Spatial determinants of productivity growth on agri-food Spanish firms: A comparison between co-operatives and investor-owned firms

Abstract

This study analyses the effect of the spatial factor, location and interaction effects among peer companies, on the productivity growth of agri-food companies in Spain. With this aim, we build a productivity growth index and apply a multi-equational Seemingly Unrelated Regression on a sample of 344 Spanish co-operatives and investor-owned firms for the period 2010-2012. Our findings show that agri-food firms are influenced by spatial factors finding interesting differences between co-operatives and investor-owned firms. With regard to the geographical location, co-operatives in the western of Spain show higher productivity growth rates, whereas investor-owned firms in the northeast of Spain present better results. The interaction effect among closer peer companies is also a relevant factor to determine the productivity growth in agri-food companies. This factor is more relevant for co-operatives than for investor-owned firms.

Key words: Agri-food companies, geographical location, Malmquist productivity index, seemingly unrelated regression, spatial interaction.

JEL Classification: D24, Q13, C31, R11, D22, P13

1. Introduction

In the last few years, the productive structure in the primary sector has changed. *"The liberalization of agricultural trade and the successive Common Agricultural Policy (CAP) reforms have moved the agricultural sector to market orientation and less protection"* (Giannakis and Bruggeman, 2015 pp.26). Therefore, agricultural companies have to handle more competitive markets in which economic conditions are constantly changing. Due to the importance of agricultural sector in the global context; a number of studies have examined productivity growth and their components in agri-food companies to determine their explicative elements (Ariyaratne et al., 2006; Esposti, 2011; Galdeano-Gómez et al., 2006; Headey et al., 2010; Notta and Vlachvei, 2007).

Among the different explicative elements, the spatial factor has been scarcely considered. By spatial factor, we are referring to the geographical location of the company and its interaction with its nearest peer companies. Previous literature includes environmental characteristics related to institutional and/or economic factors of the region in which agri-food firms are located to determine their productivity (Galdeano-Gómez et al., 2006; Galdeano-Gómez, 2008). In this sense, Giannakis and Bruggeman (2015) find territorial differences in productivity growth in the agri-food sector in Europe. Their results suggest that more developed regions, situated in the north and central European territories, are associated with higher productivity values in agri-food companies. Meanwhile, less productive agri-food companies are located in the southern European regions characterized by worst economic results. Ezcurra et al. (2008) and Stoate et al. (2009) find similar results highlighting the importance of the territorial characteristics when productivity growth for the agri-food sector is analyzed.

In addition, recent studies highlight the role of interdependences among closer peer companies on the productivity growth in agri-food sector (Aznar-Sánchez and Galdeano-Gómez, 2011; Giacomini and Mancini, 2015; Holloway and Lapar, 2007). These results seek to understand whether interrelationships between agri-food companies are a relevant element to understand their productivity results (Lombardi, 2003).

From this perspective, peer firms physically close among them develop positive externalities thanks to the synergies of joint interest and information flows between them (Giacomini and Mancini, 2015). This cooperation between neighboring companies generate positive externalities: external economies of scale, lower transport costs, transfer of information, workers and equipment or lower informational asymmetry between supply and demand which strengthens the competitive capacity of agri-food firms (García-Álvarez-Coque et al., 2015; Giacomini and Mancini, 2015).

Furthermore, relations between managers play a role in the functioning of these local systems. Business opportunities and formal and financial relationships (e.g., subcontracting) explain cooperation between enterprises by the potential economic advantages enabled by geographical proximity (Karlsson et al., 2005). Chiffoleau and Touzard (2015) explain the importance of these interactions on the competitiveness of agri-food companies. Aznar-Sánchez and Galdeano-Gómez (2011) analyze the advantages generated by an agri-food cluster in the southeast of Spain. They find that intense formal and informal mechanisms of connection between the members of this sector enhance the competitiveness and productivity of the companies located in this area.

In agricultural markets, farmers tend to form co-operatives to improve their competitiveness; reducing their limitations caused by the asymmetric information between farmers, on the one hand, and suppliers of inputs or purchasers of farm products, on the other; and improving their own income (Soboh et al., 2009). In the EU co-operatives process and trade approximately 40% of the agri-food sector's total output, with this percentage increasing to 46% in the specific case of Spain (Bijman et al., 2012). Despite the importance of the co-operatives in agricultural markets, there have been only a few works which mention the spatial dimension on co-operatives (Fousekis, 2011; Huck et al., 2006; Tribl, 2009; Zavelberg and Storm, 2015). These are focused on spatial pricing policies.

Co-operatives are constituted with a variety of objectives other than profit maximization. These objectives include maximizing members' welfare, charging market prices for inputs and refunding surplus, minimizing (maximizing) member prices for inputs (outputs). Co-operatives serve the needs of their members. Under these conditions, the spatial concentration of agri-food co-operatives has a positive effect on their market competitiveness (Tribl, 2009). Further concentration alleviates asymmetric information and increases the expected economies of scale of these companies. Comparing co-operatives and invested-owned firms (hereafter IOFs), the former seems to receive more profits of being spatially integrate given their initial weaknesses associated to the establishment of their particular characteristics (Huck et al., 2006).

