RESEARCH ARTICLE

Geographical proximity on the valuations of unlisted agrarian companies: Does distance from company to company and to strategic points matter?

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Abstract

This paper is a first attempt to examine the role played by the geography on agrarian firms' valuations. The geography was evaluated through the physical proximity from agrarian companies to other companies and to some strategic points which ease their accessibility to external economic agents. To get our purpose, we developed an empirical application on a sample of non-listed agrarian Spanish companies located in the region of Murcia over the period 2010-2015. We applied Discount Cash Flow methodology for non-listed companies to get their valuations. With this information, we used spatial econometric techniques to analyse the spatial distribution of agrarian firms' valuations and model the behavior of this variable. Our results supported the assertion that agrarian firms' valuations are conditioned by the geography. We found that firms with similar valuations tend to be grouped together in the territory. In addition, we found significant effects on agrarian firms valuations derived from the geographical proximity among closer agrarian companies and from them to external agents and transport facilities.

Introduction

The positive trends in the level of merger and acquisition activity in non-listed companies and the capital inflow from the private sector to these companies has caused a growing interest in the determination of their value (Vydrzel & Soukupová, 2013). This attention makes necessary the application of methodological foundations considering companies' particular characteristics to get accurate valuations (Rojo & García, 2005). In the agrarian sector, the knowledge of the elements which influence on non-listed companies' values is an important issue (Ribal *et al*., 2010). Sales (2002) applied the analogical-stock market methodology highlighting the

role played by total assets, an agrarian company stock market index, and the ratio of equity to total assets to determine agrarian firms' value. Declerk (2003) studied valuation ratios for food French companies during the period 1996-2001 applying the multiplier method. This author identified the turnover as a referenced value to estimate these firms' value. Vidal et al. (2004) also used the analogical-stock market procedure to obtain a global valuation for Spanish wine cooperatives applying financial and management variables. Other studies, such as Ribal *et al*. (2010), Alekneviciene *et al*. (2012, 2013) overcome the limitations derived to apply the discounted cash flow (DCF) model in agrarian non-listed firms examining the specific characteristics of this sector.

Declerk (2016) analysed firms' financial performance for the period 2002-2009 applying multiplier methodology for food companies. Previous studies focus on financial and economic characteristics to determine agrarian firms' valuations without considering other variables. The absence of additional elements in the valuation process could cause biased results due to the lack of relevant information. In this sense, Vidal *et al.* (2004) concluded that their analysed firms did not behave as it was expected according to their valuation results "due to several reasons that this econometric model does not take into account". According to these authors, other elements, such as the transport costs or facilities should be considered. Despite this recommendation, we did not find studies examining firms' valuation and considering other variables apart from the economic and financial elements.

In this context, we think that the geography could play a fundamental role in the determination of the agrarian firms' valuation. As geography we consider the effects derived from the geographical proximity between agrarian companies and other economic agents and transport facilities. Regarding previous literature, we found studies that highlight geographical proximity to other peer companies as a potential advantage for agrarian companies (Rallet & Torre, 2005; Delgado *et al.,* 2014). These studies consider that closer relationships among agrarian companies and some external agents, such as investors or financial intermediaries, cause positive effects on their productivity derived from the input-output linkages, labour market pooling and knowledge spillovers (Porter, 1998). Therefore, the interconnection among closer companies strengthens the competitive and productive capacities of agrarian companies (Chif-foleau & Touzard, 2014). We also found empirical studies that analyse the effect caused by agrarian firm's location, evaluated through its proximity to certain strategic points (such as city centres, shopping centres, road nodes, airports, train stations, technological centres and industrial parks), on these firms' results. In this sense, Davis & Schluter (2005) developed a disaggregated analysis for food industries and found relevant elements that attract food manufacturing companies to operate where they have more accessibility to other agents. Nguyen *et al.* (2012) indicated that firms are more attracted to regions with high accessibility. In fact, agrarian firms do not act in isolation during their decision-making processes but are influenced by other peer firms located nearby. Using data from a recent survey of New York State food processors, Schmidt & Keil (2013) demonstrated

