The Impact of the 2008 Economic Crisis on Dynamic Productivity Growth of the Spanish Food Manufacturing Industry. An Impulse Response Analysis.

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Abstract: The paper examines the impact of 2008 economic crisis on the dynamic productivity growth and its components using a firm-level dataset of Spanish meat processing, dairy processing and oils and fats firms. The impulse response analysis by local projections shows that the impact of crisis on dynamic productivity growth varies between sectors with negative and persistent in oils and fats, no significant in meat, and positive and persistent in dairy processing industry. The paper documents further that occurrence of crisis involves increases in dynamic technical change across industries, which are offset by the negative impact of dynamic technical inefficiency change.

Keywords: Data Envelopment Analysis; dynamic Luenberger productivity growth indicator; economic crisis; impulse response analysis; food processing industry.

1. Introduction

In 2008 the economic crisis emerged to challenge the performance of food manufacturing firms. The Spanish food processing sector is no exception. The negative impact of the economic crisis is reflected by the decrease in turnover in the Spanish food processing industry from 2008, which starts recovering after 2010 (Spanish Statistical Office, 2013). The food industry is an important sector for the Spanish economy as it represents 14% of the net sales of industry, 20% of industrial employment and 7.6% of Spanish GDP in 2012. Its importance is also demonstrated by the fact that it is one of the main exporting sectors of Spain. The main subsectors within the food industry by annual net turnover, is meat processing, followed by dairy products, and oils and fats products. Although this industry is viewed as one of the strategic sectors that should help Spanish economy to recover from current crisis, it is also vulnerable to worsening economic conditions and subsequent decrease in demand (Spanish Federation of Food and Beverage Industries, 2010). In particular, the crisis can impact productivity growth of the Spanish food manufacturing firms.

Studies present scattered evidence for the impact of economic crisis on productivity growth, both at the aggregate and firm-level. Financial crises are shown to negatively influence the potential output of OECD countries over the period 1960-2008 (Furceri and Mourougane, 2012) and both short-run and long-run decline of labor productivity in 61 countries over the period 1955-2010 (Oulton and Sebastiá-Barriel, 2013). Cerra and Saxena (2008) document the large output loss following financial and political crises in a set of 190 countries, which is highly persistent. Queralto (2011) concludes that the 1997 Asian crisis results in permanent decline in labor productivity along with a decline in technological innovations following the crisis, while Hughes and Saleheen (2012) find the worsening labor productivity in the UK since the start of 2008 economic crisis. Firm-level analysis of Poczter et al. (2014) concludes that the impact of the Asian financial crisis in 1997 on productivity growth in Indonesia is associated with a decrease during the crisis and continues falling through the post-crisis period. In contrast, Chen and Irarrazabal (2013) find that the Chilean financial crisis in 1982 had a positive impact on productivity growth between 1983 and 1996. In similar vein, Chen (2005) finds that there are productivity enhancements for Taiwan's banks during Asian financial crisis, the majority of which are from technical change, rather than changes in efficiency. Similarly, Park and Weber (2006) find that Korean banking industry experiences productivity growth brought about by technical progress that offsets declines in efficiency during the Asian financial crisis.

Given this background, this study focuses on analyzing the impact of 2008 economic crisis on the productivity growth of Spanish food manufacturing firms, and contributes to the literature in several ways. This is the first study that analyzes the impact of an economic crisis on total factor productivity growth of food manufacturing industry in the European context. Further, unlike most of previous studies on the impact of crisis on productivity which analyzed static productivity measures, this paper advances this literature by using a dynamic framework of productivity growth. By more closely evaluating the impacts of dynamic factor adjustments, we can glean more insight into how food manufacturing firms respond to an economic shock such as the recent crisis, which aspects of their business decision making are impacted more severely by such shocks, and the firms' resiliency to shocks. The dynamic productivity growth is assessed in the paper through dynamic Luenberger productivity indicator (Serra et al., 2011; Oude Lansink et al., 2013), which is decomposed into the contributions of dynamic technical inefficiency change, dynamic scale inefficiency change and dynamic technical change using Data Envelopment Analysis (DEA). The impact of the crisis is analyzed by specifying an impulse response function (IRF) estimated by the local projections method (Jordà, 2005; Teulings and Zubanov, 2014). This method allows for the robust analysis of the impact of economic crisis on productivity growth several years after its occurrence.

The remainder of this paper is organized as follows. Section 2 discusses the methods for computing dynamic Luenberger productivity growth and the impulse responses. This is followed by a presentation of the data in section 3 and the results in section 4. The last section offers concluding comments.