In order to get additional knowledge about the spatial effect on agri-food companies, this paper analyses the effects of the location and spatial interactions between peers on the productivity growth of co-operatives and IOFs. To get this purpose, we apply the Malmquist productivity index to compute the productivity growth and its components: technical efficiency and technological change. Later, we provide some results including the spatial factor in the productivity model. To do this, we apply spatial econometric techniques on a multi-equational Seemingly Unrelated Regression (SUR). The novelty of this paper is to assess the spatial effect on the productivity growth of agri-food companies distinguishing by co-operatives, considered one of the most important associations in the agri-food sector. In particular, we develop an empirical application on a paired sample of 344 Spanish agri-food co-operatives and IOFs for the period 2010-2012. We select Spanish firms because the characteristics of this country specialized in productive activities in the primary sector (Maté et al., 2009). Furthermore, we select this temporal period corresponding with financial crisis in which interrelations among companies are more intense (Hertzel and Officer, 2012).

The remainder of this paper is organized as follows. The next Section present the data and methodology. Section 3 shows the results. Finally, the discussion and policy implications are presented in Section 4.

2. Data and methodology

2.1 Data

The data used for this analysis was obtained from SABI database (Iberian Balance Analysis System), which reports information about the different economic and financial dimensions of Spanish firms. We select Spanish agri-food[1] companies following the criterion established in the National Classification of Economic Activities (NACE, 2007). We get information for 13,053 agri-food Spanish companies, 347 of them co-operatives. The sample was cleaned by removing companies with anomalies (for example negative values in their sales or assets) or missing values in financial statements.

The lack of information in some variables reduced the number of co-operatives of the sample. After this filtering process, we get 172 co-operatives. With the aim of comparing co-operatives with IOFs, we build a paired sample of 172 co-operatives and 172 IOFs. In

[1] Sector of activity has not been included as explanatory variable because of fruit and vegetables and grain sectors make up the majority of the sample.

order to avoid biased results due to the different proportion of co-operatives and IOFs in the initial sample (Lambrecht et al., 2016), we select a subsample applying a stratified random process. IOFs are stratified by the same characteristics as co-operatives in terms of size, age, subsector and geographical location. Finally, our sample is composed of 172 co-operatives and 172 IOFs, for the agri-food sector for the period 2010-2012.

Figure 1 shows the spatial distribution of the sample across Spanish geography. Spain is characterized by two patters of economic development. North of Spain, composes by more developed regions while the south of Spain includes the less developed territories.

INSERT FIGURE 1

2.2 Malmquist Productivity Index

We apply Malmquist total factor productivity (TFP) index to evaluate productivity changes of agri-food co-operatives and IOFs. The Malmquist productivity index presents some advantages in comparison with the other alternatives (Bassem, 2014). Among them, it does not require information on the input and output prices and allows the decomposition of productivity changes into two components.

The availability of decomposing Malmquist productivity index allows explaining productivity changes by either change in efficiency (whether companies are getting close to the efficient frontier) or change in the technology (whether the efficient frontier is moving outwards over time) or both. The Malmquist index is built in terms of distance functions with respect to two different time periods (Färe et al., 1994)[2].

$$D_0^t(x^{t+1}, y^{t+1}) = \min\{\theta | (x^{t+1}/\theta, y^{t+1}) \in S^t\} \qquad (1)$$

[2] Following previous literature, we compute Malmquist productivity index assuming constant return of scale (CRS) (Färe et al., 1994; Galdeano-Gómez, 2008).

and

$$D_0^{t+1}(x^t, y^t) = \min\{\theta | (x^t/\theta, y^t) \in S^{t+1}\} \tag{2}$$

The distance function (1) evaluates the maximal proportional change in output required to make (x^{t+1}, y^{t+1}) feasible in relation to technology at time t. The distance function (2) measures the maximal proportional change in the output required to make (x^t, y^t) feasible in relation to technology at time $t+1$. Based on these distances, input-oriented Malmquist productivity index can be computed as follows (Färe et al., 1994 or Coelli et al., 1998)

$$M_0(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)} \left[\frac{D_i^t(x^{t+1}, y^{t+1})}{D_i^{t+1}(x^{t+1}, y^{t+1})} \frac{D_i^t(x^t, y^t)}{D_i^{t+1}(x^t, y^t)} \right]^{1/2} \tag{3}$$

The first term represents the change in technical efficiency between t and $t+1$ while the second term evaluates the shift in technology between two periods t and $t+1$. Technical efficiency shows how much further or closer away a firm gets to the "best practice companies" situated in the frontier. An index that is higher, equal or inferior to 1 means that firms improve, stagnate or reduce their efficiency, respectively. The technological change indicates that the innovation level of the firms where index is greater than unity means improvements and stagnation or deterioration when the indexes are less than unity (Färe et al., 1994).

$$\text{Technical efficiency change} = \frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)} \tag{4}$$

$$\text{Technological change} = \left[\frac{D_i^t(x^{t+1}, y^{t+1})}{D_i^{t+1}(x^{t+1}, y^{t+1})} \frac{D_i^t(x^t, y^t)}{D_i^{t+1}(x^t, y^t)} \right]^{1/2} \tag{5}$$

The product of both components is the Malmquist productivity index. A value of $M_0 > 1$, indicates that productivity of a firm growth between t and $t + 1$ while $M_0 < 1$ shows deterioration in productivity.

We apply the bootstrap method to achieve the best approximation of the true distribution of the sample. Confidence intervals for Malmquist indices are constructed using Simar and Wilson's (1999) bootstrapping procedure. This is based on the idea of repeatedly simulating the data-generating process (DGP), usually through resampling and applying the original estimator to each simulated sample so that resulting estimates mimic the sampling distribution of the original estimator (Simar and Wilson, 2000). In order to test the results, Simar and Wilson (1999) propose a procedure which generates a large number (B) of pseudo-samples and then they apply the original estimator to these.

2.3 Inputs and outputs to compute Malmquist productivity index

Using the input-oriented Malmquist productivity index, we evaluate the maximum possible reduction of the inputs given an output vector constant. This choice is attributed to the fact that agri-food companies are focused on reduce their production cost, human resources and capital, as maximum as possible to become competitive in the current markets (Galdeano-Gómez, 2008).

