The paradox of geographical proximity for innovators: A regional study of the Spanish agri-food sector

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Abstract

This paper analyses the geographical proximity impact and the proximity paradox in a regional study of the Spanish agri-food industry. This study is mainly based on the Community Innovation Survey database, from which we get a representative group of agri-food companies in Murcia, Spain. The regional character of this research allows us to discount the institutional effects which could cause differences between companies in different regions. In addition, we consider individual innovative actors and alternative innovation outcomes. Our findings corroborate the significant impact of geographical proximity for the innovation in agri-food companies. We get differences between innovators when the geographical impact on absorptive capacities and innovation is examined: geographical proximity between agri-food companies and industrial states and R&D centres has a significant impact on firms' absorptive capacities whereas geographical distance to large companies and transport facilities play an important role in determining R&D activities. Our results corroborate the proximity paradox for the geographical dimension finding a non-linear relationship for the absorptive capacity in agri-food companies.

Keywords: agri-food companies, absorptive capacity, innovative actors, proximity paradox, geographical proximity
JEL codes: O32 Q18 R11

Introduction

There is an extensive literature focused on the role of geographical proximity on innovation. These studies are based on the theoretical argument that short distances provide more intense face-to-face interactions, strengthening the exchange of information and favouring the assimilation of external knowledge (Audretsch and Feldman, 1996). Recent research in this area is based on new assumptions with alternative proximity dimensions and non-linearities in the proximity impact on firms' innovation. In this sense, Boschma (2005) states that geographical proximity is neither a necessary nor a sufficient condition for the exchange of knowledge between economic agents but geographical proximity facilitates other proximity dimensions (institutional, cognitive and social). However, the latter are not substitutes for geographical proximity, even when the development of new technologies could propitiate alternative communication methods (Torre, 2008). Thus, Boschma and Frenken (2010 pp.5) argue: "*there is a strong claim that geographical proximity is a prime mover of network formation despite globalization, implying that a great deal of interactions still takes place between agents that are geographically proximate*". Consequently, geographical proximity is still a fundamental element to be analysed when considering innovation activity, even though there are additional elements promoting the exchange of knowledge (Rodríguez-Pose and Crescenzi, 2008). More recent studies have raised the issue of a proximity paradox (Broekel and Boschma, 2012): the impact of geographical proximity on innovation is not linear and too great a geographical proximity between economic agents might disrupt the exchange of knowledge, hence the optimal effect on innovative agents is often a combination of distances, based on different potential spillover effects.

Our study analyses the geographical proximity impact and the proximity paradox in a regional study of the Spanish agri-food industry. This regional analysis allows us to discount the institutional effects which could cause differences between companies in different regions. In this sense, knowledge is both firm and place specific providing organizational and institutional effects (Boschma and Freken, 2010). The former is based on evolutionary theory from which knowledge is firm specific and accumulated within workers skills and firms procedures (Gertler, 2003). But, knowledge has also an institutional component, so firms' procedures tend to share characteristics when they are affected by similar institutional conditions (Storper and Venables, 2004). The different institutional procedures may provide place specific assets which favours innovation activity and which would be difficult to transfer to other institutional scenarios in other regions (Boschma, 2005). Therefore, the development of a territorial specific analysis in this context suggests needing to test the role of proximity using a homogeneous sample of agents which are affected by similar institutional characteristics.

This study is mainly based on the CIS (Community Innovation Survey) database for Spain, from which we get detailed information about innovation activities over the period 2005–2007 of a representative group of agri-food companies in Murcia, Spain[1] (see Figure 1). We selected this territory because of the importance of agrarian activities in total production for this region, representing 5.4% of GDP for Murcia. This value is above the Spanish average value of 2.7% of GDP. In addition, we find that the agri-food subsector in Murcia is especially important with respect to Fruits, Cereals and Meat activities (almost 11% of industry GDP in 2017 is in Murcia – National Institute of Statistics[2]).

This study has two main objectives. The first is to test empirically the extent to which geographical proximity between companies and different innovative actors and transport facilities impact on innovation and absorptive capacity in agri-food companies, while controlling for institutional effects. From this analysis, we confirm the significant role of geographical proximity on agri-food companies' innovation identifying the most relevant innovative agents whose distance should be considered. The second objective is to corroborate the existence of non-linearities in geographical proximities for the agri-food sector. In this regard, our study provides empirical evidence for the proximity paradox. In contrast with previous studies (Hansen, 2014), we find significant non-linearities in the geographical dimension when we distinguish between innovative actors and innovation sources. Many studies on this topic seem to be more interested in mapping the existence of these geographical interactions than to determine how the degree of proximity may vary between innovative agents. Therefore, our study adds additional understanding on the way in which knowledge is exchanged between innovative actors analysing not only innovation outcomes but also firms' absorptive capacities.

[1] Spain is divided by Autonomous Communities that are territorial aggregations corresponding to the NUTS (Nomenclature of Territorial Units for Statistics) III classification. The NUTS is a hierarchical system for dividing up the territory of the European Union for analytical purposes (European Commission, 2011).

[2] www.ine.es

This paper is structured as follows. Section 2 provides some background by examining the relationship between geographical proximity and both absorptive capacity and innovation in agri-food companies. We also give some theoretical arguments about the proximity paradox in this context. Section 3 presents our empirical research starting with data and methodology. Section 4 highlights the results from the empirical research. Finally, some discussion and conclusions are presented in section 5.

2. Geographical proximity, absorptive capacity and innovation

2.1 Geographical proximity and absorptive capacity in agri-food companies

Getting access to new knowledge requires networking between linked firms (Hansen, 1999); mere exposure does not guarantee the assimilation of new information by the company. Although dense networks provide important access to new knowledge, its impact on companies, in terms of innovation and performance, depends on the extent to which a unit can absorb such new knowledge (Tsai, 2001). Zaheer and Bell (2005) demonstrated that firms that bridge structural gaps in a network tend to be better able to exploit their internal capabilities. Giuliani (2007) analyses knowledge networks in geographically close areas in the wine industry; the author finds that when firms are more densely connected in knowledge networks they have higher absorptive capacities. Giuliani and Bell (2005) find that the distribution of local resources and of knowledge affects innovation activity. The individual firm's knowledge base is an additive and distinct attribute of its systemic resources and capacities. Consequently, firms vary in their capacity to exploit opportunities (Munari et al., 2012). The differences in the amount of internal knowledge held by a firm generate an uneven and selective distribution of resources as well as knowledge being transferred and received in a close environment (Giuliani and Bell, 2005). Among a company's internal attributes, R&D efforts related to the firm's knowledge base, and thus its absorptive capacity are particularly significant (Hervas-Oliver et al. 2012). The core hypothesis behind these studies is that geographical proximity fosters interconnections between economic agents, conditioning positively their capacity to assimilate innovation (Barbosa and Faria, 2011).

