Beyond incremental innovation: the effects of industry specialization on radical innovation

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Abstract
Discontinuous or radical innovation is under-researched in the geography of innovation strand, compared to the well-researched incremental or imitative innovation. In this paper, the focus is on understanding whether discontinuous new-to-the-market innovations occur in industry agglomerations, a phenomenon mostly overlooked by scholars. The study focuses on the effect of industry specialization on the occurrence of discontinuous innovation. By analyzing a large dataset of 3,602 firms from CIS and other regional data, results show that collocation in an agglomeration has a negative influence on the occurrence of a firm’s discontinuous innovation, a pattern of innovation not facilitated by industry agglomerations.
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Discontinuous or radical innovation is under-researched in the geography of innovation strand, compared to the well-researched incremental or imitative innovation. In this paper, the focus is on understanding whether discontinuous new-to-the-market innovations occur in industry agglomerations, a phenomenon mostly overlooked by scholars. The study focuses on the effect of industry specialization on the occurrence of discontinuous innovation. By analyzing a large dataset of 3,602 firms from CIS and other regional data, results show that collocation in an agglomeration has a negative influence on the occurrence of a firm’s discontinuous innovation, a pattern of innovation not facilitated by industry agglomerations.

KEYWORDS radical innovation; localization externalities; CIS data; agglomerations

JEL CODES: O3, R1

1.-INTRODUCTION

Our study is focus on the effect of agglomerations on firm performance (e.g. McCann and Folta, 2011; Rigby and Brown, 2015; Knoben et al., 2016; Hervas-Oliver et al., 2018a). Literature on agglomerations and firm performance, however, has continuously assumed that most innovations follow a continuous or incremental innovation pattern, omitting the explanation and rationale of how agglomerations enable discontinuous or radical innovation to occur and thus overlooking the potential effect that an agglomeration can exert on a firm’s discontinuous innovation. Addressing firm-level heterogeneity, to the best of our knowledge, there is no study focusing on understanding the relationship between collocation in an agglomeration and the occurrence of discontinuous or radical innovation. In this study, we attempt to fill this gap mostly overlooked by scholars. It is aimed at deciphering whether localization externalities\(^1\), measured as industry specialization or a firm’s collocation in a relatively high own-industry employment region, exert a potential effect on a collocated firm’s discontinuous innovative performance.

In this paper, we associate discontinuity with radical innovation and use the terms interchangeably throughout the text, measuring the latter as new-to-the market innovation defined by the CIS (a significant impact on a market and on the economic activity of firms

\(^1\) Marshall (1890), Arrow (1962), and Romer (1986) put forward a concept, which was later formalized by the seminal work of Glaeser et al. (1992) and became known as the Marshall–Arrow–Romer (MAR) mode
in that market, OECD, 2005:58\textsuperscript{2}) referring to a discontinuous and totally opposed to incremental innovation. In doing so, we refer to novel knowledge that is more exploratory than exploitative in the sense of March (1991) and is neither incremental nor imitative. For that purpose, this study develops a theoretical framework aimed at deciphering and understanding the geography of discontinuous versus incremental innovation, bringing the role of firm-level heterogeneity to the center of the framework. By addressing firm-level heterogeneity, this study draws on how firms combine internal and external sources of knowledge, focusing on how localization externalities and their associated highly-intensive knowledge flows may impact that combination on a firm’s innovative performance.

Generally, very few studies have looked at radical innovation in agglomerations theoretically (Pouder and St. John, 1996; Gilbert, 2012; Hervas-Oliver, 2016) or empirically (e.g. Ostergaard and Park, 2015), the latter being restricted exclusively to case studies. Rather, literature has basically focused on describing how radical innovation was unsuccessful in clusters and that, subsequently, lock-in and decline followed (e.g. Glasmeier, 1991; Grabher, 1993; Staber and Sautter, 2011; Isaksen, 2018; being Hervas-Oliver et al., 2018b a remarkable exception). Combining geography of innovation and strategy frameworks, we posit that in agglomerations discontinuous innovation and its associated changes, however, neither frequently occur nor are facilitated. Excessive and too narrowly focused on local searching for tacit knowledge in established incumbent local industries lock-in existent technologies and restrict the flow of new ideas, knowledge and paradigms from new industries that are usually associated with radical changes. This is, in no small part, activated by the pervasive and repetitive inter-firm interactions in established local networks for firms gaining legitimacy in order to be considered “members of the network”. The latter implies frequently refusing to change from established and accepted local institutions (e.g. Scott, 1992; Glasmeier, 1991), continuously exchanging knowledge lock-in local and accepted existing technologies and thus making discontinuous innovation harder to achieve in agglomerations.

Using data from the Spanish Community of Innovation Survey and information on the localization externalities provided by the Spanish Statistical Office (INE), we test our model on 3,602 Spanish firms. Contextualizing on localization externalities that are

\textsuperscript{2} As explained below, CIS data in Spain separates incremental from radical, using the terms new-to-the-firm and new-to-the-market
measured as industry specialization or a firm’s collocation in a relatively high own-industry employment region, results show that industry specialization has a negative influence on the occurrence of a firm’s discontinuous innovation, due to the institutional uniformity (e.g. DiMaggio and Powell, 1983) existent in agglomerations.