Based on previous agri-food studies, this analysis considers the basic input variables of a production function, labor and capital. Labor component is represented by labor costs, whereas capital is defined by investment in fixed material assets (Galdeano-Gómez, 2006; Guzmán and Arcas, 2008; Soboh et al., 2012).

The output is defined as the turnover volume, which represents the operating revenue from selling the products produced, that allows an adequate evaluation of the activity of the productive unit evaluated[3] (Soboh et al., 2012; 2014).

Summary descriptive statistics of the data used to compute Malmquist productivity index are given in Table A1 (Appendix A). There is a small degree of variation in the data for the period of 2010-2012. Agri-food companies increase their turnover volume whereas human resources and capital inputs increased for cooperative companies and decrease for IOFs in the study period.

2.4 Productivity growth model with the spatial factor for co-operatives and IOFs

Previous studies that analyze productivity growth in agri-food companies assume that there is not a temporal correlation in the productivity growth. So, temporal inertia is absent in these models (Aldaz and Millán, 2003). In order to take into account temporal correlation, we use a SUR procedure. We begin by specifying a system of L equations where, in our case, each equation ($l = 1,2, \dots, L$) corresponds to a productivity growth specification for each analyzed year:

$$Y^l = X^l\beta + \varepsilon^l \tag{6}$$

where Y^l represents a (Nx1) vector of productivity growth, X^l is a (NxK) matrix of explanatory variables, β is the (Kx1) vectors of parameters to be estimated. Temporal inertia is reflected by the error term ε^l. The covariance matrix is not diagonal but has a SUR structure:

$$E[\varepsilon\acute{\varepsilon}] = \Sigma \otimes I_N \tag{7}$$

[3] To support the robustness of our results, we apply alternative proxies to measure the input variables. In particular, we propose the total number of employees as alternative of labor input (Maté and Madrid, 2011). The results are analogous under with these proxies.

ε is the $(LN \times 1)$ vector obtained after stacking the different ε^l, $\varepsilon = [\varepsilon^{1'}, \varepsilon^{2'}, ..., \varepsilon^{L'}]'$; $\Sigma(\sigma_{ij})$ is a square $(L \times L)$ matrix with $\sigma_{ij} = \mathrm{Cov}(\varepsilon_i, \varepsilon_j)$, $\otimes$ denotes the Kronecker product and I_N is the identity matrix.

Apart from temporal inertia, the location of the company, as well as, the spatial autocorrelation among companies that are closer together geographically, could be relevant elements when productivity growth in co-operatives and IOFs is analyzed. While geographical location of the company can be controlled in the model through the inclusion of their geographical coordinates, the spatial autocorrelation requires further analysis. Spatial autocorrelation is understood as the spatial association in the values of a variable between neighboring agents (Anselin, 2001). The existence of spatial autocorrelation for a variable implies that the value of this variable for an economic agent depends not only on its characteristics but also on the characteristics of its neighboring (vicinity) agents. This interdependence between geographically close economic agents, firms in our case, may induce endogeneity into the model (Anselin, 1988). Spatial econometric techniques propose different methodologies to include spatial autocorrelation overcoming this limitation. The starting point of these proposals is to define a neighborhood structure (connections among companies) which is usually codified through a $(N \times N)$ spatial weight matrix W in which the i-th indicates, with values different to zero, the companies which spatially interact with the company i. Through the W spatial weight matrix, we include the spatial interaction among agri-food companies in a SUR model with Spatial Autorregresive structure[4] which takes the following form:

[4] There is an alternative Spatial Error Model (SEM) which includes the spatial interaction coefficient in the error term. The choice between them depends on the economic interpretation of the spatial factor. In our case, we consider that the spatial interactions in productivity growth among companies are related to the externalities produced by the proximity between companies. See Mur et al. (2010) for a further analysis about SUR models with spatial effects.

$$Y^l = \rho_l WY^l + X^l\beta + \varepsilon^l \text{ with } \mathrm{E}[\varepsilon\acute{\varepsilon}] = \Sigma \otimes \mathrm{I_N} \quad (8)$$

where all the variables are defined as in Eq. (6); W is a non-negative NxN spatial weight matrix. The spatial lag on the dependent variable WY^l includes the spatial interaction effect which contrasts if the productivity growth of each company is influenced by the productivity growth of its neighbors. ρ_l, is the spatial autoregressive coefficient, which tests the significance and the value of the spatial interaction among closer peer companies in the dependent variable. In this sense, a positive spatial dependence coefficient (ρ_l) implies the existence of positive spatial interactions. Firms with high (low) productivity growth values tend to be surrounded by firms with high (low) productivity growth rates.

2.5 Spatial variables

We define two kinds of spatial variables. Firstly, the spatial variables representative of the geographical location of each company applying its geographical coordinates. Secondly, we build a variable to evaluate spatial interaction effects among agri-food companies in productivity growth differencing between co-operatives and IOFs. This variable is defined by the spatial lag term WY, where W is the spatial weight matrix. It shows the network of connections among companies (Areal et al., 2012). In particular, the i-th row of W identifies (with values different from zero) the companies that interact with the company i. In this study, we define W as a binary weight matrix based on distances. This matrix W is row-standardized. For each company i, we define its neighbors (x) as all the companies inside the circle of radius dx (with $x = 1, 2, \ldots$) from the company i (Figure 2). Matrix W is based on geographical distance and, therefore, it is strictly exogenous (Manski, 1993). Finally, Y is the variable for which we test the spatial interaction among agri-food companies. The interaction effect of each agri-food company is estimated taking into account the level of productivity growth of co-operatives and IOFs surrounding it.

