R&D Cooperation: Determinants, persistence and its effects on firms' innovative performance

Erika Raquel Badillo Enciso

de Barcelona

PhD in Economics | Erika Raquel Badillo Enciso

Universitat de Barcelona

PhD in Economics

R&D Cooperation: Determinants, persistence and its effect on firms' innovative performance

Erika Raquel Badillo Enciso

Universitat

PhD in Economics

Thesis title:

R&D Cooperation: Determinants, persistence and its effect on firms' innovative performance

PhD student:
Erika Raquel Badillo Enciso

Advisor:
Rosina Moreno Serrano

Date:
October 2014

Universitat de Barcelona

Dedico esta tesis a mis queridos padres,

Marina y Jairo

Agradecimientos

En primer lugar, doy gracias a Dios por estar conmigo en cada paso que doy y por haber puesto en mi camino a aquellas personas que han sido mi soporte y compañía durante todos estos años. Ha llegado el momento de expresar mi más sincera gratitud a todas estas personas, que de alguna u otra manera jugaron un papel en el desarrollo de esta tesis, tanto en el ámbito académico como personal.

El Dr. Jordi Suriñach, a quien estoy infinitamente agradecida, me dio la oportunidad de formar parte del grupo de investigación Anàlisi Quantitativa Regional (AQR), casi desde mi primer año de Máster, y una vez allí, de trabajar con mi directora de tesis, la Dra. Rosina Moreno. Sin lugar a dudas, he sido muy bendecida al tenerla a ella como directora de esta tesis.

A Rosina quiero expresarle mi más sincera gratitud por su apoyo incondicional, por su paciencia, su compresión, sus consejos, sus palabras de estimulo, su dedicación e implicación no sólo en la realización de esta tesis sino también en mi formación como persona y como profesional. Siempre tuvo interés y disposición para enseñarme sobre cualquier cosa. Tengo que decir que aprendí mucho de ella, de su experiencia, sus conocimientos, así como de su exigencia y 'ojo crítico' hacia mi trabajo, también de su calidad como persona y trabajadora. Esta tesis es también el fruto de todo esto. *Gracias… ¡totales! Rosina!*

Estoy muy agradecida a el grupo de investigación Anàlisi Quantitativa Regional (AQR) y a el Departamento d'Econometria, Estadística i Economía Espanyola de la Universidad de Barcelona por haberme acogido y apoyado durante todos estos años, lo cual ha sido fundamental para desarrollar esta tesis. *Gracias*! al anterior director del Grupo y del Departamento el Dr. Manuel Artis, al actual director del Departamento, el Dr. Ramon Alemany, y al actual director del Grupo el Dr. Enrique López-Bazo. Me gustaría aprovechar para agradecerle a Quique por la confianza y el soporte que recibí de su parte. A Raúl, gracias por su orientación, sus consejos y sus constantes palabras animándome (quiero decirle que recuerdo su curso de Economía Laboral en el Máster como uno de los mejores cursos que he recibido). A Esther, Jordi, Vicente, Josep Lluís, Paco, Alessia, Antonio, Jordi López, Quim y demás miembros del grupo que de alguna manera u otra me han animado en todo este proceso: *Gracias!* También de manera muy especial agradezco a Coloma, Dolors, Carmen, Alicia y Bibiana por la colaboración que siempre me brindaron.

A la actual directora del Programa de Doctorado, la Dra. Elisabet Viladecans y a Jordi Roca de UBEconomics, quiero agradecerles por la excelente gestión que realizan; los cambios que ha tenido el Programa en los últimos años sin duda han contribuido a mejorar la calidad del mismo y de sus estudiantes.

Mi formación durante estos años y esta tesis se han beneficiado de diversos seminarios, congresos y workshops a los que he asistido. En particular, agradezco los comentarios recibidos de los participantes de diversas ediciones del Simposio de la Asociación de Economía Española y de Encuentros de Economía Aplicada, así como también los participantes del GCW2013, del PhD in Economics Workshop University of Barcelona 2013 y del INFER Workshop in Urban and Regional Economics 2014.

