Spatial dynamic analysis of productivity growth of agri-food companies

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Abstract

This study analyzes the spatial dynamics in productivity growth and its components for a sample of agri-food companies in Murcia (Spain) over the period 2005-2014. We find that productivity growth of a company is related to productivity growth of neighboring companies, in both the short and long term. The marginal effects of the different factors on productivity growth are stronger in the short run rather than the long run. Land characteristics and economic territorial conditions have the largest marginal effect on productivity growth and its components. This study contributes to the existing literature by including spatial interactions in the analysis of productivity growth.

Keywords: Food and agribusiness companies, dynamic panel data, dynamic Luenberger indicator, spatial analysis.

Jel Codes: C23 D22 O13 Q13 R11

1. Introduction

Firms in the food and agribusiness sector make decisions taking into account their own capabilities and the specific territorial characteristics of the region in which they are located (Yu et al., 2014). Studies have investigated the potential competitive advantage arising from geographical proximity between peer companies (Delgado et al., 2014; Rallet and Torre 2005; Tveteras, 2002). These studies show that spatial concentration of companies positively affects productivity through input-output linkages, labor market pooling, and knowledge spillovers (Porter, 2003; Tveteras and Battese, 2006).

Focusing on the agri-food sector, Becattini (2004) and Aznar-Sánchez and Galdeano-Gómez (2011) considered the effect on the productivity of a local network between companies geographically close to one another. These studies are based on the definition of localized agri-food systems (LAFS) as a set of agri-food enterprises, business or services organizations, restaurants and institutions linked to a specific geographic area (Muchnik et al., 2007). Thus, agri-food production tends to be closely linked to the characteristics of the region and economic agents in which companies are located, making these characteristics relevant for the analysis of productivity. For example, in their analysis of productivity, Galdeano-Gómez (2008) and Hoang and Coelli (2011) accounted for the natural characteristics of the territory where the companies were producing, such as water consumption, land (permanent crops, meadows, or pasture) and fertilizers. They find a significant result of these natural characteristics on productivity growth of agri-food companies. In addition to the natural characteristics, the literature also indicates that the economic characteristics of the area are relevant to the analysis of firms' behavior (Beck et al., 2005; Cassia and Vismara, 2009; Musso and Schiavo, 2008). This suggests that the analysis of the productivity of agri-food companies should consider territorial factors, such as regional economic and financial characteristics and public policies.

In this context, the spatial concentration of agri-food companies is another relevant factor. A high density of companies in a territory generates positive externalities from one economic agent to other agents due to the synergies among them (Requier-Desjardins and Colin, 2010). These synergies are also referred to as agglomeration economies (see e.g., Tveteras and Battese, 2006). The cooperation between neighboring companies generates potential business opportunities and formal and financial relationships (e.g., subcontracting), resulting in economic advantages (Karlsson et al., 2005). The interconnection between geographically close companies is a potential advantage for agri-food companies that strengthens their competitiveness and productivity (Chiffoleau and Touzard, 2014; García-Álvarez-Coque et al., 2015; Rallet and Torre, 2005). Galdeano-Gómez et al. (2008) point out that the spillover effect generates a positive effect improving the performance of the agri-food companies located in Andalusia. The spatial concentration makes a contact networks between farmer members encouraging the direct contact and getting tacit and explicit information. The interactive feedback with other organizations or people that work in the area about environmental management practices, sharing technological advances roll out by the competitors or the successful or failure of strategic decisions of their competitors, are the drivers of this knowledge diffusion (Delgado et al., 2014; Galdeano-Gómez et al., 2008; Pede et al., 2018; Tallman et al., 2004).

In general, it is well accepted that geographical proximity increases the probability of knowledge diffusion between companies (Chiffoleau and Touzard, 2014; García-Álvarez-Coque et al., 2015; Giuliani, 2007; Läpple et al., 2016; Rallet and Torre, 2005). Most of the above-mentioned studies assume the benefit from the proximity firms (same industry) or the suppliers and demander production (Ciccone and Hall, 1996). However, these positive effects are not always given. Although, the productivity growth and agglomeration tend to be positively correlated, some studies highlight the prevalence of congestion effect. This means that there are limits to agglomeration before having a negative effect on productivity growth. This is in line with Rizov et al. (2012) and Drucker and Feser (2012). Another negative effect could be arising by involuntary knowledge spillovers thought which information escapes to other companies (Eriksson, 2011).

Thus, existing studies on the productivity of agri-food companies have not fully investigated the spatial contributions to productivity growth. In addition, previous studies on spatial contributions to productivity growth only investigated the role of regional variables and ignored the possible interaction effects among peer companies (Yu et al., 2014). Furthermore, these studies did not investigate the spatial effects on the components of productivity growth, such as technical change and technical efficiency change. Finally, previous studies were primarily conducted in the static context by applying the Malmquist index (Galdeano-Gómez, 2008; Lissitsa and Odening, 2005; Odeck, 2009). The static context does not account for the dynamic character of capital and may distort the measurement of productivity growth (Serra et al., 2014). Exceptions are the dynamic productivity growth studies of Serra et al. (2014), Oude Lansink et al. (2015), Kapelko et al. (2015), and Kapelko et al. (2017). The dynamic approach explicitly accounts for the role of adjustment costs associated with changes in the stock of quasi-fixed factors (Kapelko et al., 2015; Silva and Stefanou, 2003; Silva et al., 2015). Failure to account for adjustment costs may result in measures that confound adjustment costs with inefficiency.

In light of the foregoing, the objective of this paper is to investigate the relationship of regional characteristics and interactions between neighboring firms with the dynamic productivity growth of agri-food companies. Our empirical application tests whether specific territorial characteristics have a significant relationship with the productivity growth of agri-food companies located in the Spanish territory of Murcia. To achieve this aim, our sample included 1,238 agri-food companies located in Murcia[1]. This area represents one of the largest geographic concentrations of companies in the food and agribusiness sector in Spain (Martínez-Carrasco and Martínez, 2011). We obtained accounting and financial information for these companies from the SABI (Iberian Balance Analysis System) database. In addition, we used the CREM (Statistic Institute of Murcia) database to obtain regional characteristics for each municipality[2] (see Figure 1). This database provides information on different dimensions of Murcia municipalities, such as demography, society, economy, finances, and agriculture. Using this data, the first step of our study was to estimate the dynamic Luenberger productivity indicator and its components. Productivity growth is a reflection of changes in a firm´s use of the existing production potential and can reflect how investments enhance production potential through innovation resulting in new technologies (Kapelko et al., 2016). We analyzed productivity growth from a dynamic perspective to overcome the shortcoming of productivity measures derived from a static framework.

[1] Spain is divided into Autonomous Communities, which are territorial aggregations corresponding to the NUTS III classification. The NUTS (Nomenclature of Territorial Units for Statistics) is a hierarchical system for dividing up the territory of the European Union for analytical purposes (http://ec.europa.eu/eurostat/web/nuts).