2. Methods

2.1. Computing the dynamic Luenberger indicator and its components

The first step of our empirical strategy concerns the computation of dynamic Luenberger indicator of productivity growth, which is defined through a dynamic directional distance function. The input-oriented dynamic directional distance function with directional vectors for inputs (***g****x*) and investments (***g****I*), $\vec{D}_t^i(\mathbf{y}_t,\mathbf{k}_t,\mathbf{x}_t,\mathbf{I}_t;\mathbf{g}_x,\mathbf{g}_I)$ is defined as follows:

$$\begin{aligned}\vec{D}_t^i(\mathbf{y}_t,\mathbf{k}_t,\mathbf{x}_t,\mathbf{I}_t;\mathbf{g}_x,\mathbf{g}_I) = \max\{\beta\in\Re : (\mathbf{x}_t-\beta\mathbf{g}_x,\mathbf{I}_t+\beta\mathbf{g}_I)\in V_t(\mathbf{y}_t:\mathbf{k}_t)\},\\ \mathbf{g}_x\in\Re^N_{++},\ \mathbf{g}_I\in\Re^F_{++},(\mathbf{g}_x,\mathbf{g}_I)\neq(\mathbf{0}^N,\mathbf{0}^F)\end{aligned} \quad \mathbf{(1)}$$

if $(\mathbf{x}_t-\beta\mathbf{g}_x,\mathbf{I}+\beta\mathbf{g}_I)\in V_t(\mathbf{y}_t:\mathbf{k}_t)$ for some β, $\vec{D}_t^i(\mathbf{y}_t,\mathbf{k}_t,\mathbf{x}_t,\mathbf{I}_t;\mathbf{g}_x,\mathbf{g}_I)=-\infty$, otherwise. This distance function is a measure of the maximal translation of $(\mathbf{x}_t,\mathbf{I}_t)$ in the direction defined by the vector $(\mathbf{g}_x,\mathbf{g}_I)$, that keeps the translated input combination interior to the input requirement set $V_t(\mathbf{y}_t:\mathbf{k}_t)$. The input requirement set is defined for variable inputs ($\mathbf{x}_t$) and quasi-fixed inputs ($\mathbf{k}_t$) that produce outputs ($\mathbf{y}_t$) and formally can be represented as $V_t(\mathbf{y}_t:\mathbf{k}_t)=\{(\mathbf{x}_t,\mathbf{I}_t)$ can produce $\mathbf{y}_t$, given $\mathbf{k}_t\}$, where $\mathbf{I}_t$ are gross investments in quasi-fixed inputs (i.e. a dynamic factor). The input requirement set is assumed to have the following properties: $V_t(\mathbf{y}_t:\mathbf{k}_t)$ is a closed and nonempty set, has a lower bound, is positive monotonic in variable inputs $\mathbf{x}_t$, negative monotonic in gross investments $\mathbf{I}_t$, is a strictly convex set, output levels increase with the stock of capital and quasi-fixed inputs and are freely disposable (Silva and Stefanou, 2003). Silva and Oude Lansink (2013) demonstrate that $\vec{D}_t^i(\mathbf{y}_t,\mathbf{k}_t,\mathbf{x}_t,\mathbf{I}_t;\mathbf{g}_x,\mathbf{g}_I)\geq 0$ fully characterizes the input requirement set, $V_t(\mathbf{y}_t:\mathbf{k}_t)$, being thus an alternative primal representation of the adjustment cost production technology. See

Serra et al. (2011), Silva and Oude Lansink (2013) or Kapelko et al. (2014a) for more information regarding dynamic directional distance function.

The dynamic Luenberger indicator of productivity derives from the static indicator defined by Chambers et al. (1996) by using the dynamic directional distance function and is defined as follows (Oude Lansink et al., 2013):

$$L(\cdot) = \frac{1}{2}\left\{\begin{matrix}[\vec{D}^i_{t+1}(\mathbf{y}_t,\mathbf{k}_t,\mathbf{x}_t,\mathbf{I}_t;\mathbf{g}_x,\mathbf{g}_I) - \vec{D}^i_{t+1}(\mathbf{y}_{t+1},\mathbf{k}_{t+1},\mathbf{x}_{t+1},\mathbf{I}_{t+1};\mathbf{g}_x,\mathbf{g}_I)] \\ +[\vec{D}^i_t(\mathbf{y}_t,\mathbf{k}_t,\mathbf{x}_t,\mathbf{I}_t;\mathbf{g}_x,\mathbf{g}_I) - \vec{D}^i_t(\mathbf{y}_{t+1},\mathbf{k}_{t+1},\mathbf{x}_{t+1},\mathbf{I}_{t+1};\mathbf{g}_x,\mathbf{g}_I)]\end{matrix}\right\} \qquad \textbf{(2)}$$

