



# The significance of the interconnection of second-level cooperatives and their peer-associated cooperatives for productivity growth

María Martínez-Victoria<sup>1</sup>, MariLuz Maté-Sánchez-Val<sup>2</sup> and Narciso Arcas-Lario<sup>1</sup>

<sup>1</sup>Technical University of Cartagena, Business Economics Dept. C/ Real 3, 30201 Cartagena (Murcia), Spain <sup>2</sup>Technical University of Cartagena, Finance and Accounting Dept. C/ Real 3, 30201 Cartagena (Murcia), Spain

## Abstract

Cooperatives are especially important in current agri-food markets. These companies have responded to the current demand requirements with greater market orientation strategies to attract and satisfy customers. To do so, cooperatives have adopted different collaboration alternatives. In Spain, the most common alliance between cooperatives is materialised in second-level cooperatives, which are cooperatives integrated by at least two first-level cooperatives. The aim of this study was to analyse the interaction effects between first- and second level agri-food cooperatives on their productive growth and its components. To get this purpose, a Cobb-Douglas specification with spatial econometrics techniques was applied to evaluate this relationship. We included a spatial connectivity matrix to establish the interconnection among cooperatives of first- and second-level. Our results show a positive interaction effect highlighting the importance of these alliances on the productivity growth in the agri-food sector. The scarce amount of empirical papers explaining how second-level cooperatives influence the performance of first-level cooperatives shows the relevance of our study.

**Additional key words:** Malmquist productivity index; spatial econometric modelling; spatial interaction effects.

**Abbreviations used:** COGECA (Comité General del Cooperativismo Agrario en la UE/ General Confederation of Agricultural Cooperatives in the EU); CRS (constant return to scale); EFC (technical efficiency change); EU (European Union); GMM (generalised method of moments); IOF (investor-owned firms); IV (instrumental variables); LM (Lagrange multiplier); LR (likelihood ratio); ML (maximum likelihood); OLS (ordinary least squares); OSCAE (Observatorio Socioeconómico del Cooperativismo Agroalimentario Español/ Socioeconomic Observatory of Spanish Agri-food Cooperativism); SABI (Sistema de Análisis de Balances Ibéricos / Iberian Balance Analysis System Iberian Balance Analysis System); SEM (spatial error model); SDM (spatial Durbin model); SLM (spatial lag model); TEC (technological change); TFP (total factor productivity); VRS (variable return to scale).

**Authors' contributions:** Conceived and designed the experiments; acquisition, analysis, interpretation of data; drafting of the manuscript; critical revision of the manuscript for important intellectual content; statistical analysis: MMV, MLM and NAL. Obtaining funding: MLM and NAL.

**Citation:** Martínez-Victoria, M.; Maté-Sánchez-Val, M. L.; Arcas-Lario, N. (2017). The significance of the interconnection of second-level cooperatives and their peer-associated cooperatives for productivity growth. Spanish Journal of Agricultural Research, Volume 15, Issue 1, e0103. <https://doi.org/10.5424/sjar/2017151-10270>.

**Received:** 25 Jul 2016. **Accepted:** 02 Feb 2017.

**Copyright © 2017 INIA.** This is an open access article distributed under the terms of the Creative Commons Attribution (CC-by) Spain 3.0 License.

**Funding:** Cátedra Cajamar de Cooperativismo Agroalimentario-Universidad Politécnica de Cartagena and Seneca Foundation (Contract nº 19884/GERM/15)

**Competing interests:** The authors have declared that no competing interests exist.

**Correspondence** should be addressed to María Martínez-Victoria: [mdc.mvictoria@gmail.com](mailto:mdc.mvictoria@gmail.com)

## Introduction

In recent decades, the importance of cooperative companies in agri-food markets has been widely evident. Within the European Union (EU), there are estimated to be 21,769 agri-food cooperatives with more than six million members and sales of approximately 347,000 million euros. These cooperatives process and commercialise

over 40% of agricultural production (COGECA<sup>1</sup>, 2015). In Spain, there are approximately 3,844 cooperatives (17.4% of EU cooperatives) with approximately 350,000 members (5.8%) and more than 25,000 million euros of turnover (7.2%) (OSCAE<sup>2</sup>, 2015).

However, agri-food cooperatives also face limitations related to their limited size. This reduces their market

<sup>1</sup> COGECA: Comité General del Cooperativismo Agrario en la UE/ General Confederation of Agricultural Cooperatives in the EU.

<sup>2</sup> OSCAE: Observatorio Socioeconómico del Cooperativismo Agroalimentario Español / Socioeconomic Observatory of Spanish Agri-food Cooperativism.

power and their financial resources to undertake new research projects and major investments (Juliá & Mari, 2002). Furthermore, this sector has addressed several changes, such as trade liberalisation, globalisation, competitive pressure and new consumer demands (Hendrikse & Bijman, 2002; Giannakis & Bruggeman, 2015). As a consequence, agri-food companies have responded with greater market orientation strategies to attract and satisfy customers (Arcas-Lario & Hernández-Espallardo, 2003; Kyriakopoulos *et al.*, 2004). In this context, cooperatives have adopted different collaboration alternatives, such as alliances, to obtain the necessary resources through this horizontal expansion (Kyriakopoulos & Van Bekkum, 1999). In Spain, the most common form of collaboration among agri-food cooperatives is known as *second-level cooperatives*. There are 132 second-level cooperatives, which constitute 30% of the total turnover of agri-food cooperatives (OSCAE, 2015). Some of these second-level organisations are ranked among the top Spanish agri-food companies in terms of turnover. This relationship results from at least two first-level cooperatives acting together to develop a specific economic or business activity that allows them to act more competitively in the market (Puentes *et al.*, 2007). This collaboration between cooperatives tries to overcome the limitations they face, achieving scale economies due to a greater concentration of supply, diversification of products, the opening of new markets, the concentration of services, the purchasing of inputs together or new innovation processes (Juliá-Igual *et al.*, 2012).