2.2 Geographical proximity and innovation in agri-food companies

There is an extensive literature dealing with the effect of geographical proximity on firms' innovation (Bouba-Olga et al., 2015). Those geographically close to external agents should develop dense network structures (Granovetter, 1985). This conclusion is based on the assumption that geographical proximity favours social connections among individuals working in different local companies. Therefore, geographical proximity allows firms to connect more easily, overcoming barriers to knowledge exchange among economic agents (Tsai, 2001).

In the agri-food sector, there are only a few studies examining the impact of geographical proximity between companies and external agents on agri-food companies' innovation. Hence, Capitanio et al. (2010) conclude that interrelationships among geographically close economic agents are relevant in enhancing the innovation performance of agrarian firms. Bertolini and Giovannetti (2006) highlight that the interaction between economic agents and local environmental resources are relevant factors in the growth of these companies. Gellynck et al. (2007) explore the role of regional networks in the processes of innovation within a number of food companies. The authors find that firms enrolled in regional networks have a stronger innovation competence. Trigueros et al. (2013) examine the differences in the behaviour of innovation between agri-food and manufacturing firms. Their results suggest that environmental characteristics are more decisive in explaining innovation in agri-food companies. García-Alvarez-Coque et al. (2013) note that specific locations can provide advantages for agri-food firms in the form of local resources, such as favourable natural conditions or technological inputs. Läpple et al. (2016) undertake an external analysis considering innovation behaviour in spatially concentrated areas of agricultural activity; their study highlights the importance of local knowledge spillovers on the innovation of these companies. Hoffmann et al. (2017) find that strategic location, such as producing or processing agricultural products obtained in the territory where they are located, is a source of competitive advantage.

2.3 The proximity paradox in the geographical dimension

Regarding previous sections, the general conclusion is that geographical proximity positively impacts on innovation activities. But, this general understanding is not as simple as it was expected. Sorenson et al. (2006) highlight that the advantages of being geographically close to external knowledge sources varies with regard to the type of knowledge and, therefore, we cannot conclude there is always a general positive effect. In this sense, networks between geographically close innovative agents have also related costs to their initial establishment and maintenance which have to be taken into account when the proximity impact is examined (Eriksson et al., 2011). In addition, a negative effect in the geographical proximity impact could be caused by involuntary knowledge spillovers through which information escapes to other companies. Apart from these arguments, an excessive proximity between innovative actors could cause lock-in situations (Boschma, 2005) in which companies with similar characteristics in terms of innovation have little knowledge to exchange. Therefore, in order to get positive effects on innovation, interactions derived from geographical proximity should be established between agents with differences in terms of innovation activities. In conclusion, a high degree of geographical proximity could be considered a positive requisite to make agents more connected and promote innovation. However, proximity between innovative agents does not necessarily increase their innovative performance, and may even harm it (Broekel, 2015). This result is so called the as *proximity paradox* introduced by Boschma and Frenken (2010).

From previous arguments, we can think about an optimal distance value, in terms of geographical proximity, which maximize firms' innovation performance (Balland et al., 2010). Empirical studies testing this proximity paradox have considered two different methods. Firstly, there are studies which classify all relationships between all innovative actors into relationships with high or low geographical proximity. With this classification, these studies test which kind of relationships are the most likely to maximize innovation activity evaluated in terms of geographical (i.e., short vs long) distances (Bathelt et al., 2004). Secondly, some papers classify the relationships among innovative actors along a continuum and analyses the success of each particular relationship separately (Gilsing et al., 2007). With this aim, they introduce an individual global effect together with its quadratic form into the equation. In this way, they contrast whether there is break in the impact of proximity on innovation activity; if there is, we should get a positive effect for the global linear coefficient and a negative effect in the quadratic form. We develop our empirical study applying this second procedure.

3. Empirical analysis

3.1 Data

This study utilized the European Community Innovation Survey (CIS5) which contains information on establishments with more than 10 employees, regarding their innovation activities from 2005–2007. This period preceeds the 2007-2008 economic crisis to avoid any 'noise' that could be derived from that period. The survey is a stratified sample based on employment and sector. Because of legal obligations to complete the questionnaire, the response rate of the Spanish survey was very high (approximately 94%). We have selected private agri-food companies in Murcia (southeast of Spain on the Mediterranean coast). Our representative sample includes 231 agri-food Spanish companies. Table 1 shows the overall characteristics of the sample.

--------------------Insert Table 1----------------

Small companies account for 49% of the sample. We find that only 35% of the sample exports products to other countries. The results in Table 1 are in line with the traditional character of agri-food companies, which are typically small and focus on local markets (Trigueros et al., 2013). We also find that only 24% of these companies undertake R&D activities. The spatial distribution of the sample is also an interesting element in our analysis (see Figure 1).

-----------------------Insert Figure 1--------------------

Most companies are geographically distributed around the main city centres of Murcia, Cartagena and Lorca, and are close to the main roads. Finally, we use Google Maps (see Figure 2) to hand-collect the geographical coordinates (longitude and latitude) of different external economic agents and transport facilities in Murcia considered in our analysis.

3.2 Variable definitions

3.2.1. R&D activities

We use two variables to evaluate companies' innovation activity: R&D undertaken is a dummy variable which takes the value of one if the enterprise undertakes R&D activities, or zero otherwise. R&D intensity is computed as R&D spending per unit of sales, in thousands of euros. R&D spending is defined as intramural R&D, acquired external R&D or acquired other external knowledge. Other broader spending categories included in CIS5 (such as acquisition of machinery and equipment) have not been included in the analysis (cf. Maté and Harris, 2014).

