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Knowledge spillovers, R&D partnerships and innovation performance

Pilar Bernal [a], Martin Carree [b,c,*], Boris Lokshin [c]

[a] University of Zaragoza, Spain
[b] University of Maastricht, School of Business and Economics, PO Box 616, 6200 MD, Maastricht, the Netherlands
[c] University of Maastricht, the Netherlands

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ABSTRACT

A prime motive for innovative firms to seek collaboration is to gain access to knowledge resources. Firms that already benefit from knowledge spillovers without establishing formal collaborative agreements, may abstain from embarking on such agreements as they are costly. The propensity to (start to or continue to) collaborate with other business partners (customers, suppliers, competitors) will be associated with whether firms already benefit from access to knowledge resources, either through existing collaboration or otherwise. This research studies the interplay of formal collaboration and incoming spillovers by distinguishing four collaboration-spillovers scenarios: 'connected', 'detached', 'informed' or 'extraneous'. Using a large panel data set of Spanish firms during the period 2004–2016 we examine effects of the four scenarios on firms' propensity for continuing or starting collaboration. We subsequently estimate the effect of these scenarios on firm innovation performance. Our findings suggest that incoming knowledge spillovers may amplify or limit collaboration, but that they only partly substitute formal collaboration when it comes to impact on performance.

1. Introduction

R&D collaboration plays an important role in firms' pursuit of innovation (Laursen and Salter, 2006; Dittrich and Duysters, 2007; Enkel et al., 2009). It may facilitate access to resources that firms do not possess internally and allow partners to share the costs and risks of R&D projects (Hagedoorn, 1993; Mowery, 1998; Belderbos et al., 2012; Antonioli et al., 2017). R&D collaboration, because it relies on relational contracting, also presents a firm with costs and challenges, most importantly, with respect to knowledge management (Cassiman et al., 2009; Bogers, 2011; Laursen and Salter, 2014). On the one hand, R&D collaboration can be attractive because it creates incoming knowledge spillovers – tacit and explicit information flow – and hence has a potential to increase the variety of knowledge available to a firm (Kaiser, 2002; Belderbos et al., 2004; Feldman and Kelley, 2006; Van Beers et al., 2008; Badillo and Moreno, 2016; Hagedoorn et al., 2018; Li and Bosworth, 2020). On the other hand, involuntary outgoing knowledge spillovers or undesirable information leakage and outflow about firm's innovation effort, may discourage formal R&D collaboration (Cassiman and Veugelers, 2002; Frishammar et al., 2015).

Recognizing that the effectiveness of prior R&D collaboration likely explains firm's decisions to persist or discontinue R&D partnerships, scholars have begun to examine the role of extant collaboration with different partner types in shaping firm's decisions on adaptation of its portfolio of partners (Belderbos et al., 2018). The work takes a more dynamic view on collaboration, in recognizing that collaboration is a strategy that firms may adapt because the value they obtain from their current set of partners may change over time (Hoffmann, 2007; Asgari and Singh, 2017; de Leeuw et al., 2019). This contrasts with prior research that links knowledge spillovers to firms' propensity to collaborate which has often taken a static perspective and assumed an unceasing valuable knowledge exchange. However, especially innovation-intensive environments are characterized by rapid technological change that may make existing intangible resources such as knowledge obsolete (Dittrich and Duysters, 2007; Martinez et al., 2017). Relatedly, theoretical studies that focused on the role of knowledge spillovers in the firm's decisions to engage in collaboration often abstracted from the nature of the spillovers, treating them as an integral part of the collaboration effort (Katz 1986; d'Aspremont and Jacquemin, 1988; Kamien et al., 1992; Hinloopen, 1997; Kesteloot and Veugelers, 1997; Katsoulacos and Ulph, 1998; Li and Bosworth, 2020). We find that, despite the large body of research on R&D collaboration, and spillovers, our understanding of how the interplay between the two leads firms to adjust their R&D partnerships in order to satisfy changing

* Corresponding author. School of Business and Economics, PO Box 616, 6200 MD, Maastricht, the Netherlands.
E-mail addresses: pbernal@unizar.es (P. Bernal), m.carree@maastrichtuniversity.nl (M. Carree), b.lokshin@maastrichtuniversity.nl (B. Lokshin).

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objectives and, in that way, to secure future performance and competitiveness remains limited.

To address these shortcomings, we propose a model that aims to explain the dynamics of collaboration allowing for a better understanding of how firms adapt their (portfolio of) partnerships over time. Such adaptation may include starting, persisting, or discontinuing collaborating with a certain type of partner (cf. Belderbos et al., 2018). The novelty of our approach is the specific focus on the interplay between prior collaboration and the incoming knowledge spillovers. Although the general idea is well-received in the literature that incoming spillovers can positively influence the establishment of collaborative agreements with new and/or existing partners (Belderbos et al., 2004; Lopez, 2008; Chun and Mun, 2012), there is lack of studies that analyze how the interplay of prior formal collaboration and the levels of relevance of incoming knowledge spillovers could lead firms to critically re-assess and adapt their partnerships (portfolio) over time. Specifically, we build on the idea that collaboration strategies have been found to show different patterns based on the value chain function that they serve: upstream activities in the value chain (suppliers), downstream activities in the value chain (customers) and activities in the same chain element (competitors) (Haus-Reve et al., 2019), generating potential interrelationships since they provide resources and skills that can be complementary (Belderbos et al., 2006).

We depart from the idea that the relationship between incoming knowledge spillovers and R&D collaboration is non-trivial. In fact, we distinguish among four possible scenarios when taking into consideration this relationship. Fig. 1 illustrates the four scenarios. First, prior R&D collaboration may bring about incoming knowledge spillovers, rated by firms as relevant. We refer to this case as a "connected" information exchange. Second, despite engaging in R&D collaboration, firms can fail to benefit knowledge-wise from the respective partners. When incoming knowledge spillovers are rated as non-relevant we refer to the situation as "detached". This scenario can occur, for instance, when a partner's knowledge is too distant from the firm's core knowledge and (production) technologies (Sampson, 2007). Third, firms may benefit from the so-called exogenous spillovers – informational flows that arise even in the absence of formal collaboration. We refer to this case as "informed". Prior literature has in fact argued that firms obtain valuable spillovers, even without establishing formal agreements (see for example, Aldieri and Cincera, 2009; Filatotchev et al., 2011; Inkpen et al., 2019; Belderbos and Mohnen, 2020). There are several possible channels for such unavoidable, unintentional, and beneficial knowledge leakages: employee mobility, informal interactions and socialization due to co-location (for example within science and technology parks) and formal disclosure of innovation-related information via patents, trademarks or copyrights. Firms may also learn about new products, processes and technologies by attending trade fairs, consulting (patent) databases, and reading professional publications and thus become knowledgeable about technologies of other firms. Finally, we identify a scenario we refer to as "extraneous" when neither purposeful informational exchange nor formal R&D collaboration take place. These four scenarios inform our predictions on the relationship between incoming knowledge spillovers and the firms' propensity to be engaged in collaboration.

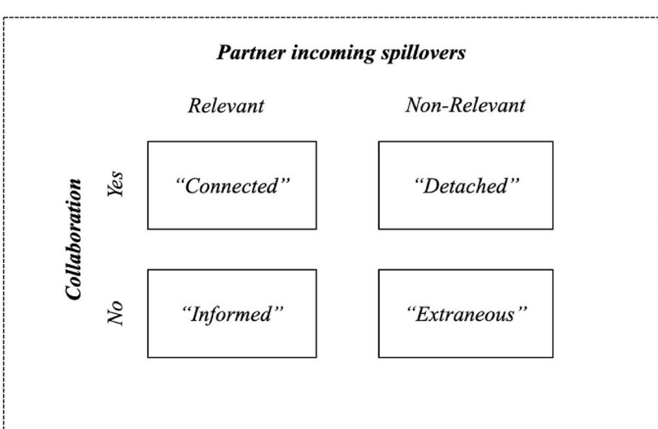

Fig. 1. Possible scenarios for the relationship between incoming knowledge spillovers and collaboration.

We test the hypotheses on a sample of Spanish firms covered by the Technological Innovation Panel survey (PITEC). The PITEC is especially suitable for our study because it contains information about the innovation activity of firms, for example, about the type of partners with which firms are engaging in R&D collaboration and the importance and sources of the incoming spillovers. The PITEC survey, in contrast to other innovation surveys in Europe, is administered on a yearly basis. Hence, the dataset allows us to identify more precisely the adaptation of collaboration strategies and the resulting innovation performance.

Our contribution to the literature is two-fold. First, we further the much-needed analysis of R&D collaboration from a dynamic point of view. In doing so, we improve our understanding of how firms adapt their partnerships over time, a topic in the literature that has received scant attention. Second, our analysis reveals that the interplay of spillovers and prior collaboration plays an important role in dictating how firms adapt their partnerships. We demonstrate that, whereas cooperation with some type of partners can be linked to subsequent cooperation with other partner types, this is very different for incoming knowledge spillovers. They tend to be linked with reduced subsequent cooperation with other partner types. We also investigate the innovation performance resulting from being in the four scenarios. This provides an indication to what extent spillovers complement or may substitute for R&D collaboration.

2. Literature background and hypotheses

2.1. *Incoming knowledge spillovers as antecedent of R&D collaboration*

In recent years, increasing attention has been given to the role of inter-firm knowledge flows – often referred to in the literature as knowledge spillovers – as important driver of R&D collaboration (Belderbos et al., 2004; Lopez, 2008; Chun and Mun, 2012; Li and Bosworth, 2020). The literature distinguishes between two kinds of spillovers. Incoming spillovers refer to the captured external information relevant for the innovation process. On the other hand, outgoing spillovers refer to the undesirable information leakage and outflows about firm's innovation effort, which firms seek to minimize (Cassiman and Veugelers, 2002; Sikombe and Phiri, 2019). Especially the incoming spillovers have been linked to increased propensity of R&D collaboration (e.g. Abramovsky et al., 2009; Badillo and Moreno, 2016). Firms can leverage spillovers while engaging in formal collaboration, as they get "connected", but also in the absence of it, as they get "informed" and gain considerable knowledge about new technologies, markets and process improvements available in the market (Whitley, 2002; Venturini et al., 2019). Such exogenous spillovers can be involuntary and undesirable as in the case of competitors or voluntary and even promoted as in the case of customers and suppliers (Atallah, 2002; Hertenstein and Williamson, 2018). By taking advantage of these knowledge flows firms may improve their know-how, and expand their technological capabilities.