which assumes constant returns to scale (CRS). This indicator provides the arithmetic average of productivity change measured by the technology at time t+1 [i.e., the first two terms in (2)] and the productivity change measured by the technology at time t [i.e., the last two terms in (2)]. The positive (negative) value of the dynamic Luenberger measure indicates growth (decline) in productivity between t and $t+1$.

The Luenberger indicator of dynamic productivity growth can be decomposed into the contributions of dynamic technical change (ΔT), dynamic technical inefficiency change under variable returns to scale (VRS) (ΔTEI) and dynamic scale inefficiency change (ΔSEI) (Kapelko et al., 2014b):

$$L(\cdot) = \Delta T + \Delta TEI + \Delta SEI \qquad \textbf{(3)}$$

Dynamic technical change is computed as the arithmetic average of the difference between the technology (represented by the frontier) at time t and time t+1, evaluated using quantities at time t [first two terms in (4)] and time t+1 [last two terms in (4)]:

$$\Delta T = \frac{1}{2}\left\{\begin{matrix}[\vec{D}^i_{t+1}(\mathbf{y}_t,\mathbf{k}_t,\mathbf{x}_t,\mathbf{I}_t;\mathbf{g}_x,\mathbf{g}_I) - \vec{D}^i_t(\mathbf{y}_t,\mathbf{k}_t,\mathbf{x}_t,\mathbf{I}_t;\mathbf{g}_x,\mathbf{g}_I)] \\ +[\vec{D}^i_{t+1}(\mathbf{y}_{t+1},\mathbf{k}_{t+1},\mathbf{x}_{t+1},\mathbf{I}_{t+1};\mathbf{g}_x,\mathbf{g}_I) - \vec{D}^i_t(\mathbf{y}_{t+1},\mathbf{k}_{t+1},\mathbf{x}_{t+1},\mathbf{I}_{t+1};\mathbf{g}_x,\mathbf{g}_I)]\end{matrix}\right\} \qquad \textbf{(4)}$$

Dynamic technical inefficiency change is the difference between the value of the dynamic directional distance function in VRS at time t and time t+1:

$$\Delta TEI = \vec{D}^i_t(\mathbf{y}_t,\mathbf{k}_t,\mathbf{x}_t,\mathbf{I}_t;\mathbf{g}_x,\mathbf{g}_I \mid VRS) - \vec{D}^i_{t+1}(\mathbf{y}_{t+1},\mathbf{k}_{t+1},\mathbf{x}_{t+1},\mathbf{I}_{t+1};\mathbf{g}_x,\mathbf{g}_I \mid VRS) \qquad \textbf{(5)}$$

Dynamic scale inefficiency change compares the difference between the values of the dynamic directional distance functions in CRS and VRS between time t and time t+1:

$$\begin{aligned}\Delta SEI &= \vec{D}^i_t(\mathbf{y}_t,\mathbf{k}_t,\mathbf{x}_t,\mathbf{I}_t;\mathbf{g}_x,\mathbf{g}_I \mid CRS) - \vec{D}^i_t(\mathbf{y}_t,\mathbf{k}_t,\mathbf{x}_t,\mathbf{I}_t;\mathbf{g}_x,\mathbf{g}_I \mid VRS) \\ &-\left[\vec{D}^i_{t+1}(\mathbf{y}_{t+1},\mathbf{k}_{t+1},\mathbf{x}_{t+1},\mathbf{I}_{t+1};\mathbf{g}_x,\mathbf{g}_I \mid CRS) - \vec{D}^i_{t+1}(\mathbf{y}_{t+1},\mathbf{k}_{t+1},\mathbf{x}_{t+1},\mathbf{I}_{t+1};\mathbf{g}_x,\mathbf{g}_I \mid VRS)\right]\end{aligned} \qquad \textbf{(6)}$$