3.2.2 Absorptive capacity

Absorptive capacity is defined as the ability of the firm to learn from external knowledge through the processes of knowledge identification, assimilation and exploitation (Cohen and Levinthal, 1990). Given the latent character of this definition, different approaches to evaluate this concept have been proposed (Escribano et al., 2009). The simplest and most often used proxies are related to measurements of R&D activities and human capital (Moilanen et. al., 2014). The latter, however, do not capture the full range of this concept. An alternative proposal is found in Zahra and George (2002). This is focused on a more complex definition based on collecting data for firms that distinguishes the different dimensions of a firms' absorptive capacity. In particular, they consider two measures of absorptive capacity: potential (acquire, assimilate) and realised (transform and apply). Following this influential study, researchers have proposed different approaches to evaluate firms' absorptive capacity, devising questionnaires to identify the components of absorptive capacity rather than use a simple proxy like R&D and/or human capital (Cho, 2014). The numerically ranked answers from the questionnaires are then used alongside factor analysis to obtain a smaller number of principal component indices that combine and represent the collected data. This approach assumes that researchers have enough information to develop adequate statements to be used in their questionnaires capturing the different steps in the assimilation of external knowledge. In contrast, our study is based on Harris and Li (2009) who used data from the Community Innovation Survey (CIS) to identify the extent to which firms make use of external information and cooperate with each other. The advantage of using CIS data is that firms are asked to report factual information on key elements of organisational learning and networking processes that can be related to absorptive capacity, i.e. external sources of knowledge or information used in innovation activities and their importance[3]; partnerships with external bodies on

[3] See Q.E4 in the CIS questionnaire where firms are asked to rank the importance of several sources of information for innovation activities (Internal sources, market sources, institutional sources, other sources). Respondents were asked to rank each factor (from not used to high importance). (http://www.ine.es/daco/daco42/daco4221/ite_cues07.pdf)

innovation co-operation[4]; and the introduction of changes in business practices[5]; all of which can be related to external knowledge spillovers and internal capabilities and thus aspects of absorptive capacity. Such data are objective in that firms are asked to state if certain activities are taking place (rather than, for example, rank their self-assessed ability to search, obtain and use information and adapt existing technologies using such new information); and CIS data is more generalizable since it is obtained from large datasets covering many countries and for significant time periods.

Applying factor analysis, Table A1 (see the appendix) shows the results using all firms in the Spanish CIS5 (i.e., covering all sectors and regions). The numbers in the first four columns of data show the correlations (greater than 0.5) between the principle component factors (PCF) extracted and the underlying variables used to build each component. These factors measure different dimensions of firms' absorptive capacity. The first captures the establishment's capacity to exploit external sources of knowledge. The second and third factors evaluate partnerships with other enterprises or institutions at both the national and international level respectively. Finally, the fourth element refers to the implementation of new organisational structures. To test the adequacy of these factors to firms' absorptive capacity, we compute the overall Kaiser–Meyer–Olkin (KMO) (Kaiser, 1960) criterion. KMO is 90.3% suggesting the factors do indeed represent different dimensions of absorptive capacities[6].

3.2.3 Geographical proximity variables

In order to evaluate the density of a firms' environment, we define two density variables: Sectorial Density (***DensSS***) establishes the number of firms operating in the same sector inside of a 500 metres buffer; Density (***Dens***) measures the diversification of the environment by calculating the density of companies operating in all industrial sectors within the buffer. In order to identify these cut-off points of 500 metres for the density variables, we apply an approach similar to Da Silva and Mc Combe (2012). This procedure is based on computing density variables considering different concentric

[4] See Q.E51 in the CIS questionnaire where firms state if they cooperated with suppliers, customers, competitors, through to research institutes at the following locations: 'Spanish national', 'European', 'United States', or in 'Other' countries. From this we could identify cooperation (coded 1 if present, 0 otherwise) at the national and international level.

[5] See Q.I1 in the CIS questionnaire. These are measured by the implementation of new business practices for organising procedures; new methods of organising work practices; new methods of organising external relationships; or implementation of changes to marketing concepts or strategies. When an activity took place it was coded as 1 (0 otherwise).

[6] Note by construction, the mean and standard deviation of each orthogonal PCF is zero and one respectively.

rings r_i from 0 to 25 kilometres radii around each company in our sample. We limit our study to a maximum radius of 25 kilometres to represent the territorial surface in Murcia. With these variables, we get that the value of 500 metres maximizes the likelihood function in our estimated models.[7] According to previous studies, these variables should capture the potential networks companies have; as the density of the environment increases, companies will enjoy positive external effects from external economies of scale and improved informational flows, which should positively impact on these firms' innovation activities and their absorptive capacity (Giuliani, 2007; Läpple et al., 2016).

We also include a variable to measure the distance from an agri-food company to the closest, largest company in the same sector (***DMinLC***), the latter we assume act as sector leaders. Closer proximity reduces problems with asymmetric information, and allows a company to react to market changes faster than other companies located further away (Pirinsky and Wang, 2006). Therefore, geographical proximity in this case provides a firm with additional external knowledge flows which could be reflected in higher absorptive capacity and innovation activities for these companies. The distance between agri-food companies and their nearest large shopping centre or local supplier market (*DminCoC*) is included since geographical proximity will strengthen the positive effects of the cognitive and social role of customers who place a premium on the agri-food firm's innovation activities (Trigueros et al., 2013). From Google Maps, we collected the geographical coordinates of twenty-nine shopping centres (12 major shopping centres including supermarkets selling agri-food products) and local supplies markets (27 local supplies markets providing agri-food products) in Murcia. Note, *DminCoC* is defined as the Euclidean distance from each company to its closest shopping centre or local market (see Figure 2a). City centres are also considered in our study as a possible positive influence on firms' innovation due to the benefits derived from closer geographical proximity to final customers which provides competitive advantages which then should be reflected in additional R&D investments and higher absorptive capacity. In particular, *DminCC* measures the distance from the company to

[7] We find only minor differences when we consider radii values close to 800 metres. The significance of our geographical variables decreased as we increased the radius, becoming generally insignificant for a radius of 1200+ metres.

its closest city centre or town in Murcia[8]. Following the National Institute of Statistics,[9] we identify fifty-seven city centres and towns in Murcia[10] corresponding to different urban areas (see Figure 2b).