Despite the importance of the alliances between cooperatives in Spanish agri-food markets, there are few empirical papers that contribute to explaining how the relationship between first- and second-level cooperatives influences cooperatives' performance. Arcas-Lario (2002) and Arcas-Lario & Hernández-Espallardo (2003) studied the advantages of being integrated in a second-level cooperative. The former conducted a survey of 278 first-level cooperatives that distribute their products through second-level cooperatives. Their results show that first-level cooperatives improve their market orientation by incorporating their products into second-level cooperatives. They obtained useful market information that allowed to improve their products in comparison with competitors. The latter got information from 278 Spanish agri-food first-level cooperatives using a questionnaire answered by the president or the director of each cooperative. These authors showed a positive effect of second-level cooperatives on the objectives of first-level cooperatives, such as increases in sales and profits, improvements in image and prestige, or product launch.

Differently from previous empirical studies, we considered the effects caused by the fact of being

interconnected with other cooperatives on their productivity growth. This paper implements a new perspective of analysis in the alliances between agri-food cooperatives applying spatial econometric techniques to connect first- and second-level cooperatives. The scarce amount of empirical papers explaining how second-level cooperatives influence the performance of first-level cooperatives highlights the relevance of our analysis.

## Material and methods

### Malmquist productivity index

The most widely used analytical tool to evaluate productivity change is the Malmquist total factor productivity (TFP) index. In the agri-food sector, this methodology is applied by several authors, *e.g.*, Galdeano-Gómez (2006) and Guzmán & Arcas (2008). The Malmquist productivity index has some advantages over alternatives (Bassem, 2014). For instance, it does not require information on the input and output prices, and it allows the decomposition of productivity changes into two components: technical efficiency change (EFC) and technological change (TEC). The former evaluates the degree to which a company's efficiency improves or worsens (catching up), while the latter reflects the change in the efficiency frontier (innovation) between two-time periods (Cooper *et al.*, 2007). This index is built in terms of distance functions (Eq. [1]) that can be either input orientated or output orientated. The former is defined as the maximum possible reduction of the inputs given an output vector constant, and the latter considers the maximum proportional expansion of the output given a specific input level constant under a reference technology. We measured productivity changes under the constant returns to scale model (CRS) for the technology and output orientation. Grifell-Tatjé & Lovell (1995) showed that Malmquist index may not correctly measure productivity changes when the variable returns to scale (VRS) model is assumed for the technology. In addition, both input orientation and output orientation provide the same technical efficiency scores when CRS technology is applied. Therefore, the choice of orientation was not relevant in our study. We selected an output orientation because, in agriculture, one usually attempts to maximize output from a given set of inputs, rather than the converse (Coelli & Prasada-Rao, 2005).

For a firm at period  $t$ , with  $t = 1, \dots, T$ , the output distance function is defined as:

$$D^t(x^t, y^t) = (\inf \{\theta : (x^t, \theta y^t) \in S^t\})^{-1} = (\sup \{\theta : (x^t, y^t/\theta) \in S^t\})^{-1} \quad [1]$$

where  $S^t$  is the production possibility set that transforms the inputs into outputs for period  $t$ ,  $x^t$  is an input vector [ $(x^t = (x_1^t, \dots, x_m^t) \in R_m^+)$ ],  $y^t$  is an output vector [ $(y^t = (y_1^t, \dots, y_n^t) \in R_n^+)$ ], and scalar  $\theta$  measures the extent to which  $y^t$  can be maximised while maintaining the input level.

The Malmquist TFP index ( $M_i$ ), which measures the productivity changes between two temporal periods,  $t$  and  $t + 1$ , can be defined as:

$$M_i(x^{t+1}, y^{t+1}, x^t, y^t) = \left[ \frac{D_i^t(x^{t+1}, y^{t+1})}{D_i^t(x^t, y^t)} \frac{D_i^{t+1}(x^{t+1}, y^{t+1})}{D_i^{t+1}(x^t, y^t)} \right]^{1/2} \quad [2]$$

where  $D_i^t(x^{t+1}, y^{t+1})$  measures the maximum expansion of output possible in  $t$ . Equation [2] is the geometric mean of two productivity indexes: the first is calculated with respect to technology in period  $t$ , and the second is calculated with respect to technology in the period  $t + 1$ .