The dynamic directional distance functions which are used to compute the Luenberger indicator of dynamic productivity growth and it components are estimated using DEA (Charnes et al., 1978; Banker et al., 1984). For example, computing the dynamic directional distance function for time t in VRS technology involves solving the following DEA model :

$$
\begin{aligned}
\vec{D}_t^i(\mathbf{y}_t,\mathbf{k}_t,\mathbf{x}_t,\mathbf{I}_t;\mathbf{g}_x,\mathbf{g}_I \mid VRS) = \max_{\beta,\gamma} \beta & \\
s.t. & \\
\mathbf{y}_{t\,m} \le \sum_{j=1}^{J} \boldsymbol{\gamma}^j \mathbf{y}_{t\,m}^j, \quad m = 1,\dots,M; & \\
\sum_{j=1}^{J} \boldsymbol{\gamma}^j \mathbf{x}_{t\,n}^j \le \mathbf{x}_{t\,n} - \beta \mathbf{g}_{x}, \; n = 1,\dots,N; & \\
\mathbf{I}_{t\,f} + \beta \mathbf{g}_{I} - \delta_f \mathbf{k}_{t\,f} \le \sum_{j=1}^{J} \boldsymbol{\gamma}^j (\mathbf{I}_{t\,f}^j - \delta_f \mathbf{k}_{t\,f}^j), \; f = 1,\dots,F; & \\
\sum_{j=1}^{J} \boldsymbol{\gamma}^j = 1 & \\
\boldsymbol{\gamma}^j \ge 0, \; j = 1,\dots,J. &
\end{aligned}
\qquad \textbf{(7)}
$$

where $\boldsymbol{\gamma}$ is an intensity vector of firm weights, and δ represents depreciation of capital.

2.2. Estimating the impact of economic crisis on dynamic Luenberger indicator and its components

In the second step of our empirical strategy, the impulse responses of dynamic productivity growth and its components to the crisis are estimated by using the local projections method. The impulse responses functions track the responses of a system's variables to impulses of a system's shocks. Formally, the impulse response function of productivity growth (or any of its components) y_t to crisis d_t, k years after its occurrence, is defined as the difference between two forecasts (Jordà, 2005; Teulings and Zubanov, 2014):

$$
\begin{aligned}
\mathrm{IRF}(k) \equiv\; & \mathrm{E}[\,\mathrm{y}_{\mathrm{t+k-1}} \mid d_{t-1} = 1, y_s, d_{s-1}, s > t] \\
& - \mathrm{E}[\,\mathrm{y}_{\mathrm{t+k-1}} \mid d_{t-1} = 0, y_s, d_{s-1}, s > t]
\end{aligned}
\qquad \textbf{(8)}
$$

where the operator E[.|.] indicates the best, mean-squared error predictor. Therefore, calculating impulse responses consists of obtaining the best, mean-squared and multi-step predictions. Until recently the most frequently applied method for calculating impulse responses is to use analytical estimator by applying an autoregressive estimation technique. In this approach impulse responses are calculated recursively by extrapolating into increasingly distant horizons from the assumed data generating process, with parameters that are estimated only once. Impulse responses estimated in this way have been criticized for: 1) being sensitive to misspecifications of the data generating process, 2) its standard errors being complicated to compute as they are highly nonlinear functions of estimated parameters. To circumvent these problems Jordà (2005) proposes the local projection method where the coefficients of impulse responses are estimated directly for each time horizon. Teulings and Zubanov (2014) proposes a correction of the Jordà (2005) method which involves including the shocks' variables occurring between the moment of forecasting at time t and the moment for which the forecast is made at $t+k$ in the regression. The corrected local projection estimating equation (Teulings and Zubanov, 2014) for dynamic productivity growth and each of its components to the crisis has the following form:

$$y_{t+k-1} = \delta_{0k} + \delta^{*}_{0k} t + \sum_{r=1}^{R} \delta_{1rk} y_{t-r} + \sum_{l=1}^{L} \delta_{2lk} d_{t-l} + \sum_{l=1}^{k-1} \gamma_{2l} d_{t+k-1-l} + v^{*}_{tk} \quad \textbf{(9)}$$

where y_t indicates the dynamic productivity growth (or its components) for a firm in year t; d_t is a dummy variable that takes the value 1 for crisis and 0 otherwise; r indicates the number of lags for y_t; l indicates the number of lags for d_t; k is a forecast horizon; δ_0 denotes firm fixed effect; δ^{*}_{0} indicates the time trend common to all firms; and the error term is defined as follows: $v^{*}_{tk} = \sum_{m=1}^{k-1} \gamma_{3m} u_{t+k-1-m} + u_{t+k-1}$. Our empirical approach is slightly simpler since we have only one occurrence of shock variables represented by the 2008 crisis, therefore we do not have the intermediated observations, i.e. crisis happening within the forecast period. Equation (9) does not impose any a priori causal structure on the relationship between crisis and dynamic productivity growth and its components. Following Teulings and Zubanov (2014), we estimate this equation using ordinary least squares (OLS) regression with heteroskedasticity and autocorrelation robust standard errors. It is estimated for each forecast horizon k following the occurrence of the crisis for for dynamic productivity growth and each of its components separately. Therefore, it corresponds to a series of individual OLS regressions.