The Euclidean distance to the closest industrial estates (***DminIS***) captures industrial territorial interrelationships where geographical proximity to other companies allows the diffusion of knowledge and easier access to different modes of transport (Mota and Castro, 2004) which facilitates a positive effect on innovation activities. We locate fifty-nine industrial estates in the province of Murcia (Figure 2c)[11]. We also include the distance to the closest research centre or university (*DminR&D*)[12]; geographical proximity to these agents is expected to benefit firms with higher innovation performance and absorptive capacities (Romijn and Albu, 2002). We measure the distance between agri-food companies and logistic centres (*DminLC*); we identify five logistic centres in Murcia using GoogleMaps (see Figure 2.e)[13]. Geographical proximity to these centres enhances firms' productive activity through lower transportation costs. In addition, easy access to logistic centres should strengthen interrelationships among companies fostering their absorptive capacity and therefore their innovation (Zaheer and Bell, 2005).

----------------------------Insert Figure 2------------------------

Finally, we include the impact of transport facilities: that is the distance from the company to the roads A-7, A-30, A-33, A-91 and AP-7 that intersect with national highways. Twenty-three different highway junctions are included (*DMinHWJ*) (see Figure 2f). We expect that companies closer to road junctions have easier access to external economic agents (Holl, 2004), thus promoting firms' absorptive capacity and innovation.

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[8] We consider both cities and towns, to maximize the geographical proximity effect.

[9] www.ine.es

10 This includes the three largest cities in Murcia (Cartagena, Murcia and Lorca) while the others city centres and towns are much smaller in size.

11 The identification of Industrial Estates in Murcia is based on the census of management of industrial activities (CREM: http://econet.carm.es/). From this database industrial estate corresponds with the geographical areas on the edge of towns planned for offices and light industry.

[12] Again, we consider both, universities (i.e., "Murcia", "Technical of Cartagena", "UCAM") and technological centres in Murcia to maximize the geographical proximity effect between agri-food companies and potential R&D centres (see Figure 3d). Geographical information for the technological centres comes from the Federación de Centros Tecnológicos in Murcia webpage (http://www.citem-rm.es/). These technological centres are defined as private and non-profit research agencies.

[13] Logistic centres refer to specialized buildings in which firms stock their products (in this case agri-food products) to be redistributed to retailers, to wholesalers, or directly to consumers.

---------------------------Insert Table 2---------------------------

3.2.4 Control variables

The size of the company is included and defined as the number of employees recorded in the CIS5 questionnaire. Empirical studies of agri-food companies have confirmed that large firms are more likely to innovate and develop more absorptive capacity to facilitate the innovation process (Cabral and Traill, 2001; Dhamvithee et al., 2005). Following the European Commission classification of Small and Medium (SME) sizes' companies, we categorise this variable into three categories: small, medium and large companies (see Table 2). We also control for the NACE (Nomenclature of Economic Activities) codes distinguishing the following subsectors: cereals, fruits and milk (see Table 1 for NACE codes). We include firms' age as the number of years since the firm was founded; older firms generally have a high probability of innovation and more capacity to assimilate external knowledge than younger companies (Huergo and Jamandreu, 2004). Finally, we control for the internationalization of the company using a dummy variable (INTERNATIONAL) which has a value of 1 if the company sells its products outside Spain (see Table 1). We expect a positive relationship between the international character of the company and their absorptive capacity and innovation (Harris and Li, 2009). Table 2 gives an overview of the variables incorporated into the model.

3.3. Econometric analysis

In order to test how geographical proximity variables influence agri-food firms' absorptive capacity, we apply a Seemingly Unrelated Regression (SUR) approach, with each of the four measures of absorptive capacity as the dependent variables. We expect better results for the GLS estimation applying SUR in comparison with OLS because we have different number of regressors across equations (Baltagi, 2011). In addition, we compute the Breusch Pagan LM test of diagonality in the error covariance matrix. This test is rejected confirming the adequacy of applying SUR estimation (see Table 3). We also compute Lagrange Multiplier (LM) tests for contrasting spatial dependence in the residuals of the SUR model (Mur et al., 2010[14]). With this objective we define a binary weight matrix W to establish a connectivity criterion. The elements of W, $\mathrm{w_{ij}}$ $(\mathrm{i}, \mathrm{j} =$

[14] Matlab codes are available in the following link: http://metodos.upct.es/falopez/Publications/index.html

$1, \ldots, n$) value of 1 if companies i and j are neighbours, and 0 in otherwise. By definition, the elements in the main diagonal are equal to 0. Based on geographical distance between companies, we consider that each company i is connected with its k nearest neighbors. Table 3 present spatial dependence LM tests for k=5 nearest neighbours[15]. These tests corroborate the absence of spatial dependence in the residuals of this model independently on the considered spatial structure.

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All equations are estimated using a log–log[16] form so that the coefficients can be interpreted as elasticities. In addition, we test for the existence of nonlinear relationships in the explanatory variables by adding, where appropriate, statistically significant squared values of these variables (see Table A2 in appendix). The estimation of the SUR approach uses a maximum likelihood approach to model the different dimensions of absorptive capacity, producing parameter estimates of the coefficients where the various geographical proximity variables are generally significant and with the expected signs (see Table 3).

Equation 1 (Table 3, first column) considers the determinants of firm level absorptive capacity related to capturing external knowledge. The density variables are both significant but with different signs; ***Dens*** is positive and significant highlighting the positive effect of agglomeration economies in strengthening the exchange of information among agents (Läpple et al., 2016). But, Sectoral Density (***DensSS***) is negative and significant, suggesting that the presence of a large number of firms operating in the same sector increases competition, generating barriers to information sharing and so limiting the exchange of knowledge (Folta et al., 2006). Regarding distance variables, proximity to Industrial Estates, technological centres and universities, and Logistic Centres all display a nonlinear relationship; close proximity has a positive effect on the firms' ability to absorb external knowledge but the further a company is from such external bodies the positive effect diminishes and then turns negative. Therefore, agri-food companies located at long distances from these economic agents will experience a negative effect on their innovation activity. Regarding the

[15] Alternative k-values where considered providing similar results but k=5 gives the highest significant values for LM tests.

[16] In order to overcome the negative values in certain variables we have rescaled these by adding to them a positive value slightly larger than the minimum negative range value.

magnitude of the coefficients, we find that the largest effects are associated with Industrial Estates and technological centres and universities.

