Technological Forecasting & Social Change 166 (2021) 120575

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

Failed and successful innovations: The role of geographic proximity and international diversity of partners in technological collaboration

Luis Santamaría [a], María Jesús Nieto [b], Alicia Rodríguez [c,*]

[a] Associate Professor, Department of Business Administration, Universidad Carlos III de Madrid. C/ Madrid, 126. 28903 Getafe, Madrid, Spain
[b] Professor of Management, Institute of Entrepreneurship and Family Business, Universidad Carlos III de Madrid. C/ Madrid, 126. 28903 Getafe, Madrid, Spain
[c] Associate Professor, Institute of Entrepreneurship and Family Business, Universidad Carlos III de Madrid. C/ Madrid, 126. 28903 Getafe, Madrid, Spain

ARTICLE INFO

Keywords:
Failed innovation
Successful innovation
International collaboration
Proximity
Diversity

ABSTRACT

We aim to clarify the role of research partnerships on the success and failure of innovation projects by examining the geographic proximity and diversity of partners. First, we argue that collaboration with geographically near partners will contribute relatively more to innovation success than it does to innovation failure, while collaboration with geographically distant partners will contribute relatively more to innovation failure than it does to innovation success. Second, we postulate that lower levels of international diversity will contribute relatively more to innovation success than it does to innovation failure, while higher levels of international diversity will contribute relatively more to innovation failure than it does to innovation success. Using a large dataset of firms for the period 2008–2013, we perform a joint analysis of failed and successful innovations. Our empirical findings support our theoretical arguments. Our results highlight the relevance of studying both failed and successful innovations and the importance of knowing their determinants to manage the innovation process successfully. Moreover, our findings should alert managers to the importance of geographic location when choosing collaboration partners. It is noteworthy that beyond a certain threshold, international diversity begins to act as a brake on innovation success and to increase the likelihood of failure.

1. Introduction

Many innovation projects fail. Despite this, scholars have traditionally focused on the analysis of successful innovations, while failed innovations have received limited attention (García-Quevedo et al., 2018). With this in mind, we focus attention on the role that technological collaboration plays in these failures. After decades of studying research partnerships, the literature has highlighted several aspects that explain their importance for business innovation. The knowledge bases and internal resources of firms are generally insufficient sources of innovation (Ireland et al., 2002; Leiponen and Helfat, 2010). For its part, technological collaboration is a mechanism to acquire external knowledge in order to plug existing gaps in the firm (van Beers and Zand, 2014) and contribute to competitiveness and value creation by sharing, integrating and combining the resources of the firm with those of the partners (Das and Teng, 2000; Hagedoorn, 1993; Miotti and Sachwald, 2003; Un and Rodríguez; 2018a). Research also exists, however, that focuses on the difficulties that technological collaboration brings (Das and Teng, 2000; Park and Ungson, 2001). High failure rates of 30–50% in partnerships are not an uncommon finding in the literature (e.g., Bleeke and Ernst, 1991; Park and Ungson, 2001). Few empirical studies, though, analyze the relation between research partnerships and the failure of innovation projects (D'Este et al., 2016; Hyll and Pippel, 2016; Lhuillery and Pfister, 2009; Lokshin et al., 2011). Despite extensive work on research partnerships, the picture is still not complete as a simultaneous analysis of the impact of collaboration on the success and failure of innovation projects is especially valuable, considering that these outcomes are closely linked (D'Este et al., 2016). Our work advances in this direction. Specifically, given the increasingly prominent role of geography in strategic management (Chakrabarti and Mitchell, 2016), we examine the contribution of technological collaboration to the success and failure of innovation by analyzing two dimensions related with the geographic location of research partners: proximity and international diversity.

One area of difficulty present in all technological collaborations is coordination, management and control (Becker and Dietz, 2004). These problems can be affected by the geographic location and diversity of the partners (Choi and Contractor, 2016). In fact, spatial aspects are relevant for the study of inter-organizational relations and innovation

* Corresponding author.
E-mail addresses: lsantama@emp.uc3m.es (L. Santamaría), mnieto@emp.uc3m.es (M.J. Nieto), alicia.rodriguez@uc3m.es (A. Rodríguez).

https://doi.org/10.1016/j.techfore.2021.120575
Received 20 January 2020; Received in revised form 11 December 2020; Accepted 1 January 2021
Available online 22 January 2021
0040-1625/

(Laursen et al., 2012; Leiponen and Helfat, 2011; Lorenzen et al., 2012). Economic geographic scholars not only view how proximity relates to distance, but also how it causes locations to be different from one another (Morgan, 2004). Interpreted in terms of distance, geographic proximity is typically seen as exerting a positive effect on collaborative knowledge creation (Howells, 2002). The interactive and social nature of collaborations requires open and easy communication channels between partners to mitigate problems and ensure success (Hansen, 2015).

On the other hand, the geographic diversity of the partners is also an important factor to consider, as it will bring both advantages and disadvantages. The heterogeneity and diversity of knowledge available in dispersed international locations and embedded in different country environments (Cantwell, 1989) offer a great opportunity to learn (Inkpen, 1998; Kim and Inkpen, 2005) and innovate (Rodan and Galunic, 2004). Previous work on technological space and geographic origin (Phene et al., 2006) and partner diversity (functional and geographic) (van Beers and Zand, 2014) presents interesting empirical evidence on the impact of the international dimension of collaboration on innovation success. The diversity inherent to each national context, however, may also hamper effective collaboration (Levina and Vaast, 2008; Parkhe, 1991) and increase its complexity and costs (Jiang et al., 2010). Managing the international diversity of partners successfully, then, is a challenge.

Bearing this in mind, we take into account both geographic dimensions—proximity and international diversity—to analyze the contribution of technological collaboration to the success and failure of innovation projects. In this way, we set out to cast more light on the dark and bright sides of technological collaboration and the best choice of partner based on geographic location. To this end, we use data from the Spanish Technological Innovation Panel for our empirical analysis. This survey provides information on a large sample of firms in different manufacturing and service sectors.

This paper contributes to the literatures on innovation management, international business and economic geography by constructing a bridge between what up to now have been separate research communities. First, in innovation management we contribute to the stream of research focused on technological collaboration by offering a more complete view of the true impact of research partnerships on firm innovativeness. To obtain this view, we jointly analyze the effect of these partnerships on the success and failure of innovation projects depending on the geographic dimensions of the collaboration. In line with this, we add to the research stream that examines factors that contribute to the failure of innovation projects (García-Quevedo et al., 2018; D'Este et al., 2016) and particularly the consequences of collaborations on innovation failures (Hyll and Pippel, 2016), with the goal of more accurately identifying those factors that should be considered when managing an alliance portfolio. Studies such as Hyll and Pippel (2016), Lhuillery and Pfister (2009) and Lokshin et al. (2011) analyze how different partnerships affect the failure of innovation projects. We extend their findings and deepen our knowledge of the relative contributions of different collaboration strategies by examining the effect of the geographic proximity and diversity of the partners in the alliance portfolio both on the success or failure of the innovation project. Our study provides an interesting comparison of the two outcomes, with results that could not be obtained via analyses of a single outcome (D'Este et al., 2016) and which enrich our understanding of the consequences of collaboration and provide a comprehensive picture of how different alliance portfolios influence innovation results.

Second, since we focus on R&D collaboration with partners in Europe, the US, China and India, and other countries, we integrate arguments from international business literature. Specifically, we add to the stream of research that examines international R&D collaboration (Choi and Contractor, 2016; Hagedoorn and Narula, 1996; Kim and Inkpen, 2005; Rodríguez et al., 2018). We go beyond previous work that analyzes international research partnerships by examining how the geographic proximity and international diversity of partners affect both the success and failure of the innovation process. In this way, we highlight the simultaneous existence of both the dark and bright sides of international R&D collaboration.

Third, we contribute to studies on innovation and economic geography (Howells, 2002; Howells and Bessant, 2012). In particular, we build on previous works focused on geographic proximity and innovation (Boschma, 2005; Letaifa and Rabeau, 2013; Lorenzen, 2005). Our examination of geographic proximity and diversity in research partnerships aligns us with research that highlights the need to consider space dimensions in collaborations (Hansen, 2015; Lorenzen et al., 2012; Rodríguez et al., 2018). Uncovering the impact of these dimensions on innovation success and failure allows us to show the importance of spatial proximity and local conditions for selecting partners in technological collaborations.

Lastly, we contribute empirically by using a broad sample of more than 12,800 firms from diverse manufacturing and service sectors for the period from 2008 to 2013. The representative sample and the long time-range make it possible for us to perform a rigorous quantitative analysis and provide comprehensive and generalizable results. In our analyses, we address and correct potential selection bias and endogeneity issues by performing an instrumental-variable estimation via a two-step model (Leoncini, 2016; Rodríguez and Nieto, 2016). Additionally, we control for path dependence since firms can learn from past successful and failed innovations (D'Este et al., 2018; Leoncini, 2016).

The paper is organized as follows. First, we review the literature on technological collaboration, with special reference to the pros and cons of collaboration and the importance of geographic context. We then go on to postulate the research hypotheses, describe the database and methodology, and present our empirical results. The paper finishes with a discussion of the results and some conclusions.

2. Literature review

2.1. Pros and cons of technological collaboration

Access to external sources of technological knowledge—particularly via collaboration—is crucial for innovation and competitiveness (Fey and Birkinshaw, 2005; Ireland et al., 2002). From the perspective of the resource-based theory, technological collaboration is valuable because it contributes to competitiveness and value creation by sharing, integrating and combining the resources of the firm with those of the partners (Das and Teng, 2000; Hagedoorn, 1993; Miotti and Sachwald, 2003). For its part, the knowledge-based perspective emphasizes the role of collaboration as a mechanism to acquire external knowledge (van Beers and Zand, 2014). And industrial organization scholars stress the role of R&D cooperation as an instrument to internalize knowledge spillovers and mitigate the disincentive effect of spillovers on R&D (De Bondt, Slaets and Cassiman, 1992; Kamien et al., 1992). The different theoretical arguments on the importance of technological collaboration have received an empirical response in the literature on innovation and technological change (Belderbos et al., 2004; Faems et al., 2005; Hoang and Rothaermel, 2005; Miotti and Sachwald, 2003; Nieto and Santamaría, 2007), with the bulk of this literature pointing out the positive effect of collaboration on innovation processes. Thus, research partnerships are no longer seen as incidental, but as an important aspect of a firm's innovation strategy.

Technological cooperation, however, can be a double-edged sword as openness to external knowledge may not only enhance the firm's resources, but also its vulnerability. Firms deciding to cooperate must carefully weigh the less favorable consequences these agreements produce. As Lokshin et al. (2011) point out, all collaborations are bumpy roads. The question to answer, though, is why this is so.