Firms that receive valuable knowledge spillovers from a specific type of partner for their innovation effort are more likely to collaborate with this type of partner. In the case that incoming spillovers from a specific type of partner are considered non-relevant for firms' innovation processes, firms may not perceive apparent opportunities for and benefits of embarking on cooperation with this type of partner. On the contrary, in the case that incoming spillovers from a specific partner type are considered relevant, firms may see some potential of additional benefits by engaging in formal collaboration with this partner type, because they expect further knowledge gains. By taking advantage of incoming spillovers from a specific type of partner, firms will improve their base of know-how, expanding their technological capacities. This enhances expected benefits of R&D collaboration, making it more likely to occur (Belderbos et al., 2004). A firm that already collaborates with a specific type of partner and profits from incoming spillovers (i.e. being 'connected') is more likely to continue such collaboration vis-à-vis a firm that fails to achieve incoming spillovers even though in a collaborative agreement (i.e. being 'detached'). A firm's capacity to identify (and extract) the value of partner knowledge often depends on the prior collaborative experience (Eisenhardt and Martin, 2000). Likewise, a firm that finds relevant knowledge spillovers from a certain partner type even in the absence of formal collaboration (i.e. being 'informed') is more likely to start collaborating vis-à-vis a firm that experiences no knowledge spillovers at all (i.e. being 'extraneous') Hence, we propose the following hypotheses:

HYPOTHESIS 1a. *A firm beforehand **connected** with a partner of a certain type is more likely to be engaged in collaboration with that **same partner type** than a firm beforehand only **detached** to such partner.*

HYPOTHESIS 1b. *A firm beforehand **informed** by a partner of a certain type is more likely to be engaged in collaboration with that **same partner type** than when such partner type is beforehand **extraneous** to the firm.*

Access to incoming knowledge spillovers from a specific type of partner may also make firms more likely to collaborate with a different type of partner. More specifically, we expect this effect to be particularly strong for 'connected' firms, that is, firms that collaborate with and for which incoming knowledge spillovers from a specific type of partner are relevant for their focal innovation effort. By perceiving incoming knowledge spillovers as relevant, collaborating firms may not only appreciate this specific source of knowledge for one type of partner but also form expectations that similar outcome may be achieved with other types of collaboration (Goerzen, 2007; Holloway and Parmigiani, 2016). Such firms may consider to have lesser opportunity to further learn from the type of partner from which they already receive relevant incoming spillovers and thus making it less necessary to establish subsequent collaborative agreements with this partner type. In order to avoid the possibility of obtaining redundant information, due to the amount of knowledge received, the company may have incentives to collaborate with a different partner type (Goerzen, 2007; Un et al., 2010). In doing so, firms will take more advantage of the knowledge obtained from a specific type of partner, by combining it with new and diverse ideas provided by other partner types, exploiting complementarities, potential synergies and enjoying more efficient coordination in the introduction of innovations (Hoang and Rothaermel, 2005; Lavie et al., 2011; Jacob et al., 2013).

In the absence of prior R&D collaboration the effects of incoming spillovers of a certain partner type on collaborating with other partner types are likely to be a bit different. Firms are likely to first seek collaboration for the partner type where the spillovers are found (see HYPOTHESIS 1b) and then only later will opt for collaboration in other types. Firms tend to be limited in their capacity to set up multiple kinds of collaborations simultaneously. So, 'informed' firms will prioritize embarking on cooperation with the specific type of partner which has proven to be promising source of information. Collaboration with other partner types is postponed. Hence, we propose the following hypotheses:

HYPOTHESIS 2a. *A firm beforehand **connected** with a partner of a certain type is more likely to be engaged in collaboration with **other partner types** than a firm beforehand only **detached** to such partner.*

HYPOTHESIS 2b. *A firm beforehand **informed** by a partner of a certain type is **less** likely to be engaged in collaboration with **other partner types** than when such partner type is beforehand **extraneous** to the firm.*

2.2. *Prior ties as antecedent of R&D collaboration*

There are a number of reasons why prior engagement in R&D collaboration with one partner type can be a precursor for the formation of new collaborative ties with the same partner type. R&D collaboration is considered an incremental learning process since firms learn how to manage their partnerships by repeatedly establishing collaborative agreements (Powell et al., 1996; Sampson, 2005; Kale and Singh, 2007; Duysters et al., 2012). Effective learning, which depends on the prior partnering experience, increases the firm's ability to identify relevant information about potential partners (Gulati and Gargiulo, 1999).

Prior research suggests that firms that collaborate with a specific type of partner have superior prospects for reaping the benefits of continued cooperation. First, these firms have improved their organizational collaborative practices and gained valuable managerial experience in managing a particular type of relationship. A certain degree of persistency in selecting firm's R&D partner types helps establish the (inter)-organizational routines that support managing of the uncertainties involved in R&D collaboration (Das and Teng 2000; Dionysiou and Tsoukas, 2013; Zheng and Yang, 2015). Furthermore, the learning effects achieved through continuous R&D cooperation can increase the effectiveness of future collaboration strategies (Nieto and Santamaría, 2007; Anand et al., 2016; Di Guardo, and Harrigan, 2016; Niesten and Jolink, 2018). Second, continued collaboration can be attractive because effective learning takes place through repeated cooperation, which builds trust and supports the exchange of tacit and fine-grained information and knowledge (Gilsing and Nooteboom 2006). Firms can rely on cooperation to signal that the company is a reliable and competent partner with valuable and scarce experience. This can help build a reputation as a trustworthy partner, and can reduce the risks of opportunism and negative referrals or lock-outs from future collaboration (Nooteboom 2004; Belderbos et al., 2015; Niesten and Jolink, 2018). These effects suggest that companies that cooperate can cooperate with more competent partners overall.

Additional reasons for continued collaboration with a certain partner type may simply be resistance towards change (inertia) or lock-in effects (Bureth et al., 1997). Adaptation costs, next to effective learning, may be an important extra reason for persistence. Hence, we propose the following hypotheses:

HYPOTHESIS 3a. *A firm beforehand **connected** with a partner of a certain type is more likely to be engaged in collaboration with that **same partner type** than a firm beforehand only **informed** by such partner.*

HYPOTHESIS 3b. *A firm beforehand **detached** to a partner of a certain type is more likely to be engaged in collaboration with that **same partner type** than when such partner type is beforehand **extraneous** to the firm.*

There are also arguments to expect prior engagement in collaboration with one partner type to be an antecedent of the formation of collaborative ties with other partner types. First, the learning effects derived from prior experience in collaboration strengthens firms' ability to manage their partnerships, regardless of the type of collaboration partner (Goerzen, 2007). Firms with experience in collaboration have already generated consistent routines for managing its partnerships, which attenuate the risk and uncertainty related to the development of distinctive partnering routines and helps firms to avoid managerial challenges associated with ties to new types of partners (Lavie and Rosenkopf, 2006). For example, a firm's practices for selecting partners, assimilating partners' knowledge, setting up and negotiating contracts and addressing contractual breaches in the course of prior R&D partnerships are considered essential in all ties and may help firms in subsequent partnerships with different partner types (Gulati, 1995; Lavie et al., 2011). Second, and according to prior research, accessing to diverse sources of knowledge by establishing ties with different partner types allows firms to extend their boundaries and to exploit synergies (Stuart, 2000; Rosenkopf and Nerkar 2001; Laursen and Salter, 2006).

Innovation research focusing on collaboration has frequently argued that each partner type has a separate space, its own perspective and access to diverse sources of knowledge, which serve different functions.

Prior research has followed the distinction of partnerships based on the value chain function that they serve (Tether, 2002; Rothaermel and Deeds 2004; Lavie et al., 2011; Haus-Reve et al., 2019). According to this, prior R&D collaboration with partners in upstream activities of the value chain (suppliers) provides firms with specific ideas about components and skills and with detailed specifications about technological development (Kang and Kang, 2010; Un et al., 2010). In contrast, prior R&D collaboration with partners in downstream activities (customers) gives firms more information about customers' needs and helps them in translating ideas into product specifications, enabling commercialization and market acceptance (Kang and Kang, 2010; Un et al., 2010; Lavie et al., 2011). Prior R&D collaboration with partners in the same chain element provides firms with a common vision, which increases adoption potential and increases R&D capabilities (Dussauge et al., 2000). However, firms may not be able to exploit the knowledge obtained from prior ties with a specific type of partner without working closely with other partner types. This is because supply chain partners bring different types of knowledge that are complementary and whose combination allows firms to develop activities that otherwise are unavailable (Tether, 2002; Faems et al., 2005; Lavie, 2007). For instance, firms may not be able to exploit the market opportunities that collaboration with customers offers without increasing the quality of the inputs and recognizing how to use new technology by collaborating with suppliers or without increasing R&D capabilities through collaboration with competitors. These potential advantages of combining collaboration with different partner types suggest enhanced return from R&D collaboration. Hence, we propose the following hypotheses:

HYPOTHESIS 4a. *A firm beforehand **connected** with a partner of a certain type is more likely to be engaged in collaboration with **other partner types** than a firm beforehand only **informed** by such partner.*

HYPOTHESIS 4b. *A firm beforehand **detached** to a partner of a certain type is more likely to be engaged in collaboration with **other partner types** than when such partner type is beforehand **extraneous** to the firm.*

2.3. The effect of the four scenarios on innovation performance

Formal collaboration may be quite costly and, therefore, compensation should be found in a superior innovation performance, for example by increased sales of newly developed products. Being in one of the four scenarios is likely to affect firm innovation performance. Formal R&D collaboration allows for both tacit and explicit knowledge exchange (Nielsen and Nielsen, 2009; Un and Asakawa, 2015). Tacit knowledge is context-specific, and arguably, is more difficult to learn (Grant, 1996; Szulanski, 1996). The fact that it is often held by individuals and is developed locally (Lall, 2000; Subramaniam, 2006) implies that its acquisition requires personal interaction, such as that facilitated within formal collaboration. Firms that are 'connected' benefit from such knowledge exchange and are likely to outperform firms that are 'detached' (little knowledge exchange) or that are only 'informed'. Obviously, firms can also obtain valuable spillovers via hiring, being more proximate to other firms and by consulting patents and attending trade-fairs, but such knowledge often remains far in terms of the context in which it was generated, hence creating knowledge distance between the creator and the receiver. Furthermore, codification of knowledge in patents, trademarks and copyrights is only partial, and can be seen as a-systematic (Un and Asakawa, 2015).