Absorptive capacity related to national cooperation (AC2) is also influenced by these geographical variables; Sectoral Density (DensSS) also has a negative and significant impact on this type of absorptive capacity, probably indicating similar congestion when competition is strong (Folta et al., 2006). The most relevant geographical variables for AC2 are related to proximity to technological centres and universities and Logistic Centres. In addition, proximity to City Centres (DminCC) and major road junctions (DminHWJ) also have a large effect (7.8% and 9.0% respectively). Absorptive capacity related to the international cooperation (AC 3) is positively related to firm density. With respect to the distance variables, the most significant effects are related to a firms' proximity to Industrial Estates (DminIS) and technological Centres and Universities (DminR&D). Proximity to large companies is also significant. Finally, absorptive capacity associated with the incorporation of new management practices (AC 4) is also affected by Density (positive and significant); proximity to Logistic Centres and Industrial States however are the most important in this equation.

Regarding the control variables, smaller company size has a negative and significant impact on absorptive capacity. This result corroborates previous findings that show a positive relationship between firm size and absorptive capacity (Cabral and Traill, 2001; Dhamvithee et al., 2005). We obtain a similar result for the age of the company; older companies have higher absorptive capacities (Huergo and Jamandreu, 2004). The internationalization of the company generally has also a positive effect on absorptive capacity (Harris and Li, 2009).

In the second stage of our analysis, we test for geographical proximity factors affecting innovation activities for agri-food companies. Here, the Heckman (1979) approach is used. This methodology is based on a two-step procedure (estimated simultaneously using a FIML approach): the first regression is a probit estimation determining whether R&D is undertaken or not. The second equation has R&D intensity as the dependent variable and introduces a correction bias (the inverse of Mills Ratio) to account for potential sample selection issues. This approach recognises that those companies that conduct R&D are not a random subset of the entire sample; rather, modelling R&D

intensity needs to consider that those with non-zero R&D levels have certain characteristics that are also linked to a company's ability to undertake R&D (failure to take into account this self-selection element could lead to biased results). The significativity of the inverse Mills Ratio confirms the adequacy of applying Heckman estimation procedure. In addition, we compute the spatial dependence Moran's I test for each equation with a spatial dependence matrix defined by the five nearest neighbours. These results indicate the lack of spatial dependence in both equations of this model.

--------------------------Insert Table 4------------------------

Table 4 presents the results[17]. Geographical proximity variables are significant in explaining both whether R&D is undertaken (Table 4 first column) as well as R&D intensity (second column)[18]. In explaining the probability of undertaking R&D activities, firms' density (Dens) is positive and significant, confirming that spatial concentration of activities fosters the development of networks between firms, which in turns allows an exchange of information that positively affects the firms' innovation activities (Läpple et al., 2016). In addition, geographical proximity to large companies (DMinLaC), Industrial Estates (DMinIS) and transport facilities, such as major road junctions (DMinHWJ), also have an important role in determining the probability of doing R&D. R&D intensity is also affected by geographical variables; here sectoral density is especially significant. In comparison to the results relating to whether R&D is undertaken, for those companies undertaking R&D activities sectoral density has a negative effect on the amount of R&D undertaken. This result is different from previous literature in this area (Läpple et al., 2016); we find that sectoral density plays a negative role which we interpret as the presence of a large number of firms operating in the same industrial sector likely increases competition, reducing external resources for investing in R&D (Folta et al., 2006). Proximity to logistic centres and large companies with similar activities is also important. In general, geographical proximity variables influence R&D intensity to a greater extent than the firm's decision to undertake R&D. The absorptive capacity coefficients confirm that higher values (ceteris paribus) have a positive effect on R&D activities, but that this differs between the two equations determining R&D. National and international cooperation especially play a fundamental role for agri-food companies in their ability to undertake R&D activities (Iammarino et

[17] We drop from this analysis non-significant variables: ***DminCoC*** , ***Cereals*** and ***Meat***. We do not find any non-linear relationships between geographical variables and R&D outputs.

[18] Note, both equations contain similar regressors, therefore, the model is identified by the fact that the probit equation is based on a non-linear relationship (Greene, 2008).

al., 2009; Maté and Harris, 2014) while external sources of knowledge and changes in management practices play an important role in R&D firms' intensity. Regarding the control variables, our results are generally as expected. In accordance with Cabral and Traill (2001), we obtain a positive and significant relationship between the size of the firm and the probability of undertaking R&D activities. We find that firms producing Fruits activities are less likely to undertake R&D activities while Support has a positive sign. Firms' age is positive and significant in the probability of undertaken R&D activities. Finally, the variable representing internationalization indicates that firms involved in exporting activities are more likely to undertake R&D (cf. Harris and Li, 2009).

5. Conclusions

We study the effects of geographical proximity on innovation in agri-food companies in Murcia. Our findings show that the geographical proximity of companies and external economic agents/transport facilities has an important impact on absorptive capacity and R&D activities. These findings inform the internal decision-making process adopted by firms themselves and aid policymakers in the design and development of agricultural and food policy. The study is carried out in a regional context, specifically in Murcia, one of the territories in which the agri-food sector is of the greatest importance for GDP. The results corroborate that geographical proximity favours firms' absorptive capacities and innovation activities fostering knowledge spillovers via the interaction of economic agents operating in close proximity. However, we also find differences when the geographical impact on absorptive capacities and innovation is examined. In this sense, geographical proximity between agri-food companies and industrial states and R&D centres (technological centres and universities) has a significant impact on firms' absorptive capacities whereas geographical distance to large companies and transport facilities play an important role in determining R&D activities. In addition, our results corroborate the proximity paradox finding a non-linear relationship with regard to absorptive capacity in agri-food companies. In particular, geographical proximity not only has a positive impact on absorptive capacity but agri-food companies located far from these economic agents experience negative effects (less absorptive capacity and innovation investments). Thus, in contrast with previous results, we find significant non-linearities in the geographical dimension when firms' absorptive capacity is examined. This non-linearity is usually ignored in models evaluating both whether R&D is undertaken and R&D intensity. Regarding density effects, we find interesting differences between both density variables. In this sense, Density, considering companies from different sectors, plays a positive effect in the likelihood of undertaking R&D activities. So, companies benefit from different externalities, but once the company has enrolled in R&D activities then R&D expenditures depend on the competitive conditions in companies' closer environments.