[2] Municipality is equivalent to LAU2. Local Administrative Units (LAU) constitute a more disaggregated territorial unit than NUTS III (Autonomous Community) for dividing up the territory of the EU (http://ec.europa.eu/eurostat/web/nuts).

Figure 1. Geographical location of Murcia Autonomous Community. Division by municipalities

Source: Statistic Institute of Murcia

After computing dynamic productivity growth for each company, the next step was to analyze the spatial behavior of productivity growth by applying an exploratory spatial analysis. Next, we investigated the relation between productivity growth and different spatial variables reflecting the characteristics of the financial and economic environment and the productivity of peer companies located close to the companies in our sample. Our results show significant relationships of these variables with the dynamic Luenberger productivity growth indicator, highlighting the importance of accounting for spatial and temporal dimensions of productivity growth when analyzing the determinants of productivity growth in agribusinesses. In addition, we distinguished between short- and long-term effects, stressing the relevance of the temporal dimension. Land characteristics and economic territorial conditions show the most relevant relationships on productivity growth and its components.

The contribution of this study to the literature on productivity growth in the agri-food sector is twofold. Firstly, we quantified spatial interactions between geographically close peer agri-food companies in Murcia. Although previous studies have considered these interactions from a theoretical perspective, studies quantifying them are scarce (Broersma and Oosterhaven, 2009; Díez-Vial, 2011). Secondly, our findings underline the importance of accounting for two types of spatial factors in productivity growth models: territorial characteristics and the productivity of neighboring peer companies.

The remainder of this paper is organized as follows. The next section presents the data and methodology. This is followed by the results of the empirical application in section 3. The discussion and conclusion are presented in section 4.

2. Material and methods

2.1 Regional characteristics

We selected a sample of agri-food companies located in Murcia because of the important weight of the agrarian sector on the global production of this region (southeast of Spain on the Mediterranean coast, see Figure 1). This territory is the major producer of fruits and vegetables in Spain attributed this to the high technology application to the production processes, high quality standards and strengthen international presence in the markets (INFO, 2017). This region export volume of 2,472 million euros, equivalent to 26.3 percent of the total agri-food exports of the region (CARM, 2017). Despite these significant figures, the south of Spain is composed by less[3] developed regions. In particular, this territory is characterized by low productivity values, which tend to be lower than the average national values (Maté et al., 2009). The identification of regional elements that promote productivity growth is therefore particularly relevant for this sector and territory.

2.2 Description of the sample

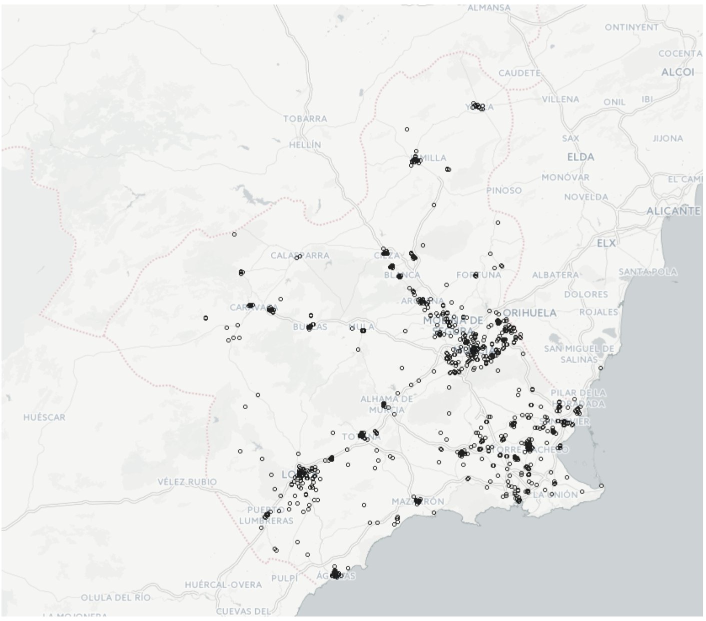
The data cover the period 2005-2014 and were obtained from the SABI database. This database contains a wide range of financial and accounting data on the different business dimensions of more than one million Spanish firms. The sample was cleaned by removing companies with anomalies (for example, negative values in their sales or assets) or missing values in financial statements. After this process, the final data set contained 1,238 observations on agri-food[4] companies over the period 2005-2014. The spatial distribution of the study sample across Murcia shows three areas with a high density of agri-food companies (see Figure 2). Firms are spatially concentrated around the three largest distribution centers for food products. These areas of high density are located in the following municipalities: Murcia, with approximately

[3] Giannakis and Bruggeman (2015), Ezcurra et al. (2008) or Stoate et al. (2009) show that more developed regions are situated in the north and central European territories while southern are characterized by worst economic results. In Spain, Maté et al. (2009) corroborate the same productivity pattern finding less productivity values in the south of Spain.

[4] Following the criterion established in the National Classification of Economics Activities (NACE, 2007). The activities included in this study correspond with the NACE codes A1.11 (Growing of cereals), A1.13 (Growing of vegetables and melons, roots and tubers), A1.2 (Growing of perennial crops), A1.4 (Animal production), A1.5 (mixed farming), A1.6 (Support activities to agriculture and post-harvest crop activities), G4.621 (wholesale of grain) and G4.631 (wholesale of fruit and vegetable). Fruit and vegetable and grain sector represent de majority of the sample (around 75 per cent).

21 percent of the agri-food companies in the sample, Lorca with approximately 11.6 percent, and Cartagena with approximately 7.6 percent (highlighted in Figure 2[5]).

Figure 2. Spatial distribution of agri-food companies across Murcia



Source: Own- elaborated with Google MyMaps

2.3 Spatial econometric modelling

In order to test for the effect of the firms' spatial distribution on their productivity, we apply spatial econometric techniques. This methodology facilitates the analysis of the effect of geographical location and the interactions between geographically close (vicinity) agents on their performance. The spatial analysis is usually structured into two steps. Firstly, an exploratory spatial analysis identifies characteristics of the spatial behavior of the target variable, in our case the productivity growth of agri-food companies. This analysis is based on graphical tools and univariate analysis, such as spatial autocorrelation tests to identify the existence of spatial autocorrelation structures in the distribution of the studied variable. Spatial autocorrelation is understood as the spatial association in the values of a variable between neighboring agents (Anselin, 2001). In other words, 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. The structure of vicinity is usually defined through the W spatial weight matrix, which is constructed in

[5] According to the Instituto de Fomento de la Región de Murcia, Murcia, Lorca, and Cartagena are the municipalities with the highest concentration of agri-food companies.