The following section details the conceptual framework of our study. Then, in the third section, we elaborate on our data and our empirical design. In the fourth section, the results are presented, together with a discussion. Finally, conclusions are developed and some areas for future research are discussed.

2.-CONCEPTUAL FRAMEWORK

2.1 Geography of innovation as industry specialization

In this study we build a theoretical framework based on a cross-fertilizing approach which integrates strategic management and economic geography perspectives, as both are necessary to handle the phenomenon of innovation in agglomerations, as previously stated in Hervas-Oliver and Albors-Garrigos (2009).

Strongly rooted in Marshall’s view of agglomeration economies, literature has shown theoretically and empirically how a firm’s collocation in an agglomeration area gives access to advantages of localization, such as the reduction of production costs, access to specialized inputs and suppliers and the better access to learning due to the presence of externalities (e.g. Porter, 1990; Glaeser et al., 1992; Feldman, 1994; Audretsch and Feldman, 1996). Industry specialization refers to a firm’s collocation in a relatively high own-industry employment region, and its logic is based on the fact that firms will locate near other firms in the same industry because there is a benefit to locating near firms that are similar and work in product-related parts. Those concentrations are usually embedded in a given institutional context that facilitates interaction, knowledge exchange and learning, complementing the short-distance advantages. Overall, industry agglomeration constitutes a knowledge-rich environment that facilitates interaction and enables industry-related local firms to innovate. Thus, innovation arises out of an interactive and systemic processes found in communities of practice or dense networks (e.g. von Hippel, 1988; Kenney, 2000). Empirical claims of these effects are supported by observations of improved firm performance (e.g. Lee, 2018; Crescenzi and Gagliardi, 2018). Industry
specialization, therefore, produces a prone-to-innovation ecosystem enabling collocated firms to gain from accessing to available external knowledge and other advantages.

2.2 Geography of innovation and firm heterogeneity: internal and external combination of knowledge

The strategy perspective based on the resource-based view of the firm (RBV) (e.g. Barney, 1991) posits that a firm’s unique internal resources influence its performance. From this internal perspective, innovation stems from better capabilities that are effectively deployed into organizational routines (Nelson and Winter, 1982), activities and other processes, such as managerial systems, skills, technological competences (R&D activities, etc.), marketing functions, etc. These unique internal capabilities are also related to and configure, especially the R&D function, the concept of absorptive capacity (AC) (Cohen and Levinthal, 1990) which is defined as “the ability of a firm to recognize the value of new external information, assimilate it and apply it to commercial ends” (pg. 128). Thus, assuming that a firm’s internal capabilities drive a firm’s innovative capacity and enhance its ability to assimilate and exploit external knowledge, then the innovation performance of a firm is built on the effective combination of internal and external sources of knowledge accessed through a firm’s AC. Thus, focusing on the AC concept, therefore, it can be stated that a firm’s internal resources determine and enable accessing to and using external knowledge and, consequently, leveraging innovation (e.g. Cohen and Levinthal, 1989, 1990).

Thus, external knowledge, in combination with internal knowledge, is very relevant for a firm’s innovation. Thus, building on the debate on innovation as a combination of internal and external sources of knowledge, we argue that the positive interaction and formation of synergies from that combination of internal and external (to-the-firm) resources facilitates innovation (e.g. Arora and Gambardella, 1990; Laursen and Salter, 2006).

This framework is adopted in the economic geography perspective (e.g. Hervas-Oliver and Albors-Garrigos, 2009; Knoben et al., 2016). Following Hervas-Oliver et al., (2018a), when addressing agglomerations, localization externalities give access to an innovation ecosystem that provides different types of externalities, such as the existence of suppliers, large highly-skilled labor pools or knowledge, all of them configuring a high-quality and knowledge-rich enabling environment that supports and reinforces that knowledge combination of internal and external knowledge. In this context, rich knowledge
(external-to-the-firm) found in agglomerations creates opportunities and incentives to be pro-active in searching strategies to access to those external sources of knowledge. Search strategy requires from building absorptive capacity (internal resources) to access to more external knowledge. Precisely, that virtuous circle or positive self-reinforcing of internal and external knowledge combination, as Escribano et al., (2009:98) state, is the way to isolate the role of absorptive capacity by studying its moderating effect on the impact of external knowledge flows on innovation performance, that is, by studying the effects of the combination on a firm’s innovation performance, a fact proved empirically (Hervas-Oliver et al., 2018a; Crescenzi and Gagliardi, 2018; Lee, 2018). In econometric terms, this implies a positive interaction effect (combination between internal and external sources of knowledge) on a collocated firm’s innovation. Therefore, we expect that industry agglomerations exert a positive effect on the combination of internal and external sources of knowledge on innovation. The issue, however, is more complex: what type of innovation, whether incremental or non-incremental are we talking about?