3. Data

Firm-level data are obtained from the SABI database, managed by Bureau van Dijk, which contains the financial accounts of Spanish companies. The study sample represents three activities of firms: meat processing (NACE Rev. 2 code 10.1), dairy processing (NACE Rev. 2 code 10.5) and oils and fats (NACE Rev. 2 code 10.4). The final data set was obtained through the removal of companies with missing observations and outliers[1] and consists of 18614 observations of meat processing firms, 4491 observations of dairy processing firms and 3530 observations of oils and fats firms for 1996-2012 period (unbalanced panel).

The input-output specification used to compute the dynamic productivity change and its components consists of one output, two variable inputs and one quasi-fixed input. Output is defined as total sales plus the change in the value of the stock and is deflated using the industrial price index for output in the meat processing industry, dairy processing industry and oils and fats, respectively. The two variable inputs are material and labor costs, which are taken directly from the SABI database and are deflated using the industrial price index for consumer non-durables and labor cost index in manufacturing, respectively. Fixed assets are considered a quasi-fixed input, measured as the beginning value of fixed assets from the balance sheet (i.e. the end value of the previous year) and are deflated using the industrial price index for capital goods. The Spanish Statistical Office is the source of all price indices used to deflate output and inputs. The dynamic factor consists of gross investments in fixed assets in year t, which are computed as the beginning value of fixed assets in year $t+1$ minus the value of fixed assets in year t plus the value of depreciation in year t[2]. Table 1 reports the descriptive statistics of the input-output data used in this study, for the whole period 1996/1997-2011/2012 and separately for firms' size groups. These size classes are distinguished based on the EU definition of firms' size, in which the category of micro/small/medium firms is comprised of enterprises employing less than 10/50/250

[1] Outliers were determined using ratios of output to input. An observation was defined as an outlier if the ratio of output over any of the three inputs was outside the interval of the median plus and minus two standard deviations.

[2] In the empirical application, the directional vectors for inputs (g_x) and investments (g_I) are the quantity of variable inputs and 20% of the size of the capital stock, respectively.

employees and which have an annual turnover not exceeding 2/10/50 million euros, respectively; firms with more than 250 employees and an annual turnover exceeding 50 million euros are defined as large (European Commission, 2003). Table 1 indicates the considerable differences between firms as shown by the relatively high values of standard deviations of variables relative to their respective means. The average values of gross investments relative to fixed assets is increasing in firm size for meat and dairy processing firms, and oils and fats firms find relative investment increases with size up to the medium category and then falls for the firms in the large size category. Across all size categories, firms in the oils and fats industry exhibit the highest labor productivity (output to labor ratio), but the lowest material productivity (output to material costs ratio).

Table 1. Descriptive statistics of the data of the Spanish meat processing, dairy processing and oils and fats industries, 1996-2012 (1000 Euro of 1995).

Variable	Meat processing industry	Dairy processing industry	Oils and fats industry
		Micro	
Fixed assets	234.44 (312.84)	224.90 (288.10)	466.43 (638.34)
Labor cost	63.83(37.28)	55.98 (36.12)	45.18 (31.54)
Material cost	358.05 (283.45)	297.37 (275.75)	534.63 (388.64)
Investments	34.30 (188.46)	37.01 (111.52)	53.51 (173.89)
Output	523.67 (369.29)	468.53 (363.55)	723.09 (483.02)
		Small	
Fixed assets	879.83 (1322.63)	971.33 (1529.920)	1399.86 (2107.58)
Labor cost	276.32 (169.06)	252.69 (158.34)	195.67 (157.75)
Material cost	1826.46 (1432.03)	1714.00 (1541.09)	2538.65 (1655.17)
Investments	136.88 (394.35)	179.67 (1061.56)	222.70 (1033.13)
Output	2567.16 (1748.22)	2548.94 (1976.43)	3415.17 (2039.03)
		Medium	
Fixed assets	4184.81 (4903.80)	4799.89 (4367.70)	4638.69 (5160.46)
Labor cost	1250.48 (851.41)	1192.48 (885.96)	725.790 (554.83)
Material cost	10632.52 (7498.59)	11607.91 (7114.07)	12147.86 (7296.94)
Investments	724.72 (1519.03)	870.58 (1429.82)	965.94 (2775.37)
Output	14241.57 (8582.16)	16318.44 (9358.36)	16046.87 (8782.65)
		Large	
Fixed assets	33067.79 (83884.08)	60418.50 (66752.74)	91971.60 (200011.80)
Labor cost	9584.24 (14109.74)	15631.04 (18883.13)	8357.29 (8712.94)
Material cost	85308.25 (94988.88)	105576.40 (98736.50)	204688.30 (215950.50)
Investments	5971.37 (22757.40)	7571.60 (13626.81)	13382.35 (58376.31)
Output	114435.20 (132774.60)	181217.30 (201251.90)	251005.30 (256416.10)