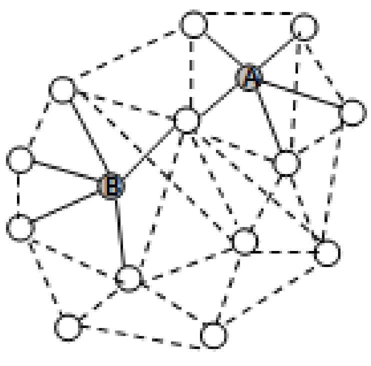
terms of geographical proximity. One of the most frequently applied spatial autocorrelation tests is Moran's test (Moran, 1948; Cliff and Ord, 1973), specified as:

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{1}$$

where y is the variable of interest, $\bar{y}$ is its average value, and subscripts i and j refer to agent i and its vicinity agent j. w_{ij} denote the different elements of the spatial weight matrix W, which is non-negative and symmetric, with diagonal elements set to zero. In particular, the i-th file of W identifies (with values different from zero) the agents that interact with agent i. One of the most controversial elements in spatial econometrics is that the spatial weight matrix W cannot be estimated and is therefore, predefined. This is a critical issue in spatial econometric modelling. One approach is to apply a selection procedure for the weights matrix based on the log-likelihood function value. In a simulation study, Stakhovych and Bijmolt (2009) demonstrated that this procedure, based on goodness-of-fit criteria, increases the probability of finding the true specification.

Following this reasoning, we considered several weight matrices defined as binary matrices W_k, with elements $w_{ij} = 1$ if the companies i and j are neighbors and $w_{ij} = 0$ otherwise. For each company i, we considered as neighbors the k nearest companies to company i in terms of geographical proximity, for k equal to 5(W_{n5}), 8(W_{n8}), and 10(W_{n10}) (see Figure 3).

Figure 3. Neighboring companies to the company according to the five number of neighbors (k=5)



Source: authors' elaboration

To determine the most adequate spatial weight structure, we computed goodness-of-fit criteria for k equal to 5, 8, and 10. We also considered an alternative spatial weight matrix defined as geographical distance, but the results were analogous.

2.4 A dynamic spatial panel data model

Given the dynamic character of the productivity growth variable, we proposed a dynamic model including a spatial autoregressive process in the dependent variable at contemporaneous time t as well as the previous period $t-1$, for $t=1,\dots,T$ (Anselin, 2001). The model is specified as:

$$\mathrm{Y_t = \tau Y_{t-1} + \delta W Y_t + \eta W Y_{t-1} + X_t \beta + \mu + \alpha_t l + \varepsilon_t}, \quad (2)$$

where Y_t is an $Nx1$ vector of the dependent variable, i.e., the productivity growth for the N companies in the sample at time t[6]. X_t is an NxK matrix of K explanatory variables and W is a non-negative $N \times N$ spatial weight matrix describing the spatial connections between the companies in the sample. A vector or matrix with subscript $t-1$ denotes its serially lagged value, and a vector or a matrix pre-multiplied by W denotes its spatially lagged value. τ, δ, and η are the response parameters of respectively, the lagged dependent variable Y_{t-1}, the lagged dependent variable in space WY_t, and the dependent variable lagged both in space and time WY_{t-1}. δ is the spatial autoregressive coefficient, η is the lagged spatial autoregressive coefficient, and β represents a $K \times 1$ vector of response parameters of the explanatory variables. $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t}, \dots, \varepsilon_{Nt})^T$ is a vector of independently and identically distributed error terms with zero mean and variance σ^2. $\mu = (\mu_1, \mu_2, \dots, \mu_N)^T$ is a vector of individual fixed effects, one for every company in the sample $i = 1, \dots, N$. α_t is the coefficient of a temporal fixed effect, one for every time point in the sample (except one to avoid perfect multicollinearity) and l is an $N \times 1$ vector of ones.

We proposed this specification due to the characteristics of our model. We restricted the spatial lag of the exogenous variables (WX) to zero because we defined the territorial characteristics using information from municipalities. In addition, we assumed that the structural character of the analyzed process causes the spatial behavior. Under these premises, Equation (2) is the appropriate specification. We found empirical applications of the spatial dynamic panel data model in Debarsy et al. (2012) and Vega and Elhorst (2013). Following these studies, we

[6] In order to measure firms' productivity growth we apply the dynamic Luenberger productivity growth indicator which allows for measuring the productivity growth in the context where firms invest in new technology and where investments may come with adjustment costs (see Annex 1 for a more elaborate presentation of the dynamic Luenberger productivity growth indicator).

applied the bias-corrected ML estimator proposed by Lee and Yu (2010) for a dynamic spatial panel data model[7] with spatial and temporal fixed effects. As N/T goes to infinity (N grows faster than T), the bias corrected ML estimations are T consistent. In our empirical application, N (1,238) is greater than T (9), and the bias-corrected estimator is therefore the appropriate estimator (Elhorst, 2010).

3. Empirical application

3.1 Description of the data and variables

Table 1 (Panel A) provides the descriptive statistics of the input and output variables used in this study, for the whole period 2005/2006-2013/2014. Table 1 (Panel B) shows the variables used to analyze the spatial sources of productivity growth. The standard deviations relative to the respective means of the inputs and outputs indicate that the firms in our sample vary in size, i.e., the coefficients of variation, computed as the ratio of the standard deviation to the mean, are all higher than five.

Table 1. Means and standard deviations of the input and output variables for 2005-2014

Panel A: Inputs and outputs (measured in thousands euros). N=1238				
Fixed assets	*Labor costs*	*Material costs*	*Investments*	*Output*
1,052.446 (5,713.585)	314.778 (1,657.951)	1,898.935 (11,945.676)	95,965 (1,530.390)	2,959.168 (14,261.772)
Panel B: Regional variables. N=1238				
Non-irrigated land	*Irrigated land*	*Bank offices*	*Tax burden*	*Unemployment*
16,537.750 (17,294.824)	10,781.543 (7,466.120)	102,162 (154.670)	992.268 (384.643)	10,932.803 (15,384.138)

The Luenberger indicator of dynamic productivity was computed with one output and three inputs (Kapelko et al., 2015, 2017). The output was estimated as the annual revenue deflated using the industrial price index for the manufacture of food products. The labor costs input was deflated using the labor cost index in manufacturing and the material costs input was

[7] The spatial component has been adjusted as a fixed effect in order to eliminate the endogeneity in our results.

deflated by the industrial price index for non-durable consumer goods. Fixed assets was measured as the begin value of fixed assets from the balance sheet and were deflated using the industrial price index for capital goods. Gross investment in fixed assets in year t was computed as the begin value of fixed assets in year $\mathrm{t}+1$ minus the begin value of fixed assets in year t plus the begin value of depreciation in year $\mathrm{t}+1$. The price indices were obtained from the Spanish Statistical Institute[8].