that increasing access to raw agricultural inputs and growing population centres are important upstream and downstream market condi-tions for improving firm growth. Holl (2013) found a significant and positive relationship between the accessibility of the company to external agents and their productivity. Läpple & Kelley (2015) analysed spatial dependence in the adoption of organic farming for almost 600 Irish drystock farmers. Their results revealed that farmers located in close proximity to one another or with easy access to interconnection channels experience benefits. Indeed, communication and interactions among farmers influence their economic and financial behaviour. However, there are no studies examining the effects of the geography on agrarian firms' valuations.

The aim of this study was to determine whether the geography, evaluated though the distance between agrarian companies and from them to some strategic points which improve their accessibility, has a significant and measurable influence on agrarian companies' values. To achieve our purpose, we developed an empirical application with a sample of 548 non-listed agrarian companies in the province of Murcia[1], Spain for the period 2010-2015. The Spanish food sector was an adequate scenario to develop this study since listed companies in the food group are very rare (Ribal *et al.*, 2010).

Material and methods

Non-listed agri-firms' valuation

The value for each firm of the sample was estimated as the Enterprise Value (EV). This value does not consider firms' financial position but it was focused on the cash flows generated by operating activities. Our premise was that geography may influence on the input-output linkages in agrarian firms altering the capacity of these companies to generate cash flows. In order to estimate the EV, we applied the DCF model. This was one of the most commonly used methods to calculate firm's value (Verginis & Taylor, 2004; Rojo & García, 2006; Dönbak & Ukav, 2016). DCF procedure discounts the free cash flows (FCF) that the firm will create in the future to present value by using an appropriate discount rate referred to as Weighted Average Cost of Capital (WACC). However, we found different specifications from this model in order to face particular characteristics of non-listed firms. In the present study, we applied Rojo & García (2005, 2006)'s

proposal to estimate the discount rate for the case of non-listed companies. The difference between Rojo & García (2005, 2006)'s approach and that commonly used based on the Capital Asset Pricing Model (CAPM) is the addition of a specific risk premium in order to take into account the higher risk faced by non-listed companies when compared to their listed counterparts. Specifically, Rojo & García (2005, 2006) compute the expected return of equity (k_e) for the case of non-listed companies by adding three components: the risk free rate (R_f), the market risk premium (P_m) and a specific risk P_e (see [1]).

$$k_e = R_f + P_m + P_e \qquad [1]$$

R_f and P_m were computed following the traditional literature (Damodaran, 2002; Baginski & Wahlen, 2003) while P_e was calculated based on the concept of total beta (Damodaran, 2002) as shown in [2].

$$P_e = \beta_i * P_m \qquad [2]$$

where the coefficient β_i is computed as the ratio of the standard deviation of financial profitability of the firm i after interest and taxes to the standard deviation of market return.

Once k_e was computed, we could estimate the WACC (k) by applying the following expression:

$$k = k_e \frac{E}{E+D} + k_d(1-\tau)\frac{D}{E+D} \qquad [3]$$

where k_d is the cost of debt, E represents equity, D is financial debt and τ is the effective tax rate.

The spatial econometric model

We part from the following spatial econometric model [4] (Anselin, 1988; Le Sage & Pace, 2010):

$$y = \rho W_L y + X\beta + u \text{ with } u = \lambda W_E u + \varepsilon \qquad [4]$$