Partnerships in which firms exchange technology and jointly perform R&D in complex intellectual property regimes are inherently difficult to manage. A plausible explanation comes from the challenges that technological collaboration brings, particularly those linked to coordination, management and control (Becker and Dietz, 2004). An initial problem is finding the right partner (Santamaría and Surroca, 2011). Even if the right partner is found, the parties need training to understand each other and to make the collaboration productive (Gulati, 1995). A problem of asymmetric information also exists, since the parties will tend to keep some information for themselves (i.e., away from the partner) to gain a better position (Cassiman et al., 2002). Partners will often put their interests before those of the alliance; moreover, cultural differences between partners can exacerbate these problems (Sadowski et al., 2005). The resource-based view suggests that resource inequalities between partners will give rise to an eventual power imbalance that can lead to a premature termination of the partnership (Das and Teng, 2000). From the perspective of a strategic behavior approach, the literature points to inter-firm rivalry as a factor that increases the likelihood of partnership instability (Kogut, 1989; Park and Ungson, 2001), especially in contexts with high levels of uncertainty. Therefore, in research partnerships the main challenges to face are related to: coordinating the different routines and organizational styles of the partners (Duysters et al., 1999); combining the partners' complementary resources appropriately (Anand and Khanna, 2000); and regulating the exploitation of the outcomes (Kale et al., 2000).

2.2. *The importance of geographic context for innovation*

The capability of firms to learn and create knowledge is affected by country-level factors such as public policies on resource endowments, supply/demand conditions of products, and culture (Porter and Rivkin, 2012). Similarly, heterogeneous distributions of technological advantages combined with knowledge localization and its spatial concentration mean that each country will possess its own distinct technological baggage (Jaffe et al., 1993). In accordance with this, Frost (2001) indicates that despite the trend towards scientific and technological parity among nations, the most technologically advanced countries are becoming ever more specialized—and are generating different types of scientific knowledge. This results in distinct national innovation systems and leads firms to create knowledge with different characteristics (Cantwell, 1989; Nelson, 1992; Patel and Pavitt, 1994). National environment, then, remains a highly significant operating milieu for firms (Cantwell and Santangelo, 1999). Indeed, national innovation systems help to explain why firms tend to have different national characters, cognitive frameworks, and ways of evaluating opportunities and risks—in short, different ways of behaving (Morgan, 2004).

In addition to the peculiarities of each national innovation system, firms in different countries also vary in their creative ability to search for novel ideas and combine them with new scientific knowledge to generate innovations (Shane, 1993; Amabile et al., 2005). These studies suggest that the culture inherent to the geographic origin of each individual and firm may be behind the differences in creative abilities (Goncalo and Staw, 2006; Van Der Vegt et al., 2005). Some aspects of culture refer to an acceptance of uncertainty and ambiguity, individualism, masculinity, and power distance (i.e., social inequality in a group) (Hofstede, 1991). Shane (1993) finds that firms are more innovative in societies characterized by a greater acceptance of uncertainty than in those that are less accepting. Goncalo and Staw (2006) state that in cultures in which individualism is more highly valued (in contrast to more group-oriented cultures), people are more creative in searching for new knowledge and generate a greater number of new ideas when performing their tasks. And Singh (2006) finds that consumers in cultures that put a high value on masculinity are more likely to adopt innovative products than are consumers in cultures where this is not the case. Lastly, in cultures characterized by low power distance, members of society and of organizations tend to treat one another in an egalitarian manner, which typically leads to more informal, direct and participative communication among managers and employees. In these settings, the work climate is conducive to generating new ideas and innovation (Van Der Vegt et al., 2005).

In summary, national idiosyncrasies concerning aspects such as R&D systems, education and training systems, networks and associational capabilities, and other cultural issues will exert an effect on how firms learn and behave. For all these reasons, therefore, we feel that the potential benefits and risks of technological collaboration will be influenced by the geographic location of the partners.

3. Theory and hypotheses

3.1. *Geographic proximity in research partnerships*

Geographic proximity has been found to be a substantial factor in the formulation, implementation and consequences of business strategy (Chakrabarti and Mitchell, 2013; 2016). In research partnership, the degree of proximity between partners is highly important for understanding the dynamics of inter-organizational collaborations (Balland, 2012; Knoben and Oerlemans, 2006). As Vissers and Dankbaar (2013) point out, knowledge-related processes benefit from proximity. Specifically, geographic proximity may be essential for some forms of knowledge exchange (Morgan, 2004).

The concept of proximity certainly goes beyond geography to include other extremely relevant factors such as cognitive, organizational or institutional dimensions (Boschma, 2005). But geographic proximity between actors is an instrument to facilitate other non-spatial proximity dimensions (Hansen, 2015; Malmberg and Maskell, 2006). Indeed, spatial proximity is related to social, cultural and cognitive proximity, and vice versa (Gertler, 1995). The different dimensions of proximity are typically highly interrelated (Knoben and Oerlemans, 2006) and it can be difficult to consider their effects on knowledge acquisition and exploitation processes separately (Presutti et al., 2011).

Geographic proximity is likely to increase the chances that firms will interact and share repertoire elements because they act in more similar contexts (Malmberg and Maskell, 2006; Teixeira et al., 2008). In fact, studies in economic geography point to the positive effects of geographic proximity on collaborative knowledge creation (Howells, 2002). The same studies, though, reveal that it is an extremely difficult task to acquire knowledge from geographically distant sources, a difficulty that in turn limits the achievement of innovations (Audretsch and Feldman, 1996; Thompson and Fox-Kean, 2005). National innovation systems are not all alike due to diverse sectoral characteristics and different systems of R&D, education, training, finance and institutional linkages, etc. (Morgan, 2004)—apart from a series of cultural aspects linked to national origin (Hofstede, 1991). Firms located in the same country, then, share ways of understanding and acting that may be useful when managing a collaboration relationship. In other words, greater geographic distance (and the resulting differences in the technological, social and legal context) can lead to a lack of a common knowledge base or of shared practices to resolve problems (Phene et al., 2006).

Regarding the inter-firm relationship, it is important to be aware that distance increases information asymmetries between partners located in different countries (van Kranenburg et al., 2014) and that greater geographic distance between partners results in slower and less effective technological transfers (Hansen and Løvås, 2004) due to increased coordination and communication difficulties (Choi and Contractor, 2016). The quality of information flows, the communication of the information and the level of commitment of the partner are important to understand the impact of geographic proximity on international technological transfers (Ghemawat, 2001; Hansen 2015).

Thus, geographic proximity between research partners can boost interaction and knowledge sharing, as well as bring greater cultural and cognitive proximity, which is valuable when sharing knowledge for innovation. In research partnerships, then, collaboration with a geographically near partner should produce better results—in terms of higher probability of innovation success and lower probability of innovation failure—than will collaboration with a geographically distant partner, which should produce worse results—in terms of lower probability of innovation success and higher probability of innovation failure. Our first hypothesis captures this idea:

> Hypothesis 1: Collaboration with a geographically near partner will contribute relatively more to the success than to the failure of innovation projects, while collaboration with a geographically distant partner will contribute relatively more to the failure than the success of innovation projects.

3.2. Geographic diversity in research collaborations

The difference that exists between the knowledge residing in a particular national context and the knowledge of the firm itself creates a potential for learning (Phene et al., 2006). And this makes it likely that the innovative capability of the firm will improve by incorporating knowledge different from its own via research partnerships. Heterogeneous knowledge is of great importance for innovation performance (Rodan and Galunic, 2004), because the mixture of a firm's own knowledge with acquired knowledge will improve the chances of generating novel ideas and innovations. In line with this, Laursen and Salter (2006) hypothesize that external search breadth influences innovative performance. Diversity, then, emerges as a crucial factor in technological collaboration (Almeida and Phene, 2004; Nieto and Santamaría, 2007), a factor that allows firms to gain access to different—and occasionally complementary—knowledge. Increased diversity in partners' industrial, organizational and national backgrounds will make it possible to achieve greater benefits in terms of resources and learning, in addition to expanding the knowledge base of firms (Bahlmann, 2015; Inkpen, 1998; van Beers and Zand, 2014).

Firms that are technological leaders in their fields usually invest overseas to increase their knowledge diversity (Cantwell and Janne, 1999). Indeed, even when great technological differences do not exist between countries, firms may continue to seek international knowledge because of its impact on diversity (Chung and Alcacer, 2002). Collaboration with foreign partners offers new opportunities that domestic partners may be unable to deliver (van Beers and Zand, 2014). Cross-border alliances can provide complementary capabilities (Lane et al., 2001) and enhance different knowledge bases and learning (Lubatkin et al., 2001). Collaboration with foreign partners delivers the advantage of providing access to country-specific resources such as a specialized workforce (Miotti and Sachwald, 2003). Collaboration with foreign suppliers can also improve access to resources and new technologies that can lead to innovation (Gulati, 1999). Additionally, collaboration with foreign customers should promote the achievement of product innovations by supplying knowledge on specific market preferences; geographic diversity of partners should make it easier to adapt existing products to consumer preferences in the different foreign markets (Lavie and Miller, 2008) and in turn boost the capability of the firm to generate innovations (van Beers and Zand, 2014). In conclusion, operating in a variety of international scenarios (i.e., geographic diversity of partners) allows firms to tap into technologies, resources and knowledge that are difficult to find in the domestic context and thereby contribute to improved innovation performance.

Although diversity brings benefits, it also increases the complexity and costs of collaboration (Jiang et al., 2010), as well as bringing some other difficulties. Laursen and Salter (2006) find that the benefits of breadth are subject to diminishing returns; put simply, too much diversity may become unproductive. The greater the technological diversity between firms in the alliance, the more each firm has to learn from the other—but the more difficult it is to share this knowledge (Oxley and Sampson, 2004). Time and effort are required to understand the norms, habits, and routines of different external knowledge channels (Peeters et al., 2014) and too much diversity can lead firms into a problem of 'over-search' and a consequent negative impact on innovation performance (Laursen and Salter, 2006). Koput (1997) provides three reasons why 'over-searching' may hamper innovation. First, firms may suffer from information overload when selecting and managing partners ('the absorptive capacity problem'). Second, some of the ideas may arrive too late to be exploited fully ('the timing problem'). And lastly, a surfeit of ideas may result in some of them not being given sufficient consideration ('the attention allocation problem').