At this stage, we have to take into account that our sample is a paired sample of 344 co-operatives and IOFs, across the Spanish territory. Therefore, the spatial density from this information is reduced. In other words, if we apply only our sample information to compute the variable WY, we will find companies without any neighbor or with a reduced number of neighbors. In this case, computed average productivity values in the neighborhood would not be representative of the real average value. To overcome this limitation, we estimate the value of WY using the productivity growth and its components of 13,053 companies which are included in our initial sample but dropped to get a paired sample of co-operatives and IOFs.

INSERT FIGURE 2

2.6 Control variables

Firms' productive characteristics (Galdeano-Gómez, 2008) include capital intensity as the ratio of non-current assets over the total assets and labor productivity measured as the profit before interest and tax over labor cost. Finally, the dimension of the company built as the number of employees. Firms' financial variables (Soboh et al., 2009) include one financial ratio representative of each financial dimension of the company. The liquidity dimension is measured by current assets to current liabilities. The profitability dimension of the company is calculated as earnings before interest and taxes on total assets. Finally, indebtedness dimension is evaluated as total liabilities over total assets. The descriptive statistics for previous variables are summarized in Table A2 (Appendix A).

3. Results

This section presents Malmquist productivity index and its components for agri-food co-operatives and IOFs. With this information, we build the SUR model with spatial effects.

3.1 Malmquist TFP results

Malmquist (input-oriented) TFP change has been calculated to determine the sources of productivity growth. An improvement in technical efficiency change shows that companies are getting close to the efficient frontier, whereas an improvement in technological change is considered as a shift in the "best-practice frontier".

Table 1 (Panel A) summarizes the results for the TFP growth, the technical efficiency change and the technological change during the period 2010-2012. First of all, in co-operatives, Malmquist productivity index increases by 4.9 per cent. While for IOFs, TFP grows by 7.8 in the studied period. We get that technical efficiency change is the main driver for the productivity growth of co-operatives (5 per cent). In accordance with this result, Galdeano-Gómez (2006) and Kondo et al. (2008) claim that co-operatives increase their efficiency due to the improvement in the quality of their products, their labor productivity and the management of the company. Moreover, Table 1 (Panel A) shows that the main source of TFP growth for IOFs is attributed to the technical efficiency change (9.79 per cent).

Odeck (2009) and Lansink (2010) show similar results highlighting the relevance of improvements in efficiency when the productivity growth in agri-food companies is studied. Furthermore, during this period, co-operatives and IOFs show a technological progress (1.43 per cent and 0.95 per cent). This indicates an expansion in the production possibilities set that occurs when there is an environmental change, as well as, increase of companies' knowledge or innovation. Although this component experiences a progress, the results suggest that technological change has less influence on the productivity growth of agri-food companies in comparison with the technical efficiency change.

Due to Malmquist index is a non-parametric technique, we do not know the real production frontier. For this reason, our initial results need to be corroborated by applying the bootstrap method to achieve a good approximation of the true distribution of the sample (Simar and Wilson, 1999). This methodology is used to check the consistence of the initial productivity results in agricultural companies (Odeck, 2009; Soboh et al. 2012). In our case, bootstrap results are shown in the Panel B (see Table 1). We re-sampled 2000 pseudo-samples and the confident intervals were constructed. For co-operatives, the productivity score (1.049) is within the confidence intervals (1.026-1.071). Relative to IOFs, the situation is similar for productivity results (1.077) which are within the confidence intervals (1.055-1.099). Therefore, we can corroborate that our results are consistent to different Malmquist estimations.

INSERT TABLE 1

3.2 SUR estimation with spatial effects for agri-food co-operatives and IOFs

Following Eq. (8), SUR model with spatial effects is calculated. We undertake an iterative process in which we estimate Eq. (8) considering different weight matrix W, each of them defined by a different radius (8, 10 and 12 kilometers of radius from each company). Finally, we select the estimation with the best fit to our model in terms of minimum likelihood values. This estimation corresponds to a weight matrix W of 10 kilometres of radius.

Table 2 and 3 shows SUR estimation for co-operatives and IOFs, respectively. As we can see, geographical location and spatial interaction are significant variables for agri-food companies. Nevertheless, we also see some differences among these kind of firms. With reference to the location of the company, we find that latitude has a negative and significant impact on the productivity growth and its components for co-operatives (Table 2). This result confirms that co-operatives in west of Spain present higher productivity values. However, productivity growth and its components in IOFs show better results in the northeast of Spain (Table 3). This area is composed by more developed regions, from an economic perspective. Thus, co-operatives show higher independence with respect to the regional development in which they are located, than IOFs.

Spatial interactions among companies influence the productivity growth and its components in agri-food co-operatives and IOFs. In particular, the technological change, in co-operatives and IOFs, is highly influenced by this effect (Tables 2 and 3). The importance of spatial interaction in the technological change could be attributed to the positives externalities generated by the interrelationships among closer companies. Specifically, the knowledge spillover or the access to new markets due to high quality infrastructure improve the technology diffusion and thus, the productivity of the agri-food companies (Aznar-Sánchez and Galdeano-Gómez, 2011; Giacomini and Mancini, 2015). In other words, the advantages generated by these interrelationships between agri-food companies expand the production possibilities set. The significant result for the spatial interaction effects indicates that companies establish an information local network in order to adopt the best financial decisions (Chiffoleau and Touzard, 2014). This interaction between companies tends to improve their competitiveness and productivity (Aznar-Sánchez and Galdeano-Gómez, 2011). These findings corroborate Aznar-Sánchez and Galdeano-Gómez (2011) and Giacomini and Mancini (2015)' results. In addition, this effect is more intense for co-operatives than for IOFs. This result coincides with previous studies developed under the spatial pricing model framework which highlight the advantages derived from the spatial concentration for agri-food cooperatives in comparison with IOFs (Fousekis, 2011).