Note: Standard deviations are in parentheses.

4. Results

The computations of dynamic Luenberger productivity growth indicator and its components were undertaken using the General Algebraic Modelling System (GAMS). Table 2 summarizes the arithmetic means of dynamic Luenberger indicator and its decomposition by industry for the entire period 1996/1997-2011/2012. The infeasible observations of the mixed period dynamic directional distance functions encountered in the calculations were excluded in the computation of averages, which is the most common practice in productivity and efficiency research. In our computations, 364 observations were found infeasible for meat processing firms (approximately 2% of the initial sample), 251 observations for dairy processing firms (approximately 6% of the initial sample) and 339 observations for oils and fats firms (approximately 10% of the initial sample). The differences between the three industries in the Luenberger indicator and its components are assessed using an adapted Li test (Simar and Zelenyuk, 2006)[3]. The results in Table 2 indicate that dynamic Luenberger productivity growth is negative for meat processing and dairy processing firms, and slightly positive for oils and fats firms. Negative dynamic technical change is the main driver of the dynamic productivity decline in the meat processing industry; the improvements in dynamic technical and scale inefficiency change are insufficient to make up for the technical regress. The dairy processing industry is characterized by a small technical regress and a small dynamic scale inefficiency decline. Dynamic technical inefficiency improves slightly over time. The oils and fats industry is also characterized by technical regress, but this effect is dominated by improvements in dynamic scale and technical inefficiency.

Table 2. Dynamic Luenberger productivity growth and its components by industry, 1996/1997-2011/2012 (mean values reported).

	Dynamic Luenberger productivity growth	Dynamic technical change	Dynamic technical inefficiency change	Dynamic scale inefficiency change
Meat processing industry	-0.004[a]	-0.039[a]	0.023[a]	0.012[a]
Dairy processing industry	-0.001[b]	-0.001[b]	0.001[b]	-0.001[b]
Oils and fats industry	0.006[c]	-0.014[c]	0.012[c]	0.007[c]

[a,b,c] denote significant differences between sectors at the critical 1% level.

2008 economic crisis and productivity growth and its components

The results of the impulse response analysis to the crisis for dynamic Luenberger productivity growth and its components for meat processing, dairy processing and oils and fats firms are presented in Table 3. These analyses were undertaken using STATA, in which corrections for heteroskedasticity and autocorrelation were applied using the cluster option to estimate standard errors. The regressions focus on three forecast periods, two lags for the dependent variable (i.e., productivity change or its components) and two lags for the crisis dummy. Crisis dummy is defined as 2008/2009 period. The forecast period, equal to three, is the maximum number of forecast periods possible with the data available. Similar results are obtained using only one lag for the dependent variable and the crisis dummy variable.

[3] This test, based on the nonparametric test of the equality of two densities developed by Li (1996), consists of computing and bootstrapping the Li statistic using DEA estimates, for which the truncated values equal to unity are smoothed by adding a small noise. The test is implemented in R with 1000 bootstrap replications. The step of smoothing is omitted in our application, because the productivity change and its components are not truncated.

Table 3. Impulse response analysis of dynamic Luenberger productivity growth and its components by industry.