Since this study covers a specific territory (Murcia), this could be considered as a limitation. So, our approach should be applied to other sectors, other areas, and indeed other countries to test whether the results obtained can be generalised, what differences emerge, and thus whether particular spatial areas in a country can benefit from fostering interrelationships between interrelated economic agents

Acknowledgements

Mariluz Maté Sánchez-Val acknowledges the financial support from Seneca Foundation. Project Number: 19884/GERM/15.

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Table 1: Sample characteristics of agri-food in Murcia, 2005-2007		
SIZE[(1)]	**Cases**	**Percentage**
Small (10 to 50 employers)	113	49
Medium (51 to 250 employers)	96	42
Large (more than 250 employers)	22	9
TOTAL	231	100
SUB- SECTOR[(2)]	**Cases**	**NACE code**
Cereals	11	111, 4621
Fruits	95	112,122, 123, 124, 125,4631,1032,1039
Milk	4	141,1053,1054
Wine	5	121, 1102
Meat	16	142, 145, 146, 147,149, 1013
Support	9	161,162, 1091
Other activities	91	NACE codes corresponding with the agri-food sector and not included before
INTERNATIONALIZATION[(3)]	**Cases**	**PERCENTAGE**
Local market	195	84%
Nacional Market	206	89%
European Market	148	64%
Other countries	82	35%
AGE[(4)]	**Cases**	**PERCENTAGE**
Middle age (5 to 24 years)	140	60%
Old (more than 25 years)	91	40%
R&D ACTIVITIES	**Cases**	**PERCENTAGE**
Undertake R&D Activities	56	24%

Source: CIS5. [(1)]CIS database does not cover micro-companies. [(2)]NACE 2009. http://ec.europa.eu/eurostat [(3)] Cases represent the count of the number of firms in the sample.. [(4)] Following Berger and Udell (1998) and the characteristics of our sample, we established two groups based on their age: middle-aged firms (10 to 24 years) and old firms (more than 25 years). No companies in the sample were in existence for less than 10 years.

Table 2. List of dependent and independent variables included in the model			
Variable	**Description**	**Mean**†	**St. dev**†
Dependent variables			
R&D undertaken	Whether the company undertook or not R&D activities during the period 2005–2007	0.2424	0.4294
R&D intensity	Level of efforts dedicated to produce product and processes improvements considering the size of the company in logarithms	0.4274	1.5254
Absorptive capacity (AC)	AC1: External sources of knowledge	-0.0740	0.9474
	AC2: partnerships with national bodies on cooperation	-0.0776	0.8899
	AC3: partnerships with international bodies on cooperation	-0.0416	0.5486
	AC4: changes in management practices	-0.0388	0.8465
Independent variables			
DensSS (*)	Number of firms of the same subsector (NACE-2007, 2 digits) within a radius of five hundred metres	4.1082	5.6435
Dens(*)	Number of total firms of all sectors within a radius of five hundred metres	18.7021	16.6127
DminLaC	Distance to the closest large firm of the agri-food sector in Murcia	8.4468	9.6081
DminCoC	Distance to the closest Commercial Centre or local supplies market	8.3369	7.6494
DminCC	Distance to the closest City Centres or Town	2.8867	6.0611
DminIS	Distance to the closest industrial state	3.9599	4.2535
DminR&D	Distance to the closest technological centre or university	13,3692	8.1925
DminLC	Distance to the closest logistic centre	14.7241	8.1466
DminHWJ	Distance to the closest major road highway junction	6.5793	4.1924
Control variables			
Small	1 if firm size is small (10-50 employees), 0 otherwise.	0.4891	0.5009
Medium	1 if firm size is medium (51-250 employees), 0 otherwise.	0.4155	0.4938
Large	1 if firm size is large (more than 250 employees), 0 otherwise	0.0952	0.2931
Milk	1 if firm main activity is Milk subsector, 0 otherwise	0.0173	0.1307
Fruits	1 if firm main activity is Fruits subsector, 0 otherwise	0.4112	0.4931
Cereals	1 if firm main activity is Cereals subsector, 0 otherwise	0.0476	0.2134
Wine	1 if firm main activity is Wine subsector, 0 otherwise	0.0216	0.1458
Meat	1 if firm main activity is Meat subsector, 0 otherwise	0.0692	0.2554
Support	1 if firm main activity is Support subsector, 0 otherwise	0.0389	0.1939
Other agri-food subsectors	1 if firm main activity is in agri-food subsector but not included before, 0 otherwise	0.3939	0.4896
Age	Age of firm (*t* minus year opened +1) in years	23.8138	12.2621
International	1 if firm import and/or export, 0 otherwise.	0.6493	0.4782

* Five hundred metres maximises the LM functions in our estimations.
† Mean and standard deviation report results for agri-food companies in Murcia.