2.3. The geography of discontinuous innovation

The creative destruction process associated with radical innovations brings new ideas and facilitates the transition from old to new paradigms (Henderson and Clark, 1990; Schumpeter, 1934). When transferring the idea of discontinuities, as opposed to incremental or imitative innovation, economic geography strands basically assume that a firm’s search strategies to access to that abundant external knowledge available in those enabling environments or industry (specialization) agglomerations are, nevertheless, fundamentally restricted to continuous or incremental innovation (e.g. Hervas-Oliver et al., 2018b; Ostergaard and Park, 2015; Glasmeier, 2001). Firms’ search strategies to access to external knowledge, however, are usually delimited to the existing lock-in and local available incumbent technologies and industries that do not promote nor facilitate the entrance of new ideas but potentially promote cognitive inertia, making local and existent technological paradigms permanent and difficult to change (Grabher, 1993; Sull, 2001; Martin and Sunley, 2006). In doing so, clusters and industry agglomerations are turned into spaces where creative destruction occurs with difficulty (Glasmeier, 1991). In this sense, we argue that a potentially excessive local search on local networks can also be a source of disadvantage for collocated firms, limiting and preventing access to information or knowledge not available in those local networks, fostering the formation of inertia.
The excessive focus on the access to existing local knowledge brings lock-in in agglomerations and prevents radical innovation from taking place (Pouder and St. John, 1996; Sull, 2001; Martin and Sunley, 2006; Hervas-Oliver and Albors-Garrigos, 2014; Hervas-Oliver, 2016; Isaksen, 2018). That strong identity and lack of heterogeneity totally contradicts the type of knowledge that Gilbert (2012:738) claims to be necessary in order to cause innovation to occur, that is, knowledge from other industries, that is, technology-distant to the local knowledge domain in the sense of Rosenkopf and Nerkar (2001). Therefore, we expect that collocation in industry agglomerations does not facilitate the occurrence of discontinuous or radical innovation.

2.4 Hypothesis development: integrating the framework

All in all, we argue that collocation in industry agglomerations does not promote nor facilitate the occurrence of discontinuous innovation as it does not cause valuable knowledge to be used in that creative destruction process. Put differently, that internal and external accessed knowledge combination and its impact on a firm’s discontinuous innovative performance will diminish for collocated firms, due to the fact that discontinuous innovation requires heterogeneous and unique knowledge from different industries and technology-distant domains which are not usually available in localization externalities. This implies that the internal and external knowledge combination and its impact on a firm’s discontinuous innovation will be negative or lower for collocated firms, because the innovation ecosystem does not favor but hurts the combinative effect and its impact on radical innovation. On the contrary, industry specialization basically favors and facilitates the occurrence of incremental or imitative innovation.

In short, it is expected that collocation in an industry agglomeration area is negatively related to the occurrence of discontinuous innovation. Having said that, this study captures discontinuity as new-to-the-market innovation, then, in econometric terms, we expect that a firm’s collocation in a relatively high own-industry employment region enables a negative combination of internal and external sources of knowledge on its new-to-the-market innovation, expecting: (i) a negative or non-significant effect of agglomeration on a firm’s new-to-the-market innovation and, (ii) a negative or statistically insignificant interaction effect (combination between internal and external sources of knowledge) on new-to-the-market innovation for collocated firms, vis-à-vis incremental innovation. Thus, our two hypothesis are stated as follows:
Hypothesis 1: Industry specialization externalities are negatively related to a firm’s introduction of new-to-the-market innovation.

Hypothesis 2: Industry specialization externalities exert a negative effect on a firm’s combination of its internal and external knowledge on introducing (incremental) new-to-the-market innovation, vis-à-vis introducing (discontinuous) new-to-the-firm innovation.

3.-EMPIRICAL DESIGN

This study utilizes firm-level and regional variables from two different databases. The firm-level data comes from the Spanish CIS 2006 covering the 2004-2006 period. Our empirical analysis covers the effects of introducing innovative activities by innovatively active firms (6,697 firms) from which 3,602 indicated the introduction of product innovation, being either incremental or radical. In particular, we follow the Oslo Manual (OECD, 2005:58) that establishes that a radical innovation is that presenting a significant impact on a market and on the economic activity of firms in that market; applying this to the Spanish CIS questionnaire, we refer to radical innovation as that occurring when firms introduce innovations that are new-to-the-market, rather than just new-to-the-company. Thus, CIS questionnaire collects in Question E.1.4 two dichotomous variables for capturing both incremental and radical innovation, noticing that in the new-to-the-market specifies the introduction to the market before the competitors:

E.1.4 Regarding the product innovations introduced during the period ..... were they....1) An innovation only for the company (The company introduced new or significantly improved goods or services for the company of which the competitors already had one in the market) ...YES....NO.

Alternatively, ....were they 2) An innovation in the market (The company introduced new goods or services in the market before the competitors) ...YES...NO.

Insert table 1 about here

In the full sample 3,602 firms introduced product innovations, that is, are all innovators. From this figure, we observed three groups: (i) those firms solely introducing new-to-the-firm innovations (1,661); (ii) firms having introduced only new-to-the-market innovations (819); (iii) and, firms having introduced both simultaneously (1,122). Our focus is mainly devoted to understanding those introducing new-to-the-market
innovations, solely or jointly with new-to-the-firm ones, constituting those that solely introduce new-to-the-firm innovations (incremental innovation), the baseline of the dependent variable. See table 1.