where y is a ($N \times 1$) vector containing the valuations for each non-listed agrarian firm i in our sample, with $i=1,\ldots,N$; X is a ($N \times (r+1)$) matrix containing a constant term and r explanatory variables. In our case, the explanatory variables are representative of the distance between each company i and a strategic point that favours accessibility between the company and other economic agents. W_L and W_E are ($N \times N$) spatial weight matrices that define, with values different from zero, the interconnections among companies; u is a ($N \times 1$) vector of the spatially correlated residuals; ε is a ($N \times 1$) vector of normally distributed errors with mean zero and variance σ^2; ρ is the spatial lag coefficient reflecting the importance of spatial autocorrelation in the valuation of non-listed Spanish companies with $0<|\rho|<1$. If this coeficient was significant, this indicates that the analysed firms' valuations depend not only on the internal firms' characteristics but also on their vicinity firms' valuation. β is a (r +1) $\times 1$ vector containing the regression coefficients for the explanatory variables, and λ is a coefficient reflecting the spatial autocorrelation of the residuals u_i. The difference between previous spatial structures (in the dependent variable ($W_L y$) vs in the error term ($W_E u$)) was explained by the source of interdependence among companies' valuation. In the first case, the spatial effect was caused by the structural character of firms' valuation variable. If this structure was significant, then we can conclude that the particular characteristics of a company influence the valuation of companies in their vicinity. In the second case, spatial interactions in the error term are explained by the omission of relevant variables into the model that generates this result.

Previous model [4] was estimated applying maximum likelihood (ML) (Elhorst, 2010). The ML estimation is the most commonly used method based on the maximization of the log-likelihood function. The significance of the spatial structure (($W_L y$) vs ($W_E u$)) can

A   B
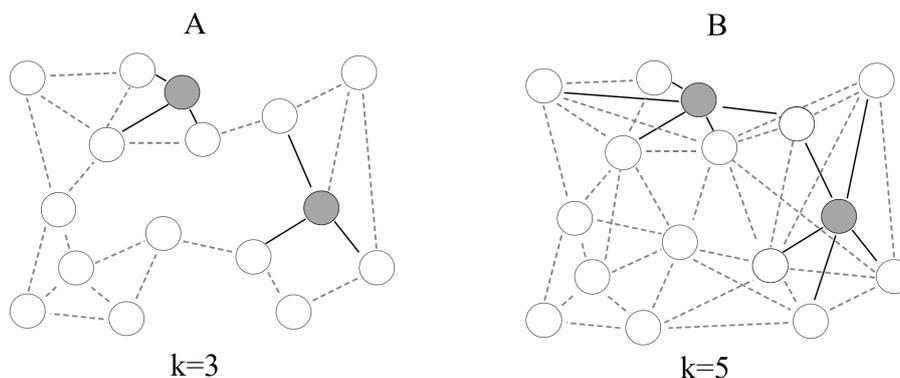
k=3   k=5

Figure 1. Example of q-nearest neighbors

be determined by computing the Lagrange Multipliers (LM) tests and their robust versions for the POOL-OLS estimation: LM-LAG (LM-LE the robust version) and LM-ERR (LM-EL the robust version) (Anselin, 1988; Anselin *et al.*, 1996). Both tests have as null hypotheses the absence of spatial autocorrelation and as alternative hypotheses the existence of a spatial autoregressive structure in the dependent variable for the LM-LAG test and a spatial dependence structure in the error term for the LM-ERR test. Following the methodology of Florax & Former (1992), from the particular to the general, we compared the values of both tests (LM-LAG and LM-ERR) and their robust versions. When representative tests of one spatial structure were significant but the others were not, then we selected the significant spatial structure according to them. For example, if we got a significant value for the LM-LAG and the LM-LE and non-significant values for the others, then we selected a model that only contains spatial autoregressive structure in the dependent variable ($W_L y$). This model is known as the Spatial Lag Model (SLM), whereas the model with only spatial autocorrelation in the error term is known as the Spatial Error Model (SEM). However, when we obtained significant values in both spatial structures, then we estimated a spatial model as [4] known as the Spatial Autocorrelation Model (SAC).

