set has implications on the measurement of technical change, we develop an iterative testing procedure for detecting technical regress and technical

[1] 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.

progress on a panel data of firms over $t = 0, ..., T$ where $T \equiv c - b$. Our testing procedure is based on the comparison of the distribution of efficiency scores for firms in the latest period of observation (2006 in our case), computed from two sets of sequential production possibilities:

1. The Forward Increasing Production Set (FIPS):

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

   The FIPS in year t is constructed from the observations in the base period (b) up until period t. First, efficiency scores of firms in 2006 are obtained from the frontier based on observations in 1996 (called the 1996 FIPS), then efficiency scores of the same firms are obtained from the frontier based on observations in 1996 and in 1997 (called the 1997 FIPS), and so on until the 2006 FIPS.

2. And the Backward Increasing Production Set (BIPS)

$$T_t^{BIPS} = \left\{ (x, y) \mid\ y \leq \sum_{\tau=c-t}^{c} \sum_i z_{i\tau} Y_{i\tau},\ x \geq \sum_{\tau=c-t}^{c} \sum_i z_{i\tau} X_{i\tau},\ \text{all } z_{i\tau} \geq 0 \right\}.$$

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

We construct as many FIPS and BIPS as they are time periods covered by the data. The test of no technical change versus technical progress between periods t and t' (consecutive periods or not) corresponds to the test of the equality of the distributions of efficiency scores for firms in the latest period of observation (2006 in our sample), 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 the equality of the distributions of efficiency scores for firms in the latest period of observation (2006 in our sample), 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. Formally, we will use a (bootstrapped) test of equality of densities (Li et al., 2009). The "graphical" identification of technical regress and technical progress is discussed in the next paragraph using a simple simulation exercise.

2.2 How to identify "technical regress"? A simulation exercise.

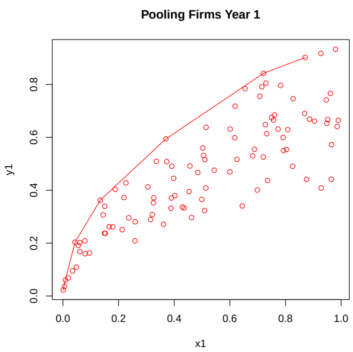
We start by generating a dataset of $N = 100$ single-input single-output firms over three years from the following equation:

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

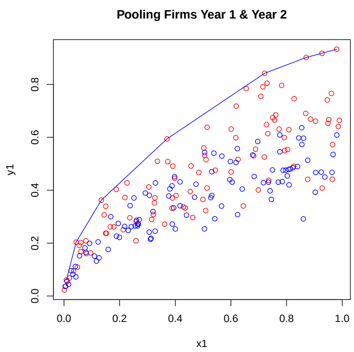
with $x_t \sim U[0,1]$ and $u_t \sim \mathcal{N}^+(0.2, 0.25)$. This procedure generates sets of data for year 1, year 2, and year 3, and incorporates an assumption of technical regress. For each year, the corresponding frontier has been obtained using DEA as shown on Figure 1. The FIPS frontier does not change over time, which is as expected since we simulated technical regress (and technical progress only can be identified by looking at the dynamics of FIPS frontiers). On the contrary, the BIPS frontier is moving over time.

Figure 1: **Forward** (FIPS) & **Backward** (BIPS) Increasing Production Sets and DEA frontiers

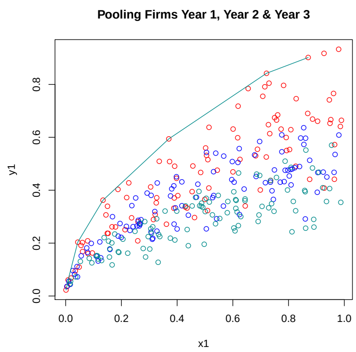
(a) DEA on FIPS ($Y1$)



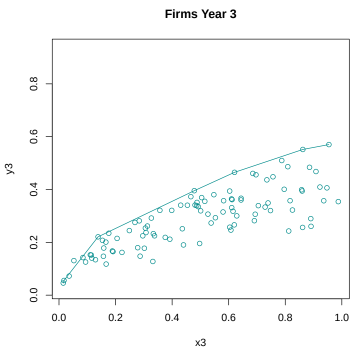
(b) DEA on FIPS ($Y1 \cup Y2$)