Using the territorial information from the municipalities of Murcia, we accounted for the specific spatial characteristics that affect each company. As we were unable to obtain more disaggregated information, we assigned to each company the corresponding value of the regional variable in its municipality as a proxy for environmental characteristics. To account for the natural characteristics of the territory, we included the ratio of the number of hectares of irrigated (*Irrigated Land*) and non-irrigated land (*Non-Irrigated Land*) in each municipality to the size of the entire region (in squared kilometers). The Mediterranean region is characterized by a dry and warm climate, which has led to a diverse pattern of agriculture. A market-oriented type of agriculture predominates, with mainly crop cultivation, including fruit trees, olive, and grapes (Olesen and Bindi, 2002). Chen et al. (2008) include this variable to reflect the actual utilization of the cultivated land in China as input on the estimation of Malmquist productivity index and their decomposition. Balcombe et al. (2008) or Odeck (2009) also included the impact of land on their productivity index. The accessibility to financial services was quantified as the number of bank offices in each municipality per square kilometer of the corresponding municipality *(Bank Offices*). The impact of taxes on the companies was also considered, i.e., the *tax burden* was measured as the per capita tax expenses in each municipality. This variable indicates how the fiscal aspect impacts on productivity growth in the agri-food sector. In a recent study, Bournakis and Mallick (2018) show higher rates of corporate taxation slow down the rate of TFP growth. They estimate the firm TFP using five different methodologies, all of these suggests that higher corporate tax payments always affect the productivity growth. The final economic factor included in this study was the *unemployment* rate for each municipality (Beck et al., 2005; Delgado et al., 2014; Musso and Schiavo, 2008).

We also accounted for the number of output (input) markets by using the number of distribution centers that sell agrarian products in each municipality per square kilometer (*Market Concentration*). As control variables, we include the *size* of the company, evaluated as the logarithm of the total assets of each company, and the logarithm of the *age* of the

[8] www.ine.es

company. Finally, to incorporate the spatial interaction effect on the productivity growth of agri-food companies, we defined different spatial weight matrices, W, according to the geographic distance between the analyzed company and its neighbors. This matrix defines the network of connections among companies. In this study, three spatial binary weight matrices W_k were defined as the k nearest neighbors, with $k = 5, 8$ and 10.

3.2 Luenberger dynamic productivity growth indicator

Table 2 presents the dynamic Luenberger productivity growth indicator and its decomposition into dynamic technical change (ΔT), dynamic technical inefficiency change (ΔPEI), and dynamic scale inefficiency change (ΔSEI) for agri-food companies in the sample. Infeasibilities can arise in the computation of productivity growth[9]. Briec and Kerstens (2009) recommend reporting any infeasibility that occurs in the empirical application. In our application, infeasibilities in the mixed period direction functions occurred for approximately three percent of the observations.

The dynamic Luenberger productivity indicator is determined for each firm for a pair of consecutive years. The average annual productivity growth of agri-food companies (1.6 percent) shows that these companies can use 1.6 percent less input and 0.32 percent more investment, while still producing the same quantity of output.

The results in Table 2 suggest a positive contribution of technical change and technical inefficiency change to productivity growth. Dynamic technical change increased productivity by around 0.74 percent per year in the sample period. Dynamic technical inefficiency change increased productivity on average by 1.8 percent per year, while the dynamic scale inefficiency change decreased productivity by 0.96 percent per year during the period 2005-2014. Technical inefficiency change was the major contributor, on average, to productivity growth. This outcome suggests that companies have focused on improving the use of their production potential. Agri-food companies tended to achieve the maximum potential output from a given amount of inputs. However, this component fluctuated considerably during the study period (see Table 2).

[9] Infeasibilities can arise in the mixed period directional distance functions. In our empirical application, we excluded these observations in the computation of averages.

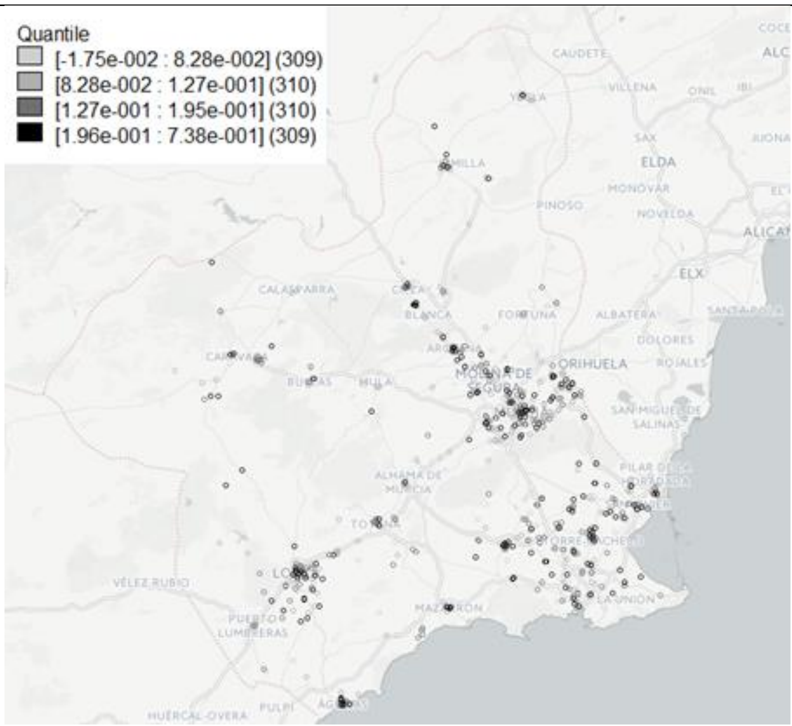
Table 2. Mean values for dynamic Luenberger productivity growth (LP) and its decomposition in technical change (ΔT), dynamic technical inefficiency change (ΔPEI), and dynamic scale inefficiency change (ΔSEI).

Years	*LP*	ΔT	ΔPEI	ΔSEI
2005-2006	-0.0697	-0.0076	-0.0572	-0.0021
2006-2007	0.0462	0.0208	0.0131	0.0123
2007-2008	-0.0466	-0.0098	-0.0607	0.0238
2008-2009	-0.0178	0.0061	0.0259	-0.0498
2009-2010	0.0426	-0.0115	0.0287	0.0245
2010-2011	0.1438	0.0413	0.1555	-0.0529
2011/2012	-0.0381	-0.0030	0.0075	-0.0426
2012/2013	-0.0630	0.0137	-0.0116	-0.0651
2013/2014	0.1473	0.0166	0.0652	0.0653
Mean 2005/2006-2013/2014	*0.0160*	*0.0074*	*0.0184*	*-0.0096*

3.3 Exploratory spatial data analysis

Using the productivity growth value for each company, we developed an exploratory spatial analysis that begins with a quartile map of the territorial distribution of the productivity growth values for the companies in the sample i. Figure 4 shows these results: the darkest color represents the companies with the highest productivity growth values. These companies tend to be located around the main production centers (see Figure 4) of Murcia, Lorca and Cartagena (Instituto de Fomento de la Región de Murcia, 2016).