El desarrollo de esta tesis y la dedicación a ella ha sido posible gracias al financiamiento recibido de la Agència de Gestió d'Ajuts Universitaris i de Recerca (AGAUR) de la Generalitat de Catalunya.

En el ámbito más personal quisiera agradecer a mis colegas, compañeros del doctorado y amigos con los que compartí muchas experiencias dentro y fuera de la universidad: Diana, Ernest, Paula, Ana, Karen, David, Arelly y en especial a mis compañeras de despacho Sandra, Esther y Celia. Esther, gracias por las discusiones que compartimos sobre nuestro ámbito de investigación y por tu cariño! ☺

Este proyecto de vida no empezó sólo hace cinco años atrás cuando llegué a Barcelona, tengo que ir un poco más atrás en el tiempo porque siempre tengo en mi mente al profesor Carlos Humberto Ortiz quien de alguna forma despertó en mí el gusto por la investigación y contribuyó a mi formación. Muchas otras personas también de la Univalle, donde hice mi carrera de Economía, han contribuido a alcanzar esta meta. A todos ellos: *Gracias!*

¿Y cómo no tener un recuerdo tan especial de mi Univalle, donde conocí a mi colega, amigo, esposo y compañero de esta aventura, Gustavo?! Gracias por tu amor, paciencia y comprensión. Por impulsarme y apoyarme en esto. Soy una afortunada por tenerte a mi lado! *Nadie como tú!* A mi familia García Cruz tengo que darle las gracias porque siempre nos han apoyado muchísimo en este proyecto de vida aquí en Barcelona.

A mis amigos, familiares y hermanos de siempre y aquellos que he conocido durante estos últimos años, que están en diferentes partes del mundo [Colombia (Cali, Bogotá, Villeta,…), Estados Unidos (Robert Lee, Denton,…), Venezuela, Francia y otros diferentes rincones del mundo] y aquí mismo en Barcelona, en Badalona (la mama, Noemi, Cristina, Isabel, Elena,

Lisette…) también quiero darles gracias por su cariño, sus oraciones y las buenas energías que sin duda me han acompañado en esta experiencia y me han ayudado a llegar hasta aquí.

Por último, gracias Janneth por siempre animarme, apoyarme y confiar en mí; Jairo Andrés gracias por tu amor de siempre, aunque sea desde la distancia (*I ♥ Manny!*); Maritza gracias porque siempre he podido contar contigo, gracias también por todos los detalles que me enviaban (el café!!! y mis galletas favoritas!!!). Andrés David, gracias por ese *"mentalícese"* no te imaginas cuánto ha significado para mí! A mi papá, quiero darle las gracias sobre todo porque siempre nos motivaste a estudiar e hiciste un gran esfuerzo por ofrecernos todo. Madre hermosa, para ti no tengo palabras, sólo tengo un corazón lleno de AMOR para ti y de GRATITUD por tu amor incondicional. A toda mi familia: *mil gracias porque sin ustedes esto no hubiera sido posible.*

Quiero decirles a mi mamá y a mi papá que esto es por ustedes, han sido mi mayor motivación.

Erika
Barcelona, octubre de 2014

Contents

List of Tables

Chapter 1:

Introduction

Introduction

1.1 General framework and motivation

Innovation is widely regarded as an essential force for starting and fuelling the engine of growth (Romer, 1986). It is recognised as a necessary ingredient for firms to remain competitive or pursue long-term advantages (Hamel, 1998; Roberts, 1998). Nowadays, thanks to the globalization and the rapid diffusion of technological knowledge, firms are forced to accelerate their rhythm of innovation and to expand their technological capabilities. Such is the case that innovation has become a key element in maintaining the competitiveness of firms, regions and countries and their positions in a given market.

Successful innovation depends on the creation, accumulation and integration of new knowledge in the innovation process. Part of this knowledge reaches firms through the interaction between firms and their environment (Asheim and Isaksen, 1997). Thus, innovation is seen as a technical and social process based on a series of interactions between several economic agents that constitute the core of the said process (López-Fernández et al., 2008; Monjon and Waelbroeck, 2003). Likewise, since innovation processes are becoming more and more complex, the rapid changes in technology are forcing firms to depend on external technological knowledge and skills in addition to internal resources.