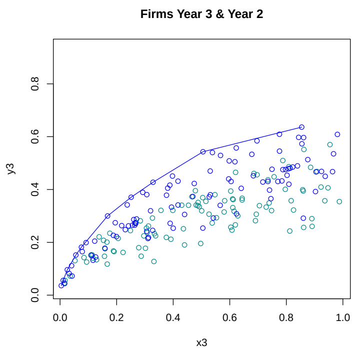
(c) DEA on FIPS ($Y1 \cup Y2 \cup Y3$)



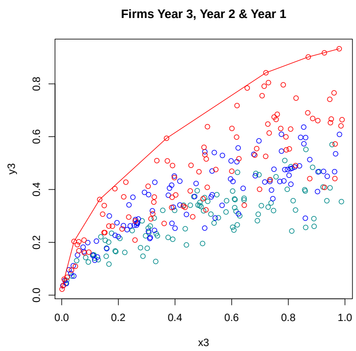
(d) DEA on BIPS ($Y3$)



(e) DEA on BIPS ($Y3 \cup Y2$)



(f) DEA on BIPS ($Y3 \cup Y2 \cup Y1$)



Next we compare the distribution of DEA-based efficiency scores (Figure 2) when:

1. efficiency scores are computed each year on the basis of the contemporaneous frontier (Figure 2a);
2. efficiency scores of firms in year 3 are computed on the basis of FIPS frontiers (Figure 2b);
3. efficiency scores of firms in year 3 are computed on the basis of BIPS frontiers (Figure 2c).

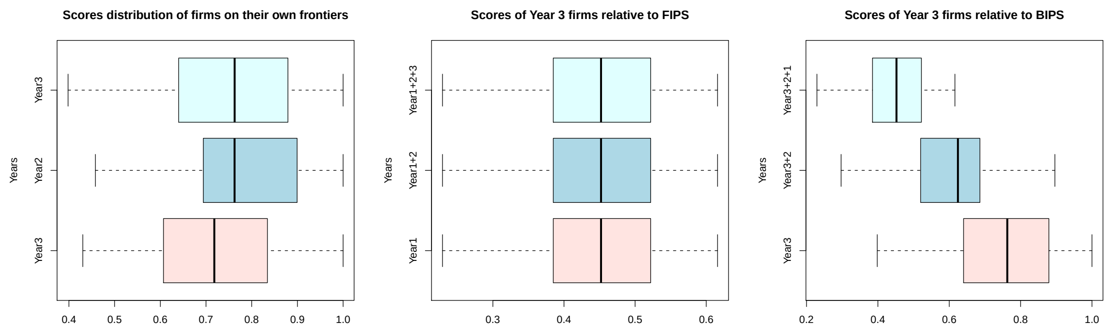
The time pattern of the distribution of efficiency scores is very different in the three cases. With contemporaneous frontiers no clear pattern appears. When considering FIPS, the distribution of efficiency scores does not change over time which indicates that there was no technical progress

Figure 2: Distribution of DEA based efficiency scores

(a) of firms each year on their contemporaneous frontiers

(b) of firms in Year 3 on FIPS frontiers

(c) of firms in Year 3 on BIPS frontiers



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 symmetric pattern of FIPS and BIPS efficiency distributions.

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 gather 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 are converted in quantity indices using appropriate price indices obtained from the French Statistical Institute (INSEE). We consider the value of production excluding trade activities. Raw materials expenditure are net of stock variation. Finally, the stock of capital is estimated at constant prices rather than historical prices and the quantity of labor is adjusted for quality.

We propose an in-depth analysis of the poultry industry and the cheese industry 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). For each sub-sector we first apply procedures to detect outliers.[2] We then use DEA to estimate the sets of FIPS and BIPS frontiers and corresponding efficiency scores for all firms 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

[2]We identify outliers on the basis of their average productivity Y/X with X an aggregate quantity index of inputs. 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).