According to Färe *et al.* (1994) and Coelli *et al.* (1998), to assume the presence of productivity inefficiencies, the Malmquist TFP index can be divided into two components (Eq. [3]), where the ratio outside brackets measures the change in efficiency (the relative position with respect to the frontier) between two periods ( $t, t + 1$ ) and the geometric mean of the two ratios inside the brackets captures the technological change (the shift of the frontier) between  $t$  and  $t + 1$ .

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

Moreover, the efficiency shows how much further or closer away a firm grows to the “best practice companies” situated in the frontier. An index that is greater than, equal to or less than 1 indicates that firms’ efficiency improves, stagnates or reduces, respectively. The technological change indicates that the innovation level of the firms where the index is greater than unity indicates improvements and stagnation or deterioration when the indexes are less than unity (Färe *et al.*, 1994). Finally, a value of  $M_i > 1$  indicates a TFP of firm growth between  $t$  and  $t + 1$ , while  $M_i < 1$  shows deterioration in productivity.

**Productivity growth model**

To analyse a productivity growth model, we based our analysis on a Cobb-Douglas specification [4]. This is one of the most widely used production function forms in economics, and it represents the relationship between production, input and output:

$$Y = L^\alpha K^\beta \quad [4]$$

where  $Y, L$  and  $K$ , respectively, refer to total production output, labour input and capital input.  $\alpha$  is the output elasticity of labour;  $\beta$  is the output elasticity of capital. A productivity growth specification can be deduced by

taking logarithmic derivative of [4]. That is:

$$\frac{dY}{Y} = \alpha \frac{dL}{L} + \beta \frac{dK}{K} \quad [5]$$

which is equivalent to:

$$G_Y = \alpha G_L + \beta G_K \quad [6]$$

where  $G_Y, G_L$  and  $G_K$ , respectively, refer to the growth rate of  $Y, L$  and  $K$ . Based on [6], we contrasted interaction effects in productive characteristics between first- and second-level cooperatives on their productivity growth. With this purpose, we built a spatial connectivity matrix  $W$ , which each element  $w_{ij}$  defines with values different from zero if cooperative  $i$  and cooperative  $j$  are connected. Once  $W$  was defined, we evaluated the significance of the interconnection among cooperatives in their productivity growth. There are different specifications to evaluate this effect. The first specification we considered is known as the endogenous spatial interaction effect, where the productivity growth of each cooperative depends on the productivity growth ( $G_Y$ ) of their associated cooperatives  $i$  depends on the productivity growth of their associated cooperatives  $j$ . The second specification considers the interconnection effect among cooperatives in the error term. Finally, the third specification allows the co-existence of endogenous and exogenous interaction effects among cooperatives. The difference between previous specifications is explained by the source of interdependence. In the first case, the spatial effect is caused by the structural character of the analysed variable. In this case, if this structure is significant, then we can conclude that the particular characteristics of a company influence the productivity growth values of their associated peer companies. In the second case, the spatial interactions in the error term are explained by the omission of relevant variables in the model that generate this result. The last case contains endogenous and exogenous interaction effects in the model. In this sense, spatial effects are caused by the structural character of the productivity growth and the explanatory variables of other units associated with them.

To show these specifications, we parted from a general panel data model that includes both individual and temporal heterogeneity in the specification. In particular, this model takes the following specification for  $i = 1, \dots, N$  individuals and  $t = 1, \dots, T$  periods:

$$G_Y = \gamma l + X\varphi + \mu + \xi + u \quad [7]$$

where  $G_Y$  is the vector of the dependent variable;  $l_{NT \times 1}$  is a vector of ones associated with the constant term parameter  $\gamma$  to be estimated;  $X_{NT \times K}$  denotes the vector of explanatory variables;  $G_L$  and  $G_K$  are the vector of  $(K \times 1)$  associated parameters  $(\alpha, \beta)$ , and  $\mu = (\mu_1, \mu_2, \dots, \mu_N)^T$  represents the invariant time effects

of each company  $i$ . This effect can be considered fixed or random. In the first case, we assume a different parameter to be estimated for each firm  $i$ , which is correlated with the explicative variables of the model, while the random specification considers that the individual effect is an independent random variable with average zero and variance  $\sigma_{\mu}^2$  (Wooldridge, 2012). The application of fixed or random specifications depends on the characteristics of the empirical application. The fixed specification assumes dependence between the unobserved heterogeneity and the explicative variables, while the random specification assumes independence in this term. However, this last assumption may be highly restrictive when we are analysing the different dimensions in a company (Martínez-Sola *et al.*, 2014). Therefore, we based our analysis on a fixed effects model.  $\xi = (\xi_p, \xi_p, \dots, \xi_T)^N$  represents time-period-specific effects invariant across individuals. Finally,  $u_{NT \times I}$  is the error terms independent and identically distributed with mean zero and variance  $\sigma^2$ .

Based on the previous specification [7], the model that contains a spatial lagged dependent variable is known as the spatial lag model (SLM) expressed in [8]:

$$G_Y = \rho W G_Y + \gamma l_{TN} + X\varphi + \mu + \xi + u \quad [8]$$

where  $W_{NT \times NT}$  is the spatial weight matrix, and  $W G_Y$  denotes the spatial lag effect of dependent variable  $G_Y$ .  $\rho$  is the spatial autoregressive coefficient, which tests the significance and the value of the spatial interaction among individuals in the dependent variable.