Figure 4. Spatial quartile distribution of the Luenberger indicator of productivity growth (first range = lower productivity growth). Average values for the period 2005-2014. N=1238.



Source: authors' estimation with Matlab

The map suggests that the spatial distribution of the productivity growth of agri-food companies is distributed according to a specific spatial pattern: *companies with the highest productivity growth are concentrated around the three largest production centers*. Although this result comes from a graphical interpretation, it provides an indication of the possible spatial behavior of the productivity growth of these companies. To confirm this finding, we computed a spatial autocorrelation test. As there is no pre-established criterion to select the W that best fits our analysis, we computed Moran's I test by applying the previously defined weight matrix W based on the k nearest neighbors with $k = 5, 8,$ and 10 (W_{n5}, W_{n8}, and W_{n10}). From these results, we selected the spatial weight matrix that maximized the Moran's test, assuming that this matrix is the most representative of the analyzed spatial structure. Table 3 shows the results of Moran's I test.

Table 3. Moran's I test based on the $k = 5, 8$, and 10 nearest neighbors to each company. Average values for the period 2005-2014.

Matrix	*LP*	ΔT	ΔTEI[(1)]
W_{n5}	0.0398**	0.0251	0.0132
	(0.013)	(0.112)	(0.371)
W_{n8}	2.6911**	2.2645**	0.0098
	(0.007)	(0.023)	(0.421)
W_{n10}	0.0210**	0.0196*	0.0041
	(0.058)	(0.077)	(0.671)

[(1)] We decomposed ΔTEI into the contribution of ΔPEI and ΔSEI, but we do not included the results because they are similar than obtained in ΔTEI.

Source: authors' estimation with Matlab

The results of Moran's test are positive and statistically significant (at the critical 5% level) for the productivity growth variable when different weight matrices are considered (Table 3, second column). The highest Moran's test value was obtained when the weight matrix of eight closest neighbors was used (W_{n8}). The significant and positive value for Moran's test reveals the presence of a positive spatial autocorrelation in the dynamic productivity growth of agri-food companies in Murcia. This implies that neighboring companies tend to be characterized by similar levels of productivity growth. The spatial autocorrelation among agri-food companies could be motivated by the higher degree of beneficial specialization possible in the areas of dense economic activity (Rizov et al., 2012). The neighbor effect between agri-food companies may arise from information provided by neighboring firms about market characteristics, prices, product quality or quantity.

This explanation also applies to the technical change component but not to the technical inefficiency component. The result of Moran's test for dynamic technical inefficiency change is not significant (at the 5% level), suggesting that although companies can receive external knowledge about new productive techniques applied by their neighbors and adopt these techniques in their production processes. The insignificant spatial effect for the technical inefficiency component suggests that utilization of the production potential is internally and individually managed and therefore depends on the own management characteristics of a company.

3.4 Panel estimation with spatial effects for agri-food companies

The previous analysis indicated the existence of a significant spatial behavior in the productivity growth and technical change of agri-food companies in Murcia. In the following step, we estimated a dynamic spatial-temporal panel data model that enabled us to assess the changes in total factor productivity growth and its components over time (Simar and Wilson, 2007[10]). Table 4 reports the spatial dynamic panel data estimations for the three dependent variables: the Luenberger indicator (LP) in Model 1, technical change (ΔT) in Model 2, and technical inefficiency change (ΔTEI) in Model 3.

The specification of the model (Equation 2) is based on a spatial autocorrelation structure in the dependent variable. From a theoretical perspective, we assumed that the structural character of the dependent variable (productivity growth) could provide significant spatial interactions among companies. To test this assumption, we computed the robust Lagrange multiplier (LM) tests (LM spatial lag (LE test) and LM spatial error (EL test)) for the non-dynamic spatial panels. The LE test has as alternative hypothesis the existence of a spatial lag process in the dependent variable, while the EL test has as alternative hypothesis a spatial error structure. Both tests rejected the null hypothesis (at 5%), confirming the existence of a spatial process in the model (see Table 4, Model 1-3). In addition, the LE test results were larger than the EL test results for the three estimations, indicating that the spatial behavior could be explained by the structural character of the analyzed variable, consistent with a spatial lag model (Florax and Folmer, 1992).

Models[11] 1-3 were estimated controlling for individual spatial and temporal fixed effects. We conducted likelihood ratio (LR) tests for the non-dynamic specification for each model to contrast the (null) hypothesis that the spatial and temporal fixed effects are jointly insignificant. Both hypotheses were rejected at 5% (Table 4: LR (spatial vs pool) and LR (temporal vs pool)) and the models were therefore estimated including these individual spatial and temporal effects. These effects were considered as fixed rather than random effects because of the characteristics of our empirical analysis: we analyzed a sample composed of companies for which the assumption of independence of the individual effects was unrealistic (Elhorst, 2013). Moreover, we computed Hausman's tests for the non-dynamic versions of these models. The results support the existence of fixed effects (Table 4).
We found that the variables representing the spatial and temporal dynamic character of the dependent variable were significant (at 5%), with some differences between models. The positive coefficients for the spatial lag in the productivity growth and technical change (0.1659

[10] In order to avoid biased results in the second part of our analysis, we computed correlations coefficients between the applied variables to compute the Luenberger productivity indicator (Table 1. Panel A) and the explanatory variables of the spatial dynamic regression (Table 1. Panel B). We did not find high correlation coefficients between these variables (above 40%).
[11] The spatial econometric models are related to the dynamic and non-dynamic specifications and not to the productivity indicator definition.

and 0.071) models indicate that the value of these variables for each company not only depends on their own characteristics but also on their neighbors' values. This result is in line with Galdeano-Gómez et al. (2008), García-Álvarez-Coque et al. (2015) and Rallet and Torre (2005), they point out that the spatial concentration makes interactive feedback with other organizations or people about environmental management practices, market characteristics, prices or sharing technological advances roll out by the competitors (Delgado et al., 2014; Galdeano-Gómez et al., 2008; Pede et al., 2018; Tallman et al., 2004). Therefore, the decisions of a company are influenced by its environment (Case, 1992). The coefficients for spatial lag were not significant for the technical inefficiency change model. However, the temporal lag was negative and significant (at 5%) in all models. This indicates that productivity growth and its components are negatively correlated over time suggesting that years with higher productivity growth (and higher contributions from technical change and technical inefficiency change) are followed by years with lower productivity growth (and contributions of its components). The negative value is consistent with Martinez-Victoria et al. (2016), who found that profitability rates of Spanish agribusiness firms display a cyclical character and adjust to equilibrium levels. Finally, the spatial and temporal coefficient was positive and significant in all models (0.0572, 0.0923, and 0.1168, respectively). This result confirms the dynamic character of the models. Productivity growth, technical change, and technical inefficiency change are therefore positively correlated to the respective values of neighboring firms in the previous year. This suggests that firms that adopt new technologies (technical change) or improve the use of their production potential (technical inefficiency change) provide positive spillovers to their neighboring firms, which materialize in the subsequent year. This result could be motivated by the transmission of information between proximal economic agents. For example, companies in dense productive areas have can benefit in terms of higher productivity growth by imitating their best positioned neighbors (Rizov et al., 2012).