In addition, problems of knowledge sharing within a global context are amplified. As mentioned, different national innovation systems and cultural idiosyncrasies complicate the relationship between partners and interfere with the capability to assimilate knowledge (Lam, 1997). If, then, the possession of highly dissimilar knowledge by the parties involved may raise particular difficulties for its shareability, it follows that the location of the partners in different geographic contexts can aggravate the problem. Consequently, although geographic diversity can help procure novel knowledge, firms may face difficulties managing excess diversity. In accordance with the previous arguments, we postulate the following hypothesis:

> Hypothesis 2: In research partnerships, lower levels of international diversity will contribute more to the success than to the failure of innovation projects, while higher levels of international diversity will contribute relatively more to the failure than to the success of innovation projects.

4. Empirical analysis

4.1. Sample

We use the Spanish Technological Innovation Panel to perform our empirical analysis. This panel collects data on firms from all sectors of the Statistical Classification of Economic Activities in the European Community (NACE) on a yearly basis from 2003. This database is compiled by Spain's National Statistics Institute, the Science and Technology Foundation, and the Foundation for Technical Innovation, based on the annual Spanish responses to the Community Innovation Survey (CIS). This database has already been used to study innovation strategies (Barge-Gil, 2010; Cuervo-Cazurra et al., 2018; Santamaría et al., 2012).

Specifically, we use an unbalanced panel of more than 12,800 manufacturing and services firms for the period from 2008 to 2013, compiled on a yearly basis. The unbalanced panel includes firms that may not have answered some of the survey questions in one or more of the years, which can cause the number of observations per time period to differ. We only use the information starting from 2008 because this is the first year that the survey collects information on collaboration with partners based in China and India, which is a key variable for our study.

4.2. Variables

4.2.1. Dependent variables

We use two dependent variables: *Successful innovation* and *Failed innovation. Successful innovation* captures the successful development of a product innovation; this is a dichotomous variable that takes value 1 when the firm introduces product innovation; otherwise its value is 0 (Bertrand and Mol, 2013; D'Este et al., 2016; Nieto and Rodríguez, 2011). *Failed innovation* captures if the activity initiated by the firm to develop or apply an innovation has been stopped; this occurs when the firm indicates: (i) it has terminated an activity or innovation project in the design stage; or (ii) has ended an innovation activity after beginning the innovation project. This is a dichotomous variable that takes value 1 when the firm terminates an innovation project; otherwise its value is 0 (D'Este et al., 2018, 2016; Leoncini, 2016; Lhuillery and Pfister, 2009).

4.2.2. Independent variables

To capture the two dimensions identified in the theoretical section—geographic proximity and geographic diversity—we need to form two different groups of explanatory variables in a similar way to that adopted by previous scholars (Rodríguez et al., 2018). For the analysis of geographic proximity, we include five dichotomous variables: (i) *Domestic collaboration,* which takes value 1 if the firm collaborates with partners based in its home country; (ii) *European collaboration*, which takes value 1 if the firm collaborates with Europe-based partners; (iii) *USA collaboration*, which takes value 1 if the firm collaborates with US-based partners; (iv) *China & India collaboration*, which takes value 1 if the firm collaborates with partners based in China or India; and (v) *Other countries collaboration*, which takes value 1 if the firm collaborates with international partners from other geographical areas (i.e., outside Europe, the US, China and India). As previously described, we analyze proximity via geographical location, accepting that spatial proximity is related to social, cultural or cognitive proximity (Gertler, 1995). For us, then, *Domestic collaboration* is the nearest collaboration, followed by *European Collaboration* and *USA collaboration*, while *China & India collaboration* and *Other countries collaboration* are the most distant.

For the analysis of geographic diversity, we use four dichotomous variables: (i) *Collaboration-one region*, which takes value 1 when the firm collaborates with partners based in only one geographic area (i.e., with partners in only one of the following regions: home country; Europe; the US; China & India; or other countries); (ii) *Collaboration-two regions*, which takes value 1 when the firm collaborates with partners in two geographic areas; (iii) *Collaboration-three regions*, which takes value 1 when the firm collaborates with partners in three geographic areas; (iv) *Collaboration-four regions*, which takes value 1 when the firm collaborates with partners in four or more geographic areas. The diversity of the collaboration will grow as the number of regions in which it takes place increases. Therefore, we interpret that *Collaboration-four regions* represents the greatest diversity.

All the independent variables are included with two-period lags, as innovation activities require time to generate results (Belderbos et al., 2004; Calantone and Stanko, 2007; Santamaría et al., 2012).

4.2.3. Control variables

Given that firms can learn how to reduce failures and improve results from previous innovation experience (D'Este et al., 2018; Leoncini, 2016), we include lagged values for the dependent variables *Successful innovation* and *Failed innovation* as covariates. Moreover, consistent with the existing literature, we include controls for innovation investments, firm-specific characteristics and industry (Belderbos et al., 2004; Laursen and Salter, 2006; Lhuillery and Pfister, 2009; Nieto and Rodríguez, 2011). First, as scholars consider R&D investment to be a crucial determinant of innovation (Becheikh et al., 2006), we control for *Innovation effort.* With this variable we gage the resources the firm dedicates to innovation activities and thereby capture the effort made to achieve innovation results. This variable is calculated by dividing the firm's total innovation expenses by its total sales (Nieto and Rodríguez, 2011); it is included in the analyses with the same two-period lags as the independent variables, because they are also innovation activities (Santamaría et al., 2012). Second, location in a science and technology park is associated with easier access to external resources and agglomeration benefits for collaboration and innovation results (Colombo and Delmastro, 2002; Vásquez-Urriago et al., 2016). Thus, we control for this effect by including *Science park*, a dichotomous variable that takes value 1 when the firm is located in such a park (Ramírez-Alesón and Fernández-Olmos, 2018). Third, since the age of the firm may affect innovation activities (García-Quevedo et al., 2014), we control for it via *New venture*, a dichotomous variable that takes value 1 if the firm is six years old or younger (Brush and Vanderwerf, 1992; Zahra et al., 2000). Fourth, due to its relevance for the firm's innovative behavior (Becheikh et al., 2006; Shefer and Frenkel, 2005), we control for *Size*. This variable is measured by the logarithm of the total number of employees (Rodríguez and Nieto, 2016). Fifth, because membership of a business group provides better access to resources (Khanna and Yafeh, 2007) and greater bargaining power that may have an impact on cooperation failures (Lhuillery and Pfister, 2009), we include a dichotomous variable *Group* that takes value 1 when the firm belongs to such a group. Sixth, we control for *Industry* by including dummy variables to capture the effects of the characteristics of the different business sectors. Lastly, since we use panel data with information for six years, we also control for possible temporal effects through *Year* dummies (Un and Rodríguez, 2018b).

5. Methodology

The outcomes under study (success and failure) are closely linked, so it is important to analyze them in a joint model in order to capture their interdependence (D'Este et al., 2016). As both dependent variables—*Successful Innovation* and *Failed Innovation*—are dichotomous, and the error terms are likely to be correlated, an extension of probit known as bivariate probit (Greene, 2000) is usually a more appropriate estimator. To test our hypotheses, then, we specify two biprobit models (models 1 and 2) that differentiate between successful and failed innovations. In model 1, we analyze Hypothesis 1 (related to geographic proximity) via the variables on collaboration with partners located in the home country, Europe, the US, China and India, and other countries. And in model 2, we examine how different degrees of geographic diversity affect the success or failure of the innovation (Hypothesis 2). For this reason, the second biprobit (model 2) uses the explanatory variables on collaboration with partners in only one region, in two regions, in three regions, and in four or more regions as indicators of the collaboration's geographic diversity. As mentioned above, these models include lagged values for the dependent variables *Successful innovations* and *Failed innovations* as covariates. The inclusion of these lagged dependent variables makes it possible to capture a potential serial correlation of the errors and account for past innovation experiences on current innovations. In this way, we are able to gage the potential effect of learning from previous innovation failures and/or successes (D'Este et al., 2018; Leoncini, 2016).

In addition, since a high proportion of firms in the sample do not perform distant or diverse collaboration activities, we need to assess and correct the potential selection bias through an instrumental-variable estimation by performing a two-step model (Leoncini, 2016; Rodríguez and Nieto, 2016). To do this, in the first step we estimate the most likely value for both distant collaboration and diverse collaboration via two panel ordered logit models.[1] These models provide us with a prediction variable that is then included in the second step in the corresponding bivariate probit model. This approach helps to mitigate problems of endogeneity and reverse causality (Antonakis et al., 2010; Leoncini, 2016). The specifications of the two biprobit models (models 1 and 2) used to test our hypotheses are detailed below.

Model 1 has the following econometric specification:

[1] In these panel ordered logit models, we include those variables that affect the likelihood of performing R&D collaborations (distant or diverse, respectively). Specifically, in both models we include: *Size by sales* (measured via the logarithm of the sales figure in period t); *International activity* (a dichotomous variable that takes value 1 when the firm sells its products/services abroad); *Intellectual property rights* (a dichotomous variable that takes value 1 when the firm registers an industrial design, brand name, or copyright in the year); *R&D offshoring* (a dichotomous variable that takes value 1 when the firm sources R&D activities from a foreign country). All these variables are included with a two-period lag. We also control for activity and time via the variables *Sector* and *Year*, respectively. The results of these two ordered logit models are available on request.