Years after crisis *(k)*	Coefficient			
	Dynamic Luenberger productivity growth	Dynamic technical change	Dynamic technical inefficiency change	Dynamic scale inefficiency change
	Meat processing industry			
1	0.004	0.079***	-0.048***	-0.001
2	-0.003	0.144***	-0.057***	-0.070***
3	0.001	0.095***	-0.032***	-0.045***
	Dairy processing industry			
1	0.048***	-0.003	0.029***	0.035***
2	0.044***	0.017***	-0.031***	0.031***
3	0.077***	0.162***	-0.124***	0.048***
	Oils and fats industry			
1	-0.027**	0.138***	-0.143***	0.033***
2	-0.033**	-0.030***	0.033*	-0.008
3	-0.039*	0.220***	-0.196***	-0.061***

***, **, * significant at 1%, 5% and 10%, respectively.

Results in Table 3 suggest that the 2008 economic crisis had no impact on dynamic productivity growth in the meat processing industry, a positive impact in the dairy processing industry and a negative impact in the oils and fats industry. In the meat processing industry, dynamic technical change improves dramatically in each of the three consecutive years; namely, by 7.9% in the first year, 14.4% in the second year and 9.5% in the third year. The positive impact of technological improvement is undone by a deterioration of the contributions of dynamic technical inefficiency change and dynamic scale inefficiency change.

Firms in the dairy processing industry react to the crisis differently. The improvement of dynamic productivity growth in the first year is solely attributed to improvements of the contributions of dynamic technical inefficiency and dynamic scale inefficiency change. In the second and third year after the crisis, firms improve their technology and their dynamic scale inefficiency. However, dynamic technical inefficiency change contributes negatively to dynamic productivity growth.

Firms in the oils and fats industry present an overall decline of dynamic productivity growth in each of the three consecutive years. This decline is mainly led by a deterioration of dynamic technical inefficiency in the first and third year, and by technical regress in the second year.

2008 economic crisis and firms' size

We further analyze the effect of economic crisis separately for firms' size groups. Table 4, 5 and 6 presents the results of the regression of (9) for micro, small, medium and large firms separately in each of the three industries.

Table 4. Impulse responses by firms' size class for meat processing industry.

Years after crisis *(k)*	Size			
	Micro	Small	Medium	Large
Dynamic Luenberger productivity growth				
1	0.003	0.005	-0.005	0.008
2	0.004	-0.007*	0.005	-0.010
3	0.008	-0.004	-0.021	0.004
Dynamic technical change				
1	0.080***	0.087***	0.080***	0.064***
2	0.168***	0.154***	0.113***	0.049*
3	0.101***	0.085***	0.113***	0.114***
Dynamic technical inefficiency change				
1	-0.081***	-0.056***	0.019	-0.023
2	0.165***	-0.025***	0.019	0.030*
3	-0.140***	-0.014	0.082***	-0.007
Dynamic scale inefficiency change				
1	0.037***	-0.027***	-0.114***	-0.021
2	0.015***	-0.138***	-0.176***	-0.067*
3	0.027***	-0.031***	-0.181***	-0.103***

***, **, * significant at 1%, 5% and 10%, respectively.

The results for the meat processing industry in Table 4 show that dynamic technical change is positive for all size classes in the three years following the 2008 economic crisis. Dynamic technical inefficiency change negatively contributes to dynamic productivity growth of micro and small firms in particular. Table 4 shows that dynamic technical efficiency improves on medium and large firms in the third and second year, respectively. Dynamic scale inefficiency change, on average, makes a negative contribution to dynamic productivity growth in response to crisis (see Table 3). However, the results per size class in Table 4 show that this does not hold for micro meat processing firms, which experience an improvement of dynamic scale efficiency, resulting in a positive contribution of dynamic scale inefficiency to dynamic productivity growth.

Table 5. Impulse responses by firms' size class for the dairy processing industry.

Years after crisis *(k)*	Size			
	Micro	Small	Medium	Large
Dynamic Luenberger productivity growth				
1	0.047***	0.053***	0.030*	0.045**
2	0.070***	0.029**	0.034	0.078**
3	0.076***	0.064***	-	0.043
Dynamic technical change				
1	0.008	0.005	-0.105***	-0.013
2	0.030***	0.015	0.003	0.015
3	0.213***	0.170***	-	0.071
Dynamic technical inefficiency change				
1	0.029*	0.043**	0.025	-0.029
2	-0.004	-0.060***	-0.054	-0.070
3	-0.127***	-0.120***	-	-0.081
Dynamic scale inefficiency change				
1	0.012	0.025*	0.140***	0.127**
2	0.022*	0.021*	0.059**	0.124*
3	0.015	0.027	-	0.047

***, **, * significant at 1%, 5% and 10%, respectively. Note that it was impossible to get responses for 3 years for medium firms as none of these firms was observed for 3 years after the crisis set in.