In this study, we did not differentiate between the spatial weight matrices W_L and W_E. From a theoretical perspective, the SAC model was identified when there were additional explicative variables apart from the spatial effects (Le Sage & Pace, 2010). Therefore, it was not necessary to apply different weight matrices. From this premise, empirical studies assume that both matrices are equal (Kelejian & Prucha, 2010). The idea behind this assumption was that the weight matrix describes the space in which you are working and the spatial variables, that are the spatial interaction mechanisms associated to each variable in the explanatory part of the model or in the error term, adapt to this space but the space does not adapt to the variable. For the common spatial neighbourhood matrix W, we considered different standardized alternatives based on the q nearest neighbours. For example, if we consider the three nearest companies to each company i (q=3), then we are assuming an interconnection structure shown in Fig. 1 where each company, represented by a circle, has its three nearest companies as neighbours (Fig. 1A). In Fig. 1A, grey colour circles represent two different companies, and the continuous lines from each of them link these companies with their neighbours according to this criterion. If we consider a connectivity criterion based on the five nearest companies to each

company i (q=5), then we have a connection structure as shown in Fig. 1B. In this case, grey colour circles also represent the companies to be considered as examples, and the continuous line connects each of them with their neighbours according to this criterion.

Based on previous q neighbour criterion, we defined the binary row standardized weight matrix W in which elements w_{ij} value one if the company i and j are neighbours and zero otherwise.

Empirical application

We part from the DCF valuation method for non-listed companies to show an empirical application on a sample of Spanish agrarian companies with the aim of testing whether the geographical proximity among peer companies and/or from these companies to certain strategic points influences the valuation of these firms in the agrarian sector.

Database

The information to develop this empirical application was obtained from SABI (Iberian Balance Analysis System) database. This database provides a wide range of information about the different business dimensions of Spanish firms. We chose Spanish agrarian companies[2] following the criterion established in the National Classification of Economics Activities (NACE, 2007). In order to avoid heterogeneity in the sample, we selected companies located in the province of Murcia in Spain (Fig. 2).

We selected this territory because of the important weight of the agrarian sector on the global production of this region (INE, 2013). Once we obtained all of the information, we removed the observations with missing information to the calculation of the EV and those having anomalies in their financial statements, *e.g.*, negative values in their sales or assets that distorted the behaviour of the firms. Companies with negative values in their cash
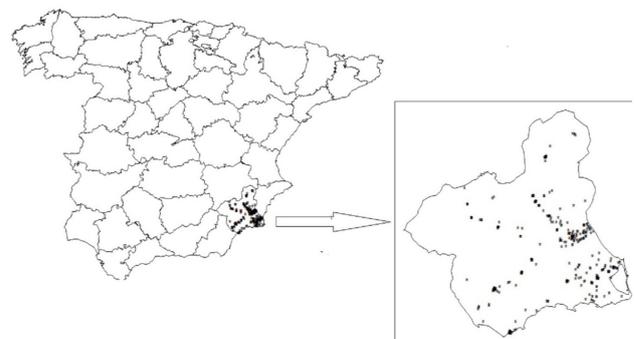

Figure 2. Firms' spatial distribution. Provincial map

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[2]Agrarian sub-sector includes the NACE codes A1.1 (Growing of non-perennial crops excluding tobacco), A1.2 (Growing of perennial crops), A1.4 (Animal production), A1.5 (mixed farming) and A1.6 (Support activities to agriculture and post-harvest crop activities).

flows were also excluded from the analysis. Furthermore, to reduce the effect of outliers in our sample, we dropped extreme values in all of the variables that were not included in the ± 3 interquartile range. Our sample contained information for 548 non listed-agrarian companies over the period 2010-2014.

In addition to firms' financial information, SABI database also provides the location of each company through the geographical coordinates of each. Finally, we also hand-collected the geographical location of some strategic points (such as airports, train stations, and city centres) in Murcia using Google-Maps.