$$\begin{aligned}\mathrm{Prob}(\mathit{Successful\,Innovation})_{\mathrm{it}} = {} & \alpha_p + \beta_{1p}(\text{Domestic collaboration})_{\mathrm{it}-2} \\ & + \beta_{2p}(\text{European collaboration})_{\mathrm{it}-2} \\ & + \beta_{3p}(\mathit{USA}\text{ collaboration})_{\mathrm{it}-2} \\ & + \beta_{4p}(\text{China \& India collaboration})_{\mathrm{it}-2} \\ & + \beta_{5p}(\text{Other countries collaborations})_{\mathrm{it}-2} \\ & + \beta_{6p}(\text{Successful innovation})_{\mathrm{it}-2} \\ & + \beta_{7p}(\text{Failed innovation})_{\mathrm{it}-2} \\ & + \beta_{8p}(\text{Innovative effort})_{\mathrm{it}-2} + \beta_{9p}(\text{Science Park})_{\mathrm{it}} \\ & + \beta_{10p}(\text{New venture})_{\mathrm{it}} + \beta_{11p}(\text{Size})_{\mathrm{it}} + \beta_{12p}(\text{Group})_{\mathrm{it}} \\ & + \beta_{13p}(\text{Prediction})_{\mathrm{it}} \\ & + \beta_{14p}(\text{Industry})_{\mathrm{it}} + \beta_{15p}\left(\sum \mathit{Year}_t\right)_{\mathrm{it}} + \varepsilon_{ip}\end{aligned}$$

$$\begin{aligned}\mathrm{Prob}(\mathit{Failed\,Innovation})_{\mathrm{it}} = {} & \alpha_p + \beta_1(\text{Domestic collaboration})_{\mathrm{it}-2} \\ & + \beta_{2p}(\text{European collaboration})_{\mathrm{it}-2} \\ & + \beta_{3p}(\text{USA collaboration})_{\mathrm{it}-2} \\ & + \beta_{4p}(\text{China \& India collaboration})_{\mathrm{it}-2} \\ & + \beta_{5p}(\text{Other countries collaborations})_{\mathrm{it}-2} \\ & + \beta_{6p}(\text{Successful innovation})_{\mathrm{it}-2} \\ & + \beta_{7p}(\text{Failed innovation})_{\mathrm{it}-2} \\ & + \beta_{8p}(\text{Innovative effort})_{\mathrm{it}-2} + \beta_{9p}(\text{Science Park})_{\mathrm{it}} \\ & + \beta_{10p}(\text{New venture})_{\mathrm{it}} + \beta_{11p}(\text{Size})_{\mathrm{it}} + \beta_{12p}(\text{Group})_{\mathrm{it}} \\ & + \beta_{13p}(\text{Prediction})\text{it} \\ & + \beta_{14p}(\text{Industry})_{\mathrm{it}} + \beta_{15p}\left(\sum \mathit{Year}_t\right)_{\mathrm{it}} + \varepsilon_{ip} \\ & (\varepsilon_{ip}, \varepsilon_{ic}) \sim \mathrm{N}(0,0,1,1,\rho)\end{aligned}$$

where α_p and α_c are the constant intercepts, β_p and β_c are the coefficient vectors, and ε_p and ε_c are the error terms, respectively, for successful and failed innovations.

Model 2 has the following econometric specification:

$$\begin{aligned}\mathrm{Prob}(\mathit{SuccessfulInnovation})_{\mathrm{it}} = {} & \alpha_p + \beta_{1p}(\text{Collaboration-oneregion})_{\mathrm{it}-2} \\ & + \beta_{2p}(\text{Collaboration-tworegions})_{\mathrm{it}-2} \\ & + \beta_{3p}(\text{Collaboration-threeregions})_{\mathrm{it}-2} \\ & + \beta_{4p}(\text{Collaboration-fourormoreregions})_{\mathrm{it}-2} \\ & + \beta_{5p}(\text{Successfulinnovation})_{\mathrm{it}-2} \\ & + \beta_{6p}(\text{Failedinnovation})_{\mathrm{it}-2} \\ & + \beta_{7p}(\text{Innovativeeffort})_{\mathrm{it}-2} + \beta_{8p}(\text{SciencePark})_{\mathrm{it}} \\ & + \beta_{9p}(\text{Newventure})_{\mathrm{it}} + \beta_{10p}(\text{Size})_{\mathrm{it}} + \beta_{11p}(\text{Group})_{\mathrm{it}} \\ & + \beta_{12p}(\text{Prediction})\text{it} \\ & + \beta_{13p}(\text{Industry})_{\mathrm{it}} + \beta_{14p}\left(\sum \mathit{Year}_t\right)_{\mathrm{it}} + \varepsilon_{ip}\end{aligned}$$

$$\begin{aligned}\mathrm{Prob}(\mathit{Failed\,Innovation})_{it} = {} & \alpha_p + \beta_{1p}(\text{Collaboration - one region})_{\mathrm{it}-2} \\ & + \beta_{2p}(\text{Collaboration - two regions})_{\mathrm{it}-2} \\ & + \beta_{3p}(\text{Collaboration - three regions})_{\mathrm{it}-2} \\ & + \beta_{4p}(\text{Collaboration - four or more regions})_{\mathrm{it}-2} \\ & + \beta_{5p}(\text{Successful innovation})_{\mathrm{it}-2} \\ & + \beta_{6p}(\text{Failed innovation})_{\mathrm{it}-2} \\ & + \beta_{7p}(\text{Innovative effort})_{\mathrm{it}-2} + \beta_{8p}(\text{Science Park})_{\mathrm{it}} \\ & + \beta_{9p}(\text{New venture})_{\mathrm{it}} + \beta_{10p}(\text{Size})_{\mathrm{it}} + \beta_{11p}(\text{Group})_{\mathrm{it}} \\ & + \beta_{12p}(\text{Prediction})\text{it} \\ & + \beta_{13p}(\text{Industry})_{\mathrm{it}} + \beta_{14p}\left(\sum \mathit{Year}_t\right)_{\mathrm{it}} + \varepsilon_{ip} \\ & (\varepsilon_{ip}, \varepsilon_{ic}) \sim N(0,0,1,1,\rho)\end{aligned}$$

where α_p and α_c are the constant intercepts, β_p and β_c are the coefficient vectors, and ε_p and ε_c are the error terms, respectively, for successful and failed innovations.

The models also generate estimates of ρ (the correlation between the error terms of the equations). Our tests reveal that the correlation between the equations are statistically significant in both models, which is an indicator that the bivariate models are more effective than the separate probit models (Greene 2000).

Additionally, to evaluate the relative influence of alternative collaboration strategies on *Successful innovation* and *Failed innovation*, we perform a set of Wald tests to determine the significances of the differences between coefficients. These tests allow us to test the differences compared by pairs for each outcome (e.g., the differences between the coefficients for *Domestic collaboration* in *Successful innovation* versus *Domestic collaboration* in *Failed innovation*). This procedure allows us to determine if the difference between coefficients is significant and whether it is possible to reach conclusions on the relative contribution of each variable to the success or failure of the innovations.

6. Descriptive statistics

Table 1 displays the descriptive statistics, correlations and collinearity diagnostics of the independent and control variables used in this study (with the exception of sector and yearly dummies). High correlation coefficients exist between the geographic proximity variables (*Domestic collaboration; European collaboration; USA collaboration; China & India collaboration*; and *Other countries collaboration*) and the geographic diversity variables (*Collaboration-one region; Collaboration-two regions; Collaboration-three regions;* and *Collaboration-four regions*). These high coefficients, however, do not indicate a problem of correlation, because the geographic proximity variables are never included with the geographic diversity variables in the same model. The former are only included in model 1, and the latter in model 2 only. In addition, in the last two columns of table 2 we display the estimation of the analysis of the variance inflation factor (VIF) to examine potential multicollinearity problems. Individual VIF values higher than 10.0, combined with average VIF values higher than 6.0, indicate a multicollinearity problem (Neter et al., 1989). The highest value is 1.50 and 1.31 in model 1 and model 2, respectively; with mean values of 1.24 and 1.14, which are below the threshold points. Thus, the values indicate that no problems of multicollinearity exist in any of the models.

Table 1 also displays the mean and standard deviations of the study's main variables. Concerning the success or failure of innovation in the full sample, the table indicates that 44.5% of innovations are successful and that 19.2% are failed. Regarding the geographic location of partners, *Domestic collaboration* and *Europe collaboration* stand out as the most frequent strategies in the sample, with percentages of 24% and

Table 1
Descriptive statistics and correlations of the independent and control variables.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	VIF[a]	VIF[b]
1. Successful innovation	1.00																		–	–
2. Failed innovation	0.26***	1.00																	–	–
3. Domestic collaboration	0.31***	0.22***	1.00																’1.41	–
4. European collaboration	0.22***	0.20***	0.45***	1.00															1.50	–
5. USA collaboration	0.12***	0.12***	0.22***	0.38***	1.00														1.33	–
6. China & India collaboration	0.09***	0.10***	0.15***	0.25***	0.35***	1.00													1.23	–
7. Other countries collaboration	0.10***	0.12***	0.20***	0.33***	0.35***	0.35***	1.00												1.28	–
8. Collaboration-one region	0.20***	0.10***	**0.75*** **	−0.06***	−0.05***	−0.03***	−0.04***	1.00											–	1.14
9. Collaboration-two regions	0.17***	0.14***	0.42***	**0.72*** **	0.05***	0.03***	0.06***	−0.11***	1.00										–	1.13
10. Collaboration-three regions	0.11***	0.11***	0.22***	0.41***	**0.49*** **	0.15***	0.35***	−0.06***	−0.03***	1.00									–	1.06
11. Collaboration-four regions	0.08***	0.11***	0.16***	0.30***	**0.57*** **	**0.63*** **	**0.60*** **	−0.04***	−0.02***	−0.01**	1.00								–	1.05
12. Previous successful innovation	0.61***	0.26***	0.33***	0.22***	0.11***	0.08***	0.10***	0.23***	0.18***	0.10***	0.08***	1.00							1.20	1.21
13. Previous failed innovation	0.22***	0.43***	0.20***	0.20***	0.12***	0.10***	0.11***	0.09***	0.14***	0.10***	0.11***	0.25***	1.00						1.11	1.11
14. Innovation effort	0.21***	0.12***	0.24***	0.14***	0.10***	0.06***	0.09***	0.16***	0.11***	0.08***	0.08***	0.21***	0.08***	1.00					1.17	1.17
15. Science park	0.08***	0.06***	0.12***	0.07***	0.05***	0.03***	0.04***	0.08***	0.05***	0.04***	0.05***	0.07***	0.06***	0.18***	1.00				1.04	1.04
16. New venture	0.01***	0.01*	0.02***	0.01**	0.01*	−0.01	0.00	0.01**	0.01**	0.003	0.003	0.002	0.007	0.02***	0.05***	1.00			1.00	1.00
17. Size	0.07***	0.06***	0.10***	0.16***	0.10***	0.06***	0.07***	0.01*	0.11***	0.08***	0.08***	0.03***	0.04***	−0.18***	−0.02***	−0.02***	1.00		1.32	1.31
18. Group	0.08***	0.07***	0.12***	0.17***	0.10***	0.06***	0.08***	0.03***	0.12***	0.09***	0.08***	0.07***	0.07***	−0.08***	0.01***	0.02***	0.45***	1.00	1.29	1.28
Number of observations	59,776	59,776	37,450	37,450	37,450	37,450	37,450	37,450	37,450	37,450	37,450	37,450	37,450	37,450	59,776	59,776	59,776	59,776		
Mean	0.44	0.19	0.24	0.08	0.02	0.01	0.02	0.18	0.06	0.16	0.01	0.49	0.20	0.04	0.04	0.01	4.07	0.41		
St. Dev.	0.49	0.39	0.43	0.27	0.14	0.09	0.13	0.38	0.23	0.12	0.09	0.50	0.40	0.11	0.20	0.11	1.75	0.49		
																		Mean VIF	1.24	1.14

***$p<0.01$, **$p<0.05$,*$p<0.10$. . [a]Models 1 (Independent variables: 3. Domestic collaboration; 4. European collaboration; 5. USA collaboration; 6. China & India collaboration; 7. Other countries collaboration). [b]Model 2. (Independent variables: 8. Collaboration-one region; 9. Collaboration-two regions; 10. Collaboration-three regions; 11. Collaboration-four regions).
Please note that the high correlation coefficients between variables 3 to 7 and variables 8 to 11 (highlighted in bold) are logical since the geographic diversity variables (8 to 11) are derived from variables 3 to 7. These high coefficients do not indicate a problem of correlation, because the geographic proximity variables (3, 4, 5, 6 and 7) are never included with the geographic diversity variables (8, 9, 10 and 11) in the same model.