Results of the impulse response analysis of dairy processing firms in Table 5 show that dynamic productivity growth is positively impacted in the first three years only for the small and micro firms. Medium and large firms experience an improvement in the first and second years. Dynamic technical change makes a positive contribution for micro firms (second and third year) and small firms (third year). Medium firms exhibit technical regress in the first year after the crisis and large firms exhibit no significant effect on dynamic technical change at all. Micro and small firms improved their dynamic technical efficiency in the first year following the crisis, but saw a significant drop in dynamic technical efficiency in the second and third year following the crisis. Hence, the improvement in dynamic technical change was largely undone by a deterioration of dynamic technical efficiency in the second and third year. Results for dynamic scale inefficiency change show that firms in all size classes improved their dynamic scale efficiency in the first and second year following the crisis.

Table 6. Impulse responses by firms' size class for oils and fats industry.

Years after crisis *(k)*	Size			
	Micro	Small	Medium	Large
Dynamic Luenberger productivity growth				
1	-0.050	-0.013	-0.018	-0.068*
2	-0.031	-0.045*	-0.067	-0.080**
3	-	-0.018	-0.042	-0.157***
Dynamic technical change				
1	0.153***	0.113***	0.203***	0.079*
2	0.008	-0.050***	-0.005	-0.089*
3	-	0.187***	0.145***	0.277***
Dynamic technical inefficiency change				
1	-0.172***	-0.168***	-0.073	0.038*
2	-0.071*	0.077**	0.068	-0.036
3	-	-0.185***	0.019	-0.042**
Dynamic scale inefficiency change				
1	-0.037***	0.087***	0.201**	-0.059
2	0.016	-0.035**	0.145	0.114*
3	-	-0.018	-0.317***	-0.243***

***, **, * significant at 1%, 5% and 10%, respectively. Note that it was impossible to get responses for 3 years for micro firms as none of these firms was observed for 3 years after the crisis set in.

The results of the impulse response analysis of oils and fats firms in Table 6 show that dynamic productivity growth is negatively impacted only for small firms in the second year and large firms in each of the three years. Dynamic technical change is positively impacted for all size groups in the first and third year following the start of the crisis, and negatively only for the small and large firms in the second year. Dynamic technical efficiency deteriorates in particular on micro (first and second year), small firms (first and third year) and large firms (third year), whereas small firms improve in the second year and large firms in the first year. Micro firms see a small deterioration of dynamic scale inefficiency change in the first year. Small, medium and large firms first improve dynamic scale inefficiency change and then deteriorate in the period following the crisis. In particular for medium sized firms, the changes are very big in the first and third year.

5. Conclusions

This paper used impulse response analysis by local projections to investigate the impact of the 2008 economic crisis on dynamic productivity growth and its components for the Spanish food processing industry. The application used panel data of firms from the meat processing industry, the dairy processing industry and the oils and fats industry over the period 1996-2012.

The results show that dynamic productivity was, on average, close to zero in the period under analysis. Dynamic technical change was on average negative, whereas dynamic technical and dynamic scale inefficiency change made positive contributions to dynamic productivity growth (with an exception of dynamic scale inefficiency change for dairy processing firms that made a slightly negative contribution). The analysis of impulse responses showed that dynamic productivity growth of the meat processing industry was not impacted by the crisis, whereas dynamic productivity growth of the dairy processing and the oils and fats industry were positively and negatively impacted by the crisis, respectively. Dynamic technical change was positively impacted, whereas dynamic technical inefficiency change was negatively impacted in most years following the crisis. Therefore, in response to crisis some innovative firms exhibit considerable resiliency by adapting quickly, while others responded slowly and fall behind. The technological progress and the growth in the gap between inefficient and efficient firms suggest that as response to crisis the few innovative food manufacturing firms shifted the frontier, while many other firms fail to adapt to technological improvements. The analysis of differences between size groups finds that micro and small firms often differed in their responses to the 2008 crisis compared to medium and large sized firms in the three industries analyzed.

Overall the results of this study imply that dairy processing firms compared to meat processing and oils and fats firms were less vulnerable to the crisis. Compared to the meat industry, the dairy relies on more basic products. Hence, the crisis may have had a smaller negative effect on the dairy industry than the meat industry. From all three industries analyzed, the oils and fats firms are the most severely impacted by the crisis. The results of this study can be used by stakeholders in the business to assess the impacts of the crisis and to enhance their knowledge about the vulnerability to macro-economic shocks.

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