Regarding firms' productive characteristics, the results show that capital intensity and labor productivity have a positive and significant impact on the productivity growth of co-operatives (Table 2). Our findings corroborate Galdeano's study (2008) that includes these variables in a productivity model for agri-food companies. The dimension of the company has also a positive and significant impact on productivity growth. This result highlights co-operatives' size as a relevant element to increase its productivity (e.g., larger co-operatives could be more productivity than smaller to achieve economies of scale, better access to the government credits or adopt new technologies more easily) (Sheng et al., 2015). By decomposition of Mamlquist index, we get that the labor productivity has a positive relationship in the technical efficiency change. While the productive characteristics (capital intensity, labor productivity and dimension) show a positive effect in the technological change (Galdeano-Gómez et al., 2006). As shown in Table 3, the results for IOFs are in the same line of findings for co-operatives (capital intensity, labor productivity and dimension have a positive impact on the productivity growth). Focus on the sources of this growth, the technical efficiency change and the technological change are positively influenced by the labor productivity and the productive characteristics respectively.

With respect to the financial variables, we find that, for co-operatives, liquidity and indebtedness have a negative and significant impact on TFP growth. Profitability has a non-significant effect (Table 2). The negative relationship between liquidity and productivity growth can be explained by the objectives and internal management in co-operatives. The members tend to exert pressure in the co-operatives with the aim to maximize prices of their products. This causes that co-operatives tend to adjust their cash budgets the maximum as possible. So, this restricts the ability to improve co-operative productivity level because it reduces the solvency of the co-operative and constrain their current operations. Relative to indebtedness, co-operatives are mainly financed by their members, who are more reluctant to take on risky of new investments (Soboh et al., 2014). Thus, the financial constraints of these kinds of firms to increase their capital due to disincentive of members to invest in the company, restricts the productivity growth (Soboh et al., 2009; 2012). Finally, the lack of significance of the profitability ratio can be explained by the objective of co-operative members, focused on the maximization of the value of their products. This activity biases co-operatives' return rates giving some degree of independence between the value of the profitability company and its productivity trend (Notta and Vlachvei, 2007). Furthermore, the results also indicate that liquidity ratios tend to present a negative effect in the technical efficiency change. However, the financial characteristics have a non-significant impact on the technological change. Unlike previous results, for IOFs, the liquidity is positive but not significant while profitability has a positive and significant impact on the productivity growth (Table 3). In this kind of firms, the profitability is an indicator of the performance of the company (Soboh et al., 2011). Thus, the objective of the IOFs and their shareholders is to maximize the profit of the firm and improve its productivity. With regard to the indebtedness, IOFs show a negative impact in the productivity growth. This suggests that productivity growth is constrained when debt increases (Soboh et al., 2014). Finally, the technical efficiency and technological change are only influenced by the profitability ratio. This means that profitability is a key factor to increase the productivity of the IOFs (Soboh et al., 2014).

4. Conclusion and policy implications

This study estimates the Malmquist productivity index and applies a multi-equational SUR with Spatial Econometrics techniques. The results suggest that both, the location and spatial interaction effects are determinant elements when the productivity of agri-food co-operatives and IOFs is analyzed.

We get that co-operatives situated in the western of Spain present higher productivity results while IOFs have better results in the northeast of Spain. In particular, this area is composed of the more developed regions of Spain. We attribute this result to co-operatives are an important support for companies in unfavourable conditions. In this sense, low technological companies with reduced size tend to form co-operatives to become more competitive (Soboh et al., 2011).

Our results also support the relevance of spatial interactions among geographically closer agri-food companies (Aznar-Sánchez and Galdeano-Gómez, 2011, Giacomini and Mancini, 2015; Holloway and Lapar, 2007). This finding is supported by the idea that vicinities establish links strengthening information flows between them (Giacomini and Mancini, 2015). In addition, spatial agglomerations generate economies of scale materialized in best access to the different firms' resources (García-Álvarez-Coque et al., 2015). Therefore, geographical proximity causes spatial interactions between agri-food companies enhancing the competitiveness and productivity of the companies located in this area.

This spatial interaction effect is more intense for co-operatives. This finding coincides with studies on spatial pricing models highlighting the need of promoting regional policies to ease the spatial integration of co-operatives with their environments to reinforce the competitiveness of these companies (Fousekis, 2011; Tribl, 2009). In this sense, spatial agglomerations will provide additional advantages to co-operatives, given their initial characteristics, in comparison with IOFs. Co-operatives geographically close will reduce their informational asymmetries in a more intense way than IOFs given the co-operative character of these firms. This allows these companies to establish more adjusted prices in the markets becoming more competitive (Huck et al., 2006). Regarding the different components of the productivity, we find that the spatial interaction is clearly observed in the technological change. That is, spatial interaction among closer companies favors flows of knowledge between them exerting a positive effect on their productivity (Jaffe et al., 1993). From an empirical perspective, studies on agri-food companies conclude that interrelationships among geographically close economic agents at regional and local levels are relevant to enhance the productive performance of agrarian firms (Fritsch and Franke, 2004). Hoffman et al. (2015) point out that specific locations can provide advantages for agri-food firms in form of local resources, such as favourable natural conditions or access to technological inputs. Therefore, previous analysis reveals a clear positive effect of spatial concentration of agricultural activity in terms of productive advantages.