Recently, several studies have emphasized that the development of new products and processes in firms largely depends on the firm's ability to build networks and partnerships as a way to incorporate external knowledge for innovation (Lundvall, 1988, 2007; Tether, 2002; Powell and Grodal, 2005; Vega-Jurado et al., 2009; Trigo and Vence, 2011). In particular, collaborative agreements have become a strategy of knowledge sharing and transfer across firms which are largely recognised as an important (quasi-market) mechanism to access such external knowledge (Schilling, 2008). Accordingly, it is becoming increasingly important for firms to cooperate with other organizations to carry out their R&D activities. Given the ultimate interest of stimulating innovation, the study of R&D cooperation has attracted the attention of both academics and policy-makers and remains an open field of research.

Indeed, policy-makers increasingly promote the development of R&D networks as part of their technological policies. Most EU and national public funding for R&D is directed at stimulating cooperation between firms, and between firms and public institutions (López, 2008). In the 'smart specialisation' strategy, where a new innovation policy concept is aimed to promote the efficient and effective use of public investment in research, the European Commission emphasized that it needs to be based on a strong partnership between businesses, public entities and knowledge institutions, since such partnerships are recognised as essential for success. (European Commission, 2012). Having this in mind, the results obtained from research on cooperation strategies should have important implications for public policy.

In this context, this dissertation focuses on the study of firms' cooperative agreements with other actors in the innovation system (firms, universities, public or private research institutions) with the objective of performing innovation activities. Specifically, the thesis provides new evidence on three broad issues: 1) the determinants of firms' R&D cooperation, 2) the dynamic behaviour of such R&D cooperation and 3) the impact of R&D cooperation strategies on firms' innovative performance.

Throughout this dissertation cooperation is defined as the active participation with other enterprises or non-commercial institutions on innovation activities. Both partners do not necessarily need to gain a commercial benefit. This definition excludes pure contracting out of work where there is no active co-operation. Considering the type of partner with whom agreements are formed, we can identify three types of cooperation: horizontal (with competitors or other enterprises of the same sector), vertical (with suppliers of equipment, materials, components or software or with customers or clients) and institutional (with consultants, commercial labs, or private R&D institutes, universities or other higher education institutions, government or public research institutes, or technological centres).

The data used in this dissertation are draw from the Spanish Technological Innovation Panel (PITEC). This panel data results from the combined effort of the Spanish National Statistics Institute (INE), the Spanish Foundation for Science and Technology (FECYT), and the Foundation for Technical Innovation (COTEC) with the intention of having a database available which would make it possible to analyse the innovation behaviour of Spanish firms and how it evolves. Firms participation in PITEC survey is mandatory by law which ensures a large and consistent sample size and a high response rate. The panel survey follows the Oslo Manual methodology applied in the Community Innovation Survey with respect to the selection of variables and indicators (OECD, 2005). It is important to point out that, depending on the data availability and the objectives of each study, the time period covered is not the same for the different chapters in this thesis. While the first study uses the surveys 2006 and 2008, the second uses surveys 2004, 2006, 2008 and 2010, and the third one ranges from 2004 to 2011.

1.2 Outline of the thesis

The remainder of this dissertation consists of three essays with a marked empirical orientation which are intended to be a contribution to the literature on Innovation Economics. Each of the chapters constitutes a separate piece of research in itself and is developed according to its own structure and methodological framework. A final chapter summarizes the main findings and directions for future research.