Table 2
Successful and failed innovation by geographic location of partners and international geographic diversity.

	Successful innovation	Failed innovation
Geographic location of partners		
Domestic collaboration	75.5	34.3
Europe collaboration	83.9	46.2
USA collaboration	88.9	54.7
China & India collaboration	90.9	60.1
Other countries collaboration	87.7	55.0
Geographic diversity		
Collaboration-one region	71.1	27.6
Collaboration-two regions	83.2	43.1
Collaboration-three regions	88.4	53.7
Collaboration-four regions	90.4	64.9

Percentages of observations.

8.3%, respectively; *USA collaboration* and *Other countries collaboration* follow with 2% in both cases. *China & India collaboration* displays the lowest frequency in the sample.

Table 2 provides an overview of the distribution of the R&D collaboration strategies and the percentages of successful and failed innovations. Concerning innovation performance according to geographic location of the partner, *Domestic collaboration* has the lowest percentage of *Successful innovations* (75.5%) and *Failed innovations* (34.5%). In contrast, *China & India collaboration* displays the greatest percentage of both *Successful innovations* (90.9%) and *Failed innovations* (60.1%).

Concerning the success and failure of innovations according to international geographic diversity, the percentages of *Successful innovations* and *Failed innovations* increase with greater international geographic diversity in the collaboration. *Collaboration-one region* displays the lowest percentages of successful innovations (71.1%) and failed innovations (27.6%). Conversely, *Collaboration-four regions* has the highest percentage of both *Successful innovations* (90.4%) and *Failed innovations* (64.9%).

7. Empirical results

Table 3 presents the results of the bivariate probit model specified to analyze the impact of partners' geographic proximity on innovation outcomes (Hypothesis 1). The ρ parameter is highly significant in the model, signaling that the error structures of the equations are correlated. This suggests that successful and failed innovations are not independent and that the bivariate model is the correct specification.

In addition, Table 4 displays the results of the Wald tests used to statistically analyze the differences in the coefficients of the geographic proximity variables (*Domestic, European, USA, China & India* and *Other countries collaboration*) on both innovation outcomes. Thus, a comparative analysis of the contribution to the likelihood of innovation success and innovation failure is offered for each variable.

Hypothesis 1 postulates that, in research partnerships, different degrees of geographic proximity will exert a differentiated effect on success and failure of innovation projects. To test this hypothesis, we compare by pairs the coefficients for each of the variables in the successful and failed innovation columns (see the coefficients in both columns of Table 3 and the *Comparison tests* in Table 4).

A comparison of the estimates for *Domestic collaboration* reveals that the coefficient for this geographically near option is higher for successful innovations than it is for failed innovations. In other words, *Domestic collaboration* contributes more to the likelihood of innovation success than it does to the likelihood of failure. The difference between both coefficients is significant, which indicates a greater relative contribution to the likelihood of success than to failure and is coherent with Hypothesis 1. The coefficients for *European collaboration* are also positive and significant. In this case, however, the difference between the coefficients is not significant. This result indicates that collaboration with partners in Europe contributes to the likelihood of both the success and failure of innovation; it does not, though, allow us to conclude that this type of collaboration contributes relatively more to success. We obtain similar results for *USA collaboration* and *China & India collaboration* regarding innovation success; in both cases the coefficients are positive and not significant. Differences emerge, however, in the results for innovation failure. The coefficient for *USA collaboration* is negative and not significant, while the coefficient for *China & India collaboration* is positive and significant. No significant differences exist between the coefficients for innovation success and innovation failure for the two types of collaboration. Lastly, the estimate for *Other countries collaboration* is negative and significant for successful innovation outcomes; in contrast, it is positive and significant for failed innovation outcomes. In addition, the difference between the coefficients is significant, which

Table 3
Geographic proximity in the research partnership and successful and failed innovations.

	Model 1 Successful innovation	Failed innovation
Domestic collaboration	0.292***	0.187***
	(0.0207)	(0.0212)
European collaboration	0.0734**	0.103***
	(0.0353)	(0.0325)
USA collaboration	0.0585	−0.0552
	(0.0706)	(0.0600)
China & India collaboration	0.127	0.225***
	(0.107)	(0.0862)
Other countries collaboration	−0.123*	0.150**
	(0.0718)	(0.0629)
Previous successful innovations	1.540***	0.373***
	(0.0178)	(0.0197)
Previous failed innovations	0.154***	1.093***
	(0.0203)	(0.0187)
Innovation effort	1.582***	0.948***
	(0.0835)	(0.0797)
Science park	0.188***	0.0715*
	(0.0418)	(0.0410)
New venture	−0.103	−0.197**
	(0.0867)	(0.0917)
Size	0.0661***	−0.00324
	(0.00818)	(0.00865)
Group	−0.0504***	0.00166
	(0.0193)	(0.0204)
Prediction	0.123***	0.0943***
	(0.00819)	(0.00853)
Industry	Included	Included
Year	Included	Included
Intercept	−3.312***	−2.931***
	(0.105)	(0.114)
ρ	0.198***	
	(0.0123)	
Number of observations	37,450	
Wald test of full model (x^2)	19,959.9***	
Log. Likelihood	−29,253.4	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4
Geographic proximity. Wald tests results.

Comparison Tests
$\beta^{\text{Domestic collaboration}}$ (Successful) $>$ $\beta^{\text{Domestic collaboration}}$ (Failed): $\chi^2 = 13.87$***
$\beta^{\text{European collaboration}}$ (Successful) $<$ $\beta^{\text{European collaboration}}$ (Failed): $\chi^2 = 0.43$
$\beta^{\text{USA collaboration}}$ (Successful) $>$ $\beta^{\text{USA collaboration}}$ (Failed): $\chi^2 = 1.65$
$\beta^{\text{China \& India collaboration}}$ (Successful) $<$ $\beta^{\text{China \& India collaboration}}$(Failed): $\chi^2 = 1.65$
$\beta^{\text{Other countries collaboration}}$ (Successful) $<$ $\beta^{\text{Other countries collaboration}}$(Failed): $\chi^2 = 8.99$***

Wald tests comparing the differences between collaboration coefficient estimates in each of the successful and failed innovation equations in model 1.

indicates that the contribution to the likelihood of innovation failure of *Other countries collaboration* is relatively greater than its contribution to the likelihood of innovation success.

In summary, our findings provide empirical support for Hypothesis 1. We find that *Domestic collaboration* (the option with the highest degree of geographic proximity) exerts by far the greatest impact on the likelihood of achieving successful innovations, with the rest of the options trailing a long way behind. On the other hand, we also find that research partnerships with greater degrees of proximity (e.g., *Domestic collaboration*) contribute more to innovation success than they do to innovation failure. In contrast, more geographically distant collaborations (i.e., international partnerships) either contribute more to innovation failure (*Other countries collaboration*) or display no significant differences in their contributions to success and failure (*European, USA* and *China & India collaborations*).

Table 5 displays the estimations of the bivariate probit model analyzing the role of partners' geographic diversity on innovation outcomes (Hypothesis 2). As in the previous model, the error structures of the equations are correlated (the ρ parameter is highly significant), indicating that the bivariate model is the correct specification. Likewise, Table 6 contains the results of the Wald tests used to statistically analyze the differences in the relation of the geographic diversity variables (from one region to four or more regions) on innovation success and failure.

Hypothesis 2 postulates that in research partnerships different degrees of international diversity will exert a differentiated effect on the success and failure of innovation projects. To analyze this hypothesis, it is necessary to compare the estimates for *Successful* and *Failed innovations* for each variable (see the coefficients in both columns of Table 5 and the comparison tests in Table 6). The coefficients for *Collaboration-one region, Collaboration-two regions and Collaboration-three regions* are positive and significant for both *Successful innovation* and *Failed innovation*—with higher coefficients found in all three cases for *Successful innovation* than those for *Failed innovation*. The difference between the coefficients for *Successful innovation* and *Failed innovation* for *Collaboration-one region* is positive and significant, whereas the differences between these coefficients for *Collaboration-two regions* and *Collaboration-three regions* are not significant. These results suggest that collaboration in one region contributes relatively more to the probability of innovation success than it does to failure. For *Collaboration-four regions* the coefficient for innovation failure is greater than that for innovation success (the Wald test indicates that the difference is significant). This finding shows that the highest level of diversity in research partnership contributes relatively more to the likelihood of innovation failure than it does to success. Given that we find that low levels of diversity (one-region) contribute relatively more to success than they do to failure, and that high levels of diversity (four or more regions) contribute relatively more to failure than they do to success, these results offer empirical support for Hypothesis 2.

In regard to the control variables, it is important to note the robustness and consistency of the results in both models. Previous innovation success and failure are positively and significantly related with both innovation outcomes (*Successful innovation* and *Failed innovation)*. These findings highlight the importance of controlling for the path dependence of previous innovations as factors that may affect the capacity to assimilate and integrate knowledge. The results for the rest of the control variables also reveal the key roles of innovation effort, on-park location and firm size in making greater contributions to innovation success than to failure. Other research finds that innovation effort typically relates to success. As far as its link to failure is concerned, this finding may be a simple numbers game: the more innovation projects firms are involved in, the greater the likelihood that one of them will fail. In any case, the net effect is significantly favorable to success. Another factor that contributes relatively more to innovation success than to innovation failure is being located in science and technology parks. The access to resources, agglomeration benefits and greater interaction with knowledge-intensive firms offered by these locations improves innovation performance. For its part, firm size contributes positively and significantly to success, a contribution that clearly outweighs that to failure. Once again, this is as expected, a result that is explained by the theoretical advantages in resources that large firms hold over their smaller counterparts.

An additional notable result is provided by *New venture,* as being a recently created firm is negatively and significantly related to innovation failure (though the relation is not significant in the case of innovation success). In contrast, membership of a business group is negatively and

Table 5
International geographic diversity in research partnerships and successful and failed innovations.