This study uses the variables as follows: *Incremental_product* is a dependent variable indicating whether an enterprise has introduced a *new-to-the-firm*, capturing incremental or imitative innovation, product or service during the research period. This variable is measured as a dummy variable and has a value of 1 if the firm has introduced a new or improved product and/or service during the studied period, and 0 otherwise. Then, the variable *Radical_product* is a dependent variable indicating whether a firm has introduced a *new-to-the-market innovation*, also valued as dichotomous as the other previous variable.

The variable *Internal_Capabilities* captures a firm’s internal resources of knowledge. The latter is the knowledge base or innovation capability. In constructing this variable we have drawn on the work of Cohen and Levintahl (1990), Escribano et al., (2009) and Lane et al. (2006) who emphasize the importance of human resources and the R&D activities. Thus, this variable is constructed from a factor analysis that includes R&D internal expenditures, and the percentage of human resources devoted to R&D in relation to total employees. The resulting scores from a principal component analysis (PCA) represent the absorptive capacities, generating a single component (explaining 51.3%; KMO = 0.7, p<0.01). As usual in such analyses, we include control variables, such as Size, measured as the total number of employees, *Industry* classification, measured using 2-digit NACE-93 industry classification as dummies, and the OECD’s classification of low-, medium- and high technology intensive industries.

Following Hervas-Oliver et al., (2018a), external sources of knowledge (*External_sources*) capture the role of un-traded interdependencies or externalities from related industries within value chains without monetary transactions (Saxenian, 1994). These variables arose from the question: *how important have the following information sources been for the innovation activities of your enterprise?* This variable is measured on a four digit scale from 0 to 3, including: learning from interactions with *Suppliers* and *Customers*, and/or through *Trade Associations and* participation in *Events*. By focusing on these four knowledge sources we address the external search strategies of firms and/or the external sources of knowledge they accessed. In a similar way to Laursen and Salter
(2006) and with the purpose of using a single indicator for external sources of knowledge (due to methodological requirements below explained with the logit corrections on interactions) we constructed this variable as follows. Each of the four sources are coded with either 1 when the firm in question reports that it uses the source to a high degree, and 0 in cases where there is only no, low, or medium use. Afterwards, the scores for the use of the four sources are added up so that each firm gets a score of 0 when no knowledge sources are used to a high degree, while the firm gets the value of 4 when all knowledge sources are used to a high degree (Cronbach’s alpha coefficient = 0.71). Firms in the CIS questionnaire are geographically placed on a regional basis according to the location of the enterprises’ innovation activities expenditures or primary research and development facilities, at NUTS 2. We use the latter information in order to connect CIS data with a regional dataset containing localization indicators.

The regional level data comes from the INE (Spanish Statistics Institute), the same governmental body which administers the CIS itself. The specific source is the 2001 Census of firms, which is presented using NACE-93 industry classification for each region (Spain comprises 17 regions plus Ceuta and Melilla, which are small cities in the Northern part of Africa not included in the study). The location quotient for measuring industry specialization is defined as LQ = /Lij/Li)/(Lj/L) where Lij is the number of jobs in the industry i in a region j, Li is the total number of jobs in the industry i in the country, Lj is the number of jobs in a region j, and L is the total number of jobs in the country. If the LQ is more than 1 the region is more specialized in an industry than the country’s average and so we would conclude that that industry benefits from Marshallian localization economies (Bergman and Feser 1999, Porter, 2003). Basing the LQs on 2001 information limits any possible simultaneity bias; whenever possible the regional indicators are measured before the reference period of the CIS data (2004-2006). Additionally, for the sake of regional heterogeneity control, we also include Population size and Density of the region variables, from data sourced from INE with reference to 2001. The study includes a total of 3,602 firms ranged over 181 industries. The LQs are

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3 The regions are Andalucía 01; Aragón 02; Asturias 03; Balears 04; Canarias 05; Cantabria 06; Castilla y León 07; Castilla-La Mancha 08; Cataluña 09; Comunidad Valenciana 10; Extremadura 11; Galicia 12; Madrid 13; Murcia 14; Navarra 15; País Vasco 16; Rioja 17.
calculated for a matrix of the 181 industries at 3 digit NACE codes for 17 regions. Regional dummies also control for regional heterogeneity.

We control the selection by using Heckman (1979) and also test whether data suffers from common method bias using Harman’s single factor test (Greene & Organ, 1973); that is, loading all variables into an exploratory factor analysis and examining the rotated factor solution. No common method variance is identified\(^4\).

4. Results

Table 2 shows the descriptive statistics and correlation matrix. See table 2.

Insert table 2 about here

Insert table 3 here

As our dependent variable (Radical_product vs Incremental_product) is binary, our econometric specifications follow a logit model. In table 3 results from logit analysis testing the introduction of new-to-the-industry (Radical_product, 819 firms) versus new-to-the-firm (Incremental_product, 1,661 firms) are presented. The first specification covers the full sample for that dependent variable (N=2,480), then Specification 2 shows interactions for those firms. Additionally, for the purpose of testing interaction from hypothesis 2 it is also necessary to split the sample in two subsamples indicating a firm’s collocation in relatively high (LQ>1) and low (LQ<1) agglomeration areas. Specifications 3 and 4 represent the collocated (LQ>1, N=1,663) and non-collocated (LQ<1; N=813) firms and interactions for hypothesis 2. Methodologically, the reason of this split is because following Ai and Norton (2003), the nonlinear nature of the logit model means that the marginal effect on an interaction effect is not simply the coefficient (and associated odds ratio) of their interaction. We split the sample into two groups (see McCann and Folta, 2011), addressing firms’ locations in LQs lower or higher than 1 because econometrically it is necessary due to the third order effect (LQ, Internal_Capabilities and External_Sources variables) and its difficulty to be treated in