Chapter 2, *What Drives the Choice of the Type of Partner in R&D Cooperation? Evidence for Spanish Manufactures and Services*, is aimed at analysing the heterogeneity in firms' decisions to engage in R&D cooperation, taking into account the type of partner (competitors, suppliers or customers, and research institutions) and the sector to which the firm belongs (manufactures or services). Although there are several studies on this issue, so far the results are mixed and do not provide a consistent picture of this phenomenon. Previous studies have tended to treat the decisions to establish different types of cooperation as independent. However, the evidence shows that firms make simultaneous agreements with different types of partners (Belderbos et al., 2004, 2006), and therefore the decisions regarding the type of cooperation partner may not be independent from each other and this should be considered explicitly. Similarly, most of the previous empirical literature on the determinants of R&D cooperation rarely considers the service sector in their analyses. However, given the current increasing importance of this sector in most industrialized countries and the distinct nature of the innovative processes between manufacturing and service firms (Hoffman et al., 1998; Vega-Jurado et al., 2009) we consider it appropriate and relevant to explore and deep on the differences between manufacturing and service firms in relation to the driving factors forcing the formation of cooperation agreements. In this regard, in this chapter we address both aspects in a single run. To this end, we estimate multivariate probit models which explicitly consider the interrelations between the different R&D cooperation strategies and perform the analysis separately for manufacturing and services. Besides, we deal with endogeneity problems present in this kind of analysis via the inclusion of lagged explanatoty variables and through a control function approach.

Chapter 3, *Are R&D collaborative agreements persistent at the firm level? Empirical evidence for the Spanish case*, provides evidence on the dynamics in firms' R&D cooperation behaviour. Our main objective is to analyse if R&D collaborative agreements are persistent at the firm level, and in such a case, to study what are the main drivers of this phenomenon. R&D cooperation activities at the firm level can be persistent due to true state dependence, this implying that cooperating in a given period enhances the probability of doing it in the subsequent period. And it can also be a consequence of firms' individual heterogeneity, so that certain firms have certain characteristics that make them more likely to carry out technological alliances. A first objective of the chapter deals with the distinction between these two drivers. A second contribution of the chapter deals with the differentiated persistence pattern of collaboration agreements for three different types of partners: customers and/or suppliers, competitors and institutions. We specifically explore the degree of the persistence in R&D collaborative activities when considering them separately as well as the possibility of finding crossed-persistence across these different partner types. The analysis in this chapter begins by providing explanations of why cooperation could show state dependence over time. Then, to investigate persistence in cooperation we estimate transition probabilities as well as random-effects dynamic probit models and an alternative specification based on the Wooldridge's (2005) correction that accounts for the initial conditions of the dependent variables.

Chapter 4, *Does absorptive capacity determine collaborative research returns to innovation? A geographical dimension*, examines the impact of research collaboration with different and diverse geographical areas on innovative performance, taking into account how this impact may vary according to the absorptive capacity of the firm. There are some papers with national studies on the differences between national and international research alliances with respect to the impact on innovation output (see e.g. Miotti and Sachwald, 2003; Cincera et al., 2003; Lööf, 2009; Arvanitis and Bolli, 2013), nevertheless, in our study we give a step forward and disaggregate the geographical scope of the international alliances to explore the effect of collaborative research with partners in particular geographical areas. In addition, we consider that firms can form more than one type of alliance geographically speaking and evaluate the impact of such diversity. A third contribution of this chapter is to analyse the role played by the absorptive capacity of the firm in the relationship between collaborative research and innovation performance. The empirical strategy consists of a two-stage selection model estimated using the Wooldridge's (1995) consistent estimator for panel data with sample selection.

This thesis is based on the following three research articles:

i. Badillo, E.R. and Moreno, R. (2012) What Drives the Choice of the Type of Partner in R&D Cooperation? Evidence for Spanish Manufactures and Services. Currently, the paper is under review in a journal listed in the ISI-JCR. A previous version of this paper was published in the working papers series of the *Research Institute of Applied Economics, IREA* (Working Paper 2012/13) and in the working papers series of the *Regional Quantitative Analysis Group, AQR* (Working Paper 2014/06). Different versions of this study have been presented at the XV Encuentro de Economía Aplicada (2012) and at the XXXVII Simposio de la Asociación Española de Economía (2012).