The results of our study have policies implications. Firstly, they support the importance of the spatial dimension in the design of regional policies to promote agri-food firms productivity. Secondly, we identify the areas where agri-food companies need to improve their productivity standards. Hence, this result could help policymakers to design agri-food policies in order to improve the competitive position of agri-food companies according to their geographical location given special relevance to the played role by co-operatives in these territories. Finally, policymakers should promote the spatial interactions among agri-food companies in order to overcome limitations from informational asymmetries in co-operatives and get advantage positions in current markets.

This study presents some limitations which could be considered as future studies. In this sense, we find limitations from the available information. Further research could also look into different explanatory factors in a larger sample of agri-food companies and focus on other countries, in order to test our results in other scenarios. In addition, our results highlight the need of considering spatial interactions among agri-food companies to avoid biased estimations from the omission of relevant information when productivity growth is examined. Therefore, future studies should consider a productivity index that explicitly include the spatial interaction effects when agri-food companies are analysed. In this sense, we would expect that the spatial index reduces the spatial effect we get in the model. However, further analysis is needed in this research area defining spatial index and testing their implications in regional analysis.

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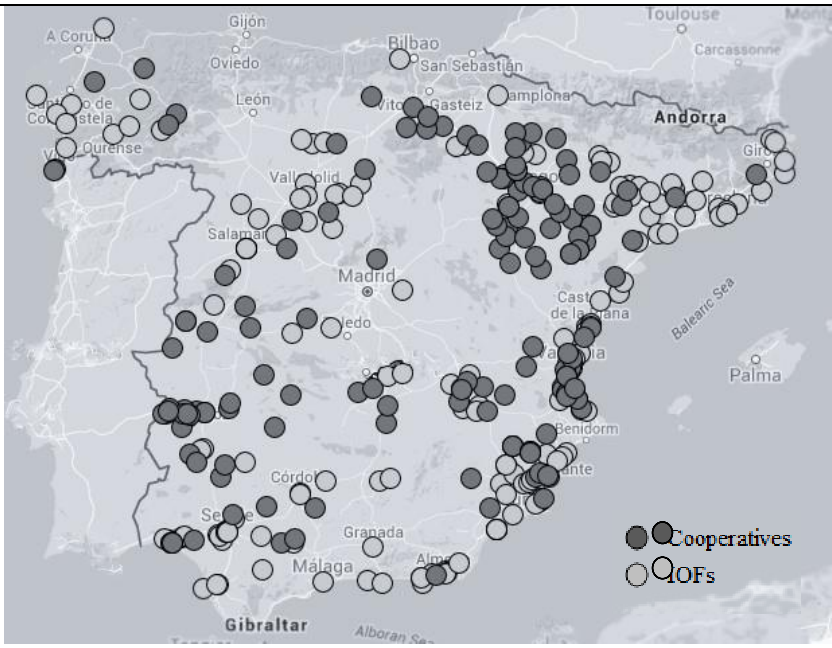
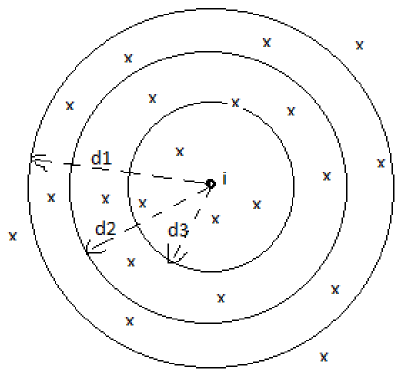
Figure 1. Spatial distribution of agri-food co-operatives and IOFs



Source: author´s estimation with Google My Maps

Figure 2. Neighbors companies (x) to the company i according to different distances d1, d2 and d3



Source: author´s estimation

Table 1. Malmquist index and its components for co-operatives and IOFs, 2010-2012

	Total Factor Productivity (TFP)		Technical Efficiency Change (TEC)		Technological Change (TE)	
Panel A: Average Malmquist results and its components						
	Coop	IOFs	Coop	IOFs	Coop	IOFs
Mean	1.0490	1.0777	1.0500	1.0979	1.0143	1.0095
Min	0.5066	0.5049	0.4327	0.4219	0.2010	0.3021
Max	1.9889	1.9827	1.9864	1.9592	1.3450	1.3410
Std. dev	0.2920	0.2767	0.3452	0.3540	0.2748	0.2733
t-test[(1)]	1.7761 (0.0379)**		1.1666 (0.1218)		-0.3239 (0.3730)	
Panel B: Bootstrap results for Malmquist index and its components						
Mean	1.0490	1.0777	1.0500	1.0979	1.0143	1.0095
Lower B	1.0261	1.0558	1.0228	1.0708	0.9937	0.9891
Upper B	1.0719	1.0997	1.0772	1.1251	1.0349	1.0299
Std. Dev	0.0116	0.0112	0.0138	0.0138	0.0105	0.0104

p-value in parentheses (*) significant at 10%. (**) significant at 5%. (***) significant at 1%. [(1)] We apply t-test in order to verify if the mean of TFP and its components of co-operatives and IOFs is different (Greene, 2008).