\(^4\) Two-step Heckman procedures check for potential selection problems when restricting the sample to innovative active firms. Thus, one inverse Mills ratio (\(\lambda\) variable) is generated and used for controlling coefficients, which are not significant. No common method variance is identified. Both available upon request.
logit regressions. Subsequently, we proceeded to apply Ai and Norton’s (2003) recommendations to examine the interactions. As mentioned above, the regional literature has usually recommended to set the cut-off point at 1 value (e.g. Bergman and Feser 1999), even though this is just a convention. Corrections and graphic results of the sample geography split are shown below.

Clearly, in table 3 it is shown a negative effect of LQs on the dependent variable (Radical_product), significant at p<0.1 in the specification 2, an effect that persists negatively through all specifications (1, 3 and 4), albeit not being significant, but clearly indicating the negative or null effect of agglomerations on radical innovation, signaling at least a neutral or non-enabling effect. This result confirms hypothesis 1 that industry specialization does not facilitate radical product development (Radical_product). In short, as all Specifications show, addressing radical innovation, it is observed how localization externalities are negatively related to the occurrence of radical (Radical_product) innovation, vis-à-vis incremental (Incremental_product) innovation.

Then, addressing all firms (N= 2,480; all firms, Specification 1 and 2), individual effects in table 3 for InternalCapabilities and ExternalSources variables are positive and significantly related to the introduction of radical innovation product, accounting for 0.491 and 0.0977, both significantly at p<0.01 and p<0.05, respectively (Specification 1). The same result is found for Specification 2 (InternalCapabilities variable 0.642 and ExternalSources variable 0.102, respectively at p<0.01 for internal sources and p<0.05 for external sources, Specification 2). These results indicate that firm heterogeneity matters for discontinuous innovation to occur and both internal and external sources of knowledge positively impact on the innovative output, regardless of the industry specialization.

Then, in Specifications 2, 3 and 4 (table 3) we test the interaction effects signaled in hypothesis 2 for all firms (N=2,480) and for the two groups of high (LQ>1, 1,663; Specification 3) and low (LQ<1, 813; Specification 4) concentration, looking specially at Specification 3 for the case of whether a firm’s collocation in a relatively high own-industry employment region causes a negative combination of its internal and external knowledge on its radical innovation, as is signaled in hypothesis 2.

In table 3, the interactions between internal capabilities and external knowledge source variables (InternalCapabilities X External_sources variable) and its effect on radical
innovation performance shown in specifications are negative, pointing out that a firm’s collocation in a relatively high own-industry employment region does not enable a positive combination of its internal and external knowledge on its radical innovative performance but a negative one, corroborating previous findings about the fact that agglomerations do not positively relate to the occurrence of radical innovation, as is accounted in the LQ variable. Specifically, Specification 2 (all firms, -0.187, significant at p<0.05) shows negative impacts on radical innovation, a point that is reinforced and strengthened in Specification 3 (LQ>1; -0.299 at p<0.01) for the case of high concentration (LQ>1), vanishing in Specification 4 (LQ<1; 0.0511 at p>0.1) for low concentration, totally in line with hypothesis 2.

Specifically, the result from the interaction in Specification 3 confirms hypothesis 2 about the fact that the combination of internal and external sources of knowledge negatively impact on a firm’s radical innovative performance when a firm collocates in a relatively high own-industry employment region (LQ>1), vis-à-vis incremental innovators. This result from Specification 3 shows how a firm collocation in a relatively high own-industry employment region renders a negative combination of its internal and external knowledge on its radical innovation. Complementary, Specification 4 indicates that when firms are collocated in relatively low own-industry employment regions (LQ<1) that combination has no significant effect on radical innovative performance (0.003 insignificant), that is, outside agglomerations radical innovation is not constrained or impeded by industry specialization.

In short, collocation in a relatively high own-industry employment region (LQ>1) is negatively related to a firm’s introduction of radical innovation, vis-à-vis introducing incremental innovation. Hypothesis 2 is confirmed. Corrections are presented graphically in figures A-1 to A-6 in order to reinforce the results of interactions from logit analysis (following the abovementioned Ai and Norton, 2003). See Appendix I. For this reason, in Table 3 coefficients are used in order to show graphical corrections, instead of odds ratios. For the sake of brevity, we focus on the graphic correction effects of the interactions for interpreting results of interactions from Specification 3 (figures A-3 and A-4) that is directly related to hypothesis 2. See table 3. See Appendix I for all figures (A1-to-A6).
Figure A-3 (table 3, referring to LQs>1, Specification 3) shows the size effect of the interaction (LQ>1) when a firm is located in a region characterized by (relatively high own-industry employment) localization externalities and its relationship with radical innovation outcome (Radical_innovation). Then, figure A-4 (table 3, referring to LQs>1, Specification 3) shows the statistical significance of that size effect (of the interaction), reinforcing graphically the pervasive negative impact of the interaction on the innovative output and its statistical significance and confirming hypothesis 2.