Since both tacit and explicit knowledge have been shown to be critical for superior innovation performance (Von Krogh, Ichijo, and Nonaka, 2000; Nielsen and Nielsen, 2009; Pérez-Luño et al., 2019), we put forth that firms that are 'connected' to benefit most in terms of innovation performance, followed by firms that are only 'informed' and 'detached'. In short, we propose that spillovers matter to innovation performance:

HYPOTHESIS 5a. *A firm **connected** with a partner type will have a superior innovation performance compared to a firm which is **detached** to such partner type.*

HYPOTHESIS 5b. *A firm **informed** by a partner type will have a superior innovation performance compared to when that partner type is **extraneous** to the firm.*

And, in addition, that formal collaboration also matters:

HYPOTHESIS 6a. *A firm **connected** with a partner type will have a superior innovation performance compared to a firm which is **informed** by a partner type.*

HYPOTHESIS 6b. *A firm **detached** to a partner type will have a superior innovation performance compared to when that partner type is **extraneous** to the firm.*

3. Methods

3.1. Sample

To test our hypotheses we use data from the Technological Innovation Panel (PITEC). The National Institute of Statistics (INE), the Spanish Foundation for Science and Technology (FECYT) and the Spanish Foundation for Technological Innovation (COTEC) develop the database that provides information of the innovative activities of a large sample of Spanish firms. PITEC is based on Community Innovation Survey (CIS) framework, which follows the Oslo Manual (OECD, 2005).[1] These data have been previously used to study the determinants of firms' innovation performance (Vega Jurado, Gutiérrez Gracia, and Fernández de Lucio, 2009), to analyze the impact of collaboration strategies (De Marchi, 2012; Belderbos et al., 2015) and the determinants of R&D activities (Barge-Gil and López, 2014), among others.

PITEC has several advantages for our research. Firstly, the PITEC questionnaire, in contrast to other innovation surveys, is administered on a yearly basis. Hence, the dataset has a sizeable longitudinal dimension allowing to construct time-varying variables from 2004 to 2016.[2] About 80% of firms (10,323 of 12,849) are included in all waves of the survey, which makes the structure of the sample only slightly unbalanced (see Table 1). Secondly, PITEC provides annual information about the collaborative agreements established by firms included in the sample, the type of partner with which they collaborate, the value of the incoming spillovers from each type of partner and firms' innovation performance, our key variables of interest. Thirdly, the survey covers firms operating in all sectors of the Spanish economy, which allows generalizability of our findings. Fourthly, the PITEC is a CIS-type database. CIS data are widely used by policy observers to provide innovation indicators and by economists to analyze a variety of topics related to innovation (Cassiman and Veugelers, 2002; Raymond et al., 2010; Czarnitzki and Toole, 2011). Therefore, throughout this study, we are able to use widely accepted innovation indicators and variables.

We estimate two models, a R&D collaboration model and an

[1] The dataset, the questionnaire and the description of each variable is available at the website: https://services.icono.fecyt.es/PITEC/Paginas/descarga_bbdd.aspx. In order to avoid firms being identified some variables are "anonymized". López (2012) shows that the expected biases due to this anonymization are small, comparing regressions that use original and harmonized data alternatively.

[2] The PITEC data files are available from 2003 to 2016. There is no established or planned date for the dissemination of subsequent periods.

Table 1
Panel structure of the sample (number of firms = 12,849; T = 13).

	Number of surveys												
	1	2	3	4	5	6	7	8	9	10	11	12	13
Number of firms	1	3	4	3	10	7	4	4	5	5	0	2,480	10,323
Percentage	0.01	0.02	0.03	0.02	0.08	0.05	0.03	0.03	0.04	0.04	0	19.30	80.34

Innovation performance model, on a sample of 73,692 observations (for which all information on the variables used in the model is available) on 12,849 firms covering the 2004 to 2016 time period.[3] Table 2 lists the sample frequency of observations by firm size and industry over the estimation period. In our sample about 75% of observations are from small and medium-sized firms (up to 200 employees), while about 25% are from large firms.

3.2. Variables

Dependent variable in the R&D collaboration model: R&D collaboration with a partner type is a binary variable that takes the value 1 if a firm reported engagement in collaboration[4] with a partner type, that is customer, supplier or competitor, respectively, in the survey of year t, and 0 otherwise.[5] *Dependent variable in the Innovation performance model: Innovation performance,* is measured as the fraction of the firm's total turnover in year t related to the firms' products introduced during the years t-2, t-1 and t that have been considered "new to the market". That is, we focus on (radical) product innovation.

Independent variables. Connected, detached, informed and *extraneous* are the independent variables and represent the four possible scenarios in the relationship between incoming knowledge spillovers and previous R&D collaboration. To construct each of these variables for each partner type, we use information about past R&D collaboration and incoming knowledge spillovers. PITEC questionnaire asks firms to rate on a Likert scale (1–4) the importance of various external sources of information for the firm's innovation process (4 = High Importance; 3 = Moderate importance; 2 = Low importance; 1 = Not answered).[6] To measure the relevance of the incoming knowledge spillovers, we used the scores of importance of information obtained from customers, suppliers and competitors to create three categorical variables that capture the relevance of each type of incoming spillover for the firms' innovation. Firms that assign a score 3 or 4 to the information obtained from a specific partner type perceive the incoming spillovers as relevant and those that assign a score 1 or 2 perceive them as non-relevant.

Connected. Connected firms are those that have engaged in R&D collaboration with a specific type of partner in the survey in year t-1 and have rated the incoming knowledge spillovers from this specific type of partner in year t-1 as relevant. Those firms receive the value 1 and 0 otherwise. *Detached.* Detached firms are those that have engaged in R&D collaboration with a specific type of partner in the survey in year t-1 and have rated the incoming knowledge spillovers from this specific type of partner in year t-1 as non-relevant. Those firms receive the value 1 and 0 otherwise. *Informed.* Informed firms are those that have not engaged in R&D collaboration with a specific type of partner in the survey in year t-1 and have rated the incoming knowledge spillovers from this specific type of partner in year t-1 as relevant. Those firms receive the value 1 and 0 otherwise. *Extraneous.* Extraneous firms are those that have not engaged in R&D collaboration with a specific type of partner in the survey in year t-1 and have rated the incoming knowledge spillovers from this specific type of partner in year t-1 as non-relevant. It constitutes the base or 'left-out' category.

Control variables. We account for the effect that access to other external sources of information may have. PITEC provides information about the relevance that firms give to the information that they receive from universities, public research organisms, technological centers, conferences, scientific journals and professional associations. The knowledge that these sources generate may be very useful for firms, since researchers are more likely to be engaged on real world problems since many fields of research, by their nature, involve considerable interaction with industrial practice (Rosenberg and Nelson, 1994). In this way, having access to this knowledge may lead firms to improve their base of know-how and therefore may enlarge firms' incentives to collaborate with customers, suppliers and competitors, as the likelihood of exploiting complementarities increases (Tether and Tajar, 2008).[7] We used a factor analysis to reduce six items (information from universities, information from public research organisms, information from technological centers, information from conferences, information from scientific journals and information from professional associations) into two factors, *institutional incoming spillovers* and *other sources incoming spillovers*, with acceptable Cronbach alphas (0.7085 and 0.7057, respectively).[8] One factor (representing institutional incoming spillovers) emphasizes information from universities, information from research organisms and information from technological centers items, and the other factor (representing other sources incoming spillovers) emphasizes information from conferences, information from scientific journals and information from professional associations items.

In addition, we take into account firm *size*. Several papers have pointed out that firm size affects the propensity to collaborate. Given that larger firms have more resources, they can more easily handle the establishment of collaborative agreements (Cohen and Klepper, 1996; Belderbos et al., 2006). Following Miotti and Sachwald (2003), we use the logarithm of the number of employees as a measure of firm's size. *R&D intensity* is another common and important control variable. Firms with higher investments in innovation are expected to have a better developed capacity to recognize and assimilate external knowledge from

[3] Although the information is available from 2003 on, a large number of firms were incorporated into the data set as of 2004. In order to have a sample with a similar and comparable number of firms for each period, we use information for 2004–2016 (Barge-Gil and López, 2014).

[4] In the PITEC questionnaire, the collaboration question is formulated as follows: In the period from t-2 to t, did your company collaborate in any of its innovation activities with other companies or entities? Collaboration for innovation consists of active participation in innovation activities with other companies or non-commercial entities. It is not necessary for both parties to extract a commercial benefit. The mere subcontracting of works without active collaboration is excluded.

[5] The partner is assumed to be a competitor in case it is indicated as "competitor or firm from the same industry" by the respondent.

[6] In the PITEC questionnaire, the incoming knowledge spillovers question is formulated as follows: In the period from t-2 to t, how important each of these sources have been for your innovation activities?.

[7] Santoro et al. (2020) show how informal cooperation with 'distant' partners (including scanning for ideas, meetings, conferences and sharing facilities) are an important source of knowledge acquisition.

[8] We carried out the same analysis but creating two variables through their averages (i.e. the average of information from universities, information from research organisms and information from technological centers items constitutes the variable "Institutional incoming spillovers" and the average of information from conferences, information from scientific journals and information from professional associations items constitutes the variable "Other sources incoming spillovers"), and the resulting empirical results were virtually identical.

Table 2
Firms by size and sector.

CODE	INDUSTRY	Whole sample	%	≥ 200 employees	<200 employees
01, 02, 03	Agriculture, forestry and fishing	994	1.35	130	864
05, 06, 07, 08, 09	Extractive industries	295	0.40	47	248
10, 11, 12	Food products, Beverages, and tobacco products	5631	7.64	1695	3936
13	Textiles	1534	2.08	123	1411
14	Clothing	542	0.74	128	414
15	Leather and related products	413	0.56	53	360
16	Wood and cork	606	0.82	106	500
17	Paper and paper products	801	1.09	287	514
18	Printing and reproduction of recorded media	470	0.64	64	406
19	Petroleum Industry	29	0.04	29	0
20	Chemicals	5244	7.12	722	4522
21	Pharmaceutical products	1543	2.09	729	814
22	Rubber and plastic products	2862	3.88	503	2359
23	Other non-metallic mineral products	2202	2.99	566	1636
24	Basic metals	1314	1.78	634	680
25	Fabricated metal products, except machinery and equipment	4265	5.79	570	3695
26	Computer, electronic and optical products	2512	3.41	323	2189
27	Electrical equipment	2281	3.10	416	1865
28	Machinery and equipment	5663	7.68	589	5074
29	Motor vehicles, trailers and semi-trailers	2321	3.15	1120	1201
30 (exc. 301, 303)	Other transport equipment	282	0.38	96	186
301	Building of ships and boats	150	0.20	38	112
303	Air and spacecraft and related machinery	184	0.25	96	88
31	Furniture	1285	1.74	146	1139
32	Other manufacturing	1106	1.50	142	964
33	Repair and installation of machinery and equipment	602	0.82	72	530
35, 36	Energy and water	588	0.80	386	202
37, 38, 39	Sanitation, waste management and decontamination	616	0.84	194	422
41, 42, 43	Construction	2112	2.87	898	1214
45, 46, 47	Commerce	4330	5.88	1383	2947
49, 50, 51, 52, 53	Transport and storage	1173	1.59	746	427
55, 56	Hostelry	362	0.49	263	99
61	Telecommunications	398	0.54	162	236
62	Programming, consultancy and other activities	4844	6.57	618	4226
58, 59, 60, 63	Other information services and communications	1628	2.21	374	1254
64, 65, 66	Financial and insurance activities	1628	2.21	1142	486
68	Real estate	218	0.30	54	164
72	R&D services	1278	1.73	90	1188
69, 70, 71, 73, 74, 75	Other activities	5526	7.50	845	4681
77, 78, 79, 80, 81, 82	Administrative and support service activities	1339	1.82	768	571
85 (exc. 854)	Education	337	0.46	35	302
86, 87, 88	Health activities and social services	1403	1.90	840	563
90, 91, 92, 93	Arts, entertainment and recreation activities	192	0.26	88	104
95, 96	Other services	589	0.80	95	494
	Total	73,692	100	18,405	55,287