Table 2. SUR estimations for cooperative companies

			Total factor productivity change			Technical efficiency change			Technological change		
			2012	**2011**	**2010**	**2012**	**2011**	**2010**	**2012**	**2011**	**2010**
Productive Characteristics	Capital Intensity		0.1252	0.1563	0.1771	0.0400	0.0968	0.0145	0.2151	0.1745	0.1613
			(0.025)**	(0.019)**	(0.012)**	(0.743)	(0.464)	(0.485)	(0.029)**	(0.066)*	(0.089)*
	Labor Productivity		0.1371	0.1458	0.1263	0.1692	0.1378	0.0955	0.0342	-0.0247	0.0192
			(0.000)***	(0.000)***	(0.000)***	(0.002)***	(0.001)***	(0.048)**	(0.088)*	(0.310)	(0.070)*
	Dimension		0.0289	0.0416	0.0321	0.0347	0.0467	0.0140	0.0912	0.0881	0.144
			(0.075)*	(0.066)*	(0.071)*	(0.199)	(0.115)	(0.485)	(0.000)***	(0.000)***	(0.000)***
Financial characteristics	Liquidity		-0.0158	-0.0260	-0.0209	-0.0330	-0.0535	-0.0429	-0.0265	-0.0162	-0.0154
			(0.038)**	(0.000)***	(0.000)***	(0.005)***	(0.001)***	(0.028)**	(0.048)	(0.074)*	(0.102)
	Profitability		0.4372	0.3245	0.1123	0.0465	0.1677	(0.195	0.0245	0.0985	0.0684
			(0.299)	(0.480)	(0.714)	(0.905)	(0.894)	(0.648)	(0.078)*	(0.595)	0(.854)
	Indebtedness		-0.4921	-0.5221	-0.3697	0.1143	-0.2682	-0.3691	-0.0891	0.0334	0.0470
			(0.001)***	(0.000)***	(0.008)***	(0.374)	(0.035)**	(0.077)*	(0.128)	(0.520)	(0.745)
Spatial factor	Location	Longitude	0.0184	0.0141	0.0130	0.0254	0.0162	0.0118	-0.0106	-0.0395	0.0365
			(0.101)	(0.143)	(0.141)	(0.121)	(0.186)	(0.170)	(0.011)**	(0.381)	(0.775)
		Latitude	-0.0211	-0.0390	-0.0261	0.0192	-0.0489	-0.0367	-0.0153	-0.0150	-0.0256
			(0.003)***	(0.015)**	(0.008)***	(0.333)	(0.023)**	(0.028)**	(0.000)***	(0.000)***	(0.000)***
	Spillover		0.0912	0.0607	0.1407	0.0153	0.0605	0.0337	0.0215	0.0451	0.0184
			(0.064)*	(0.120)	(0.030)**	(0.655)	(0.263)	(0.136)	(0.019)**	(0.013)**	(0.025)**
	CTE		0.1936	0.5895	0.6836	0.9358	0.6265	0.4416	0.1883	0.1403	0.2384
			(0.077)*	(0.063)*	(0.048)**	(0.023)**	(0.049)**	(0.054)*	(0.000)***	(0.000)***	(0.000)***
R square			0.3045			0.4032			0.3156		
Chi-square (p-value)			53.695 (0.000)			58.904 (0.000)			65.932 (0.000)		

p-value in parenthesis. (*) significant at 10% (**) significant at 5% (***) significant at 1%

Table 3. SUR estimations for IOFs

			Total factor productivity change			Technical efficiency change			Technological change		
			2012	**2011**	**2010**	**2012**	**2011**	**2010**	**2012**	**2011**	**2010**
Productive characteristics	Capital Intensity		0.1404 (0.017)**	0.2054 (0.015)**	0 .1985 (0.015)**	0.1558 (0.052)*	-0.0800 (0.365)	0.1429 (0.051)*	0.1071 (0.000)***	0.1332 (0.002)**	0.2361 (0.066)*
	Labor Productivity		0.0864 (0.000)***	0.0814 (0.005)***	-0.3263 (0.241)	0.0922 (0.003)***	0.0857 (0.002)**	0.0865 (0.003)**	0.0536 (0.000)***	0.0454 (0.002)**	0.5186 (0.000)***
	Dimension		0.0305 (0.018)**	0.0289 (0.054)*	0.0363 (0.012)**	0.1558 (0.309)	0.0193 (0.056)*	0.0382 (0.013)*	0.0107 (0.005)**	0.0110 (0.000)***	0.0152 (0.000)***
Financial characteristics	Liquidity		0.0024 (0.669)	0.0017 (0.725)	0.0084 (0.368)	0.0117 (0.168)	-0.0281 (0.007)**	-0.0174 (0.112)	0.0029 (0.991)	0.0011 (0.985)	0.0084 (0.645)
	Profitability		0.7764 (0.000)***	0.7631 (0.000)***	0.7988 (0.001)***	0.6964 (0.000)***	0.2585 (0.406)	0.5752 (0.003)**	0.1284 (0.009)**	0.1658 (0.015)**	0.2348 (0.484)
	Indebtedness		-0.1239 (0.000)***	-0.2083 (0.000)***	-0.0697 (0.158)	-0.0038 (0.968)	-0.5186 (0.000)***	-0.1366 (0.872)	0.0065 (0.176)	-0.0211 (0.635)	-0.0354 (0.812)
Spatial factor	Location	Longitude	0.0102 (0.095)*	0.0092 (0.147)	0.0110 (0.077)*	0.0189 (0.007)**	0.0107 (0.193)	0.0161 (0.013)**	0.0112 (0.002)**	0.0178 (0.000)***	0.0156 (0.000)***
		Latitude	0.0244 (0.017)**	0.0270 (0.018)**	0.0173 (0.172)	0.0251 (0.079)*	0.0397 (0.008)**	0.0115 (0.368)	0.0148 (0.000)***	0.0145 (0.000)***	0.0152 (0.000)***
	Spillover		0.0219 (0.065)*	0.0690 (0.028)**	0.0701 (0.258)	0.0176 (0.402)	0.0936 (0.001)***	0.0033 (0.837)	0.0503 (0.000)***	0.0503 (0.000)***	0.0604 (0.000)***
	CTE		0.4189 (0.045)**	0.5895 (0.033)**	0.3017 (0.061)*	0.3358 (0.006)**	0.2789 (0.000)***	0.1076 (0.000)***	0.1857 (0.000)***	0.1351 (0.000)***	0.1231 (0.000)***
R square Chi-square (p-value)			0.4276 51.491(0.000)			0.3049 44.974(0.000)			0.3256 43.68(0.000)		

p-value in parenthesis. (*) significant at 10% (**) significant at 5% (***) significant at 1%