Table 1: Poultry industry in 2006

Variable	mean	std dev	min	1st quart.	3rd quart.	max	N
Y	20657	24246	858	5354	25380	128556	151
Y/K	11.26	39.88	0.35	1.98	5.86	342.03	151
Y/L	225.47	421.96	27.68	111.63	199.86	4585.55	151
Y/M	1.69	2.56	0.96	1.20	1.41	31.32	151

change between all time periods by testing the equality of the distribution of efficiency scores using a (bootstrapped) test of equality of densities (Li et al., 2009).[3]

3.1 Poultry industry

This industry represents about 5% of the food industry (based on total sales). In 2006, there were 151 firms which are very heterogenous in size (Table 1). The ratio of production over raw materials is rather homogenous as this ratio is in the range [1.20 - 1.41] for 50% of the firms. Partial productivity of labor and capital is more variable. The average efficiency score for firms in 2006 is 0.91 and most firms have an efficiency score larger than 0.88 meaning that the performances are not too heterogenous (see Table 2) even when the small subset of firms with very high level of partial productivity of labor or capital is included.

Table 2: Distribution of technical efficiency scores in 2006 (poultry industry)

year	mean	std dev	min	1st quart.	median	3rd quart.
2006	0.91	0.071	0.60	0.88	0.92	0.97

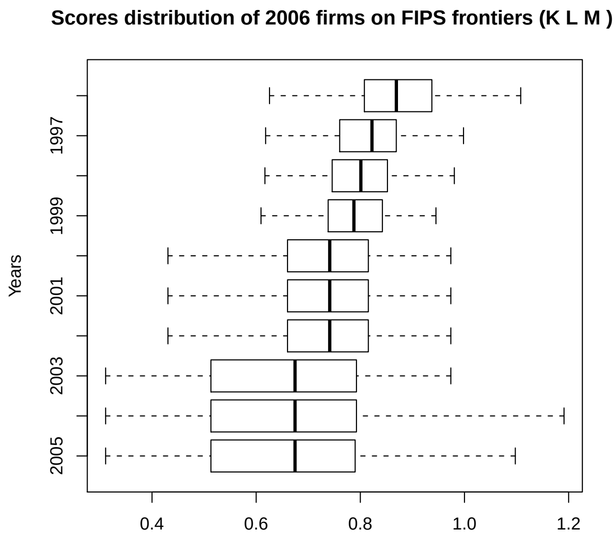
Technical change can be analysed from the graphs showing the distribution of efficiency scores based on the sequential FIPS and BIPS (Figure 3) but formal testing is needed to assess significant technical progress or technical regress. The graphs and tests comparing all pairs of distributions indicate that, over the 1996-2006 period, this industry has experienced a period of technical progress (from 1996 to 2003) followed by a period of technical regress (2004-2005). More precisely our testing procedure indicates that significant technical progress has occurred in 1997, 2000 and 2003 while the poultry industry experienced significant technical regress at the end of the period (2004-2005).[4]

As we detected two main periods for technical change (technical progress up to 2003 and technical regress then), we compute the Malmquist index over 1996-2002 and 2004-2006 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 3.[5]

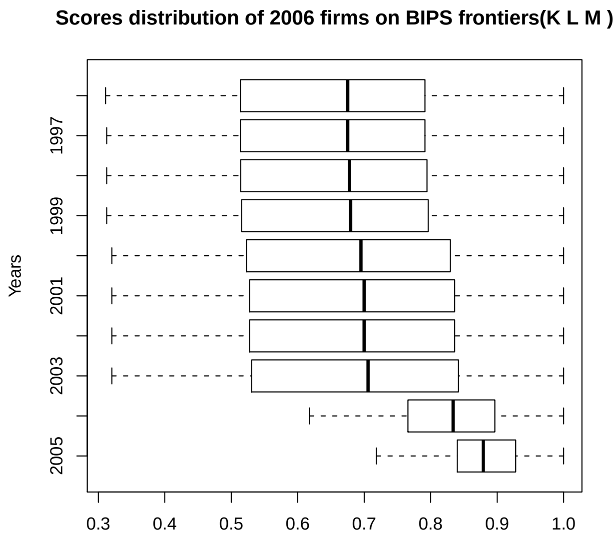
[3]Implemented using R-packages FEAR Wilson (2008) and NP Hayfield and Racine (2008).
[4]Results of tests are not shown due to paper length limitation.
[5]We exclude 2003 because of some data problems still unresolved for that particular year.

Figure 3: Evolution of efficiency scores in the poultry industry

(a) Firms in 2006 on FIPS frontiers



(b) Firms in 2006 on BIPS frontiers



The Malmquist index (MI) indicates that productivity has remained constant over the 1996-2002 years, while it has increased by 5% on average over the 2004-2006 years. There is no evidence of (pure) technical change (Δ Tech. $= 1$) between 1996 and 2002, while negative technical change between 2004 and 2006 is confirmed. The productivity increase at the end of the period is due to an increase in pure efficiency (+11%) and scale efficiency (+5%).