collaborative agreements (Cohen and Levinthal, 1990; Kim, 1998). Following previous literature (Belderbos et al., 2004; Nieto and Santamaría, 2007) we proxy this variable through the ratio between total innovation expenditures and total sales. A further control variable relates to whether the firm has *formal IP*. By relying on formal IP mechanisms such as patents, trademarks, and copyrights firms translate (part of) their tacit knowledge into codified or explicit knowledge as filing for patents requires disclosure about the nature of the invention (Hall et al., 2014). Consequently, other firms, such as competitors, can more easily access this information. We added to our model a dummy variable taking value 1 if the focal firm has applied for patents, trademarks, or copyrights, else 0. Previous research has pointed out that firms that are *part of a group*, defined in the Oslo manual (OECD, 2005) as an association of enterprises bound together by legal or financial links, are expected to reduce their propensity to be engaged in (outside) collaborative agreements. The point is that those firms could obtain from the group the resources they need, not having to look for resources externally (Tether, 2002). We use a binary variable indicating whether an enterprise belongs to a group. This variable takes the value 1 if the company belongs to a group and 0 otherwise (Tether, 2002; Miotti and Sachwald, 2003). We include *institutional collaboration* (e.g. with universities) as a control variable as we expect this type of collaboration to be a valuable source of knowledge that may increase firms' propensity to collaborate with customers, suppliers and competitors. We also control for the *extent of internationalization*, because it could increase the technological needs of firms and hence, the predisposition to establish collaborative agreements (Galende and Suárez González, 1999). To proxy this variable, we use the propensity to export, that is the ratio between exports and sales (Nieto and Santamaría, 2007). Finally, we include a set of industry dummies, that classifies firms under study by sector according to the CNAE 2009 code, and time dummies, as the need for collaboration and the use of particular partner types may differ across industries and across years (Miotti and Sachwald, 2003; Auh and Menguc, 2005).

Our innovation performance model is estimated with and without the lagged dependent variable innovation performance. It can be seen as a control variable, since it is expected that firms' innovation performance is partly determined by its past innovation performance. Moreover, Carree et al. (2019) show that incorporation reduces concerns of reversed causality.

3.3. Descriptive statistics

Table 3 presents the descriptive statistics for the variables used in the estimation as well as their bivariate correlations. The correlations among the independent and control variables are never high, 0.4 or less in absolute terms, with the exception of the control variables *Size* and *Group* (0.488). VIF values are below 2 and, hence, well below the cut-off point of 10 (Chatterjee et al., 2000) implying that multicollinearity is not a concern. Additionally, we report that supplier collaboration is the most frequent type of R&D collaboration, with 17.1% of firms reporting collaboration with this type of partner, followed by customer collaboration (13% of firms) and competitor collaboration (8.7%). To be 'connected' with customers, suppliers and competitors is generally more frequently observed (11%, 13.6% and 5.5%, respectively) than to be 'detached' to them (1.9%, 3.6% and 3.2%, respectively), but observed much less frequently than to be 'informed' by them (47.1%, 44.2% and 36%, respectively).

3.4. Analysis

To test our hypotheses we estimate two models. First, a model in which we explain firms' propensity to engage in R&D collaboration with three different partner types, which is tested using a multivariate Probit model. The empirical model consists of a system of three equations, one for each type of partner and accounts for possible (contemporaneous) interdependencies between the establishment of collaborative agreements with customers, suppliers and competitors. The dependent variables are dichotomous and represent the propensity (likelihood) of collaboration with customers, suppliers and competitors. We estimate this non-linear model via simulated maximum likelihood using a multivariate Probit model.[9] Second, an innovation performance model, tested using a random effects panel Tobit model (Grimpe and Kaiser, 2010). Since the innovation performance variable is a doubled censored variable, representing the percentage of sales of products new to the market that, by definition, ranges between 0 and 100, an appropriate methodology is a Tobit regression (Greene, 2000). In addition, since the literature has found that variables that reflect the innovation performance of organizations may present problems of asymmetry and deviation from normality (Filippucci et al., 1996; Laursen and Salter, 2006), we have calculated the logarithmic transformation of the dependent variable. Following previous literature (Laursen and Salter, 2006), we create our final variable as: Innovation performance = ln (1 + share in turnover of "new to the market").

4. Results

Table 4 reports the results from the multivariate Probit model that explains the propensity of firms to engage in R&D collaboration with three different partner types.[10] Models 1, 2 and 3 are baseline models that include control variables only (measured in the previous period) impacting the probability to be engaged in R&D collaboration with each of the three types of partners (customers, suppliers, and competitors, respectively). Correlation coefficients (rho) of the error terms in the system of equations are positive, ranging from 0.410 to 0.764, and highly significant - in line with the notion of interdependency between the collaborations with the different partner types. Models 4, 5 and 6 introduce the direct effects of R&D collaboration with customers, suppliers and competitors in the previous period, without considering spillovers. These models are presented to show the extent to which the scenarios used in Models 7, 8 and 9 (of which they are restricted versions) improve our predictive power. The latter models are the full models used to test the hypotheses, including the effect of being connected, detached and informed[11] by customers, suppliers and competitors in the previous period, on the probability to be engaged in R&D collaboration with customers, suppliers and competitors. The likelihood ratio (LR) test shows a significant improvement in the fit of the model when including all variables. Hence, the full models are preferred.

4.1. Incoming knowledge spillovers as antecedent of R&D collaboration

4.1.1. Hypotheses 1a and 1b

Results in Models 7–9 in Table 4 indicate that firms that are *connected* with a specific partner type have a stronger propensity to collaborate with this specific partner type compared to firms that are *detached* to this partner type. When comparing estimated coefficients for different types of partners we observe that coefficients for *connected* exceed those for *detached* in magnitude. Model 7 shows for customers that the coefficients for *connected* and *detached* are $\beta = 1.979$ and $\beta = 1.730$, respectively. Model 8 shows for suppliers coefficients of $\beta = 1.796$ and $\beta = 1.662$, respectively. Model 9 shows for competitors coefficients of $\beta = 1.782$ and $\beta = 1.697$, respectively. All coefficients are significant at the 0.1% level. We used a Wald test to check whether the differences between the connected and detached coefficients are statistically significant and found that they are: customers: p-value = 0.000; suppliers: p-value = 0.000; competitors: p-value = 0.014. This provides support for hypothesis 1a. In line with hypothesis 1b, being *informed* by a specific partner type has a stronger effect on the propensity to collaborate with this specific partner type than being *extraneous* to this partner type (informed by customers: $\beta = 0.171$, $p < 0.001$; informed by suppliers: $\beta = 0.108$, $p < 0.001$; informed by competitors: $\beta = 0.104$, $p < 0.001$).

4.1.2. Hypotheses 2a and 2b

There is little evidence that being connected with one partner type has a stronger effect on the propensity to collaborate with *another* partner type vis-à-vis being detached (see Models 7–9, Table 4). One clear exception is that being connected with customers ($\beta = 0.262$, $p < 0.001$) appears to have a stronger effect on the propensity to collaborate with suppliers than being detached to customers ($\beta = 0.155$, $p < 0.001$). A Wald test also shows this difference to be significant. The results for the five other possible cross-partner type effects provide no further support for hypothesis 2a.

The results on being informed by one partner type having a more negative effect on the propensity to collaborate with *another* partner type vis-à-vis being extraneous are more clear-cut. In five out of six possible cross-partner type effects there is a significant negative effect of being informed. Being informed by suppliers ($\beta = -0.080$, $p < 0.001$) has a negative effect on the propensity to collaborate with customers compared to being extraneous to suppliers. Being informed by competitors ($\beta = -0.035$, $p < 0.1$) appears to reduce the propensity to collaborate with customers compared to being extraneous to competitors. Being informed by suppliers ($\beta = -0.057$, $p < 0.001$) has a negative effect on the propensity to collaborate with competitors compared to being extraneous to suppliers. Being informed by customers ($\beta = -0.030$, $p < 0.1$) appears to reduce the propensity to collaborate with suppliers compared to being extraneous to customers. Finally, being informed by customers ($\beta = -0.038$, $p < 0.1$) appears to reduce the propensity to collaborate with competitors compared to being extraneous to customers. The other cross-effect has an insignificant coefficient. Being informed by competitors ($\beta = 0.026$, $p > 0.1$) appears not to have a different effect on the propensity to collaborate with suppliers compared to being extraneous to competitors. These results imply that hypothesis 2b receives partial support as in the majority of cases, being informed reduces the likelihood of collaboration with other types.

[9] We apply Roodman's command cmp in Stata StataCorp. (2013). Stata Statistical Software: Release 13.

[10] We carried out the same analysis but including institutional partners as a fourth type, though not being a business partner. The results are available upon request but show that the effects for the three types of business partners as discussed are virtually identical.

[11] Extraneous is the left-out (base) category in the analysis.

4.2. Prior ties as antecedent of R&D collaboration

4.2.1. Hypotheses 3a and 3b

Our results for Models 4,5 and 6 in Table 4 already highlight that prior collaboration with customers, suppliers and competitors has a positive and significant effect on the propensity to collaborate with, respectively, customers, suppliers and competitors (prior collaboration with customers: $\beta = 1.826$, $p < 0.001$; prior collaboration with suppliers: $\beta = 1.704$, $p < 0.001$; prior collaboration with competitors: $\beta = 1.696$, $p < 0.001$). We now test our hypotheses 3a and 3b.

The results of Models 7, 8 and 9 indicate that firms that are *connected* with a specific partner type have a stronger propensity to collaborate with this specific partner type than firms that are *informed* by this partner type. Model 7 shows for customers that the coefficients for *connected* and *informed* are $\beta = 1.979$ and $\beta = 0.171$, respectively. Model 8 shows these coefficients for suppliers to be $\beta = 1.796$ and $\beta = 0.108$, respectively. Model 9 shows them for competitors to be $\beta = 1.782$ and $\beta = 0.104$, respectively. All coefficients are significant at the 0.1% level. We used a Wald test to check whether the differences between the connected and informed coefficients are statistically significant and found that they are in all cases (p-value = 0.000). Therefore, our hypothesis 3a receives support. Models 7–9 also show that being *detached* to a specific partner type has a stronger effect on the propensity to collaborate with this specific partner type than being *extraneous* to this partner type (detached to customers: $\beta = 1.730$, $p < 0.001$; detached to suppliers: $\beta = 1.662$, $p < 0.001$; detached to competitors: $\beta = 1.697$, $p < 0.001$). This supports our hypothesis 3b.