	Model 2 Successful innovation	Failed innovation
Collaboration-one region	0.300***	0.175***
	(0.0211)	(0.0217)
Collaboration-two regions	0.330***	0.259***
	(0.0368)	(0.0338)
Collaboration-three regions	0.422***	0.367***
	(0.0712)	(0.0586)
Collaboration-four regions	0.157	0.521***
	(0.0982)	(0.0840)
Previous successful innovations	1.535***	0.371***
	(0.0179)	(0.0198)
Previous failed innovations	0.152***	1.091***
	(0.0203)	(0.0188)
Innovation effort	1.556***	0.929***
	(0.0834)	(0.0796)
Science park	0.191***	0.0737*
	(0.0418)	(0.0410)
New venture	−0.105	−0.202**
	(0.0868)	(0.0918)
Size	0.0666***	−0.00360
	(0.00802)	(0.00838)
Group	−0.0499***	0.00145
	(0.0192)	(0.0203)
Prediction	0.184***	0.141***
	(0.0118)	(0.0119)
Intercept	−2.782***	−2.797***
	(0.101)	(0.110)
ρ	0.197***	
	(0.0123)	
Number of observations	37,450	
Wald test of full model (x^2)	19,990.3***	
Log. Likelihood	−29,234.7	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6
International geographic diversity. Wald test results.

Comparison tests
$\beta^{\text{Collaboration-one region}}$ (Successful) > $\beta^{\text{Collaboration-one regions}}$ (Failed): $\chi^2 = 18.74$***
$\beta^{\text{Collaboration-two regions}}$ (Successful) > $\beta^{\text{Collaboration-two regions}}$ (Failed): $\chi^2 = 2.22$
$\beta^{\text{Collaboration-three region}}$ (Successful) > $\beta^{\text{Collaboration-three regions}}$ (Failed): $\chi^2 = 0.39$
$\beta^{\text{Collaboration-four regions}}$ (Successful) < $\beta^{\text{Collaboration-four regions}}$ (Failed): $\chi^2 = 8.69$***

Wald tests comparing the differences between collaboration coefficient estimates in each of the successful and failed innovation equations in model 2.

significantly related to innovation success (though the relation is not significant in the case of innovation failure).[2] Lastly, the coefficients for the prediction variables are positive and significant, for both innovation success and innovation failure in the two models (1 and 2). This finding provides support for the use of two-stage models in the analysis.

8. Discussion and conclusions

As we advance into the 21st century, the importance of technological collaboration for improving the innovation capability of firms is practically beyond all doubt. Collaboration is a tool that makes it possible to share resources (physical, financial, knowledge, etc.) with partners, reduce costs and uncertainty, and obtain economies of scale and scope (Becker and Dietz, 2004; Das and Teng, 2000; Hagedoorn, 1993). Moreover, research partnerships help internalize knowledge spillovers, reducing the potential disincentive effect that investment in innovation activities can bring (De Bondt et al., 1992; Kamien et al., 1992). Wide-ranging research highlights the positive contribution of research partnerships to innovativeness (Belderbos et al., 2004; Faems et al., 2005; Hoang and Rothaermel, 2005). Despite the benefits that technological collaboration delivers, however, we must not forget that this organizational solution also brings some disadvantages related with difficulties of coordination and management (Becker and Dietz, 2004), power imbalance (Das and Teng, 2000) or partnership instability (Park and Ungson, 2001), among others. To the best of our knowledge, the simultaneous analysis of the contribution of research partnerships to the success and failure of innovation projects has been a neglected issue. In this study, we offer theoretical arguments and empirical evidence on this under-researched topic from one particular perspective: the geographic dimension of research partnerships. More specifically, we focus on the effects of geographic proximity and the international diversity of partners on both innovation failure and success.

Our empirical results, based on a wide sample of manufacturing and service firms covering a long time period (2008–2013), provide support for our hypotheses. Regarding geographic proximity, we argue that this dimension will exert a differentiated effect on failed and successful innovations. The importance of knowledge as a trigger for innovation and the need (in the case of collaborations) for good interaction between the parties to transfer this knowledge effectively suggest that nearer destinations will have an advantage over more distant ones (Vissers and Dankbaar, 2013). Our results do in fact show that nearer collaboration (i.e., domestic collaboration) is the only one that contributes significantly more to the likelihood of innovation success than to failure. Collaboration with partners from Europe, the US, and China and India contributes positively to success, but this contribution is not significantly greater than the effect exerted on the likelihood of failure. For its part, collaboration with other countries (i.e., Australia, South America or Africa) contributes more to failure than it does to success. This finding leads us to conclude that proximity plays an important role in aiding interaction and knowledge sharing. Although more geographically distant partners may be able to supply valuable information that can generate more innovations, the difficulties of managing these partnerships diminishes its net effect. This does not mean that international collaborations are not effective, but that caution needs to be exercised when selecting foreign partners for particular projects. Care must be taken to consider the cons (management and control problems; more inefficient knowledge transfer; greater risk of opportunistic behavior; cultural differences; etc.), as well as the pros (novel knowledge; different technological baggage; etc.).

Concerning geographic diversity, we argue that international diversity will exert a differentiated effect on failed and successful innovations. Our empirical findings provide support for our theoretical arguments. As expected, lower levels of international diversity (one region) contribute more to the success than to the failure of innovation projects. The positive relation of geographic diversity with innovation success is due to the access gained to a range of technologies, resources and knowledge (van Beers and Zand, 2014), along with the country-specific resources of the different locations (Miotti and Sachwald, 2003). Additionally, as postulated, our findings show that higher levels of diversity (four or more regions) will contribute more to the failure than to the success of innovation. When firms collaborate with partners with the highest levels of geographic diversity, the likelihood of innovation failure is higher than the likelihood of innovation success. The higher coordination costs and complexity involved in managing diversity (Jiang et al., 2010), problems that grow when firms collaborate simultaneously with partners from different geographic regions, could explain why this greater geographic diversity augments the probability of innovation failure. In summary, beyond a certain threshold, diversity more strongly reveals its dark side and begins to act as a brake on innovation success and increase the likelihood of failure.

In answering the unexplored questions considered in this paper, we contribute to the literature in different ways. We bring together and integrate works on innovation management, economic geography and international business to open up a previously under-researched area. In particular, we provide new insights to the stream of research focused on failure in collaborations (Park and Ungson, 2001). Although collaborations to boost innovation are known to suffer high rates of failure, few studies offer empirical evidence on the unsuccessful outcomes of innovation (D'Este et al., 2016; Hyll and Pippel, 2016; Lhuillery and Pfister, 2009; Lokshin et al., 2011). Specifically, we advance on these works by analyzing the effect of the geographic proximity and international diversity of the partners in the alliance portfolio on the success and failure of the innovation project. We also contribute to the literature on international R&D collaboration by casting light on the geographic dimension of collaboration. Studies exist that analyze the impact of collaboration with R&D foreign-based partners on different measures of innovation success (e.g., Colombo et al., 2009; Phene et al., 2006; Rodríguez et al., 2018; van Beers and Zand, 2014). In addition to considering international origin, however, our work takes into account two key dimensions for selecting international research partners—geographic proximity and diversity—and examines their impact on both the success and failure of the innovation process. Lastly, we contribute to the literature on innovation and economic geography (Howells, 2002; Howells and Bessant, 2012), in particular to the stream of research focused on the study of geographic proximity and innovation (Boschma, 2005; Letaifa and Rabeau, 2013). Our study provides support for the impact of the geographic dimension on the success and failure of innovation projects when choosing collaboration partners, and with it we join previous research that demonstrates that spatial factors are important to understand business decisions and implications (Chakrabarti and Mitchell, 2013; 2016). The paper also contributes empirically by using panel data with a representative sample of firms from diverse manufacturing and service sectors and a long time-range. In our analyses, we control for path dependence since firms can learn from past successful and failed innovations (D'Este et al., 2018; Leoncini, 2016); we also address crucial issues such as potential selection bias and endogeneity.

This paper also offers some interesting managerial implications. The

[2] We have performed additional analyses to determine if different types of firms could benefit from the distance or diversity of R&D collaborations. Specifically, we have analyzed the interactions of the distance and diversity of R&D collaborations with several firm-level characteristics such as new venture, science park location, large size, or membership of a business group. For this last characteristic (*Group*), some interesting results emerged, such as the finding that the interaction between group subsidiaries and the highest level of diversity (*Collaboration-four regions*) contributes more to innovation success than it does to failure. In any event, the main results related to the study's hypotheses remain unchanged for all the additional analyses performed. Thus, the inclusion of these interactions does not alter the paper's conclusions. The results of all these additional analyses are available from the authors on request.

conclusions reached in our study make it possible to identify which alliance portfolios offer the best chances of success and/or minimize the chances of failure. Geographically nearer partners make a greater net contribution to innovation success. And on the other side of the coin, more distant partners—those based in other countries outside Europe and the US—contribute positively to success, but their impact on increased innovation failure throws doubt on the real value of the collaboration. Collaboration with partners in Europe or the US exerts similar impacts on the likelihood of innovation success and failure. Bearing in mind these potential consequences, the selection of partner(s) should be made with great caution to reduce the disadvantages associated with more distant collaboration. Likewise, the diversity of partners in research partnerships should be managed carefully. Counting on a portfolio of diverse partners will bring numerous benefits for innovation, but sharing and managing such highly dissimilar knowledge and coordinating the efforts of the globally dispersed partners are linked to higher probabilities of failure. In conclusion, our results should alert managers to the importance of geographic origin when looking for the strongest partners.

The limitations of this paper offer opportunities for future research to extend its findings in several ways. We use a large-scale survey which provides a broad view of a representative sample of firms and accurate information about their innovation processes, but it does suffer from limitations related to the depth of this information. Future studies could advance in this stream by using richer measures of successful and failed innovations. Specifically, the availability of more sophisticated measures of the number of failed innovations, the costs generated by failed projects, etc. would be useful to quantify more exactly the implications of different collaborative modes. Indeed, the database we use does not provide this type of individualized information on the characteristics of the partners and the projects, or the links formed between partners. It would also be interesting to know where partners are located (e.g., their proximity to rural or metropolitan areas), and if they are members of international networks or integrated in international clusters. Future research with this information could explore factors such as collaboration experience with the same partner, alliance experience in the same geographic area, or the technical nature of the project. Moreover, it would be useful to consider the role of information and communications technology (ICT) as a tool to mitigate the difficulties inherent in working with more distant partners. All this information would be interesting given that these factors can affect the success and failure of collaboration projects. In addition, examining firm-level characteristics (e.g., group membership or start-up firms) and the sectoral characteristics (e.g., the technological intensity of the activity) could offer a more accurate picture of the relations between proximity and diversity and the success and failure of innovation. In line with this, other studies could be limited to firms in certain sectors or activities whose characteristics make them worthy of study. This approach could help identify sectors in which the proximity of the partner is crucial for the success of the collaboration (e.g., for their high levels of tacit knowledge). Conversely, in those sectors in which the activity revolves around codifiable knowledge, the distance of the partner should not be such a decisive factor for the success of the collaboration.