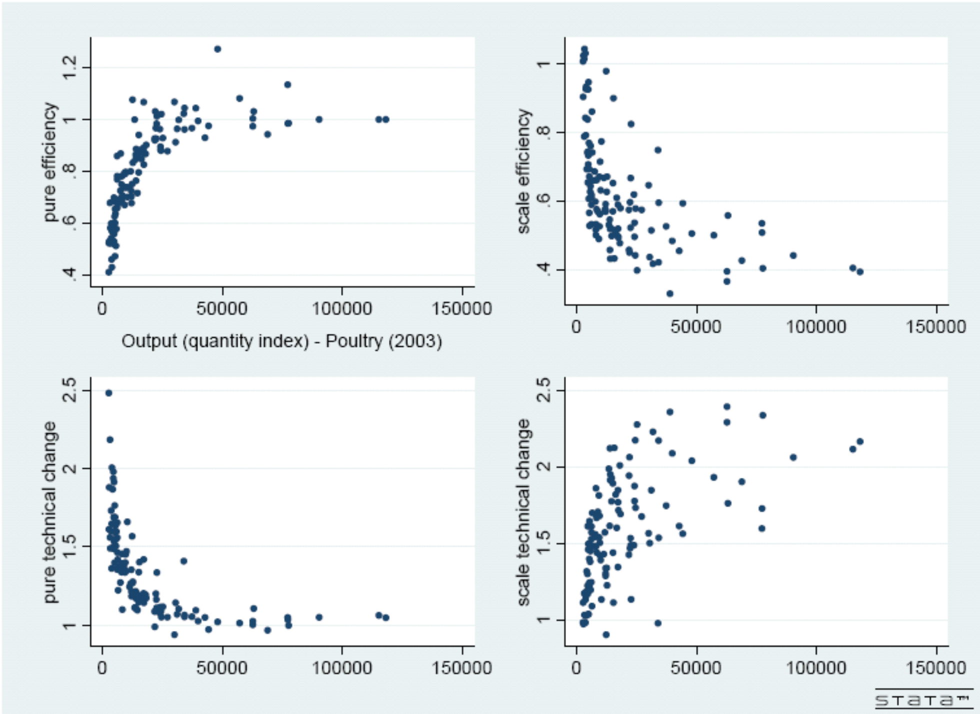
Table 3: Decomposition of the Malmquist index (MI) (poultry industry)

Year 1	Year 2	MI	Δ Pure Eff.	Δ Scale Eff.	Δ Tech.	Δ Scale Tech.
1996	2006	0.95	1.03	1.01	0.96	0.96
1996	2002	1.00	1.02	1.00	1.00	0.98
2004	2006	1.05	1.11	1.05	0.95	0.96

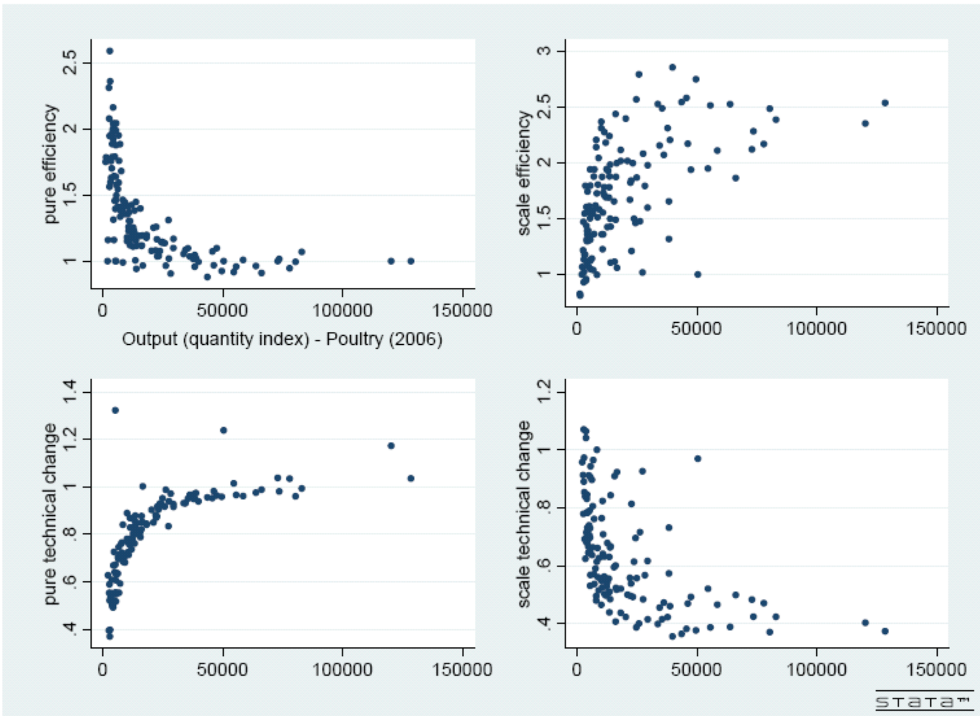
The drivers of productivity change are quite different for small and large firms (see Figures 4 and for the 1996-2003 and 2003-2006 periods respectively). Small firms experienced greater negative change in pure efficiency while technical efficiency of large firms was maintained in most cases over the first sub-period (Figure 4a). Most firms experienced negative change in scale efficiency, the strongest effects being observed for large firms. The (pure) technical change had a stronger (positive) impact on small firms while change in scale technology mostly benefited large firms. The patterns are reversed on the second sub-period (Figure 4b).