4.2.2. Hypotheses 4a and 4b

Our findings from Models 4, 5 and 6 indicate that prior collaboration with customers, suppliers and competitors has a positive and significant effect on the propensity to collaborate with other partner types (collaboration with customers: prior collaboration with suppliers: $\beta = 0.208$; prior collaboration with competitors: $\beta = 0.245$; collaboration with suppliers: prior collaboration with customers: $\beta = 0.260$; prior collaboration with competitors: $\beta = 0.161$; collaboration with competitors: prior collaboration with customers: $\beta = 0.223$; prior collaboration with suppliers: $\beta = 0.170$). All these effects are significant at the 0.1% level. We now turn to testing the two hypotheses 4a and 4b.

The results of Models 7, 8 and 9 show that firms that are *connected* with a specific partner type have a stronger propensity to collaborate with another partner type compared to firms that are *informed* by this specific partner type. In Model 7 we have that for customer collaboration the coefficient for connected with suppliers ($\beta = 0.161$, $p < 0.001$) exceeds that of informed by suppliers ($\beta = -0.080$, $p < 0.001$) and that for connected with competitors ($\beta = 0.241$, $p < 0.001$) exceeds that of informed by competitors ($\beta = -0.035$, $p < 0.1$). In Model 8 we find for supplier collaboration that the coefficient for connected with customers ($\beta = 0.262$, $p < 0.001$) is higher than that for informed by customers ($\beta = -0.030$, $p < 0.1$) and that for connected with competitors ($\beta = 0.166$, $p < 0.001$) is higher than that for informed by competitors ($\beta = 0.026$, $p > 0.1$). Likewise, Model 9 shows that for competitor collaboration the coefficient for connected with customers ($\beta = 0.192$, $p < 0.001$) exceeds that of informed by customers ($\beta = -0.038$, $p < 0.1$) and that connected with suppliers ($\beta = 0.131$, $p < 0.001$) exceeds that of informed by suppliers ($\beta = -0.057$, $p < 0.001$). We used a Wald test to check whether the differences between the connected and informed coefficients are statistically significant and found that they are in all cases (p-value = 0.000). This provides evidence for our hypothesis 4a.

Our results also show that being *detached* to a specific partner type has a stronger effect on the propensity to collaborate with other partner type than being *extraneous* to this specific partner type (collaboration with customers: detached to suppliers: $\beta = 0.174$, $p < 0.001$; detached to competitors: $\beta = 0.206$, $p < 0.001$; collaboration with suppliers: detached to customers: $\beta = 0.155$, $p < 0.001$; detached to competitors: $\beta = 0.199$, $p < 0.001$; collaboration with competitors: detached to customers: $\beta = 0.196$, $p < 0.001$; detached to suppliers: $\beta = 0.149$, $p < 0.001$). This supports our hypothesis 4b.

Most of the control variables have a significant effect. Prior institutional incoming spillovers and prior other sources incoming spillovers have a positive and significant effect on the propensity to be engaged in R&D collaboration with customers, suppliers and competitors. This result, which is consistent with other studies on Spanish firms using PITEC data, clearly emphasizes that information from institutional sources helps to develop the capacity to understand and utilize basic research and to better capture positive externalities generated by other partner types (Díez-Vial and Fernández-Olmos, 2014). Firm size and R&D intensity have a positive and significant influence on the propensity to be engaged in customer, supplier or competitor collaboration. Having formal IP mechanisms has a positive and significant effect on the propensity to be engaged in customer, supplier or competitor collaboration. Part of a group has also a positive and significant effect on the propensity to be engaged in customer or supplier collaboration, but not with competitors. Firms that belong to the same group are generally dedicated to similar activities, reducing the need to collaborate horizontally (outside the group). Collaboration with institutions has a positive and significant effect on the propensity to be engaged in customer, supplier or competitor collaboration. The development of international activities has a positive and significant effect on the propensity to be engaged in customer and supplier collaboration but has no significant effect on the propensity to collaborate with competitors. Time and industry dummy variables are jointly significant.

Table 5 reports the Tobit estimates for the innovation performance equation. We estimate two sets of models: one excluding and one including as the lagged innovation performance (as additional control variable). Model 1 and Model 4 are the baseline models that include the effect of the control variables in the previous period on innovation performance. Model 2 and Model 5 introduce the effects of R&D collaboration with customers, suppliers and competitors in the previous period, without considering spillovers. Model 3 and Model 6 are the full models, which include the effect of being connected, detached and informed[12] by customers, suppliers and competitors in the previous period on innovation performance. The likelihood ratio (LR) test shows a significant improvement in the fit of the models when including all variables. Hence, the full models are preferred. Additionally, this ratio shows that Model 6 has a better explanatory power compared with Model 3. Therefore, the results are going to be explained using Model 6 (though very close to those of Model 3). Most of the control variables have a significant effect on innovation performance, except being part of a group.

4.3. The effect of the four scenarios on innovation performance

4.3.1. Hypotheses 5a and 5b

The results in Model 6 show that there is no evidence that firms being connected with one partner type have a superior innovation performance compared with being detached to this partner type (connected with customers: $\beta = 0.038$, $p < 0.001$; detached to customers: $\beta = 0.036$, $p < 0.001$; connected with suppliers: $\beta = 0.007$, $p > 0.1$; detached to suppliers: $\beta = 0.016$, $p < 0.05$; connected with competitors: $\beta = 0.015$, $p < 0.05$; detached to competitors: $\beta = 0.018$, $p < 0.05$). A Wald test shows that the difference for customers is not significant. Therefore, our hypothesis 5a is rejected. Our results also show that there is little evidence that firms' being informed by one partner type have a superior performance than those being extraneous to this specific partner type. The exception is found for customers (informed by customers: $\beta = 0.037$, $p < 0.001$; informed by suppliers: $\beta = -0.012$, $p < 0.001$; informed by competitors: $\beta = 0.001$, $p > 0.1$). Therefore, our hypothesis 5b finds little support, only for collaboration with customers.

[12] Extraneous is the left-out (base) category in the analysis.

Table 3
Descriptive statistics and correlation matrix (n = 73,692).

Variables	Mean	Std. Dev.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
Collaboration with customers (t)	0.130	0.336	1																								
Collaboration with suppliers (t)	0.171	0.37	0.435	1																							
Collaboration with competitors (t)	0.087	0.282	0.352	0.286	1																						
Innovation performance (t)	0.087	0.282	0.102	0.055	0.062	1																					
Connected customer (t-1)	0.110	0.313	0.620	0.310	0.259	0.082	1																				
Detached customer (t-1)	0.019	0.138	0.201	0.091	0.087	0.022	−0.049	1																			
Informed customer (t-1)	0.471	0.499	−0.212	−0.106	−0.084	0.048	−0.332	−0.133	1																		
Connected supplier (t-1)	0.136	0.343	0.279	0.558	0.196	0.036	0.354	0.086	−0.112	1																	
Detached supplier (t-1)	0.036	0.186	0.139	0.23	0.099	0.027	0.150	0.122	−0.094	−0.077	1																
Informed supplier (t-1)	0.442	0.496	−0.138	−0.2324	−0.097	−0.014	−0.163	−0.080	0.295	−0.353	−0.172	1															
Connected competitor (t-1)	0.055	0.229	0.259	0.203	0.487	0.056	0.305	0.047	−0.070	0.222	0.084	−0.092	1														
Detached competitor (t-1)	0.032	0.177	0.124	0.105	0.313	0.022	0.112	0.131	−0.085	0.089	0.094	−0.070	−0.044	1													
Informed competitor (t-1)	0.360	0.480	−0.012	0.002	−0.111	0.025	0.007	−0.071	0.389	0.010	−0.040	0.220	−0.182	−0.138	1												
R&D intensity (t-1)	0.058	0.132	0.161	0.032	0.128	0.159	0.158	0.049	0.005	0.014	0.038	−0.031	0.111	0.068	0.013	1											
Size (t-1)	4.226	1.594	0.070	0.206	0.099	−0.057	0.063	0.009	−0.059	0.194	0.044	−0.021	0.094	0.028	−0.003	−0.286	1										
Exports (t-1)	0.220	0.295	0.070	0.056	0.008	0.039	0.082	−0.009	0.050	0.052	0.012	−0.011	0.021	−0.011	0.053	−0.051	0.102	1									
Group (t-1)	0.432	0.495	0.084	0.139	0.058	−0.027	0.081	0.018	−0.041	0.126	0.039	−0.035	0.064	0.006	0.013	−0.125	0.488	0.141	1								
Institutional incoming spillover (t-1)	0.019	1.009	0.218	0.169	0.202	0.067	0.212	0.056	0.003	0.154	0.066	−0.019	0.187	0.093	0.076	0.177	0.063	0.061	0.085	1							
Other sources incoming spillover (t-1)	0.043	0.996	0.118	0.101	0.109	0.084	0.141	0.005	0.245	0.132	−0.004	0.188	0.136	0.016	0.288	0.088	0.027	0.035	0.008	−0.029	1						
Formal IP (t-1)	0.302	0.459	0.093	0.098	0.081	0.112	0.096	0.013	0.051	0.097	0.032	−0.007	0.085	0.022	0.067	0.071	0.069	0.074	0.031	0.100	0.141	1					
Collaboration with Institutions (t-1)	0.248	0.431	0.353	0.299	0.293	0.091	0.385	0.147	−0.120	0.316	0.160	−0.174	0.291	0.190	−0.028	0.182	0.075	0.067	0.081	0.465	0.108	0.142	1				
Innovation performance (t-1)	0.087	0.172	0.092	0.045	0.054	0.582	0.094	0.025	0.051	0.040	0.033	−0.011	0.058	0.023	0.027	0.166	−0.069	0.042	−0.031	0.070	0.093	0.116	0.097	1			
Collaboration with customers (t-1)	0.129	0.336	0.661	0.327	0.277	0.086	0.910	0.366	−0.364	0.365	0.190	−0.185	0.304	0.159	−0.022	0.167	0.062	0.073	0.083	0.221	0.134	0.095	0.420	0.0986	1		
Collaboration with suppliers (t-1)	0.172	0.377	0.323	0.624	0.227	0.046	0.396	0.139	0.1492	0.870	0.424	−0.406	0.243	0.128	−0.010	0.031	0.198	0.054	0.134	0.172	0.118	0.104	0.366	0.0532	0.4264	1	
Collaboration with competitors (t-1)	0.088	0.284	0.287	0.230	0.590	0.059	0.318	0.120	−0.110	0.236	0.127	−0.119	0.781	0.589	−0.234	0.132	0.094	0.009	0.055	0.210	0.120	0.083	0.355	0.0619	0.3459	0.2773	1

Table 4
Multivariate Probit models of the propensity to have collaborative agreements.