Variables

Firms' values

In order to estimate the EV, the DCF model was disaggregated into two stages. A first stage focused on the current value of future cash flows and a second stage which calculates the residual value (RV) (or continuing value) (Jennergren, 2008; Ribal *et al*., 2010). The EV for each company for the year 2014 was calculated as [5].

$$EV_{2014} = \sum_{t=1}^{l} \frac{FCF_t}{(1+k)^t} + \frac{RV_l}{(1+k)^l} \qquad [5]$$

where t represents every year in the period from 2015 to 2019 and l the number of years of this period (l=5). FCF was calculated for each company in t using the standard formula [6]

$$FCF = EBIT(1 - \tau) + D\&A + Imp - \Delta WC - I \qquad [6]$$

where EBIT is the earning before interests and taxes; D&A, depreciation and amortization; *Imp*, impairments; ΔWC, working capital changes; and I, investments in non-current assets. Depreciation and amortization as well as impairments related to non-current assets are added to EBIT (earnings before interest and taxes) in so far as they do not involve a cash outlay while working capital variation was considered in order to take into account those sales and purchases on credit recognized in EBIT that have not yet generated a cash movement. Therefore, in order to estimate future FCF for the next five years (2015-2019) we had to assume the evolution of the main components of FCF. In this regard, we fitted a linear regression based on data on each company's historical sales and extrapolated future sales based on the linear model fitted (Alekneviciene *et al*., 2013). Once future sales were estimated, we projected the rest of the components of FCF by applying the mean of the annual past values of the proportion (ratio) that each FCF component represents with respect to historical sales (Alekneviciene *et al*., 2012).

We got the discount rate (WACC) applying the previous expression [3] for non-listed companies. The cost of debt (k_d) was calculated as the ratio of interest expenses to the financial debt of the company. As usual when implementing DCF, the risk free rate (R_f) was proxied by the 10-year government bond interest rates. We obtained this information from the webpage www.datosmacro.com, which provides financial sector information about different Spanish markets. The market risk premium (P_m) was considered to be the average historical differential between market returns and risk-free rates during the last years. We got this information from Damodaran's webpage[3] which provides market risk premiums by industries and countries. The specific business risk (P_e) was computed according to expression [2] where financial profitability of the firm i after interest and taxes (*i.e*., ROE) was obtained from firms' accounting information and market return from Damodaran's webpage. Finally, we determined the *RV* by applying the Gordon model that assumes that FCF will grow at a constant rate (g) after the estimation period. Analytically:

$$RV_l = FCF_{l+1} \frac{(1+g)}{(K-g)} \qquad [7]$$

In our case, g was considered to be 1.5%, which was the long-term GDP growth expected for Spain in the next 20 years (PricewaterhouseCoopers, 2013).

Explanatory variables

Explanatory variables in this analysis were representative of the distance between each company in the sample and a strategic point. In order to determine the geographical distance between each company and these strategic points, we built an algorithm in R software. Following previous literature, we considered these strategic points: a) industrial parks, b) shopping centres, c) road nodes, d) airports, e) train stations, f) technological centres and g) city centres. Apart from these variables, we also included control variables to take into account the characteristics of each company. In this regard, we defined the age and the size of the company, establishing different categories for each variable. Following Bergel & Udell's (1998) study, we defined four groups of companies according to their ages: infant (0 to 2 years), adolescent (3 to 4 years), middle-aged (5 to 24 years) and old (more than 25 years). The variable size was based on the number of employees. From this information, we followed the Commission Recommendation 2003/361/ EC (OJEU, 2003) to determine different groups. Micro was composed of companies with fewer than 10 workers. Small was defined as the set of companies

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with between 11 and 50 employees. Medium refers to companies with 50 to 250 employees. Finally, Large indicates the group of companies with more than 250 employees. Small and young firms have specific characteristics, such as informational asymmetries, that make them riskier and with a higher probability of bankruptcy (Dhawan, 2001; Chava & Jarrow, 2004; Vassalou & Xing, 2004; Chen, 2010). Therefore, we expected that these companies would present lower valuations. In this sense, the high bankrupt's risk was reflected in the DCF model with a higher discount rate (WACC) influencing negatively on firms' valuations.