Figure 4: Productivity decomposition for the 1996-2002 and 2004-2006 periods

(a) Pure & scale efficiency, pure & scale technical change *vs* firm size (period 1996-2002)



(b) Pure & scale efficiency, pure & scale technical change *vs* firm size (period 2004-2006)



3.2 Cheese industry

This industry represents about 8% of the food industry (based on total sales). The 189 firms observed in 2006 are heterogenous in size (Table 4). As for the poultry industry, the ratio of output over raw materials is rather homogeneous as 50% of the values are in the range 1.16 to 1.34. Partial productivity of labor and capital is more variable than in the poultry industry. Compared to the chicken meat industry, partial productivity of labor is higher while partial productivity of capital and raw materials is lower. The average efficiency score of firms in 2006 is 0.88 in average and three-fourth of these firms have an efficiency score larger than 0.80 meaning that the performances are not too heterogenous. The average efficiency score is lower in average than the average efficiency score measured in the poultry industry.

Table 4: Cheese Industry in 2006

Variable	**mean**	**std dev**	**min**	**1st quart.**	**3rd quart.**	**max**	**N**
Y	48710	110841	223	6693	45032	1.00e+06	189
Y/K	151.33	1875.05	0.07	1.34	4.29	23943.32	163
Y/L	457.99	1400.64	9.29	176.91	357.88	18051.00	189
Y/M	1.28	0.23	0.57	1.16	1.34	2.88	189

On Figure 5, the distribution of efficiency scores for firms in 2006 based on the FIPS frontiers remains almost constant. The tests confirm that the equality between all pairs of distributions cannot be rejected and hence that there was no technical progress over the entire study period.

Table 5: Distribution of technical efficiency scores in 2006 (cheese industry)

year	**mean**	**std dev**	**min**	**1st quart.**	**median**	**3rd quart.**
2006	0.88	0.099	0.36	0.80	0.88	0.97