Dependent Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
	Customer	Supplier	Competitor	Customer	Supplier	Competitor	Customer	Supplier	Competitor
R&D intensity	0.796***	0.450***	0.599***	0.489***	0.365***	0.399***	0.479***	0.366***	0.393***
	(0.052)	(0.054)	(0.056)	(0.060)	(0.061)	(0.064)	(0.060)	(0.061)	(0.064)
Size	0.061***	0.151***	0.094***	0.036***	0.102***	0.059***	0.038***	0.099***	0.059***
	(0.005)	(0.004)	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)
Exports	0.124***	0.060***	0.045*	0.079***	0.043*	0.040	0.068**	0.044*	0.038
	(0.023)	(0.021)	(0.027)	(0.027)	(0.024)	(0.030)	(0.027)	(0.025)	(0.031)
Group	0.136***	0.099***	−0.020	0.080***	0.060***	−0.024	0.080***	0.060***	−0.027
	(0.015)	(0.013)	(0.017)	(0.017)	(0.015)	(0.019)	(0.017)	(0.015)	(0.019)
Institutional incoming spillover	0.096***	0.055***	0.133***	0.101***	0.063***	0.114***	0.096***	0.057***	0.111***
	(0.007)	(0.006)	(0.007)	(0.008)	(0.007)	(0.008)	(0.008)	(0.007)	(0.008)
Other sources incoming spillover	0.136***	0.109***	0.149***	0.060***	0.043***	0.081***	0.050***	0.028***	0.077***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.007)	(0.009)
Formal IP	0.081***	0.128***	0.081***	0.052***	0.079***	0.057***	0.046***	0.078***	0.055***
	(0.014)	(0.012)	(0.015)	(0.016)	(0.014)	(0.017)	(0.016)	(0.014)	(0.017)
Institutional t-1	0.907***	0.778***	0.770***	0.252***	0.173***	0.235***	0.250***	0.183***	0.234***
	(0.015)	(0.014)	(0.016)	(0.019)	(0.017)	(0.021)	(0.019)	(0.017)	(0.021)
Connected customer t-1							1.979***	0.262***	0.192***
							(0.024)	(0.023)	(0.028)
Detached customer t-1							1.730***	0.155***	0.196***
							(0.038)	(0.041)	(0.046)
Informed customer t-1							0.171***	−0.030*	−0.038*
							(0.020)	(0.017)	(0.021)
Connected supplier t-1							0.161***	1.796***	0.131***
							(0.023)	(0.020)	(0.025)
Detached supplier t-1							0.174***	1.662***	0.149***
							(0.034)	(0.029)	(0.037)
Informed supplier t-1							−0.080***	0.108***	−0.057***
							(0.018)	(0.017)	(0.020)
Connected competitor t-1							0.241***	0.166***	1.782***
							(0.028)	(0.028)	(0.027)
Detached competitor t-1							0.206***	0.199***	1.697***
							(0.034)	(0.033)	(0.030)
Informed competitor t-1							−0.035*	0.026	0.104***
							(0.018)	(0.016)	(0.021)
Customers t-1				1.826***	0.260***	0.223***			
				(0.018)	(0.019)	(0.022)			
Suppliers t-1				0.208***	1.704***	0.170***			
				(0.019)	(0.015)	(0.021)			
Competitors t-1				0.245***	0.161***	1.696***			
				(0.022)	(0.022)	(0.020)			
Constant	−2.365***	−2.301***	−2.244***	−2.291***	−2.167***	−2.205***	−2.313***	−2.195***	−2.201***
	(0.064)	(0.059)	(0.065)	(0.074)	(0.066)	(0.073)	(0.075)	(0.066)	(0.074)
Rho2	0.752***			0.759***			0.764***		
	(0.010)			(0.012)			(0.012)		
Rho3	0.545***	0.438***		0.502***	0.410***		0.505***	0.412***	
	(0.011)	(0.010)		(0.013)	(0.012)		(0.013)	(0.012)	
Number of observations	73,692			73,692			73,692		
Log likelihood	−64,733.936			−48,049.315			−47,923.5		
Chi squared	20,362.73			53,731.97			53,983.60		

Industry dummies and years dummies included. Robust standard errors in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

4.3.2. *Hypotheses 6a and 6b*

Firms' being connected with suppliers or competitors are found to obtain a superior innovation performance compared with being informed by suppliers or competitors, respectively (connected with customers: $\beta = 0.038$, $p < 0.001$; informed by customers: $\beta = 0.037$, $p < 0.001$; connected with suppliers: $\beta = 0.007$, $p > 0.1$; informed by suppliers: $\beta = -0.012$, $p < 0.01$; connected with competitors: $\beta = 0.015$, $p < 0.05$; informed by competitors: $\beta = -0.001$, $p > 0.1$). A Wald test shows that the difference for customers is not significant while the differences for suppliers and competitors are. This provides partial support for our hypothesis 6a. Our results show that firms' being detached to a specific partner type have a superior innovation performance compared with being extraneous to this partner type (detached to customers: $\beta = 0.037$, $p < 0.001$; detached to suppliers: $\beta = 0.016$, $p < 0.05$; detached to competitors: $\beta = 0.018$, $p < 0.05$). This provides support for our hypothesis 6b.

5. Additional analyses

We performed additional analyses to further explore the interplay between prior collaboration and the incoming knowledge spillovers. First, to confirm the robustness of our results, we repeated our analysis in the sub-sample of manufacturing firms. Second, we investigate whether spillovers occur more in certain geographical areas (science and technology parks) and whether they occur more when firms expand their R&D staff. Third, to account for the fact that the PITEC survey suffers from an overlap between waves, since some variables are related to a three-year period, we carried out the multivariate Probit analysis using a sample without any overlap in the measurement period.

Table 5
Random effects Tobit models for the effects of the three scenarios on innovation performance (New to the market).

Dependent Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	New to the market	New to the market	New to the market	New to the market	New to the market	New to the market
R&D intensity	0.233*** (0.015)	0.228*** (0.015)	0.225*** (0.015)	0.164*** (0.013)	0.160*** (0.013)	0.157*** (0.013)
Size	0.004* (0.002)	0.003 (0.002)	0.003 (0.002)	0.005*** (0.001)	0.004*** (0.001)	0.005*** (0.001)
Exports	0.036*** (0.007)	0.036*** (0.007)	0.035*** (0.007)	0.026*** (0.006)	0.025*** (0.006)	0.024*** (0.006)
Group	0.005 (0.005)	0.005 (0.005)	0.005 (0.005)	0.006 (0.004)	0.006 (0.004)	0.006 (0.004)
Institutional incoming spillover	0.013*** (0.001)	0.012*** (0.001)	0.010*** (0.002)	0.010*** (0.001)	0.009*** (0.001)	0.008*** (0.001)
Other sources incoming spillover	0.025*** (0.001)	0.023*** (0.001)	0.019*** (0.001)	0.019*** (0.001)	0.018*** (0.001)	0.014*** (0.001)
Innovation performance t-1				0.707*** (0.008)	0.707*** (0.008)	0.706*** (0.008)
Formal IP	0.059*** (0.003)	0.058*** (0.003)	0.057*** (0.003)	0.048*** (0.003)	0.047*** (0.003)	0.047*** (0.003)
Institutional t-1	0.050*** (0.004)	0.037*** (0.004)	0.037*** (0.004)	0.039*** (0.003)	0.029*** (0.004)	0.029*** (0.004)
Connected customer t-1			0.048*** (0.006)			0.038*** (0.005)
Detached customer t-1			0.050*** (0.010)			0.037*** (0.009)
Informed customer t-1			0.044*** (0.004)			0.037*** (0.003)
Connected supplier t-1			0.007 (0.005)			0.007 (0.005)
Detached supplier t-1			0.025*** (0.008)			0.016** (0.007)
Informed supplier t-1			−0.012*** (0.003)			−0.012*** (0.003)
Connected competitor t-1			0.021*** (0.007)			0.015** (0.006)
Detached competitor t-1			0.018** (0.008)			0.018** (0.007)
Informed competitor t-1			−0.001 (0.003)			−0.001 (0.003)
Customers t-1		0.018*** (0.005)			0.012*** (0.004)	
Suppliers t-1		0.019*** (0.004)			0.016*** (0.004)	
Competitors t-1		0.020*** (0.005)			0.017*** (0.005)	
Constant	−0.315*** (0.030)	−0.312*** (0.030)	−0.325*** (0.030)	−0.290*** (0.021)	−0.287*** (0.021)	−0.297*** (0.021)
Number of observations	73,692	73,692	73,692	73,692	73,692	73,692
Log likelihood	−29,554.848	−29,523.98	−29,460.004	−25,953.443	−25,929.906	−25,874.966
Chi squared	2250.35	2310.62	2431.76	9202.70	9251.53	9348.42

Industry dummies and years dummies included. Robust standard errors in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01.

5.1. *Manufacturing firms*

Table 6 reports the results from the multivariate Probit model that explains the propensity of firms to engage in R&D collaboration with three different partner types for manufacturing firms. As can be seen in the table, the conclusions that can be derived are unchanged as the findings obtained are equivalent to our main results that are shown in Table 4. This result provides consistency and demonstrates that our findings are robust. The results displayed in Table 7 for the innovation performance Tobit model are also very close to those in Table 5. The one exception is that the results for collaboration with competitors (‘connected’ and ‘detached’) are not significant anymore in Table 7. Hence, for the manufacturing subset there is less support for hypothesis 6a/b compared to using the complete dataset. Apparently, collaboration in manufacturing industries is far from a guarantee for increased innovation performance.

5.2. *Science and technology parks and hiring R&D staff*

Firms can obtain valuable knowledge spillovers even without establishing collaborative agreements (Aldieri and Cincera, 2009; Filatotchev et al., 2011; Belenzon and Schankerman, 2013; Inkpen et al., 2019; Belderbos and Mohnen, 2020). These spillovers go beyond ‘public knowledge’ and require specific channels to pass into the organization. There are several possible channels for such knowledge leakage and here we concentrate on employee mobility and co-location. The interaction between firms facilitates learning and lead them to create knowledge collectively (Moran, 2005). We further investigate whether knowledge gains are stronger when the two potential channels of knowledge spillovers are present. The first variable measures whether a firm is located in a science or technology park. Being located in science and technology parks has been found to constitute an important vehicle of knowledge spillovers (Diez-Vial and Fernández-Olmos, 2015 and 2017). The second variable measures whether a firm increases its R&D staff (also a binary variable, 1 = yes, 0 = no). The idea is that incoming R&D staff is often attracted from other firms making it more likely to also benefit from knowledge from where they came from (Castillo et al., 2020).