Results

To begin, we analyse the spatial distribution of the value of the companies in our sample (see Fig. 3). We got that companies with the higher values tend to be concentrated among themselves and close to the main city centres in Murcia (Cartagena and Murcia). In order to corroborate this finding, we estimated the Global Moran's I test to find spatial autocorrelation in non-listed agrarian companies. Global Moran's I represents the regression coefficient of Wy on y (Anselin, 1988), where y is the representative variable of agrarian firms' value. Therefore, a significant Global Moran's I test means that each agrarian company valuation depends not only on the own firm's characteristics but also on the valuations of its vicinity peer companies. The global Moran's I is given by [8]:

$$I = \frac{z'Wz}{z'z} \qquad [8]$$

where z=(y- $\overline{y}$)/σ_y with y is a vector of the valuations for the non-listed agrarian companies i, with i=1,…,548. y
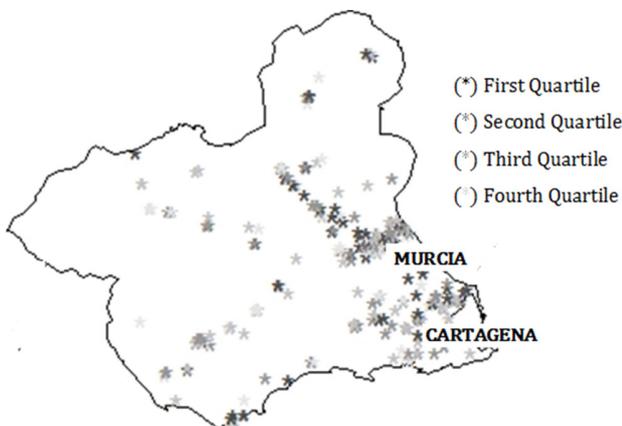
is the arithmetic mean of y, and σ_y the standard deviation of y. W is the standardized weight matrix built based on the q nearest neighbour criterion.

Resulting values of the Global Moran's I tests (Table 1) indicated a significant and positive spatial autocorrelation for agrarian firms' values. In this sense, p-values were less than 0.1 and 0.05 for q=3 and q=5, respectively. Therefore, the null hypothesis of non-spatial auto-correlation was rejected. This means that agrarian firms' valuations were related to their neighbour firms' valuations at a certain distances. For q=8 this spatial effect became non-significant. Thus, the interaction effect in agrarian firms' valuations vanished with the distance[4].

To get a better understanding of the previous spatial pattern, we applied spatial econometric methods. We propose a spatial econometric model to analyse the effects of the geographical proximity among peer agrarian companies and from these companies to some strategic points on the valuation of these companies. The former was tested by analysing the existence of a significant spatial autocorrelation structure into the model. The latter was contrasted including as explanatory variables different factors representative of the distance from each company to the strategic points. With this aim, we parted from a pool OLS model and test spatial autocorrelation in this process.

The first column in Table 2 shows pool OLS estimation results. Based on this structure, we computed the spatial Lagrange Multipliers (LM) tests to determine if there was a signifi-cant spatial structure into the model and, in this case, determine the more adequate spatial structure (SLM vs SEM). LM tests indicated that the hypotheses of no spatially lagged dependent variable (LM-LAG) and of non-spatially auto-correlated error (LM-ERR) term were rejected. LM-EL and LM-LE tests reject the null hypothesis of absence of spatial dependence. Therefore, both spatial structures (LAG and ERROR) were significant, and we estimated a SAC model as proposed in [4] to control for both spatial autocorrelation structures. The adjusted R^2 indicated that SAC model best described the data in comparison with the OLS (0.3633 vs 0.2781 respectively), In addition,

Figure 3. Quartile map. Spatial distribution of agrarian firms' valuation in Murcia, Spain. Source: Own elaborated

(*) First Quartile
(*) Second Quartile
(*) Third Quartile
( ) Fourth Quartile

Table 1. Moran's I test considering different weight matrix based on q nearest neighbors.