Additionally, similar effects are shown in figures A-1 and A-2 for the case of all firms’ sample (Specification 2), showing the size effect (table 3, figure A-1 for all firms) and the statistical significance (table 3, figure A-2 for all firms), confirming the negative and significant interaction effect on radical innovative performance. Lastly, figures A-5 (size effect) and A-6 (statistical significance) show the same for Specification 4 of LQ<1, showing an insignificant effect of the interaction on the innovative output. The explanation is based on the fact that a non-enabling environment (LQ<1) does not hamper nor make difficult the combination of both sources of knowledge, even though it does not positively influence it, that is, it is rather neutral for the case of radical innovation to occur. This latter result is interesting as it also reinforces hypothesis 2 from a different angle. See figures A-1 to A-6 in the Appendix I.

Lastly, in Table A-1 (see Appendix II) we check results and conduct a robustness check by changing the sample and the dependent variable, taking the value of 1 when a firm simultaneously introduces both new-to-the-market and new-to-the-firm (1,122 firms) innovations, versus taking the value 0 when a firm introducing only new-to-the-firm innovation (1,661 firms). Hypothesis 1 and 2 are checked and confirmed. For the sake of brevity and space limit in the article, additional figures of interactions plus explanations are available upon request. See Table A-1 in Appendix II for more details.

In summary, and according to results, it can be stated that localization externalities are negatively related to a firm’s new-to-the-market innovative performance, that is, industry specialization does not facilitate radical innovation. Additionally, and looking at interactions, it is observed that localization externalities produce a negative effect on a firm’s combination of its internal and external knowledge on its new-to-the-market innovative performance, vis-à-vis incremental innovation, indicating clearly that industry agglomerations do not enable but negatively influence the occurrence of radical
innovation, vis-à-vis incremental innovation. The two hypotheses are, therefore, confirmed.

As regards control variables for other regional effects, such as Population and Density, it is worth mentioning the poor role of the former capturing the positive and significant (only in Table A-1, see Appendix I) and the null effects of the latter (in Table 3). Similarly, both Regions and Industry variables present effects of variation, in relationship with radical innovation, while Size shows a positive relationship with the dependent variable, indicating the influence of size and its related resources, which are necessary for the introduction of radical innovation. Lastly, we have conducted a RAMSEY test to check linearity of data with no problems found.

5.-CONCLUSIONS

Addressing localization externalities through industry specialization measures at the firm level, to the best of our knowledge, there is no study focusing on understanding the relationship between collocation in agglomeration and the occurrence of discontinuous or radical innovation. The empirical results suggest that a firm’s introduction of radical innovation strongly depends on its internal assets and potential absorptive capabilities, finding no positive effect associated with its location in areas that were exposed to high-quality externally available knowledgeable inflows, that is, in regions of localization externalities measured as industry specialization. Additionally, the study has also evidenced that a firm’s collocation in a relatively high own-industry employment region enables a negative and non-complementary combination of internal and external sources of knowledge on introducing discontinuous or exploratory innovation, vis-à-vis introducing incremental (new-to-the-firm) innovation. In other words, a firm’s collocation in areas of industry specialization or relatively high own-industry employment region does not positively influence the occurrence of radical innovation but hampers and makes difficult the use of external knowledge in combination with internal knowledge for the introduction of radical innovation. Industry specialization, however, does support incremental or imitative innovation. As shown in the results, our study has confirmed the two stated hypotheses.

5 Industry dummies and OECD classification into low-, medium-, and high-technology intensity. Both present similar results.
How does this non-enabling mechanism work for industry specialization? The rich environment found in areas of high industry specialization, or relatively high own-industry employment regions, provides access to localization externalities by collocated firms close to other firms in the same industry. These externalities promote a highly-intensive and repetitive inter-firm interaction that makes possible the recombination of internal and external sources of knowledge, enticing a very rich interactive learning. This knowledge circulation based on incremental innovation is centered around locally embedded and technology-related knowledge lock-in existing and accepted technologies and frameworks that provided *institutional uniformity* (e.g. DiMaggio and Powell, 1983; Gilbert, 2012; Tan et al., 2013; Ostergaard and Park, 2015), linked to potential cognitive inertia (Glasmeier, 1991) due to institutional identity. As a result, this *conformity*, in part due to the acceptance of a local and institutionalized collective identity (Staber and Sutter, 2011), does not promote the entrance of new ideas, technologies or paradigms and the industry agglomeration or cluster potentially may end suffering inertia, in line with previous literature (e.g. Glasmeier, 1991; Poudier and St. John, 1996; Sull, 2001; Martins and Sunley, 2006). Results strongly suggest that industry agglomeration regions, do promote incremental innovation embedded into existent knowledge and paradigms, but it does not pay-off for discontinuity. Thus, successful and complementary combination of internal and external knowledge sources does not account for discontinuous innovation occurring.

Our study has some limitations. First of all, this study is based on cross-sectional data, due to CIS anonymity. Secondly, this study also is limited because of the dependent variables covering the construct of radical and incremental innovation, due to CIS requirements.