The data for these two variables are not available for the entire period, so we did not include them in the main analysis. But they are available for the majority of observations (51,568 to be precise) and we can tabulate in Table 8 the correlations between the two variables and the four scenarios. Location in the geographic space and its R&D staff additions appear to matter for the amount and value of the obtained spillovers, especially so for customers and competitors.

5.3. *Overlap*

Following the design of the CIS questionnaire, in the PITEC survey some variables are collected retrospectively over a three-year period, that is, companies are asked about their innovation activities in the last three years. This specific characteristic of the dataset may have consequences on the precision of the longitudinal information we use for the empirical analysis (D’Este, Marzucchi and Rentocchini, 2017) since the way the survey proceeds generates an overlap between waves (D’Este, Marzucchi and Rentocchini, 2017; Pellegrino, 2018).

Previous research on this issue utilizing CIS based panels (for example, Raymond et al., 2010) claims that the overlap does not substantially alter the results. They have found that the effect of the overlap is not important, arguing that its magnitude is not sufficient to consider that the results are driven by the overlapping effect. In a similar vein, Clausen and Pohjola (2013) argued that the overlap is a minor issue. In any case, and in the spirit of providing additional consistency to our results, we take this issue into account in the analysis. In our case, the questions pertaining to collaboration, incoming knowledge spillovers and innovation performance are related to a three-year window. The overlap for collaboration could be especially important since it involves both dependent and independent variable in our hypotheses 3a/b. Our first strategy to deal with the overlapping issue is to introduce appropriate time dummies as controls (Clausen and Pohjola, 2013). The results are those already commented upon and shown in Table 4. Our second strategy is to repeat the analysis using a sample without any overlap in the period (i.e. we have considered four waves: 2004 (which contains information about 2003 and 2004), 2007 (which contains information about 2005, 2006 and 2007), 2010 (which contains

Table 6
Multivariate Probit models of the propensity to have collaborative agreements for manufacturing firms.

Dependent Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
	Customer	Supplier	Competitor	Customer	Supplier	Competitor	Customer	Supplier	Competitor
R&D intensity	1.107***	0.536***	1.013***	0.794***	0.460***	0.770***	0.775***	0.458***	0.752***
	(0.100)	(0.103)	(0.116)	(0.117)	(0.117)	(0.132)	(0.117)	(0.117)	(0.132)
Size	0.060***	0.167***	0.102***	0.047***	0.114***	0.066***	0.048***	0.112***	0.064***
	(0.008)	(0.007)	(0.009)	(0.009)	(0.008)	(0.010)	(0.009)	(0.008)	(0.010)
Exports	0.179***	0.103***	0.082**	0.108***	0.061**	0.057	0.099***	0.060**	0.054
	(0.028)	(0.026)	(0.034)	(0.033)	(0.030)	(0.038)	(0.033)	(0.030)	(0.039)
Group	0.208***	0.120***	0.050**	0.116***	0.071***	0.030	0.118***	0.073***	0.029
	(0.020)	(0.018)	(0.024)	(0.023)	(0.020)	(0.027)	(0.023)	(0.020)	(0.027)
Institutional incoming spillover	0.090***	0.066***	0.125***	0.103***	0.080***	0.113***	0.100***	0.070***	0.108***
	(0.000)	(0.008)	(0.010)	(0.010)	(0.009)	(0.012)	(0.011)	(0.010)	(0.012)
Other sources incoming spillover	0.134***	0.110***	0.141***	0.057***	0.048***	0.073***	0.046***	0.025***	0.058***
	(0.009)	(0.008)	(0.010)	(0.010)	(0.009)	(0.012)	(0.011)	(0.010)	(0.013)
Formal IP	0.029*	0.088***	0.068***	0.014	0.058***	0.054**	0.011	0.056***	0.049**
	(0.018)	(0.016)	(0.021)	(0.021)	(0.018)	(0.024)	(0.021)	(0.019)	(0.024)
Institutional t-1	0.937***	0.860***	0.720***	0.270***	0.218***	0.213***	0.270***	0.229***	0.215***
	(0.019)	(0.018)	(0.023)	(0.024)	(0.022)	(0.029)	(0.024)	(0.022)	(0.029)
Connected customer t-1							2.039***	0.326***	0.266***
							(0.033)	(0.031)	(0.039)
Detached customer t-1							1.756***	0.195***	0.219***
							(0.054)	(0.059)	(0.070)
Informed customer t-1							0.178***	0.008	−0.008
							(0.027)	(0.023)	(0.031)
Connected supplier t-1							0.189***	1.799***	0.156***
							(0.031)	(0.026)	(0.036)
Detached supplier t-1							0.210***	1.656***	0.134**
							(0.047)	(0.040)	(0.055)
Informed supplier t-1							−0.039	0.109***	−0.021
							(0.025)	(0.023)	(0.030)
Connected competitor t-1							0.155***	0.131***	1.771***
							(0.041)	(0.039)	(0.039)
Detached competitor t-1							0.134***	0.118**	1.674***
							(0.052)	(0.050)	(0.046)
Informed competitor t-1							−0.065***	0.029	0.107***
							(0.023)	(0.021)	(0.029)
Customers t-1				1.875***	0.300***	0.268***			
				(0.025)	(0.025)	(0.031)			
Suppliers t-1				0.218***	1.705***	0.170***			
				(0.025)	(0.021)	(0.029)			
Competitors t-1				0.182***	0.110***	1.676***			
				(0.032)	(0.031)	(0.029)			
Constant	−2.111***	−1.804***	−1.248***	−2.405***	−2.018***	−1.868***	−2.473***	−2.082***	−1.869***
	(0.271)	(0.261)	(0.269)	(0.344)	(0.310)	(0.301)	(0.347)	(0.312)	(0.303)
Rho2	0.817***			0.821***			0.825***		
	(0.013)			(0.016)			(0.016)		
Rho3	0.559***	0.454***		0.513***	0.427***		0.514***	0.427***	
	(0.015)	(0.014)		(0.018)	(0.017)		(0.018)	(0.017)	
Number of observations	43,842			43,842			43,842		
Log likelihood	−36,089.165			−26,660.586			−26,590.949		
Chi squared	10,372.89			29,230.05			29,369.33		

Industry dummies and years dummies included. Robust standard errors in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01.

information about 2008, 2009 and 2010), 2013 (which contains information about 2011, 2012 and 2013) and 2016 (which contains information about 2014, 2015 and 2016). In Table 9 we observe that the estimated effects are largely consistent with our main results, suggesting limited bias, although reduced standard errors, due to the overlapping of time periods in relevant PITEC questions.

6. Conclusion and discussion

This paper empirically tests a dynamic model of collaboration based on the interplay between prior R&D collaboration and incoming knowledge spillovers, with particular emphasis on the study of how firms restructure the set of partnerships with which they link with the aim of ensuring that collaboration for innovation remains beneficial. Despite the increasing importance and the growing attention devoted to knowledge spillovers in both theory and practice, most prior investigations have taken a more static view linking spillovers to collaboration (Belderbos et al., 2004; Lopez, 2008; Chun and Mun, 2012). This has limited our understanding of how knowledge spillovers influence firms' need to adapt their partnerships over time (Dittrich and Duysters, 2007). In contrast with most prior studies (Laursen and Salter, 2006; Bahemia and Squire, 2010), we take a more dynamic point of view and propose that the relevance of incoming knowledge spillovers, together with prior R&D collaboration, prone firms to re-assess and restructure their portfolios. Empirically, we draw on yearly panel data of Spanish firms, for the period 2004–2016. Our analysis shows that the propensity to be engaged in R&D collaboration with a particular type of partner depends on the type of partner for which firms have access to incoming spillovers, their level of relevance and also on their prior collaborative behavior.

Table 7
Random effects Tobit models for the effects of the three scenarios on innovation performance for manufacturing firms.

Dependent Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	New to the market	New to the market	New to the market	New to the market	New to the market	New to the market
R&D intensity	0.266*** (0.028)	0.264*** (0.028)	0.259*** (0.028)	0.230*** (0.025)	0.228*** (0.025)	0.224*** (0.025)
Size	0.016*** (0.003)	0.015*** (0.003)	0.015*** (0.003)	0.015*** (0.002)	0.015*** (0.002)	0.015*** (0.002)
Exports	0.015** (0.009)	0.015* (0.009)	0.014 (0.009)	0.012 (0.007)	0.012 (0.007)	0.010 (0.007)
Group	0.004 (0.006)	0.004 (0.006)	0.003 (0.006)	0.003 (0.005)	0.003 (0.005)	0.003 (0.005)
Institutional incoming spillover	0.009*** (0.002)	0.009*** (0.002)	0.007*** (0.002)	0.007*** (0.002)	0.006*** (0.002)	0.005** (0.002)
Other sources incoming spillover	0.020*** (0.002)	0.019*** (0.002)	0.014*** (0.002)	0.015*** (0.002)	0.014*** (0.002)	0.010*** (0.002)
Innovation performance t-1				0.676*** (0.010)	0.675*** (0.010)	0.675*** (0.010)
Formal IP	0.057*** (0.004)	0.056*** (0.004)	0.056*** (0.004)	0.049*** (0.004)	0.049*** (0.004)	0.048*** (0.004)
Institutional t-1	0.036*** (0.005)	0.028*** (0.005)	0.028*** (0.005)	0.031*** (0.004)	0.025*** (0.005)	0.025*** (0.005)
Connected customer t-1			0.044*** (0.008)			0.037*** (0.007)
Detached customer t-1			0.040*** (0.014)			0.035*** (0.013)
Informed customer t-1			0.041*** (0.005)			0.035*** (0.004)
Connected supplier t-1			0.005 (0.007)			0.005 (0.006)
Detached supplier t-1			0.032*** (0.010)			0.018* (0.009)
Informed supplier t-1			−0.003 (0.004)			−0.003 (0.004)
Connected competitor t-1			0.012 (0.009)			0.004 (0.009)
Detached competitor t-1			0.003 (0.012)			−0.002 (0.011)
Informed competitor t-1			−0.002 (0.004)			−0.002 (0.004)
Customers t-1		0.013** (0.006)			0.011* (0.006)	
Suppliers t-1		0.013*** (0.006)			0.010* (0.005)	
Competitors t-1		0.008 (0.007)			0.002 (0.007)	
Constant	−0.273*** (0.160)	−0.279*** (0.159)	−0.292*** (0.159)	−0.254*** (0.110)	−0.257*** (0.110)	−0.269*** (0.109)
Number of observations	43,842	43,842	43,842	43,842	43,842	43,842
Log likelihood	−17,414.615	−17,406.735	−17,368.807	−15,329.159	−15,323.736	−15,292.251
Chi squared	985.03	1000.54	1072.94	4950.48	4959.37	5011.94

Table 8
Correlations between the four scenarios and Business Park and R&D Hiring.