ii. Badillo, E.R. and Moreno, R. (2013) Are R&D Collaborative Agreements Persistent at the Firm Level? Empirical Evidence for the Spanish Case. The paper is now under the process of revise and resubmit in a journal listed in the ISI-JCR. A previous version of this paper was published in the *SEARCH Working Paper Collection* (WP4/30), in the working papers series of the *Research Institute of Applied Economics-IREA* (Working Paper 2014/10) and in the working papers series of the *Regional Quantitative Analysis Group-AQR* (Working Paper 2014/05). It was presented at the XVI Encuentros de Economía Aplicada (2013), the International Conference: The Governance of a Complex World "Innovation and Cooperation as Entrepreneurial Challenges" (2013), the PhD in Economics Workshop University of Barcelona (2013) and the XXXVIII Simposio de la Asociación Española de Economía (2013).

iii. Badillo, E.R. and Moreno, R. (2014) Does Absorptive Capacity Determine Collaborative Research Returns to Innovation? A Geographical Dimension. This paper has been presented in the XVII Encuentros de Economía Aplicada (2014) and in the INFER Workshop in Urban and Regional Economics (2014) and has been accepted for presentation in the XXXIX Simposio de la Asociación Española de Economía (2014).

References

Arvanitis, S. and Bolli, T. (2013) A comparison of national and international innovation cooperation in five European countries, *Review of Industrial Organization*, 43, 163–191.

Asheim, B. and Isaksen, A. (1997) Location, agglomeration and innovation: towards regional innovation systems in Norway, *European Planning Studies*, 5(3), 299–330.

Belderbos, R., Carree, M.A., Diederen, B., Lokshin, B. and Veugelers, R. (2004) Heterogeneity in R&D co-operation strategies, *International Journal of Industrial Organization*, 22(8/9), 1237–63.

Belderbos R., Carree M. and Lokshin B. (2006) Complementarity in R&D cooperation strategies, *Review of Industrial Organization*, 28(4), 401–426.

Cincera, M., Kempen, L., Van Pottelsberghe, B., Veugelers, R. and Villegas, C. (2003) Productivity growth, R&D and the role of international collaborative agreements: Some evidence for Belgian manufacturing companies, *Brussels Economic Review,* 46(3), 107-140.

European Commission (2012) Guide to Research and Innovation Strategies for Smart Specialisations (RIS 3). *Smart Specialisation Platform*.

Hamel, G. (1998) Strategy innovation and the quest for value, *Sloan Management Review*, 39(2), 7-14.

Hoffman, K., Milady, P., Bessant, J. and Perren, L. (1998) Small firms, R&D, technology and innovation in the UK: A literature review, *Technovation*, 18, 39–55.

Lööf, H. (2009) Multinational enterprises and innovation: Firm level evidence on spillover via R&D collaboration, *Journal of Evolutionary Economics*, 19(1), 41–71.

López, A. (2008) Determinants of R&D cooperation: Evidence from Spanish manufacturing firms, *International Journal of Industrial Organization*, 26(1), 113-136.

López-Fernández, C., Serrano-Bedia, A.M. and García-Piqueres, G. (2008) Patterns of institutional cooperation in R&D for Spanish innovative firms in the manufacturing and service sectors, *Management Research News*, 31(11), 811-829.

Lundvall, B.-Å. (1988) Innovation as an interactive process: From user–producer interaction to the national system of innovation. In: Dosi, G. Freeman, C., Nelson, R., Silverberg, G., Soete, L. (Eds.), *Technical Change and Economic Theory*. Pinter, London, 349–369.

Lundvall, B.-Å. (2007) National innovation system: analytical focusing device and policy learning tool, *Working Paper* R2007:004, ITPS – Swedish Institute for Growth Policy Studies.

Miotti, L. and Sachwald, F. (2003) Cooperative R&D: Why and with whom? An integrated framework of analysis, *Research Policy*, 32(8), 1481–99.

Monjon, S. and Waelbroeck, P. (2003) Assessing spillovers from universities to firms: evidence from French firm-level data, *International Journal of Industrial Organization*, 21(9), 1255-70.