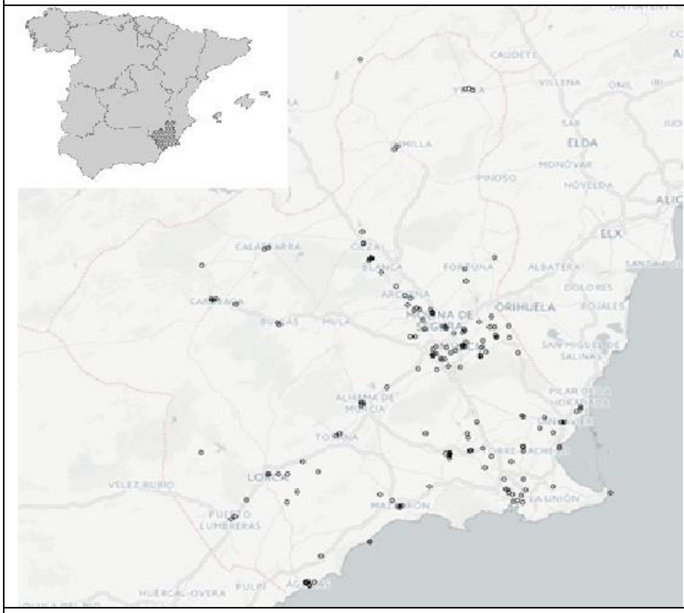
Table 3: SUR model for firms' absorptive capacities in agri-food business, Murcia, 2005-2007				
Variables	AC1: External sources of knowledge	AC2: partnerships with national bodies on cooperation	AC3: partnerships with international bodies on cooperation	AC4: changes in management practices
Constant	0.4240*** (0.000)	0.4311*** (0.004)	0.4766*** (0.000)	0.4342*** (0.000)
Dens	0.0228** (0.045)	-0.0076 (0.789)	0.0665* (0.068)	0.0433** (0.021)
DensSS	-0.0832** (0.036)	-0.0432** (0.018)	0.0450 (0.519)	0.0213 (0.644)
DMinLaC	-0.0145** (0.012)	-0.0112** (0.013)	-0.0136** (0.011)	-0.0299** (0.053)
DMinCoC	-0.0441** (0.016)	-0.1198 (0.728)	0.0022 (0.745)	-0.0233* (0.071)
DMinCC	-0.0187** (0.021)	-0.0212** (0.025)	0.0003 (0.933)	-0.0021 (0.775)
DMinIS	-0.0975** (0.021)	-0.0852** (0.036)	-0.0693*** (0.002)	-0.0758** (0.025)
DMinIS^2	0.0345*** (0.000)	-	0.0223* (0.079)	0.0113** (0.037)
DMinR&D	-0.0934*** (0.009)	-0.0992* (0.077)	-0.0711** (0.022)	-0.0112* (0.076)
DMinR&D^2	0.0239** (0.044)	0.0354* (0.075)	-	-
DMinLC	-0.0211*** (0.000)	-0.0938*** (0.000)	-0.0313** (0.045)	-0.0635** (0.048)
DMinLC^2	0.1161 (0.201)	0.0312*** (0.000)	-	0.0577*** (0.031)
DMinHWJ	-0.0299* (0.085)	-0.0776** (0.012)	0.0099 (0.210)	-0.0549 (0.621)
Small Companies	-0.3301*** (0.000)	-0.2932** (0.033)	-0.3489*** (0.000)	-0.3558 (0.264)
Medium Companies	-0.2635** (0.004)	-0.2762** (0.040)	-0.3177** (0.002)	-0.3432** (0.041)
Age	0.3143** (0.007)	0.2522** (0.056)	-0.0044 (0.740)	0.2588** (0.057)
International	0.1832** (0.009)	0.0670 (0.326)	0.1667** (0.059)	0.0881*** (0.035)
Cereals	0.0486 (0.732)	-0.2296** (0.018)	0.0077 (0.651)	-0.1328*** (0.015)
Fruits	-0.1173* (0.085)	-0.1196** (0.055)	-0.1051** (0.011)	0.0771 (0.122)
Meat	0.1202 (0.308)	-0.0391 (0.717)	-0.1191** (0.017)	-0.1221* (0.017)
Support	0.1688 (0.291)	-0.1804 (0.224)	0.1332 (0.377)	-0.1665 (0.116)
R^2	0.2877	0.3123	0.3388	0.3145
N	231	231	231	231
Breusch Pagan Test[a]	39.3508 (0.0000)			
Spatial Dependence tests[b]: LM_SUR-ERR	4.2883 (0.368)			
Spatial Dependence tests[b]: LM*-SUR-ERR	1.9509 (0.744)			
Spatial Dependence tests[b]: LM-SUR-LAG	6.1030 (0.391)			
Spatial Dependence tests[b]: LM*-SUR-LAG	3.7676 (0.438)			

Standard errors in parenthesis. (***), (**), (*) significant at 1%, 5% and 10% levels respectively. [a]The null hypothesis confirms diagonality in the error covariance matrix. The test is distributed as $\chi^2$with 6 degrees of freedom. [b] Based on procedures set out in Mur et al. (2010). LM_SUR-ERR test contrast the existence of spatial dependence in the error term of the model. LM_SUR-LAG test contrast the existence of spatial dependence in the dependent variable.

Table 4. Heckman two step estimation: (1) Probit model to evaluate the determinants of firms' probability of undertaking R&D or not. (2) Determinants of R&D intensity		
Variables[a]	R&D Undertaken or Not (Marginal effects[a])	R&D Intensity
Dens	0.0127** (0.028)	0.0083 (0.198)
DensSS	-0.0039 (0.185)	-0.0161** (0.021)
DMinLaC	-0.0365** (0.017)	-0.4952** (0.038)
DMinCC	0.0419 (0.142)	-0.0128** (0.031)
DMinIS	-0.0413** (0.018)	-0.0213** (0.024)
DMinR&D	0.0033 (0.887)	-0.0462*** (0.021)
DMinLC	0.0068 (0.731)	-0.0279*** (0.018)
DMinHWJ	-0.0441* (0.093)	0.3973 (0.207)
Small Companies	-0.3789** (0.062)	1.0851 (0.258)
Medium Companies	-0.2535** (0.002)	-0.6185*** (0.002)
Age	0.0042** (0.036)	-0.7451 (0.568)
International	0.1438** (0.039)	-0.3336 (0.859)
Fruits	-0.1372** (0.041)	0.0767 (0.452)
Support	0.2823** (0.060)	0.0257 (0.625)
AC1: External sources of knowledge	0.2735*** (0.000)	0.4411*** (0.027)
AC2: partnerships with national bodies on cooperation	0.3557** (0.001)	0.2964** (0.052)
AC3: partnerships with international bodies on cooperation	0.4941* (0.075)	0.0817 (0.238)
AC4: changes in management practices	0.3872 (0.311)	0.6962* (0.086)
Inverse of Mills Ratio	-	1.3060** (0.061)
N (number of observations)	231	56
Moran I test [b]	0.1120 (0.554)	0.0661 (0.825)