	Customer			
	Connected	Detached	Informed	Extraneous
Business Park	0.1422	0.0170	−0.0195	−0.0778
R&D Hiring	0.1194	0.0382	0.0348	−0.1235
	Supplier **Connected**	**Detached**	**Informed**	**Extraneous**
Business Park	0.0440	0.0361	−0.0266	−0.0181
R&D Hiring	0.0889	0.0363	−0.0056	−0.0704
	Competitor **Connected**	**Detached**	**Informed**	**Extraneous**
Business Park	0.1328	0.0400	−0.0037	−0.0754
R&D Hiring	0.0993	0.0540	0.0438	−0.1086

Our results for the four scenarios for the effects related to a specific partner type on embarking or continuing cooperation with *that* type can be summarized as follows. For each of customer, supplier and competitor collaboration we have that being ‘connected’ has the strongest positive effect, quickly followed by being ‘detached’, and ‘informed’ still having a more positive effect than ‘extraneous’. Our results for the effects on embarking or continuing cooperation with *another* type are in short as follows. Being ‘connected’ and being ‘detached’ appear to have an equally positive effect. The one exception is the effect of customer partner type on (future) collaborating with suppliers, where being ‘connected’ displays a stronger effect. Being ‘informed’ appears to reduce collaboration with other partner types (when compared to the ‘extraneous’ basis scenario) when the other type is either customer or competitor collaboration. This result does not extend towards supplier collaboration where being ‘informed’ or ‘extraneous’ have similar (no) effects.

Firms having access to relevant incoming spillovers from a specific type of partner lead them to perceive potential benefits and gains deriving from collaboration with this partner type, thus being more likely to collaborate with this type of partner. Relevant incoming spillovers act as a conduit for R&D collaboration. We also observe that, compared with detached firms, only connected firms with customers are more likely to collaborate with a different type of partner, in particular with suppliers. This may mean that obtaining relevant incoming spillovers from customers plays a key role for firms that have collaborated with this type of partner to decide to collaborate with suppliers. This is consistent with the idea that supplier collaboration offers a large amount of potential advantages of integration between value chain partners (Frohlich and Westbrook, 2001). Such integration enhances coordination and facilitates understanding along value chain steps, preventing mistakes and delays.

An interesting and hypothesized pattern for ‘informed’ firms by a specific partner type gained (at least some) empirical support. They are less likely to collaborate with a *different* type of partner, compared with ‘extraneous’ firms. This highlights that, in the absence of prior collaboration, obtaining relevant incoming spillovers makes firms hesitate to turn their attention towards other possible types of collaboration, with the important exception of suppliers. This reinforces the idea that collaboration with suppliers is seen as a source of complementarity effects and potential benefits. Supplier collaboration is (double) more prevalent than competitor collaboration.

By collaborating with competitors, firms are exposed to risks related to information leakage and opportunistic behaviors (Un and Rodríguez, 2018). The paradox is that knowledge exchanged when firms collaborate with rivals could be used in both collaboration and in competition (Atallah, 2002; Oxley and Sampson, 2004; Laursen and Salter, 2014). There is always an inherent risk of opportunistic behavior, since partners could first collaborate to jointly create value and then individually compete for the created value (Ritala and Hurmelinna-Laukkanen, 2013). This potential problem is aggravated because, as collaborating partners are in the same industry, they are quite capable of understanding each other’s technology and knowledge, being able to easily internalize it (Cassiman and Veugelers, 2002). Hence, firms that have been benefiting from relevant incoming spillovers from competitors may hesitate to also cooperate with them, since they may be satisfied with the knowledge obtained without running the increased risk of collaboration. Despite such claims, we fail to find sizeable differences between the effect of the scenarios on competitor collaboration versus customer and supplier collaboration. Also for competitors, being ‘informed’ increases

Table 9
Multivariate Probit models of the propensity to have collaborative agreements without overlap (t-1 is three years before).

Dependent Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
	Customer	Supplier	Competitor	Customer	Supplier	Competitor	Customer	Supplier	Competitor
R&D intensity	0.760***	0.594***	0.763***	0.622***	0.550***	0.629***	0.614***	0.552***	0.624***
	(0.093)	(0.096)	(0.100)	(0.098)	(0.100)	(0.104)	(0.098)	(0.100)	(0.104)
Size	0.083***	0.177***	0.113***	0.063***	0.142***	0.086***	0.065***	0.141***	0.086***
	(0.009)	(0.008)	(0.010)	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)	(0.010)
Exports	0.152***	0.099**	0.100**	0.117***	0.080*	0.088*	0.106**	0.080*	0.078
	(0.043)	(0.040)	(0.050)	(0.045)	(0.042)	(0.051)	(0.045)	(0.042)	(0.052)
Group	0.152***	0.111***	−0.015	0.125***	0.090***	−0.007	0.123***	0.089***	−0.0411
	(0.027)	(0.025)	(0.030)	(0.028)	(0.026)	(0.031)	(0.028)	(0.026)	(0.031)
Institutional incoming spillover	0.110***	0.070***	0.135***	0.103***	0.068***	0.118***	0.100***	0.066***	0.117***
	(0.012)	(0.011)	(0.013)	(0.013)	(0.012)	(0.014)	(0.013)	(0.012)	(0.014)
Other sources incoming spillover	0.106***	0.094***	0.101***	0.062***	0.050***	0.057***	0.056***	0.045***	0.056***
	(0.012)	(0.011)	(0.013)	(0.012)	(0.011)	(0.014)	(0.014)	(0.012)	(0.015)
Formal IP	0.105***	0.115***	0.082***	0.084***	0.076***	0.052*	0.078***	0.076***	0.050*
	(0.024)	(0.023)	(0.028)	(0.026)	(0.024)	(0.029)	(0.026)	(0.024)	(0.029)
Institutional t-1	0.728***	0.610***	0.626***	0.314***	0.203***	0.300***	0.313***	0.208***	0.297***
	(0.027)	(0.026)	(0.030)	(0.031)	(0.029)	(0.034)	(0.031)	(0.030)	(0.034)
Connected customer t-1							1.165***	0.287***	0.227***
							(0.040)	(0.040)	(0.046)
Detached customer t-1							0.835***	0.138*	0.042
							(0.069)	(0.071)	(0.082)
Informed customer t-1							0.107***	−0.023	−0.005
							(0.032)	(0.028)	(0.035)
Connected supplier t-1							0.099***	0.991***	0.107**
							(0.038)	(0.034)	(0.042)
Detached supplier t-1							0.067	0.864***	0.067
							(0.057)	(0.052)	(0.063)
Informed supplier t-1							−0.077**	0.050**	−0.083**
							(0.030)	(0.028)	(0.034)
Connected competitor t-1							0.227***	0.146***	0.980***
							(0.047)	(0.047)	(0.047)
Detached competitor t-1							0.160***	0.173***	0.803***
							(0.058)	(0.057)	(0.057)
Informed competitor t-1							−0.028	−0.002	0.037
							(0.029)	(0.027)	(0.034)
Customers t-1				1.045***	0.277***	0.211***			
				(0.032)	(0.033)	(0.037)			
Suppliers t-1				0.135***	0.935***	0.147***			
				(0.032)	(0.028)	(0.035)			
Competitors t-1				0.218***	0.158***	0.897***			
				(0.037)	(0.037)	(0.036)			
Constant	−2.360***	−2.475***	−2.180***	−2.252***	−2.337***	−2.076***	−2.232***	−2.332***	−2.044***
	(0.108)	(0.105)	(0.107)	(0.113)	(0.109)	(0.110)	(0.114)	(0.110)	(0.111)
Rho2	0.801***			0.790***			0.791***		
	(0.019)			(0.020)			(0.020)		
Rho3	0.593***	0.503***		0.558***	0.482***		0.556***	0.482***	
	(0.020)	(0.019)		(0.021)	(0.020)		(0.021)	(0.020)	
Number of observations	20,925			20,925			20,925		
Log likelihood	−19,533.984			−17,947.371			−17,911.467		
Chi squared	5338.16			8511.39			8583.20		

Industry dummies and years dummies included. Robust standard errors in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

the likelihood for competitor cooperation more than being 'extraneous'.

We confirm the key role that prior collaboration with a specific type of partner plays on the propensity to collaborate with this type of partner, regardless of the relevance of incoming spillovers of this type of partner. This result explains the clear trend of firms towards persistence in collaboration, being considered as the most common pattern of collaboration (Belderbos et al., 2015). Finally, we found that prior collaboration with a specific partner, regardless of the relevance of incoming spillovers of this type of partner, also plays a crucial role for the propensity to collaborate with different partner types. This result highlights the potential complementarities that firms perceive from collaboration with different partner types and learning effects in cooperation. Our simultaneous equations analysis clearly shows how collaborative agreements between different partner types tend to be interrelated.

This study has some managerial implications. Those are mainly linked to the innovation performance results. Cooperation and incoming spillovers may reinforce each other but can also be substitutes. Given that cooperation may be more costly to achieve, firms may seek to rely on incoming spillovers. The results, for example, show that incoming spillovers from customers are equally effective in achieving 'new to the market' innovation compared to formal cooperation with customers. This is, however, not the case for suppliers and competitors, where incoming spillovers appear not to help, but where bundling of resources through cooperation can make a firm outperform in terms of 'new to the market' innovation. A large portfolio of collaborative agreements with market participants may come with considerable costs and a careful consideration of when incoming spillovers are sufficient pays off. Continued cooperation due to managerial inertia or lock-in effects may lead to reduced performance.

We note a number of limitations of our study. First, we only have information about the presence or absence of collaboration with partner types and not about the number of partners. Although this limitation holds for all studies using CIS innovation datasets, it hampers a richer understanding of the dynamic development of collaborative agreements. Future versions of the Community Innovation Survey and the datasets based on its framework could be enriched with some questions in that direction. Second, given that our database provides information about Spanish firms, some aspects of collaboration patterns may be specific to firms operating in this country. Thus, as a future research line, we propose the extension of this analysis to other countries to analyze the generalizability of our findings. Third, the paper has but one measure for innovation performance, while there are many others, for example in the domain of process innovation. The interrelationship between R&D collaboration and spillovers over time, coupled with how various dimensions of innovation performance develop, are interesting avenues for future research. The speed at which firms can adapt and improve their cooperation portfolio in case its benefits to innovation tends to diminish, is likely one of the more critical strategic competences to compete in nowadays economy.

Declaration of competing interest

None.

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Appendix 1. Factor Analysis

Importance of sources for innovation activities	Institutional	Other
(From 1 = not answered to 4 = high importance)	**Sources**	**Sources**
Universities	**0.8166**	0.2425
Research organisms	**0.8716**	0.2304
Technological centers	**0.8135**	0.2343
Conferences	0.1857	**0.8735**
Scientific journals	0.2373	**0.8621**
Professional associations	0.3031	**0.7672**
Cronbach alpha	**0.7085**	**0.7057**

Notes. Extraction method: Principal component analysis.
Rotation method: Varimax with Kaiser normalization.

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