**REFERENCES**


TABLES

Table 1. Description of the sample of Spanish firms in the CIS data

<table>
<thead>
<tr>
<th>Decision</th>
<th>All firms</th>
<th>LQ&gt;1</th>
<th>LQ≤1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Only new-to-the-market</td>
<td>819</td>
<td>545</td>
<td>274</td>
</tr>
<tr>
<td>Only new-to-the-firm</td>
<td>1,661</td>
<td>1,122</td>
<td>539</td>
</tr>
<tr>
<td>Subtotal</td>
<td>2,480</td>
<td>1,663</td>
<td>813</td>
</tr>
<tr>
<td>New-to-the-market and new-to-the-firm</td>
<td>1,122</td>
<td>754</td>
<td>368</td>
</tr>
</tbody>
</table>

| Total                                         | 3,602     | 2,417| 1,181|

Source: own

Table 2. Descriptive statistics and correlation matrix

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>SD</th>
<th>MIN</th>
<th>MAX</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
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<tbody>
<tr>
<td>1</td>
<td>Size</td>
<td>3.664</td>
<td>0.014</td>
<td>3.636</td>
<td>3.692</td>
<td>1.0</td>
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<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>2</td>
<td>Med_tech</td>
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<td>0.006</td>
<td>0.491</td>
<td>0.515</td>
<td>0.102*</td>
<td>1.0</td>
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<td>High_tech</td>
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<td>0.004</td>
<td>0.103</td>
<td>0.118</td>
<td>-0.137*</td>
<td>-0.348*</td>
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<td>0.024</td>
<td>1.821</td>
<td>1.916</td>
<td>0.129*</td>
<td>0.061*</td>
<td>-0.048*</td>
<td>1.0</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Internal</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Capabilities</td>
<td>-0.004</td>
<td>0.012</td>
<td>-0.028</td>
<td>0.019</td>
<td>-0.363*</td>
<td>-0.085*</td>
<td>0.251*</td>
<td>-0.035*</td>
<td>1.0</td>
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<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>External</td>
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<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
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<tr>
<td>6</td>
<td>Sources</td>
<td>0.629</td>
<td>0.010</td>
<td>0.608</td>
<td>0.649</td>
<td>0.055*</td>
<td>0.031*</td>
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<td>0.031*</td>
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<td>Population</td>
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<td>3,856,461</td>
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<td>-0.040*</td>
<td>0.096*</td>
<td>-0.112*</td>
<td>-0.001</td>
<td>0.028*</td>
<td>1.0</td>
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</tr>
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<td>Density</td>
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<td>2,298,189</td>
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<td>0.171*</td>
<td>0.019</td>
<td>0.052*</td>
<td>0.023</td>
<td>0.357*</td>
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<tr>
<td>9</td>
<td>Incremental product</td>
<td>0.539</td>
<td>0.006</td>
<td>0.525</td>
<td>0.549</td>
<td>0.199*</td>
<td>0.164*</td>
<td>0.013</td>
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<td>0.152*</td>
<td>0.082*</td>
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<tr>
<td>10</td>
<td>Radical product</td>
<td>0.289</td>
<td>0.005</td>
<td>0.278</td>
<td>0.300</td>
<td>0.130*</td>
<td>0.095*</td>
<td>0.039*</td>
<td>0.016</td>
<td>0.034*</td>
<td>0.131*</td>
<td>0.073*</td>
<td>0.022</td>
</tr>
</tbody>
</table>

*p<0.01
Table 3. Logistic regression measuring the likelihood of introducing new-to-the-firm (Radical_product) vs new-to-the-market (Incremental_product) product innovation in relatively high- (LQ>1) and low- (LQ<1) industry agglomerations.

Solely Radical_product innovation (819) versus solely Incremental_product innovation (baseline) (1,661) (Yes=1; No=0); N = 2,480

<table>
<thead>
<tr>
<th>Firms included</th>
<th>All firms</th>
<th>All firms</th>
<th>LQ&gt;1</th>
<th>LQ&lt;=1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Specification</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>Intercept</td>
<td>-0.648**</td>
<td>-0.655**</td>
<td>-0.859**</td>
<td>0.240</td>
</tr>
<tr>
<td></td>
<td>(0.278)</td>
<td>(0.278)</td>
<td>(0.340)</td>
<td>(0.542)</td>
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<td>LQs</td>
<td>-2.33e-06</td>
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<td>-2.76e-06</td>
<td>-1.83e-06</td>
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<tr>
<td></td>
<td>(1.48e-06)</td>
<td>(1.48e-06)</td>
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<tr>
<td>Size</td>
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<td>0.0198</td>
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<td>-0.0562</td>
</tr>
<tr>
<td></td>
<td>(0.0448)</td>
<td>(0.0448)</td>
<td>(0.0532)</td>
<td>(0.0855)</td>
</tr>
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<td>Internal_Capabilities</td>
<td>0.491***</td>
<td>0.642***</td>
<td>0.746***</td>
<td>0.490***</td>
</tr>
<tr>
<td></td>
<td>(0.0859)</td>
<td>(0.108)</td>
<td>(0.148)</td>
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<tr>
<td>External_Sources</td>
<td>0.0977**</td>
<td>0.102**</td>
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<td>(0.0491)</td>
<td>(0.0490)</td>
<td>(0.0600)</td>
<td>(0.0886)</td>
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<tr>
<td>Internal_Capabilities X External_Sources</td>
<td>-0.187**</td>
<td>-0.299***</td>
<td>0.0511</td>
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<tr>
<td></td>
<td>(0.0774)</td>
<td>(0.104)</td>
<td>(0.139)</td>
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</tr>
<tr>
<td>Regions</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
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<tr>
<td>Industry</td>
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<td>YES</td>
<td>YES</td>
<td>YES</td>
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<td>Population</td>
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<tr>
<td></td>
<td>(0.00992)</td>
<td>(0.00992)</td>
<td>(0.0119)</td>
<td>(0.0198)</td>
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<tr>
<td>Density</td>
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<td>-0.0347</td>
<td>-0.0363</td>
<td>-0.364</td>
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<tr>
<td></td>
<td>(0.0231)</td>
<td>(0.0231)</td>
<td>(0.0267)</td>
<td>(0.329)</td>
</tr>
<tr>
<td>Lr Chi-Squared</td>
<td>81.01***</td>
<td>86.9***</td>
<td>49.13***</td>
<td>59.26***</td>
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<tr>
<td>Log-Likelihood</td>
<td>-1532.6</td>
<td>-1529.7</td>
<td>-494.9</td>
<td>-1022.3</td>
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<tr>
<td>N</td>
<td>2480</td>
<td>2480</td>
<td>1,663</td>
<td>813</td>
</tr>
</tbody>
</table>