	$q = 3$	$q = 5$	$q = 8$
Morans' I test	1.1325*	1.4261**	0.9872
p-value	0.0825	0.0335	0.2058

*,**: significant at 10% and 5%, respectively

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[4] q=8 corresponds with a radius of approximately 10 kilometers of distance from each company.

Table 2. Estimations of the agrarian valuation on locational variables

	POOL-OLS estimation	**SAC Model**
Constant	6.9814*** (0.000)	1.8401*** (0.000)
Distance to technological centres	-1.8872** (0.0515)	-4.0716*** (0.0003)
Distance to train stations	-1.3683** (0.0116)	-4.7056** (0.0213)
Distance to industrial parks	-1.6891* (0.0930)	-3.0034* (0.0537)
Distance to shopping centres	-1.7783* (0.0119)	-1.9532** (0.0132)
Distance to city centres	-0.4395 (0.9256)	-2.8063 (0.5562)
Distance to airports	-0.2887 (0.3281)	-0.0206 (0.9702)
Distance to roads nodes	-2.1265** (0.0372)	-2.3396** (0.0691)
Control variables		
Midle age [1]	0.4042 (0.3655)	0.3560 (0.3603)
Old age	0.7406** (0.0265)	0.6959** (0.0105)
Small size firm [2]	1.4335*** (0.000)	1.3259*** (0.0000)
Medium size firm	2.6229*** (0.000)	2.2578*** (0.0000)
Rho	-	2.5391** (0.0164)
Lambda	-	0.6004*** (0.000)
Post estimation tests		
R^2	0.2973	0.3812
Adjusted R^2	0.2781	0.3633
LM-LAG	11.373*** (0.0033)	-
LM-LE	3.9772** (0.0227)	-
LM-ERR	10.395*** (0.0012)	-
LM-EL	6.0734** (0.0137)	-
LR test (POOL-OLS *vs* SAC)	-	18.719*** (0.000)

p-values in brackets. *,**,***: significant at 10%, 5%, 1%, respectively. [1] Regarding the age of the firm, the sample did not include any "infant" company with available information. Therefore, this category was dropped from the analysis. "Adolescent" is the referenced category for the age. [2] About the size of the company, the sample did not include any non-listed "large" company with available information. Therefore, this category was eliminated. Micro size companies was the referenced category. POOL-OLS refers to Ordinary Least Square estimation. SAC is the Spatial Autocorrelation Model. LM represents the Lagrange Multipliers tests.

we computed the likelihood ratio (LR) test[5] based on the log likelihood function values of nested models. In this way, we tested goodness of adjustment of the SAC model in comparison with the pool OLS estimation. The significant value of this test also corroborated that the SAC model works better in our specification.

Regarding the coefficients of the SAC model (Table 2, 2nd column), we found that spatial autocorrelation effects had an important influence on agrarian firms' value. In this sense, both, the spatial lag (2.5391) and the spatial error (0.6004) were positive and significant. In addition, the spatial lag coefficient seemed to be more relevant in terms of its value highlighting the structural character across the space of agrarian firms' valuation. Regarding the explicative variables representative of the distance from companies to strategic points, we got that

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[5] The LR test was defined as minus two times the difference between the value of the log-likelihood function un the restricted model and the value of the log-likehood function of the unrestricted model: -2* (logL$_{resticted}$ - log-L$_{unrestricted}$). This test was distributed as Chi-square with degrees of freedom equal to the number of restrictions imposed (Elhorst, 2010).

the representative variable of the distance from firms to technological centres was significant and negative (-4.0716) indicating that short distances between the company and technological centres increased the value of the company. Variables of the distance between the company and industrial parks (-3.0034) and shopping centres (-1.9532) were also negative and significant. Previous variables could be seen as representative of links with external agents that favour the integration of this company in the markets. Our results indicated that agrarian companies located closer to these strategic points presented higher valuations. Contrary to what we expected, we found that geographical proximity from companies to city centres was not significant in the model.