Declarations of Competing Interest

None

Acknowledgements

This project was funded by the Government Research Agency of Spanish Ministry of Science and Innovation (PID2019-106874GB-I00/AEI/10.13039/501100011033) and Spanish Ministry of Economy and Business (ECO2017-87514-P). All authors have contributed equally to this paper.

References

Antonakis, J., Bendahan, S., Jacquart, P., Lalive, R., 2010. On making causal claims: a review and recommendations. Leadersh Q 21 (6), 1086–1120.

Almeida, P., Phene, A., 2004. Subsidiaries and knowledge creation: the influence of the MNC and host country on innovation. Strat. Manag. J. 25, 847–864.

Amabile, T.M., Barsade, S.G., Mueller, J.S., Staw, B.M., 2005. Affect and creativity at work. Adm. Sci. Q. 50 (3), 367–403.

Anand, B.N., Khanna, T., 2000. Do firms learn to create value? The case of alliances. Strat. Manag. J. 21, 295–315.

Audretsch, D.B., Feldman, M.P. 1996. R&D spillovers and the geography of innovation and production. Am. Econ. Rev., 630–640.

Bahlmann, M.D. 2015. Finding value in geographic diversity through prior experience and knowledge integration: a study of ventures' innovative performance. Ind. Corporate Change, doi: 10.1093/icc/dtv041.

Balland, P.A., 2012. Proximity and the evolution of collaboration networks: evidence from research and development projects within the global navigation satellite system (GNSS) industry. Reg. Stud. 46 (6), 741–756.

Barge-Gil, A., 2010. Open, semi-open and closed innovators: towards an explanation of degree of openness. Industry and Innovation 17 (6), 577–607. https://doi.org/10.1080/13662716.2010.530839.

Becheikh, N., Landry, R., Amara, N., 2006. Lessons from innovation empirical studies in the manufacturing sector: a systematic review of the literature from 1993-2003. Technovation 26, 644–664.

Becker, W., Dietz, J., 2004. R&D cooperation and innovation activities of firms—Evidence for the German manufacturing industry. Res. Policy 33 (2), 209–223.

Belderbos, R., Carree, M., Lokshin, B., 2004. Cooperative R&D and firm performance. Res. Policy 33 (10), 1477–1492.

Bertrand, O., Mol, M.J., 2013. The antecedents and innovation effects of domestic and offshore R&D outsourcing: the contingent impact of cognitive distance and absorptive capacity. Strat. Manag. J. 34 (6), 751–760.

Bleeke, J., Ernst, D., 1991. The way to win in cross-border alliances. Harv. Bus. Rev. 69 (6), 127–135.

Boschma, R., 2005. Proximity and innovation: a critical assessment. Reg. Stud. 39 (1), 61–74.

Brush, C.G., Vanderwerf, P.A., 1992. A comparison of methods and sources for obtaining estimates of new venture performance. J. Bus. Vent. 7, 157–170.

Calantone, R.J., Stanko, M.A., 2007. Drivers of outsourced innovation: an exploratory study. J. Product Innov. Manag. 24, 230–241.

Cantwell, J., 1989. Technological Innovation and Multinational Corporations. Blackwell, Oxford,.

Cantwell, J., Janne, O., 1999. Technological globalisation and innovative centres: the role of corporate technological leadership and locational hierarchy. Res. Policy 28 (2), 119–144.

Cantwell, J., Santangelo, G.D., 1999. The frontier of international technology networks: sourcing abroad the most highly tacit capabilities. Inf. Econ. Policy 11 (1), 101–123.

Cassiman, B., Perez-Castrillo, D., Veugelers, R., 2002. Endogeneizing know-how flows through the nature of R&D investments. Int. J. Ind Organiz. 20, 775–799.

Chakrabarti, A., Mitchell, W., 2013. The persistent effect of geographic distance in acquisition target selection. Org. Sci. 24 (6), 1805–1826.

Chakrabarti, A., Mitchell, W., 2016. The role of geographic distance in completing related acquisitions: evidence from U.S. chemical manufacturers. Strat. Manag. J. 37, 673–694.

Choi, J., Contractor, F.J., 2016. Choosing an appropriate alliance governance mode: the role of institutional, cultural and geographical distance in international research & development (R&D) collaborations. J Int. Bus. Stud. 47 (2), 210–232.

Chung, W., Alcácer, J., 2002. Knowledge seeking and location choice of foreign direct investment in the United States. Manage. Sci. 48 (12), 1534–1554.

Colombo, M.G., Delmastro, M., 2002. How effective are technology incubators?: evidence from Italy. Res. Policy 31 (7), 1103–1122.

Colombo, M.G., Grilli, L., Murtinu, S., Piscitello, L., Piva, E., 2009. Effects of international R&D alliances on performance of high-tech start-ups: a longitudinal analysis. Strategic Entrepreneur. J. 3 (4), 346–368.

Cuervo-Cazurra, A., Nieto, M.J., Rodríguez, A., 2018. The impact of R&D sources on new product development: sources of funds and the diversity versus control of knowledge debate. Long Range Plann. 51 (5), 649–665.

Das, T.K., Teng, B.S., 2000. Instabilities of strategic alliances: an internal tensions perspective. Org. Sci. 11 (1), 77–101.

De Bondt, R., Slaets, P., Cassiman, B., 1992. The degree of spillovers and the number of rivals for maximum effective R &D. Int. J. Ind Organiz. 10 (1), 35–54.

D'Este, P., Amara, N., Olmos-Peñuela, J., 2016. Fostering novelty while reducing failure: balancing the twin challenges of product innovation. Technol. Forecast. Soc. Change 113, 280–292.

D'Este, P., Marzucchi, A., Rentocchini, F., 2018. Exploring and yet failing less: learning from past and current exploration in R&D. Ind. Corporate Change 27 (3), 525–553.

Duysters, G., Kok, G., Vaandrager, M., 1999. Crafting successful strategic technology alliances. R&D Manag. 29 (4), 343–351.

Faems, D., Van Looy, B., Debackere, K., 2005. Interorganizational collaboration and innovation: toward a portfolio approach. J. Product Innov. Manag. 22, 238–250.

Fey, C.F., Birkinshaw, J., 2005. External sources of knowledge, governance mode, and R&D performance. J. Manag. 31 (4), 597–621.

Frost, T.S., 2001. The geographic sources of foreign subsidiaries' innovations. Strat. Manag. J. 22 (2), 101–123.

García-Quevedo, J., Pellegrino, G., Vivarelli, M., 2014. R&D drivers and age: are young firms different? Res. Policy 43 (9), 1544–1556.