The spatial panel data specification with spatial interdependences in the error term is known as the spatial error model (SEM) expressed in [9]:

$$G_Y = \gamma l + X\varphi + \mu + \xi + u \text{ with } u = \lambda W u + \varepsilon \quad [9]$$

where  $W_{NT \times NT}$  is the spatial weight matrix;  $W u$  denotes the spatial lag effect of error term  $u$ ;  $\lambda$  is the spatial autoregressive coefficient in the error term.

The final specification that takes into account the co-existence of separable endogenous and exogenous interaction effects is known as the spatial Durbin model (SDM) and is defined as [10]:

$$G_Y = \rho W Y + \gamma l_{TN} + X\varphi + W X \theta + \mu + \xi + u \quad [10]$$

where  $W_{NT \times NT}$  is the spatial weight matrix;  $W Y$  denotes the spatial lag effect of the endogenous term;  $W X$  is the exogenous interaction for explicative variables  $G_L$  and  $G_K$ ;  $\rho$  is the spatial autoregressive coefficient, which tests

the significance and the value of the spatial interactions among individuals in the dependent variable;  $\theta$  represents unknown parameters to be estimated.

Previous models [7]-[10] have been estimated by applying maximum likelihood (ML) (Ord, 1975; Elhorst, 2010), instrumental variables (IV) or the generalised method of moments (GMM) (Fingleton & Le Gallo, 2008). The ML estimation is the most commonly used method based on the maximisation of the log-likelihood function.

## Data

The information to develop this study was obtained from the Iberian Balance Analysis System (SABI) database<sup>3</sup>, which provides a wide range of information on the different business dimensions of Spanish firms. We selected Spanish agri-food companies based on the criterion established in the National Classification of Economic Activities (NACE, 2007). Once we obtained all the information about agri-food second-level cooperatives, we eliminated the companies with anomalies in their financial statements. Our final sample comprised information for 265 agri-food companies over the period 2012-2015. Of these 265 cooperatives, 218 were first-level cooperatives that were integrated into 45 second-level organisations. In addition, to determine the cooperatives associated to each of them, we hand collected this information from the webpages of each of these cooperatives. Table 1

**Table 1.** Distribution of the sample in function of age and size of the cooperatives

	Total	First-level co-ops	Second-level co-ops
<b>Panel A: Age</b> <sup>1</sup>			
Infant	1	0	1
Adolescent	1	1	0
Middle-aged	44	23	21
Old	136	113	23
<b>Panel B: Size</b> <sup>2</sup>			
Micro	81	71	10
Small	82	62	20
Medium	44	33	11
Large	13	9	4

<sup>1</sup> Groups for age were established following Berger & Udell (1998). <sup>2</sup> Groups for size were established following EC (2003).

<sup>3</sup> SABI: Sistema de Análisis de Balances Ibéricos or Iberian Balance Analysis System database is managed by Bureau van Dijk. The financial information provided by SABI is elaborated applying the Spanish General Accounting Plan (2007). But financial information of cooperatives is also affected by a specific normative EHA/3360/2010 (BOE, 2010) developed for cooperatives. The application of different normative could cause differences in some accounting magnitudes between cooperatives and non-cooperatives. We have tested that the accounting magnitudes we have considered in our analysis to compute the variables are not affected by differences between these regulations.

**Table 2.** Malmquist productivity growth and its components. Mean values 2012-2015

	Agri-food cooperatives		
	TFP	EFC	TEC
Whole sample	1.045	1.063	0.984
First-level cooperatives	1.056	1.074	0.985
Second-level cooperatives	1.016	1.035	0.982

TFP, total factor productivity; EFC, technical efficiency change; TEC, technological change

shows the composition of our sample. Table 1 shows, in general terms, the distribution of the sample in categories relative to the age and the size of the firm for first- and second-level cooperatives. The high number of micro and small cooperatives shows an important issue, the limited dimension of the cooperatives.

## Variables

### *Inputs and outputs to compute Malmquist productivity index*

Based on previous agri-food studies, this analysis used one output and two inputs to compute Malmquist productivity index. The output was defined as the turnover volume, which represents the operating revenue from selling the products produced; this allows an adequate evaluation of the activity of the productive unit examined (Soboh *et al.*, 2012; 2014). The inputs<sup>4</sup> were represented by the labour costs and fixed assets (Galdeano-Gómez, 2006; Guzmán & Arcas, 2008; Soboh *et al.*, 2012).

### *Variables to estimate the productivity growth model*

Productivity growth was evaluated through the Malmquist productivity index. The explicative variables, labour and capital growth, were built as the growth rates of employees and capital intensity defined as fixed assets on total assets. Finally, we defined the interconnection among first- and second-level companies by a binary weight matrix  $Wc$ , where its elements  $w_{ij}$  were valued one if companies  $i$  and  $j$  are connected and zero otherwise. The elements of the main diagonal were valued zero by definition (Anselin, 1988). This matrix was row standardized.

## Results

### Malmquist productivity index

Table 2 summarises the results for the technical efficiency, technological change and total factor productivity from the period between 2012 and 2015.