Next, we explore the territorial and firm characteristics included in the models. We obtained a positive and significant coefficient for both irrigated and non-irrigated land. Hence, the abundance of land in a region is positively associated with the productivity growth (and its components). The accessibility to financial services (*Bank offices*) also has a positive relationship with productivity growth and its components. This indicator measures the outreach of the financial sector in terms of accessibility to banks' physical outlets. For the *Tax burden*, the results show a negative and significant effect on productivity growth and technical change. This result is in line with Bournakis and Mallick (2018) study who found that higher rates of corporate taxes slow down the rate of TFP growth. *Unemployment* also had a negative and significant relationship with productivity growth, consistent with the expectation that companies located in regions with poor economic characteristics and restrictive policies have lower productivity growth rates (Beck et al., 2005; Maté et al., 2009; Musso and Schiavo, 2008). The results for *Market concentration* suggest that a high density of agri-food companies is associated with higher productivity growth and a higher contribution of technical inefficiency change, but with a lower contribution of technical change. Finally, productivity growth and its components present a positive relationship with the size and age of the company, suggesting that larger and more mature firms have higher productivity growth rates. These positive relationships are consistent with the findings of Kapelko et al. (2016), who found that size and age have a positive impact on the productivity growth of Spanish meat processing and oils and fats companies.

Table 4. Estimated coefficients (p-values in parentheses) of the dynamic spatial panel data models with spatial and temporal fixed effects: productivity growth (Model 1), technical change (Model 2), and technical inefficiency (Model 3).

	Model 1 (LP)	Model 2 (ΔT)	Model 3 (ΔTEI)
W*L	0.1659^{***}	0.0710^{***}	0.1079
	(0.000)	(0.000)	(0.439)
L (temporal lag1)	-0.2674^{***}	-0.4667^{***}	-0.4663^{***}
	(0.000)	(0.000)	(0.000)
W*L(temporal lag1)	0.0572^{**}	0.0923^{***}	0.1168^{***}
	(0.007)	(0.000)	(0.000)
Irrigated land	0.3911^{***}	0.1499^{***}	0.2205^{***}
	(0.000)	(0.000)	(0.000)
Non-irrigated land	0.2157^{***}	0.0784^{***}	0.1093^{**}
	(0.000)	(0.000)	(0.015)
Bank offices	0.1309^{***}	0.4118^{*}	0.7862^{***}
	(0.000)	(0.015)	(0.000)
Tax burden	-0.1256^{*}	-0.2458^{**}	0.1021
	(0.059)	(0.008)	(0.345)
Unemployment	-0.3701^{***}	-0.4108	-0.3149^{***}
	(0.000)	(0.3737)	(0.000)
Market concentration	0.1098^{***}	-0.4535^{***}	0.1498^{***}
	(0.000)	(0.000)	(0.000)
Size	0.0205^{**}	0.0291^{*}	-0.0111
	(0.059)	(0.057)	(0.520)
Age	0.1711^{***}	0.3413^{***}	0.1254^{***}
	(0.000)	(0.000)	(0.000)
R2	0.4678	0.2754	0.4501
Log-LIK Durbin	-10228.98	-13553.656	-14959.399
Robust LM spatial lag (LM-LE) non-dynamic model	92.2941^{***}	75.2565^{***}	67.1818^{***}
	(0.000)	(0.000)	(0.000)
Robust LM spatial error(LM-EL) non-dynamic model	30.3568^{***}	16.4171^{***}	14.358^{***}
	(0.000)	(0.000)	(0.000)

LR non-dynamic (spatial vs pool)	1028.2101*** (0.000)	1245.8990*** (0.000)	1023.2672*** (0.000)
LR (temporal vs pool) non-dynamic model	86.5981*** (0.000)	51.2359*** (0.000)	48.6591*** (0.000)
Hausman's test for non-dynamic models	7.1131*** (0.000)	4.8543*** (0.000)	6.5585*** (0.000)
(*) significant at 10% (**) significant at 5% (***) significant at 1%.			

The initially estimated coefficients in Equation (2) do not represent the marginal changes in the dependent variable as a consequence of changes in the explanatory variables. The coefficients in Table 4 therefore cannot be directly interpreted, and a further partial derivative analysis is needed to quantify the contribution of each variable to the dependent variables (LeSage and Pace, 2010). The dynamic spatial model enables the decomposition of the estimated coefficients into short- and long-term marginal effects. Table 5 presents these results.

Table 5. Marginal short- and long-term effects (p-values in parentheses) for the dynamic spatial panel models: productivity growth (L), technical change (T), and technical inefficiency (TE)

	Model 1: LP		Model 2: ΔT		Model 3: ΔTEI	
	Short term	Long term	Short term	Long term	Short term	Long term
Irrigated land	0.0097** (0.043)	0.0081** (0.044)	0.0107* (0.069)	0.0079* (0.069)	0.004** (0.041)	0.003** (0.041)
Non-irrigated land	0.0204** (0.044)	0.0171** (0.033)	0.0191* (0.076)	0.0142* (0.077)	0.0096** (0.033)	0.0071** (0.044)
Bank offices	0.0067** (0.034)	0.0056** (0.044)	0.0048* (0.075)	0.0036* (0.075)	0.0032** (0.041)	0.0024* (0.054)
Tax burden	-0.003** (0.043)	-0.007** (0.025)	-0.0028* (0.079)	-0.0021* (0.071)	0.0006** (0.031)	0.0004** (0.031)
Unemployment	-0.0174** (0.022)	-0.0146* (0.056)	-0.0058** (0.044)	-0.0043** (0.044)	-0.0097** (0.031)	-0.0073** (0.032)
Spatial concentration	0.0053** (0.044)	0.0045** (0.044)	-0.0047* (0.068)	-0.0035* (0.068)	0.0037** (0.021)	0.0028** (0.032)
Size	0.0001** (0.066)	0.0001* (0.055)	0.0033** (0.057)	0.0025* (0.065)	0.0034* (0.089)	0.0025** (0.031)
Age	0.0087** (0.044)	0.0073* (0.077)	0.0033** (0.066)	0.0002* (0.065)	0.0001* (0.056)	0.0001** (0.022)
. (*) significant at 10%.(**) significant at 5%. (***) significant at 1%						

The results in Table 5 show that irrigated land and non-irrigated land have a significant and positive relationship with productivity growth and its components in the short and long term.