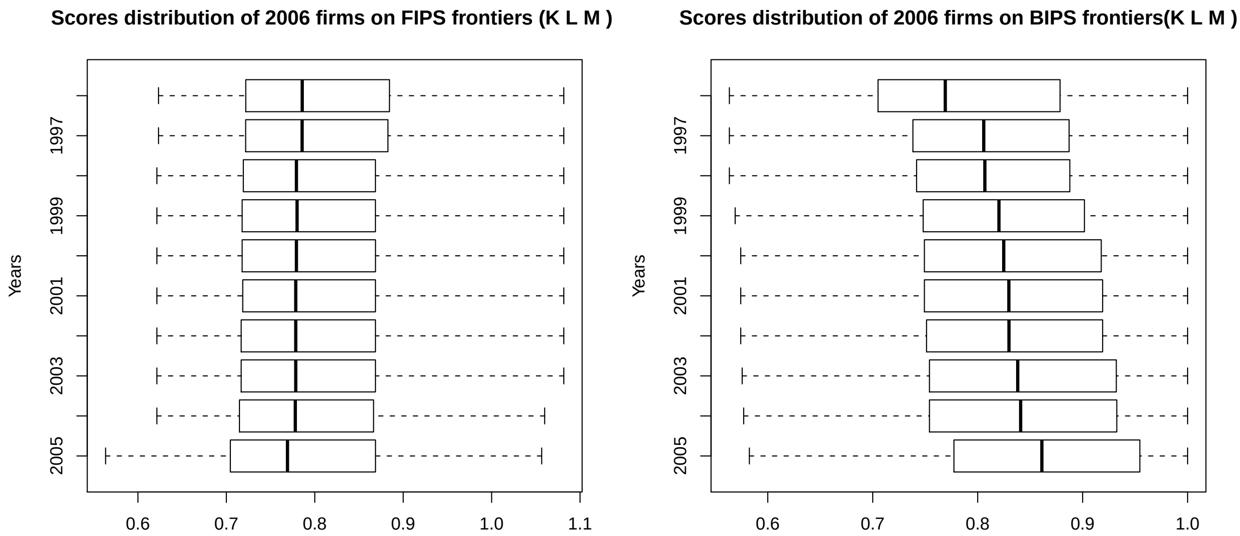
The analysis of the BIPS frontiers and formal tests indicate the presence of technical regress at the beginning of the period (1997) and non-significant technical change in subsequent years (see Figure 4). This is confirmed by computing the Malmquist index over the period (Table 6). The figures indicate 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, environmental), has been accompanied by a reduction in the inefficiency of firms.

Table 6: 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	2006	0.96	1.05	0.96	0.93	1.02

Figure 5: Evolution of efficiency scores in the Cheese industry

(a) Firms in 2006 on FIPS frontiers (b) Firms in 2006 on BIPS frontiers



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 2003 followed by a period of technical regress from 2003 to 2006. Technical regress might be a consequence of higher constraints exerted on the industry such as stricter environmental or sanitary regulations that might have increased the cost of production over time. 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.

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.

References

Bontemps, C., Maigné, E., Réquillart, V., 2011. La productivité de l'agro-alimentaire français de 1996 à 2006. Economie et prévision. Forthcoming.

Buccola, S., Fujii, Y., Xia, Y., 2000. Size and productivity in the u.s. milling and baking industries. American Journal of Agricultural Economics 82(4), 865–880.

Chaaban, J., Réquillart, V., Trévisiol, A., 2005. The role of technical efficiency in takeovers: Evidence from the french cheese industry, 1985-2000. Agribusiness 21 (4), 545 – 564.

Cooper, W. W., Seiford, L., Tone, K., 2007. Data envelopment analysis: A comprehensive text with models, applications, references and DEA-solver software. Springer.

Diewert, W. E., 1980. Aggregation problems in the measurement of capital. In: The Measurement of Capital. NBER Chapters. National Bureau of Economic Research, Inc, pp. 433–538.

Fischer, C., Schornberg, S., 2007. Assessing the competitiveness situation of eu food and drink manufacturing industries: An index-based approach. Agribusiness 23 (4), 473 – 495.

Gopinath, M., 2003. Cross-country differences in technology: the case of the food processing industry. Canadian Journal of Agricultural Economics 51(1), 97–107.

Hayfield, T., Racine, J. S., 7 2008. Nonparametric econometrics: The np package. Journal of Statistical Software 27 (5), 1–32.

Li, Q., Maasoumi, E., Racine, J. S., 2009. A nonparametric test for equality of distributions with mixed categorical and continuous data. Journal of Econometrics 148 (2), 186 – 200.

Morrison, C., Diewert, W. E., 1990. New techniques in the measurement of multifactor productivity. Journal of Productivity Analysis 1 (4), 267 – 285.

Simar, L., Wilson, P., 1998. Productivity growth in industrialized countries. Papers 9810, Catholique de Louvain - Institut de statistique.
URL `http://ideas.repec.org/p/fth/louvis/9810.html`

Tulkens, H., Van den Eeckaut, P., April 1995. Non-frontier measures of efficiency, progress and regress for time series data. International Journal of Production Economics 39 (1-2), 83–97.

Wilson, P. W., July 1993. Detecting outliers in deterministic nonparametric frontier models with multiple outputs. Journal of Business & Economic Statistics 11 (3), 319–23.

Wilson, P. W., December 2008. Fear: A software package for frontier efficiency analysis with r. Socio-Economic Planning Sciences 42 (4), 247–254.