We found that the change in TFP increased by 4.5% during the analysed period. In addition, EFC was the main driver of productivity growth by 6.3%, while the TEC decreased by 1.6%. Regarding differences between first- and second-level cooperatives, we found that they have a similar tendency in terms of productivity and its components. However, first-level cooperatives had higher growth rates than second-level cooperatives.

For more detailed outcomes, Table 3 shows the productivity growth of first- and second- level cooperatives for each year. These findings showed that first-level cooperatives present better results every year. TFP, EFC and TEC were higher for first-level cooperatives than second-level organisations. For example, from 2012-2013, the former grew by 15.1% in TFP, while the second increased 10.8%. We also decomposed the TFP change into EFC and TEC. The results showed that EFC was the main driver of the productivity growth of both first- and second-level cooperatives. Differently from previous literature on productivity, we split up our sample between first- and second-level cooperatives.

When we differentiated between first- and second-level cooperatives, we found that second-level cooperatives showed lower TFP, EFC and TEC than first-level cooperatives.

### Panel estimation with spatial interaction effects for agri-food cooperatives

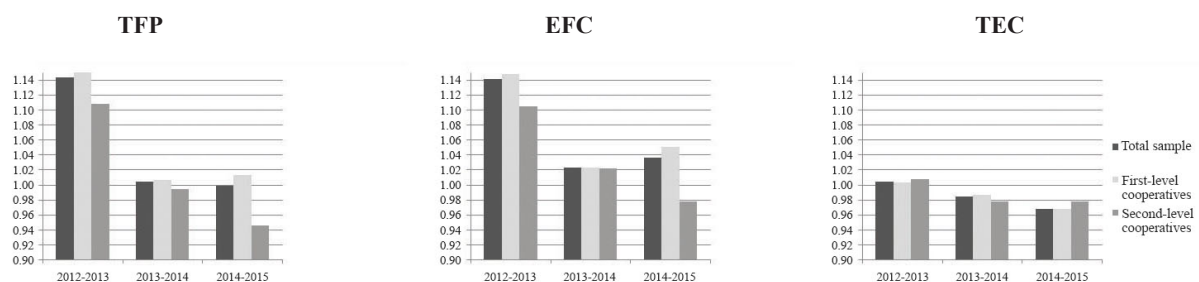
To test whether inter-organisational relationships produced a significant effect on the productivity growth of interconnected companies, we estimated a productivity growth model with spatial interaction effects [8]-[10]. In particular, Table 4's columns (1)-(4) present the estimation results of the productivity growth model when adopting a non-spatial panel model including individual and temporal heterogeneity [7] and tests whether the SLM, SEM and SDM were significant structures for this model.

Taking the ordinary least squares (OLS) model

<sup>4</sup> To support the robustness of our results, we applied alternative proxies to measure the input variables. In particular, we proposed the total number of employees as an alternative of labour input (Maté & Madrid, 2011). The results were analogous under these proxies.

**Table 3.** Malmquist productivity growth and its components, 2012-2015

Year	Sample	Agri-food cooperatives		
		TFP	EFC	TEC
2012-2013	Whole sample	1.143	1.141	1.004
	First-level cooperatives	1.151	1.149	1.003
	Second-level cooperatives	1.108	1.106	1.006
2013-2014	Whole sample	1.004	1.024	0.984
	First-level cooperatives	1.007	1.024	0.986
	Second-level cooperatives	0.994	1.022	0.977
2014-2015	Whole sample	0.999	1.036	0.966
	First-level cooperatives	1.013	1.051	0.966
	Second-level cooperatives	0.946	0.979	0.977



TFP, total factor productivity; EFC, technical efficiency change; TEC, technological change

as point of departure, the likelihood ratio (LR) test was performed to check the individual and temporal heterogeneity. The column (2) includes variable ( $\mu_i$ ), which represents the effects of the individual unobserved variable time invariant and specific for each company  $i$ . To identify the more adequate model from the OLS and panel data with an individual heterogeneity estimation, we computed the LR test. This test (94.2112,  $p < 0.01$ ) indicated that spatial heterogeneity ( $\xi_i$ ) must be incorporated in the productivity growth model. The column (3) controls the temporal heterogeneity (in our model. In this case, the LR test (20.1741,  $p < 0.01$ ) was significant; thus, we rejected the null hypothesis of non-temporal heterogeneity. Finally, the column (4) showed the estimation results when individual and temporal fixed effects were included (this estimation is known as the two-way model). For this estimation, the LR test (36.3951,  $p < 0.01$ ) was significant, indicating that this model fixes better than the previous OLS model. Thus, we selected this two-way panel data to model productivity growth in agri-food companies.

Based on this estimation (column 4, Table 4), we applied Lagrange Multiplier (LM) tests to determine whether there was a spatial interaction structure in the model and, in this case, to determine the more adequate spatial structure. LM tests determined whether the SLM [8] or the SEM [9] were significant structures to be considered in these specifications. Both, the hypothesis of no spatially lagged dependent variable, LM Spatial

Lag (LM-LAG) and its robust version (LM-LE), and the hypothesis of no spatially autocorrelated error term, LM Spatial Error (LM-ERR) and its robust version (LM-EL) were rejected at 5% when the two-way fixed effect panel model was considered (column 4, Table 4).