Appendix

Table A1
Descriptive statistics of inputs and outputs used in Malmquist Productivity Index model

						Panel A Co-operative companies
Type	Variable		2012	2011	2010	Mean
Output	Turnover	Average	1.841.277	1.812.928	1.775.467	1.746.438
		Std dev	1.867.915	1.795.307	1.694.149	1.725.561
		Max	8.530.315	8.487.379	7.822.881	8.530.315
		Min	12.243	18.298	34.364	12.243
Input	Fixed Assets	Average	867.644	848.844	814.352	831.804
		Std dev	1.051.000	1.049.673	1.013.127	1.022.701
		Max	4.934.240	4.970.675	5.099.041	5.099.041
		Min	2.091	3.653	6.485	2.091
	Labour Costs	Average	241.360	231.960	218.084	225.667
		Std dev	266.921	242.980	225.986	238.176
		Max	1.745.894	1.387.862	1.353.697	1.745.894
		Min	12.943	16.836	16.375	12.943
						Panel B IOFs
Output	Turnover	Average	1.872.573	1.765.202	1.665.736	1.736.735
		Std dev	2.195.845	1.993.740	1.857.762	1.985.543
		Max	9.777.336	7.963.217	7.521.207	9.777.336
		Min	20.492	15.283	14.273	14.273
Input	Fixed Assets	Average	779.752	780.732	783.675	773.078
		Std dev	883.157	887.167	891.660	88.093
		Max	4.344.580	4.441.911	4.511.303	4.511.303
		Min	2.093	7.963	10.163	2.093
	Labour Costs	Average	178.423	182.084	175.719	178.084
		Std dev	258.975	273.127	270.503	267.073
		Max	1.391.527	1.658.857	1.897.185	1.897.185
		Min	7.200	6.400	5.700	5.700

Source: Author´s computation

Table A2
Descriptive statistics of variables used in SUR estimation

						Panel A Co-operative companies
Type	Variable		2012	2011	2010	Mean
Productive	Capital Intensity	Average	0.4779	0.4832	0.4931	0.4847
		Std dev	0.2572	0.2399	0.2378	0.2447
		Max	0.9851	09968	0.9952	0.9968
		Min	0.0011	0.0044	0.0092	0.0011
	Labour product.	Average	0.4460	0.3621	0.3361	0.3400
		Std dev	1.4170	1.0129	0.7532	1.093
		Max	16.070	8.6293	5.4136	16.0704
		Min	0.0017	0.0012	0.0017	0.0012
	Dimension	Average	9.7906	9.8372	9.9767	9.8682
		Std dev	17.4718	18.9960	18.7653	18.3870
		Max	120	124	150	150
		Min	1	1	1	1
Financial	Liquidity	Average	1.7087	1.6416	1.9312	1.6056
		Std dev	1.5120	1.4457	1.9387	1.5348
		Max	8.5796	10.237	10.127	8.9096
		Min	0.1445	0.0294	0.0434	0.0294
	Profitability	Average	0.0232	0.0120	0.017	0.0177
		Std dev	0.0776	0.0722	0.1087	0.0740
		Max	0.4277	0.3565	0.4139	0.4277
		Min	-0.1734	-0.1632	-0.1919	-0.1919
	Indebtedness	Average	0.5127	0.5191	0.4925	0.5048
		Std dev	0.2832	0.2824	0.2868	0.2837
		Max	0.9621	0.9597	0.9566	0.9621
		Min	0.1815	0.1920	0.1899	0.1815
						Panel B IOFs
Productive	Capital	Average	0.5030	0.5097	0.5121	0.5083
		Std dev	0.2629	0.2648	0.2702	0.2655
		Max	0.9967	0.9953	0.9992	0.9992
		Min	0.0073	0.0067	0.0087	0.0067
	Labour product.	Average	0.7040	0.6501	1.1659	0.8400
		Std dev	1.1493	1.0092	1.7119	1.3430
		Max	6.9442	7.1234	12.092	12.092
		Min	0.0034	0.0026	0.0116	0.0026
	Dimension	Average	8.6860	9.0348	8.7616	8.8275
		Std dev	12.4085	13.248	13.2830	12.962
		Max	85	89	89	89

		Min	1	1	1	1
Financial	Liquidity	Average	1.9339	1.9093	1.8631	1.9021
		Std dev	2.0560	1.9457	1.8078	1.9357
		Max	8.8671	8.8317	8.7702	8.8671
		Min	0.0799	0.0422	0.0341	0.0422
	Profitability	Average	0.0642	0.0684	0.1051	0.0791
		Std dev	0.1288	0.1109	0.1272	0.1237
		Max	0.5107	0.4277	0.5073	0.5107
		Min	-0.1898	-0.1996	-0.1713	-0.1996
	Indebtedness	Average	0.3456	0.3784	0.4220	0.3820
		Std dev	0.2760	0.2918	0.2993	0.2938
		Max	0.9696	0.9582	0.9581	0.9696
		Min	0.0114	0.0210	0.0155	0.0114

Source: Author´s computation