The marginal effect of these variables was larger in the short term than the long term, and the effect was larger for non-irrigated land. This could be explained by the territorial characteristics of Murcia, where agricultural land is a relatively scarce resource and intensively used for fruit and vegetable production. Furthermore, water scarcity in this region means that non-irrigated land provides a competitive advantage (Martínez-Carrasco and Martínez, 2011). Tax burden and employment were negatively and significantly related to productivity growth in the short and long term, indicating that the economic environment is important for fostering productivity growth with higher short-term effects. Market concentration had a larger marginal effect in the short term than in the long term, suggesting that the advantages related to the presence of neighboring firms quickly materialize, i.e., spillovers occur mostly in the short term.

Overall, the results in Table 5 indicate that the effects of regional factors and spatial correlation mostly occurred in the short term rather than the long term, i.e., companies quickly pick up the effects of changes in regional conditions. This suggests that these factors can provide a temporary (dis)advantage and that their effect flattens off in the long run. The most important factors affecting productivity growth were non-irrigated land (2%) and unemployment (1.74%), whereas technological change was mostly affected by irrigated (1.07%) and non-irrigated land (1.91%).

4. Discussion and conclusion

This study investigated the relationship of regional characteristics, and interactions between neighboring firms with dynamic productivity growth of agri-food companies in Murcia. The results demonstrated that spatial effects do matter in the explanation of dynamic productivity growth. The distribution of agri-food companies across Murcia follows a specific spatial pattern: companies with highest productivity growth were concentrated around the largest production centers.

Consistent with other studies, our results indicate that several territorial factors are positively related to the dynamic productivity growth of the agri-food companies located in Murcia. In our case, the penetration of financial services (e.g., easier physical access to bank offices), the tax burden, and the density of companies were all significantly associated with dynamic productivity growth. A closer look at the productivity growth and its components revealed several temporal and spatial effects. The current productivity growth of a company was negatively associated with productivity growth in the previous year. This negative sign is consistent with a cyclical character of productivity growth and suggests adjustment to equilibrium productivity growth levels. In addition, we found positive spatial interactions in the productivity growth and technical change between neighboring peer companies. In other words, agri-food companies with high productivity growth or high technical change values are more likely surrounded by peer companies with high productivity growth values and technical change. This suggests the presence of positive spillovers from one company to their neighboring firms, which occur through the adoption of new technologies that are already in place on neighboring firms. In addition, this effect has a specific temporal character as it materializes in the subsequent year. These results suggest that companies in dense productive areas have better access to external information about new technologies that help to improve their productivity. This could motivate an interaction effect between geographically close companies. Finally, our results on the marginal effects show that the coefficients of the explanatory variables are larger in the short run than in the long run suggesting that these variables can create temporary competitive (dis)advantages which flatten off in the long-run. Also the results show that the largest marginal effects occur for irrigated and non-irrigated land and for unemployment, suggesting the resource scarcity of land, water and labor.

This study suggests that future research should paying particular attention to the role of proximity with peer companies in agri-food companies in the assessment of productivity growth. Furthermore, future research could assess the effect of other spatial explanatory variables such as distance to technological centers, industrial parks, road nodes or train stations. Further research should also account for potential differences between agricultural subsectors either by including this as explanatory variable in the model or by analyzing the role of spatial factors for specific subsectors. Moreover, in the particular case of the agri-food industry studies that identify drivers of knowledge diffusion on productivity growth are limited. Finally, we would like to highlight some limitations of this study which could be considered in future studies. Firstly, our study used the on geographical distance between agri-food companies as an indicator of proximity; future research could consider alternative indicators of proximity such as commercial relationships or networks. Secondly, our sample only covers the fruit and vegetable region of Murcia and more research is needed to investigate whether the results can be generalized to other regions and other agricultural sectors.

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Annex 1:

Dynamic Luenberger productivity growth indicator

The dynamic models assume the nexus of production decisions over time and the presence of adjustment costs associated with the quasi-fixed factors (Silva and Stefanou, 2003; Kapelko et al., 2015). The dynamic framework of productivity growth is based on the production technology that relates at times t the vectors of variable inputs x_t, gross investment I_t (which is the change in quasi-fixed factors), and quasi-fixed factors k_t to the vector of output y_t. In a dynamic approach, the source of the intertemporal link between production decisions is the adjustment costs connected with changes in the levels of quasi-fixed factors.

We used the Luenberger Indicator of dynamic productivity growth. The production input requirement set is represented as $\mathrm{V_t}(y_t: k_t) = \{(x_t, I_t) \text{ can produce } y_t, \text{given } k_t\}$. The properties of the input set are defined by Silva and Stefanou (2003) and Silva et al. (2015). The input-oriented dynamic directional distance function with directional vectors for inputs (g_x) and investments (g_I) is defined as follows (see Silva et al., 2015):

$$\vec{\mathrm{D}}_{\mathrm{t}}^{\mathrm{i}}(y_t, k_{t,} x_t, I_{t,};\ g_x, g_I) = \max\{\beta \in \mathbb{R} : (x_t - \beta g_x, I_{t,} + \beta g_I) \in \mathrm{V_t}(y_t: k_t)\}, \quad (1.\mathrm{A})$$

$$\mathrm{g_x} \in \Re_{++}^{\mathrm{N}},\ \mathrm{g_I} \in \Re_{++}^{\mathrm{F}}, (g_x, g_I) \neq (0^{\mathrm{N}}, 0^{\mathrm{F}}),$$

if $(x_t - \beta g_x, I_{t,} + \beta g_I) \in \mathrm{V_t}(\mathrm{y_t}: \mathrm{k_t})$ for some β, then $\vec{\mathrm{D}}_{\mathrm{t}}^{\mathrm{i}}(y_t, k_{t,} x_t, I_{t,};\ g_x, g_I) = -\infty$.

In Equation (1.A), y_t is the output vector, k_t is the capital stock vector, x_t is the input vector, $\mathrm{I_t}$ is the vector of gross investments, and(g_x, g_I) are directional vectors that determine the direction in which $\vec{\mathrm{D}}_{\mathrm{t}}^{\mathrm{i}}$ is defined. This function measures the distance of (x_t, I_t) to the boundary of $\mathrm{V_t}(y_t: k_t)$ in a specific direction $(g_x, g_I) \neq (0^{\mathrm{N}}, 0^{\mathrm{F}})$, where $\beta \mathrm{g_x}$ is subtracted from x_t and βg_I is added to $\mathrm{I_t}$, i.e., simultaneously contracting variable inputs and expanding dynamic factors. Therefore, $\vec{\mathrm{D}}_{\mathrm{t}}^{\mathrm{i}}(y_t, k_{t,} x_t, I_{t,};\ g_x, g_I) \geq 0$ fully characterizes the input requirement set $\mathrm{V_t}(y_t: k_t)$, which is a primal alternative representation of the adjustment cost production technology.