We followed the LeSage & Pace (2010) methodology that recommends estimate a SDM [10] when both LM tests are rejected. Once we get SDM estimation, the Wald tests were computed to contrast whether the SDM can be simplified to the SLM or whether it can be simplified to the SEM. Both tests were positive and significant (12.3032,  $p < 0.01$  and 13.3576,  $p < 0.05$ , respectively), indicating that the SDM better adjusts this specification than SLM or SEM.

The initial estimated coefficients in the previous SDM (column 5, Table 4) did not represent marginal changes in the productivity growth as consequence of changes in the explicative variables, but these coefficients require a decomposition process of the total effect into direct and indirect effects (LeSage & Pace, 2010). The direct effect captures the effects of changes in the explicative variables in company  $i$  on the productivity growth of company  $i$ . The indirect effect measures the effect of any change in the explicative variable of interconnected companies  $j$  with company  $i$  on the productivity growth of company  $i$ . Table 5 reports direct, indirect and total effects based on the previous SDM estimation. Regarding the direct effects, we obtained a positive and significant sign for the explicative variables, labour and capital

**Table 4.** Panel estimations of productivity growth model (N=265; T=3)

Determinants	(1) Pooled OLS	(2) Spatial fixed effects	(3) Time-period fixed effects	(4) Spatial and time-period fixed effects	(5) Spatial Durbin model
Labour growth	0.1714*** (0.004)	0.1265*** (0.0013)	0.1710*** (0.0048)	0.1248*** (0.0036)	0.1287*** (0.0032)
Capital growth	0.0696*** (0.019)	0.1369*** (0.0034)	0.0712 (0.1022)	0.1384*** (0.0029)	0.0938** (0.043)
Constant	0.9904*** (0.000)	-	-	-	-
W*TFPch	-	-	-	-	0.2360*** (0.0000)
W*Labour growth	-	-	-	-	-0.0336*** (0.863)
W*Capital growth	-	-	-	-	0.2175*** (0.000)
R <sup>2</sup>	0.0385	0.0497	0.0182	0.0482	0.3526
Log L	-44.9750	-90.1989	-127.2175	-80.119	-
LM spatial lag	2.4502 (0.118)	2.7358* (0.098)	0.7726 (0.379)	3.3158* (0.058)	-
LM spatial error	2.4265 (0.119)	1.7953 (0.180)	0.7948 (0.373)	3.2021* (0.061)	-
Robust LM spatial lag (LM-LE)	0.0406 (0.840)	8.8152*** (0.003)	0.0192 (0.890)	3.7419* (0.053)	-
Robust LM spatial error (LM-EL)	0.0169 (0.897)	7.8747*** (0.005)	0.0414 (0.839)	3.4700* (0.062)	-
LR (spatial vs pool)	-	94.2112*** (0.0009)	-	-	-
LR (temporal vs pool)	-	-	20.1741*** (0.0002)	-	-
LR (individual and temporal vs pool)	-	-	-	36.3951*** (0.0000)	-
Wald test spatial lag (Durbin vs SLM)	-	-	-	-	12.3032*** (p=0.0053)
Wald test spatial error (Durbin vs SEM)	-	-	-	-	13.3576** (p=0.0363)

OLS, ordinary least squares; W, spatial weight matrix; TFPch, total factor productivity change; L, likelihood; LM, Lagrange multiplier; LE, robust version of LM spatial lag; EL, robust version of LM spatial error. *p*-value in parenthesis. \*, \*\*, \*\*\*: significant at 10%, 5% and 1%, respectively.

growth. Moreover, our results relate labour and capital growth in connected companies with company with the productivity growth in company *i*. These coefficients were evaluated through the indirect effects in Table 5. As we can observe, labour growth productivity was not significant, while we found a significant and positive sign for capital growth. Therefore, an increase in the capital growth of associated companies to company *i* of one unit will cause a 17.13% increase in the productivity growth of company *i*. These, companies experience a positive effect if they associate with other cooperatives investing in capital. Our results supported the need for considering productive characteristics and interconnections among first- and second-order

cooperatives when agri-food cooperatives' productivity growth is examined.

## Discussion

The important weight of alliances in overcoming the limitation of cooperatives derives from cooperatives' information asymmetry, financial constraints and limited size, which prevent them from being more competitive in the market. Consequently, the number of cooperatives integrating with other cooperatives has increased in recent years. This collaboration plays a main role in the agri-food market, characterised by continuous changes to

**Table 5.** Direct and indirect effects estimates based on the coefficient estimates of the spatial Durbin model (SDM) reported in Table 4

	(1) Direct effect	(2) Indirect effect	(3) Total effect
Labour growth	0.1367 (0.0289)**	-0.0601 (0.7202)	0.0766 (0.0338)**
Capital growth	0.0796 (0.0696)*	0.1713 (0.000)***	0.2509 (0.000)***

*p*-value in parenthesis. \*, \*\*, \*\*\*: significant at 10%, 5% and 1%, respectively.

open and more globalised economies and new consumer demands, where competence is becoming more intense. In general, we found different theoretical studies that determine the advantages of second-level cooperatives. However, despite the importance of these alliances, their effects on the productivity of cooperatives have been scarcely considered in the cooperatives literature. Galdeano-Gómez (2006) or Kondo *et al.* (2008) analysed the effects on productivity growth derived from the own firm characteristics. However, they did not consider the effect caused by interconnected companies.