García-Quevedo, J., Segarra-Blasco, A., Teruel, M., 2018. Financial constraints and the failure of innovation projects. Technol. Forecast. Soc. Change 127, 127–140.
Gertler, M.S. 1995. "Being There": proximity, organization, and culture in the development and adoption of advanced manufacturing technologies. Econ. Geogr., 1–26.
Ghemawat, P., 2001. Distance still matters. Harv. Bus. Rev. 79 (8), 137–147.
Goncalo, J.A., Staw, B.M., 2006. Individualism–collectivism and group creativity. Organ. Behav. Hum. Decis. Process. 100 (1), 96–109.
Greene, W., 2000. Econometric Analysis, 4th Ed. Prentice Hall, Upper Saddle River, N.J.
Gulati, R., 1995. Does familiarity breed trust? The implications of repeated ties for contractual choice in alliances. Acad. Manag. J. 38, 85–112.
Gulati, R., 1999. Network location and learning: the influence of network resources and firm capabilities on alliance formation. Strat. Manag. J. 20 (5), 397–420.
Hagedoorn, J., 1993. Interorganizational modes of cooperation. Strat. Manag. J. 14, 371–385.
Hagedoorn, J., Narula, R. 1996. Choosing organizational modes of strategic technology partnering: international and sectoral differences. J. Int. Bus. Stud., 265–284.
Hansen, T., 2015. Substitution or overlap? The relations between geographical and non-spatial proximity dimensions in collaborative innovation projects. Reg. Stud. 49 (10), 1672–1684.
Hansen, M.T., Løvås, B., 2004. How do multinational companies leverage technological competencies? Moving from single to interdependent explanations. Strat. Manag. J. 25 (8–9), 801–822.
Hoang, H., Rothaermel, F.T., 2005. The effect of general and partner-specific alliance experience on joint R&D project performance. Acad. Manag. J. 48 (2), 332–345.
Howells, J.R., 2002. Tacit knowledge, innovation and economic geography. Urban Stud. 39 (5–6), 871–884.
Howells, J., Bessant, J., 2012. Introduction: innovation and economic geography: a review and analysis. J. Econ. Geogr. 12 (5), 929–942.
Hofstede, G., 1991. Cultures and Organisations-Software of the mind: Intercultural Cooperation and Its Importance For Survival. McGraw-Hill.
Hyll, W., Pippel, G., 2016. Types of cooperation partners as determinants of innovation failures. Technol. Anal. Strat. Manag. 28 (4), 462–476.
Inkpen, A.C., 1998. Learning and knowledge acquisition through international strategic alliances. The Acad. Manag. Execut. 12 (4), 69–80.
Ireland, R.D., Hitt, M.A., Vaidyanath, D., 2002. Alliance management as a source of competitive advantage. J. Manag. 28 (3), 413–446.
Jaffe, A., Trajtenberg, M., Henderson, R., 1993. Geographic localization of knowledge spillovers as evidenced by patent citations. Q. J. Econ. 108 (3), 577–598.
Jiang, R.J., Tao, Q.T., Santoro, M.D., 2010. Alliance portfolio diversity and firm performance. Strat. Manag. J. 31 (10), 1136–1144.
Kale, P., Singh, H., Perlmutter, H., 2000. Learning and protection of proprietary assets in strategic alliances: building relational capital. Strat. Manag. J. 21, 217–237.
Kamien, M.I., Muller, E., Zang, I. 1992. Research joint ventures and R&D cartels. Am. Econ. Rev., 1293–1306.
Khanna, T., Yafeh, Y., 2007. Business groups in emerging markets: paragons or parasites? J. Econ. Lit. 45, 331–372.
Kim, C.S., Inkpen, A.C., 2005. Cross-border R&D alliances, absorptive capacity and technology learning. J. Int. Manag. 11 (3), 313–329.
Knoben, J., Oerlemans, L.A., 2006. Proximity and inter-organizational collaboration: a literature review. Int. J. Manag. Rev. 8 (2), 71–89.
Kogut, B. 1989. The stability of joint ventures: reciprocity and competitive rivalry. J Ind Econ, 183–198.
Koput, K.W., 1997. A chaotic model of innovative search: some answers, many questions. Org. Sci. 8 (5), 528–542.
Lam, A., 1997. Embedded firms, embedded knowledge: problems of collaboration and knowledge transfer in global cooperative ventures. Org. Stud. 18 (6), 973–996.
Lane, P.J., Salk, J.E., Lyles, M.A., 2001. Absorptive capacity, learning, and performance in international joint ventures. Strat. Manag. J. 22 (12), 1139–1161.
Laursen, K., Masciarelli, F., Prencipe, A., 2012. Regions matter: how localized social capital affects innovation and external knowledge acquisition. Org. Sci. 23 (1), 177–193.
Laursen, K., Salter, A., 2006. Open for innovation: the role of openness in explaining innovation performance among U.K. manufacturing firms. Strat. Manag. J. 27, 131–150.
Lavie, D., Miller, S.R., 2008. Alliance portfolio internationalization and firm performance. Org. Sci. 19 (4), 623–646.
Leiponen, A., Helfat, C.E., 2010. Innovation objectives, knowledge sources, and the benefits of breadth. Strat. Manag. J. 31 (2), 224–236.
Leiponen, A., Helfat, C.E., 2011. Location, decentralization, and knowledge sources for innovation. Org. Sci. 22 (3), 641–658.
Leoncini, R., 2016. Learning-by-failing: an empirical exercise on CIS data. Res. Policy 45 (2), 376–386.
Letaifa, S.B., Rabeau, Y., 2013. Too close to collaborate? How geographic proximity could impede entrepreneurship and innovation. J. Bus. Res. 66 (10), 2071–2078.
Levina, N., Vaast, E., 2008. Innovating or doing as told? Status differences and overlapping boundaries in offshore collaboration. MIS Q. 307–332.
Lhuillery, S., Pfister, E., 2009. R&D cooperation and failures in innovation projects: empirical evidence from French CIS data. Res. Policy 38 (1), 45–57.
Lokshin, B., Hagedoorn, J., Letterie, W., 2011. The bumpy road of technology partnerships: understanding causes and consequences of partnership mal-functioning. Res. Policy 40 (2), 297–308.
Lorenzen, M., 2005. Introduction: knowledge and geography. Ind. Innov. 12 (4), 399–407.
Lorenzen, M., Maurer, I., Staber, U., 2012. Space and inter-organizational relations. Ind. Innov. 19 (3), 181–186.
Lubatkin, M., Florin, J., Lane, P., 2001. Learning together and apart: a model of reciprocal interfirm learning. Human Relat. 54 (10), 1353–1382.
Malmberg, A., Maskell, P., 2006. Localized learning revisited. Growth Change 37 (1), 1–18.
Miotti, L., Sachwald, F., 2003. Co-operative R&D: why and with whom?: an integrated framework of analysis. Res. Policy 32 (8), 1481–1499.
Morgan, K., 2004. The exaggerated death of geography: learning, proximity and territorial innovation systems. J. Econ. Geogr. 4 (1), 3–21.
Nelson, R.R., 1992. National innovation systems: a retrospective on a study. Ind. Corp. Change 1 (2), 347–374.
Neter, J., Wasserman, W., Kutner, M.H., 1989. Applied Regression Models. Irwin, Homewood, IL.
Nieto, M.J., Rodríguez, A., 2011. Offshoring of R&D: looking abroad to improve innovation performance. J. Int. Bus. Stud. 42, 345–361.
Nieto, M.J., Santamaría, L., 2007. The importance of diverse collaborative networks for the novelty of product innovation. Technovation 27 (6), 367–377.
Oxley, J.E., Sampson, R.C., 2004. The scope and governance of international R&D alliances. Strat. Manag. J. 25 (8–9), 723–749.
Park, S.H., Ungson, G.R., 2001. Interfirm rivalry and managerial complexity: a conceptual framework of alliance failure. Org. Sci. 12 (1), 37–53.
Parkhe, A., 1991. Interfirm diversity, organizational learning, and longevity in global strategic alliances. J. Int. Bus. Stud. 579–601.
Patel, P., Pavitt, K., 1994. Uneven (and divergent) technological accumulation among advanced countries: evidence and a framework of explanation. Ind. Corp. Change 3 (3), 759–787.
Peeters, C., Massini, S., Lewin, A.Y., 2014. Sources of variation in the efficiency of adopting management innovation: the role of absorptive capacity routines, managerial attention and organizational legitimacy. Org. Stud. 35 (9), 1343–1371.
Phene, A., Fladmoe-Lindquist, K., Marsh, L., 2006. Breakthrough innovations in the U.S. biotechnology industry: the effects of technological space and geographic origin. Strat. Manag. J. 27, 369–388.
Porter, M.E., Rivkin, J.W., 2012. Choosing the United States. Harv. Bus. Rev. 90 (3), 80–93.
Presutti, M., Boari, C., Majocchi, A., 2011. The importance of proximity for the start-ups' knowledge acquisition and exploitation. Journal of Small Business Management 49 (3), 361–389.
Ramírez-Alesón, M., Fernández-Olmos, M., 2018. Unravelling the effects of Science Parks on the innovation performance of NTBFs. J. Technol. Transf. 43 (2), 482–505.
Rodan, S., Galunic, D.C., 2004. More than network structure: how knowledge heterogeneity influences managerial performance and innovativeness. Strat. Manag. J. 25, 541–556.
Rodríguez, A., Nieto, M.J., Santamaría, L., 2018. International collaboration and innovation in professional and technological knowledge-intensive services. Industry & Innovation 25 (4), 408–431. https://doi.org/10.1080/13662716.2017.1414752.
Rodríguez, A., Nieto, M.J., 2016. Does R&D offshoring lead to SME growth? Different governance modes and the mediating role of innovation. Strat. Manag. J. 37 (8), 1734–1753.
Sadowski, B., Duysters, G., Sadowski-Rasters, G. 2005. On the termination of strategic technology alliances: an exploratory study. Eindhoven Centre for Innovation Studies, The Netherlands. Working Paper 05.12.
Santamaría, L., Surroca, J., 2011. Matching the Goals and Impacts of R&D Collaboration. Eur. Manag. Rev. 8 (2), 95–109.
Santamaría, L., Nieto, M.J., Miles, I., 2012. Service innovation in manufacturing firms: evidence from Spain. Technovation 32 (2), 144–155.
Shane, S., 1993. Cultural influences on national rates of innovation. J. Bus. Vent. 8 (1), 59–73.
Shefer, D., Frenkel, A., 2005. R&D, firm size and innovation: an empirical analysis. Technov. 25 (1), 25–32.
Singh, S., 2006. Cultural differences in, and influences on, consumers' propensity to adopt innovations. Int. Mark. Rev. 23 (2), 173–191.
Teixeira, A.A., Santos, P., Oliveira Brochado, A., 2008. International R&D Cooperation between low-tech SMEs: the role of cultural and geographical proximity. Eur. Plan. Stud. 16 (6), 785–810.
Thompson, P., Fox-Kean, M. 2005. Patent citations and the geography of knowledge spillovers: a reassessment. Am. Econ. Rev., 450–460.
Un, C.A., Rodríguez, A., 2018a. Local and global knowledge complementarity: R&D collaborations and innovation of foreign and domestic firms. J. Int. Manag. 24 (2), 137–152.
Un, C.A., Rodríguez, A., 2018b. Learning from R&D outsourcing vs. learning by R&D outsourcing. Technovation 72, 24–33.
Vásquez-Urriago, Á.R., Barge-Gil, A., Modrego, A., 2016. Science and technology parks and cooperation for innovation: empirical evidence from Spain. Res. Policy 45 (1), 137–147.

van Beers, C., Zand, F., 2014. R&D cooperation, partner diversity, and innovation performance: an empirical analysis. J. Prod. Inn. Manag. 31, 292–312.

Van Der Vegt, G.S., Van de Vliert, E., Huang, X, 2005. Location-level links between diversity and innovative climate depend on national power distance. Acad. Manag. J. 48 (6), 1171–1182.

van Kranenburg, H., Hagedoorn, J., Lorenz-Orlean, S., 2014. Distance costs and the degree of inter-partner involvement in international relational-based technology alliances. Global Strat. J. 4, 280–291.

Vissers, G., Dankbaar, B., 2013. Knowledge and Proximity. Eur. Plan. Stud. 21 (5), 700–721.

Zahra, S.A., Ireland, R.D., Hitt, M.A., 2000. International expansion by new venture firms: international diversity, mode of market entry, technological learning, and performance. Acad. Manag. J. 43 (5), 925–950.

Luis Santamaría is an Associate Professor of Accounting at the Department of Business Administration at University Carlos III of Madrid (Spain). He holds a Ph. D. in Business Administration from Autonomous University of Barcelona (Spain). He is the Director of Master in Management (UC3M-ESCP Europe). His research interests center on two fields: Management of Innovation and Control Systems. His research has been published in journals as *Research Policy, Technovation, R&D Management, Journal of Small Business Management, Information & Management, Industry and Innovation,* among many others. He can be reached at lsantama@emp.uc3m.es

María Jesús Nieto is Professor of Strategic Management at University Carlos III of Madrid (Spain). She holds a PhD in Economic from this University. She is the Director of MSc in Entrepreneurship and Deputy Director of Research Institute of Family Business and Entrepreneurship. Her current research interests include internationalization, innovation management and strategic alliances. Her research has been published in journals as *Strategic Management Journal, Journal of International Business Studies, Long Range Planning, Research Policy, Technovation, Journal of World Business*, among many others. She can be reached at mnieto@emp.uc3m.es.

Alicia Rodríguez is an Associate Professor at University Carlos III of Madrid (Spain). She holds a PhD in Strategic Management from this University (with Honors). She studies firms' innovation and internationalization strategies, with a particular focus on offshoring and knowledge intensive activities. Her research has been published in leading journals such as *Strategic Management Journal, Journal of International Business Studies, Long Range Planning, Journal of International Management, Technovation, Industry and Innovation*, among others. She has been a Visiting Scholar at the D'Amore-McKim School of Business at Northeastern University (Boston, USA) in 2012 and 2017. She can be reached at alicia.rodriguez@uc3m.es