Following Chambers et al. (1996), who developed the Luenberger indicator in the static context, Oude Lansink et al. (2015) extended this indicator to the dynamic context using the dynamic directional input distance function:

$$L = \frac{1}{2}\{[\vec{D}^i_{t+1}(y_t, k_{t,} x_t, I_{t,};\ g_x, g_I) - \vec{D}^i_{t+1}(y_{t+1}, k_{t+1,} x_{t+1}, I_{t+1,};\ g_x, g_I)]\} + \{[\vec{D}^i_t(y_t, k_{t,} x_t, I_{t,};\ g_x, g_I) - \vec{D}^i_t(y_{t+1}, k_{t+1,} x_{t+1}, I_{t+1,};\ g_x, g_I)]\} \quad (2.A)$$

The Luenberger indicator of dynamic productivity growth can be divided into dynamic technical change (ΔT) and dynamic technical inefficiency (ΔTEI), as follows:

$$L = \Delta T + \Delta TEI. \quad (3.A)$$

Dynamic technical change (ΔT) is computed as the arithmetic average of the difference between the technology at time t and $t+1$, evaluated using quantities at time t and $t+1$:

$$\Delta T = \frac{1}{2}\left\{\left[\vec{D}^i_{t+1}(y_t, k_{t,} x_t, I_{t,}; g_x, g_I) - [\vec{D}^i_t(y_t, k_{t,} x_t, I_{t,}; g_x, g_I)\right]\right\} + \left\{\vec{D}^i_{t+1}(y_{t+1}, k_{t+1,} x_{t+1}, I_{t+1,}; g_x, g_I) - \vec{D}^i_t(y_{t+1}, k_{t+1,} x_{t+1}, I_{t+1,}; g_x, g_I)]\right\} \quad (4.A)$$

Dynamic technical inefficiency change (ΔTEI) is the difference between the value of the dynamic directional distance function at time t and $t+1$. This component measures the change in the distance from the VRS frontier in period t compared to period $t+1$:

$$\Delta TEI = \vec{D}^i_t(y_t, k_{t,} x_t, I_{t,};\ g_x, g_I) - \vec{D}^i_{t+1}(y_{t+1}, k_{t+1,} x_{t+1}, I_{t+1,};\ g_x, g_I) \quad (5.A)$$

Kapelko et al. (2015) developed the Luenberger indicator in the context of variable returns to scale (VRS). From this perspective, the dynamic technical inefficiency change (ΔTEI) can be decomposed into the contribution of dynamic technical inefficiency change (ΔPEI) under VRS and the dynamic scale inefficiency change (ΔSEI) as follows:

$$\Delta PEI = \vec{D}^i_t(y_t, k_{t,} x_t, I_{t,}; g_x, g_I | VRS) - \vec{D}^i_{t+1}(y_{t+1}, k_{t+1,} x_{t+1}, I_{t+1,}; g_x, g_I | VRS), \quad (6.A)$$

$$\Delta SEI = \vec{D}^i_t(y_t, k_{t,} x_t, I_{t,}; g_x, g_I | CRS) - \vec{D}^i_t(y_t, k_{t,} x_t, I_{t,}; g_x, g_I | VRS)$$

$$- [\vec{D}^i_{t+1}(y_{t+1}, k_{t+1,} x_{t+1}, I_{t+1,}; g_x, g_I | CRS) - \vec{D}^i_{t+1}(y_{t+1}, k_{t+1,} x_{t+1}, I_{t+1,}; g_x, g_I | VRS). \quad (7.A)$$

Dynamic technical inefficiency change (ΔPEI) measures the difference between the dynamic directional distance function in period t and $\mathrm{t}+1$ under the VRS assumption. Scale inefficiency in period t (static context) measures the difference between the distance function under CRS and VRS, whereas dynamic scale inefficiency change (ΔSEI) measures the difference between scale inefficiency in period t and $\mathrm{t}+1$.

Dynamic productivity growth is computed using Data Envelopment Analysis (DEA), which is a non-parametric technique that, unlike parametric approaches such as Stochastic Frontier Analysis, does not require assumptions about the functional form of the production frontier and the distribution of inefficiency. The estimation of dynamic productivity growth requires solving four linear programming (LP) models across two consecutive years: two single period LP models and two cross-period LP models. Productivity growth is estimated by solving the following DEA model:

$$\vec{\mathrm{D}}_{\mathrm{t}}^{\mathrm{i}}\left(\mathrm{y}_{\mathrm{t}}, \mathrm{k}_{\mathrm{t},} \mathrm{x}_{\mathrm{t}}, \mathrm{I}_{\mathrm{t},};\ \mathrm{g}_{\mathrm{x}}, \mathrm{g}_{\mathrm{I}} \mid \mathrm{VRS}\right) = \max_{\beta,\gamma} \beta \tag{8.A}$$

$$s.t.$$

$$\mathrm{y}_{\mathrm{t\,m}} \leq \sum_{\mathrm{j}=1}^{\mathrm{J}} \gamma^{\mathrm{j}}\, \mathrm{Y}_{\mathrm{t\ m}}^{\mathrm{j}}, \mathrm{m} = 1, \dots, \mathrm{M};$$

$$\sum_{\mathrm{j}=1}^{\mathrm{J}} \gamma^{\mathrm{j}}\, \mathrm{X}_{\mathrm{t\ n}}^{\mathrm{j}} \leq \mathrm{X}_{\mathrm{t\ n}} - \beta \mathrm{g}_{\mathrm{x}_{\mathrm{n}}}, \mathrm{n} = 1, \dots, \mathrm{N};$$

$$\mathrm{I}_{\mathrm{t\ f}} + \beta \mathrm{g}_{\mathrm{I}_{\mathrm{f}}} - \delta_{\mathrm{f}} \mathrm{k}_{\mathrm{t\,f}} \leq \sum_{\mathrm{j}=1}^{\mathrm{J}} \gamma^{\mathrm{j}}\, (\mathrm{I}_{\mathrm{t\ f}}^{\mathrm{j}} - \delta_{\mathrm{f}} \mathrm{k}_{\mathrm{t\,f}}^{\mathrm{j}}), \mathrm{f} = 1, \dots, \mathrm{F};$$

$$\gamma^{j} \geq 0, j = 1, \dots, J.$$

In Equation (8.A), γ is an intensity vector and δ is the rate of capital depreciation, which is specific to each firm. In our empirical application, the directional vector $(\mathrm{g}_{\mathrm{x}}, \mathrm{g}_{\mathrm{I}})$ contains the quantity of variable inputs and 20 percent of the size of capital stocks. The other three DEA models to be solved are modifications of the model presented in Equation (8.A), see e.g., Oude Lansink et al. (2015) for more details.