To shed additional light on this research area, we developed an empirical application on a sample of 265 agri-food companies over the period 2012-2015. Of these 265 cooperatives, 218 were first-level cooperatives, which were integrated into 45 second-level organisations. We estimated spatial panel data applied on a traditional productivity growth model. Our results indicated that, apart from the direct effects of the labour and capital investments of cooperatives on their own productivity growth, there was an additional indirect effect of the investments in the productivity factors of interconnected cooperatives. In particular, we found that capital investments in a cooperative had positive effects on the productivity growth of its interconnected cooperatives. These results may be explained by the fact that cooperatives face capital investments constraints because of agency problems with cooperatives' members. The disincentive of members to acquire high risk and the separation between owner and management functions may reduce the contributions of members to their cooperatives (Jensen & Meckling, 1976; Cook, 1995).

In this situation, cooperatives perceive alliances as a way to take advantage of and secure their productive structures from their associated cooperatives. This positive interaction between cooperatives constitute relevant mechanisms for stakeholders in their company decisions. This formula offers a greater concentration of cooperatives' supply providing a better position in front of the companies that act in the same markets. Also, this association provides a channel to obtain more economic resources required to be more competitive in the current agri-food markets. For

previous reasons, agri-food policies should discourage the individualist mentality of the cooperative members and stimulate cooperation among companies to overcome their limitations. In addition, cooperatives' managers should analyse the productive characteristics of their peer companies when they are deciding on their association with other cooperatives. Moreover, considering the existence of significant indirect effect generated between first- and second-level cooperatives would be a good opportunity for strengthening cooperative associations in order to obtain the resources required to be more competitive in the current markets.

Finally, future research in this area is needed to test our results in other scenarios. With this purpose, alternative databases should be considered. SABI gets accounting information from companies which deliver their Financial Statements in the Accounting Registers. Cooperatives have not to deliver their Financial Statements in the Accounting Registers while non-cooperative companies are obligated by law. Therefore, the application of SABI database could cause a selection bias providing a lower percentage of cooperatives, in relation with the total population, in comparison with non-cooperatives. This is a limitation of our study which will be considered in future studies.

## References

- Anselin L, 1988. Spatial econometrics: Methods and models. Kluwer Acad. Publ., Dordrecht, The Netherlands. <https://doi.org/10.1007/978-94-015-7799-1>
- Arcas-Lario N, 2002. Contribución de las cooperativas agrarias de segundo grado a la orientación al mercado de sus cooperativas asociadas: efectos en el desempeño de la relación. CIRIEC-España 41: 139-161.
- Arcas-Lario N, Hernández-Espallardo M, 2003. Co-ordination and performance of Spanish second-level agricultural cooperatives: The impact of relationship characteristics. Eur Rev Agr Econ 30 (4): 487-507. <https://doi.org/10.1093/erae/30.4.487>
- Bassem BS, 2014. Total factor productivity change of MENA microfinance institutions: A Malmquist productivity index approach. Econ Model 39: 182-189. <https://doi.org/10.1016/j.econmod.2014.02.035>
- Berger AN, Udell GF, 1998. The economics of small business finance: The roles of private equity and debt markets in the financial growth cycle. J Bank Financ 22 (6-8): 613-673. [https://doi.org/10.1016/S0378-4266\(98\)00038-7](https://doi.org/10.1016/S0378-4266(98)00038-7)
- BOE, 2010. Order EHA/3360/2010 of 21 December, that approves the rules on the accounting aspects of cooperative firms. Boletín Oficial del Estado (Spain) No. 316, 21/12/10.
- Coelli TJ, Prasada-Rao DS, Battese GE, 1998. An introduction to efficiency and productivity analysis. Kluwer Acad.