Dependent variable: (0) new-to-the-firm innovation (1,661 firms), (1) new-to-the-market innovation (819 firms); ***p<0.01; **p<0.05; p<0.1; Industry baseline: low-tech (also including industry 3-digit NACE codes).
APPENDIX I-FIGURES

Figure A-1 Measuring interactions with radical product innovation (all firms, Specification 2)

Figure A-2 Z-statistics (significance) of the size effect of the interaction with radical product innovation (all firms, Specification 2), using marginal effects

Figure A-3 Measuring interactions with radical product innovation (LQ>1, Specification 3)

Figure A-4, Z-statistics (significance) of the size effect of the interaction with radical product innovation (LQ>1, Specification 3), using marginal effects
Figure A-5 Measuring interactions with radical product innovation (LQ<1, Specification 4)

Figure A-6, Z-statistics (significance) of the size effect of the interaction with radical product innovation (LQ<1, Specification 4), using marginal effects
APPENDIX II

In table A-1, we check results by changing the sample and the dependent variable, taking the value of 1 when a firm *simultaneously* introduces both new-to-the-market and new-to-the-firm (1,122 firms) innovations, versus taking the value 0 when a firm introducing only new-to-the-firm innovation (1,661 firms). Obviously, we also conduct the geographical split (LQ>1 and LQ<1) in order to check industry agglomerations. Put different, we confront simultaneous innovators (introducing both types) versus incremental innovators (introducing only incremental). Thus, we seek to see statistical differences between those firms that develop and introduce some sort of discontinuous or exploratory innovation, versus those that only develop incremental one, testing the influence of industry specialization. Overall, in both cases (Table 3 and robustness checks in Table A-1), we are contrasting type of innovators and the influence from locating in industry agglomerations. In general, according to table A-1, we can see that the results fully coincide with those from Table 3, that is, the LQ variable is negative and significant (at p<0.05 in Specifications 6 and 7) and the interaction effects from LQ>1 (Specification 7) are negative and statistically significant (-0.333 at p<0.01). Hypothesis 1 and 2 are checked and confirmed.

<table>
<thead>
<tr>
<th>Table A-1. Logistic regression measuring the likelihood of introducing new-to-the-firm (<em>Radical_product</em>) and new-to-the-market (<em>Incremental_product</em>) <em>simultaneously</em> product innovation vs solely new-to-the-market (<em>Incremental_product</em>) product innovation, in relatively high- (LQ&gt;1) and low- (LQ&lt;1) industry agglomerations.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Firms included</strong></td>
</tr>
<tr>
<td><strong>Specification</strong></td>
</tr>
<tr>
<td>Interception</td>
</tr>
<tr>
<td>(0.259)</td>
</tr>
<tr>
<td>LQs</td>
</tr>
<tr>
<td>(1.40e-06)</td>
</tr>
<tr>
<td>Size</td>
</tr>
<tr>
<td>(0.0399)</td>
</tr>
<tr>
<td>Internal Capabilities</td>
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<td>(0.0845)</td>
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<td>External Sources</td>
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<td>Internal Capabilities X External Sources</td>
</tr>
<tr>
<td>(0.0775)</td>
</tr>
<tr>
<td>Regions</td>
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<td>---------</td>
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<tr>
<td>Industry</td>
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<td>Population</td>
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</tr>
<tr>
<td>Density</td>
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<tr>
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</tr>
<tr>
<td>Lr Chi-Squared</td>
</tr>
<tr>
<td>Log-Likelihood</td>
</tr>
<tr>
<td>N</td>
</tr>
</tbody>
</table>

Dependent variable: (0) solely new-to-the-firm innovation (1,661 firms), (1) new-to-the-market innovation and new-to-the-firm simultaneously (1,122); ***p<0.01; **p<0.05; p<0.1; Industry baseline: low-tech (also including industry 3-digit NACE codes).