About the representative variables of the geographical proximity from companies to transport centres, we got a negative and significant effect for road nodes (-2.3396) and train stations (-4.7056) on agrarian firms value. Therefore, agrarian companies situated at a short distance from the train stations or road nodes will get higher valuations. Distance to airport was non-significant.

Finally, control variables indicated that the size and the age of the variable had a positive and significant result on agrarian firms' valuation. In other words, mature and large firms will have higher valuations.

Discussion

This study was a first step in understanding the mechanisms from which the geography influence on agrarian firms' valuations. As a difference from previous studies, we considered not only financial and economic variables but also environmental variables related to firms' geographic proximity from companies to other external agents and facilities. Our results showed significant geographical effects on firms' valuation. In this sense, we got that agrarian companies with similar values tended to be grouped in the territory. Moreover, this effect had a structural character highlighting the fact that nearby companies will strength their input-output linkages causing interdependences in their economic and financial behaviour (Rallet & Torre, 2005, Delgado et al., 2014). Agrarian firms do not act in isolation during their decision-making processes but were influenced by other peer firms located nearby (as in Nguyen et al., 2012). Therefore, a company surrounded by firms with economic or financial difficulties will receive negative external shocks. This will increase their specific risk decreasing its value. The opposite will happen when the company is surrounded by companies with good economic and financial results. In this sense,

the advantages derived from shorter distances between companies in the agrarian sector can be attributed to the benefits associated with labour pooling, decreasing costs of intermediate inputs and/or technological spillovers (Schmidtner et al., 2012).

Apart from this geographical effect, we also found significant results when the proximity from firms to other external agents and transport facilities was considered. In this case, agrarian companies geographically closer to clustered activities (industrial parks or technological centres) and/or transport nodes (train stations, road nodes), received a positive effect on their valuations. From this perspective, closer distances eased the interconnections among economic agents strengthening the input-output linkages among companies. This result coincides with previous studies which analysed firms' accessibility to external agents and transport facilities on their productivity. These studies found relevant elements that attract food manufacturing companies to operate where they have more accessibility to other agents (Davis & Schluter, 2005; Targa et al., 2006, Holl, 2013, Läpple & Kelley, 2015). Nevertheless, previous literature was focused on accessibility effects on agrarian firms' productivity or growth. Our contribution was focused on firms' valuation finding also a positive effect. Control variables gave a positive sign for the size and the age of the company. These results coincide with previous empirical tests (Dhawan, 2001; Chava & Jarrow, 2004; Vassalou & Xing, 2004; Chen, 2010) that have related size and age variables to risk and business failure. This higher risk will increase the discount rate decreasing firms' values according to the DCF model.

Our paper is a first step into the analysis of the geography on firms' valuation. Thus, a promising avenue of research in this context might be to deem in the effects of the geographical proximity on agrarian firms' valuation considering other scenarios. Another aspect that has not been addressed due to the lack of data was the temporal dimension. Accounting for longer time series would contribute to further discussions on the effects of geographical proximity on the valuation of agrarian firms. In addition, other locational aspects, such as agglomerations effects, accessibility and proximity to the other markets, could also be considered when the valuation of agrarian companies was examined. Finally, further research about the strategic points' relevance is needed to identify some open questions in this study: *why does proximity to industrial parks is relevant on agrarian firms' valuations but to city centres is does not?* We think that this result could be explained by the specific agrarian characteristics which give more relevance to the market accessibility throughout other channels. Nevertheless, next studies should be developed examining the importance for agrarian

companies to be close to the city centres and the optimal distances.

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