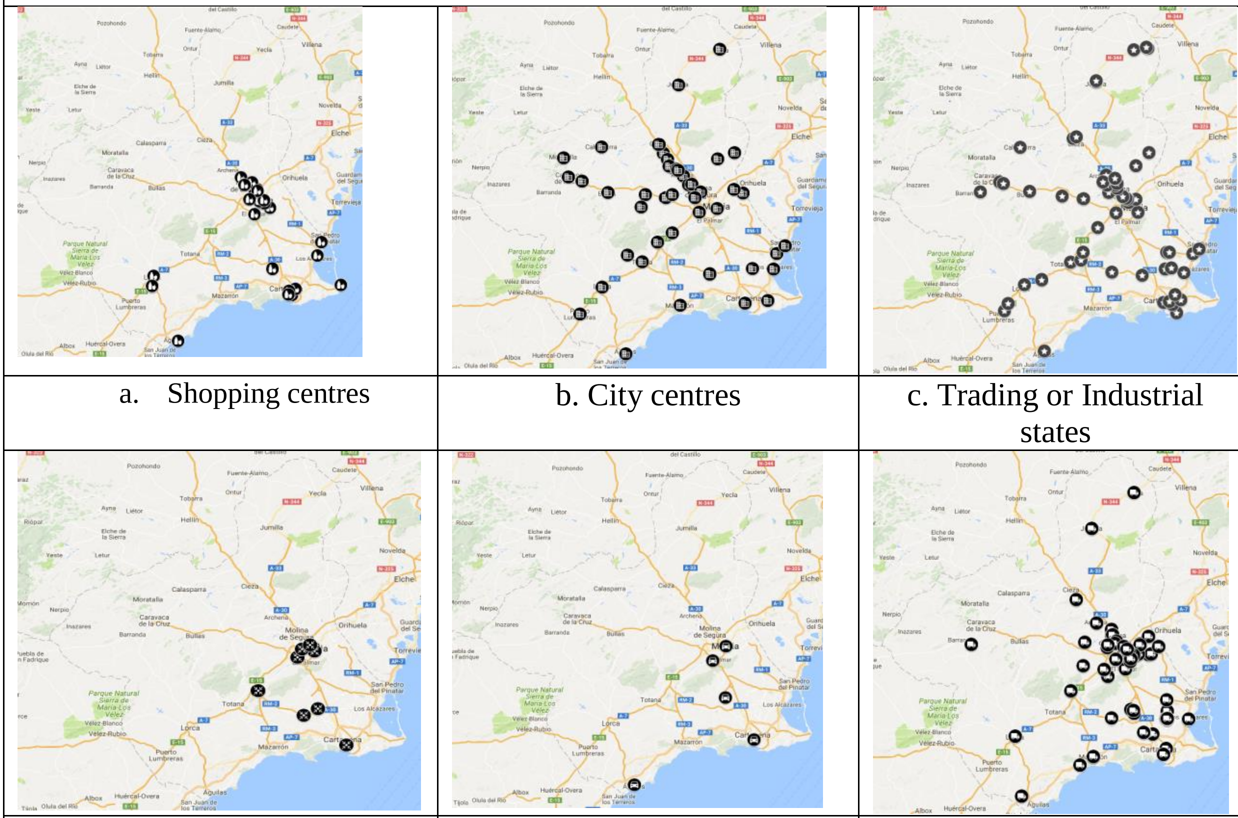
[a] Coefficients and p-values based on delta method developed for the Heckman model (see Vance, 2009, for details). ***/**/* significant at 1/5/10% levels. [b] The null hypothesis confirms the absence of spatial dependence in the error term of these estimations. The standardised Morans' I test follows a normal distribution.

Figure 1: Spatial distribution of agri-food firms in Murcia, 2005-2007



Source: CIS5

Figure 2: Spatial distribution of external economic agents and transport facilities



a. Shopping centres

b. City centres

c. Trading or Industrial states

d. Universities and R&D centres

e. Logistic centres and facilities

f. Road junctions

Source: GoogleMaps

Table A1. Factor loadings from PFA model. Spain. CIS5

Variable	External knowledge	National cooperation	International cooperation	Business innovation	KMO
Sources of knowledge/info for innovation					
Suppliers	0.7578				0.9842
Clients/customers	0.7896				0.9488
Competitors	0.8014				0.9478
Conferences/trade fairs/exhibitions	0.7838				0.9714
Scientific journals and trade/technical publications	0.7424				0.9348
Professional/industry associations	0.7651				0.9482
Technical/industry standards	0.7946				0.9573
Consultants/labs/R&D institutes	0.7815				0.9572
Co-operation partners on innovation activities (national/international)					
Clients/customers (national)		0.6799			0.8988
Competitors (national)		0.6903			0.8878
Consultants/labs/R&D institutes (national)		0.6395			0.9036
Government/research organisations (national)		0.5952			0.8660
Clients/customers (international)			0.5158		0.8928
Competitors (international)			0.6433		0.8467
Consultants/labs/R&D institutes (international)			0.7421		0.8476
Government/research organisations (international)			0.7921		0.8228
Areas of changes of business structure and HRM practices					
New business practices				0.8158	0.8854
New work practices				0.8035	0.9036
New external relations				0.8264	0.8854
New marketing strategies				0.6621	0.9380
Overall KMO					0.9038

Table A.2. Significance values for F tests in ANOVA analysis to check linearities in the coefficients of SUR estimation				
	Absorptive Capacity 1	Absorptive Capacity 2	Absorptive Capacity 3	Absorptive Capacity 4
Density	0.1876 (0.665)	0.4568 (0.500)	0.9730 (0.326)	0.0430 (0.836)
Density Sector	0.0041 (0.949)	0.0595 (0.807)	0.0182 (0.893)	0.3032 (0.583)
DMinLaC	0.5213 (0.471)	0.0017 (0.967)	0.1171 (0.732)	0.5885 (0.444)
DMinCoC	1.6491 (0.201)	0.6719 (0.412)	1.5846 (0.210)	1.5930 (0.209)
DMinCC	1.3491 (0.248)	0.0037 (0.955)	0.6983 (0.405)	0.1258 (0.723)
DMinIS	7.9371*** (0.000)	1.2668 (0.262)	3.0077* (0.098)	5.4761** (0.021)
DMinR&D	2.8801* (0.092)	3.4817** (0.064)	0.3158 (0.605)	0.3421 (0.559)
DMinLC	3.4050* (0.067)	5.3489** (0.022)	1.5376 (0.217)	3.5695* (0.061)
DMinHWJ	0.0601 (0.802)	0.0141 (0.906)	0.7239 (0.396)	1.2852 (0.259)
Standard errors in parenthesis. (***), (**), (*) significant at 1%, 5% and 10% levels respectively				