- Publ., Massachusetts, USA. <https://doi.org/10.1007/978-1-4615-5493-6>
- Coelli TJ, Prasada-Rao DS, 2005. Total factor productivity growth in agriculture: A Malmquist index analysis of 93 countries, 1980-2000. *Agr Econ* 32 (1): 115-134. <https://doi.org/10.1111/j.0169-5150.2004.00018.x>
- COGECA, 2015. Development of agricultural cooperatives in the EU, 2014. COGECA, European Agro-cooperatives. <http://www.agro-alimentarias.coop/ficheros/doc/04519.pdf>. [01 July 2016].
- Cook ML, 1995. The future of US agricultural cooperatives: A neo-institutional approach. *Am J Agr Econ* 77 (5): 1153-1159. <https://doi.org/10.2307/1243338>
- Cooper WW, Seiford LM, Kaoru T, 2007. Data envelopment analysis a comprehensive text with models, applications, references and DEA-solver software. Springer, NY.
- Elhorst JP, 2010. Applied spatial econometrics: Raising the bar. *Spat Econ Anal* 5 (1): 9-28. <https://doi.org/10.1080/17421770903541772>
- EC, 2003. Commission recommendation of 6 May 2003 concerning the definition of micro, small, and medium-sized enterprises. 2003/361/EC. Official Journal of the European Union, Ref. L124/36 dd. 20/05/03.
- Färe R, Grosskopf S, Knox-Lovell CA, 1994. Production frontiers. Cambridge University Press, Cambridge.
- Fingleton B, Le Gallo J, 2008. Estimating spatial models with endogenous variables, a spatial lag and spatially dependent disturbances: Finite sample properties. *Papers in Regional Science* 87 (3): 319-339. <https://doi.org/10.1111/j.1435-5957.2008.00187.x>
- Galdeano-Gómez E, 2006. Productivity and efficiency analysis of horticultural co-operatives. *Span J Agric Res* 4 (3): 191-201. <https://doi.org/10.5424/sjar/2006043-194>
- Giannakis E, Bruggeman A, 2015. The highly variable economic performance of European agriculture. *Land Use Policy* 45: 26-35. <https://doi.org/10.1016/j.landusepol.2014.12.009>
- Griffell-Tatjé E, Lovell CAK, 1995. A note on the Malmquist productivity index. *Econ Lett* 47 (2): 169-175. [https://doi.org/10.1016/0165-1765\(94\)00497-P](https://doi.org/10.1016/0165-1765(94)00497-P)
- Guzmán I, Arcas N, 2008. The usefulness of accounting information in the measurement of technical efficiency in agricultural cooperatives. *Ann Public Coop Econ* 79 (1): 107-131. <https://doi.org/10.1111/j.1467-8292.2007.00354.x>
- Hendrikse G, Bijman J, 2002. On the emergence of new growers' associations: Self-selection versus countervailing power. *Eur Rev Agr Econ* 29 (2): 255-269. <https://doi.org/10.1093/eurrag/29.2.255>
- Jensen MC, Meckling WH, 1976. Theory of the firm: managerial behavior, agency costs and ownership structure. *J Financ Econ* 3 (4): 305-360. [https://doi.org/10.1016/0304-405X\(76\)90026-X](https://doi.org/10.1016/0304-405X(76)90026-X)
- Juliá JF, Marí S, 2002. Farm co-operatives and the social economy: the case of Spain. *J Rural Coop* 30: 119-133.
- Juliá-Igual JF, Meliá-Martí E, García-Martínez G, 2012. Strategies developed by leading EU agrifood cooperatives in their growth models. *Service Business* 6 (1): 27-46. <https://doi.org/10.1007/s11628-011-0129-3>
- Kondo K, Yamamoto Y, Sasaki J. 2008, Measuring total factor productivity change for agricultural cooperatives in Japan: A nonparametric Malmquist indices approach. *J Rural Coop* 36 (2):101-114.
- Kyriakopoulos K, Van Bakkum OF, 1999. Market orientation of European agricultural cooperatives: Strategic and structural issues. IX Eur Congr Agric Econ, Warsaw (Poland), Aug 24-28. pp: 148-164.
- Kyriakopoulos K, Meulenber M, Nilsson J, 2004. The impact of cooperative structure and firm culture on market orientation and performance. *Agribusiness* 20 (4): 379-396. <https://doi.org/10.1002/agr.20021>
- LeSage JP, Pace RK, 2010. Spatial econometric models. In: Handbook of applied spatial analysis, pp: 355-376. Springer Berlin Heidelberg. [https://doi.org/10.1007/978-3-642-03647-7\\_18](https://doi.org/10.1007/978-3-642-03647-7_18)
- Maté ML, Madrid A, 2011. A spatial efficiency index proposal: An empirical application to SMEs productivity. *Ann Region Sci* 47 (2): 353-371. <https://doi.org/10.1007/s00168-010-0382-8>
- Martínez-Sola C, García-Teruel PJ, Martínez-Solano P, 2014. Trade credit and SME profitability. *Small Busin Econ* 42 (3): 561-577. <https://doi.org/10.1007/s11187-013-9491-y>
- NACE, 2007. Statistical classification of economic activities in the European Community (NACE). Eurostat, statistics explained. [http://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary:Statistical\\_classification\\_of\\_economic\\_activities\\_in\\_the\\_European\\_Community\\_\(NACE\)](http://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary:Statistical_classification_of_economic_activities_in_the_European_Community_(NACE)).
- Ord K, 1975. Estimation methods for models of spatial interaction. *J Am Stat Assoc* 70 (349): 120-126. <https://doi.org/10.1080/01621459.1975.10480272>
- OSCAE, 2015. Macromagnitudes del cooperativismo agroalimentario español 2014. <http://www.agro-alimentarias.coop>. [20 June 2016].
- Puentes R, Antequera JM, Velasco M, 2007. Las sociedades cooperativas de segundo grado y su relación jurídica con socios. *REVESCO* 93 (3): 98-143.
- Soboh R, Oude-Lansink A, Van Dijk G, 2012. Efficiency of cooperatives and investor-owned firms revisited. *J Agr Econ* 63 (1): 142-157. <https://doi.org/10.1111/j.1477-9552.2011.00324.x>
- Soboh R, Oude-Lansink A, Giensen G, Van Dijk G, 2014. Efficiency of European dairy processing firms. *NJAS- Wageningen J Life Sci* 70-71: 53-59. <https://doi.org/10.1016/j.njas.2014.05.003>
- Wooldridge J, 2012. Introductory econometrics: A modern approach. Cengage Learning.