OECD (2005) *Oslo Manual, Guidelines for collecting and interpreting innovation*, 3rd edition, OECD, Paris.

Powell, W.W. and Grodal, S. (2005) Networks of innovators. In: Fagerberg, J., Mowery, D.C., Nelson, R.R. (Eds.), *The Oxford Handbook of Innovation*. Oxford University Press, Oxford, 56–85.

Roberts, R. (1998) Managing Innovation: The pursuit of competitive advantage and the design of intense environments, *Research Policy*, 27(2), 159-175.

Romer, P.M. (1986) Increasing returns and long-run growth, *Journal of Political Economy*, 94(5), 1002-37.

Schilling, M.A. (2008) Understanding the alliance data, *Strategic Management Journal*, 30(3), 233-260.

Tether, B.S. (2002) Who co-operates for innovation, and why: An empirical analysis, *Research Policy*, 31(6), 947-967.

Trigo, A. and Vence, X. (2011) Scope and patterns of innovation cooperation in Spanish service enterprises, *Research Policy*, 41(3), 602-613.

Vega-Jurado J., Gutiérrez-Gracia A. and Fernández-de-Lucio I. (2009) Does external knowledge sourcing matter for innovation? Evidence from the Spanish manufacturing industry, *Industrial and Corporate Change*, 18(4), 637–670.

Wooldridge, J.M. (1995) Selection corrections for panel data models under conditional mean independence assumptions, *Journal of Econometrics*, 68, 115–232.

Wooldridge, J.M. (2005) Simple Solutions to the Initial Conditions Problem in Dynamic Nonlinear Panel Data Models with Unobserved Heterogeneity, *Journal of Applied Econometrics*, 20, 39–54.

Chapter 2:

What Drives the Choice of the Type of Partner in R&D Cooperation? Evidence for Spanish Manufactures and Services

What Drives the Choice of the Type of Partner in R&D Cooperation? Evidence for Spanish Manufactures and Services

2.1 Introduction

The importance of collaborative research networks has been one of the main issues in innovation studies. Some studies examining the effects of R&D cooperation highlight its importance as an input for firms' economic performance. As Faems et al. (2005) argue, the economic success is determined by the combination of the strategies of cooperation in R&D and the complementary mechanisms that are generated between them. The theoretical work of D'Aspremont and Jacquemin (1988) shows that cooperation has a positive impact on competitiveness and even on economic welfare[1]. Miotti and Sachwald (2003), Belderbos et al. (2004a), Lööf and Broström (2008), and Aschhoff and Schmidt (2008), among others, provide empirical evidence showing that firms' economic performance is influenced positively by R&D cooperation agreements.

Given such importance and the growing interest in this phenomenon, the main objective of this chapter is to examine the determinants in the choice of different R&D cooperation partners as a strategy to carry out innovation activities. Although many aspects of cooperation in R&D have been examined in previous works, few studies have focused on the heterogeneity of the motivations of such cooperation according to its various forms (with suppliers and/or customers, research institutions and competitors). When this is

[1] Nevertheless, it has also been pointed that welfare could be reduced if firms collude in output and hence, alliance strategies should not be supported if they involve product market collusion (Greenlee and Cassiman, 1999; Goeree and Helland, 2010).

considered (Tether, 2002; Miotti and Sachwald, 2003; López, 2008; Arranz and Arroyabe, 2008; Segarra-Blasco and Arauzo-Carod, 2008; Abramovsky et al., 2009), the studies have in common that they treat these different cooperation strategies as independent, without taking into account possible correlation among them (see Belderbos et al., 2004b, as an exception). In this chapter we will therefore study how the motivations for carrying out R&D cooperation agreements may be different according to the type of partnership chosen while controlling for the possible correlation between such R&D cooperation strategies. With this purpose, we estimate a multivariate probit model with three binary equations, each one representing one type of cooperation chosen by firms: cooperation with competitors, with suppliers and/or customers, and with research institutions.

Additionally, given the current increasing importance of the service sector in most industrialized countries and the distinct nature of the orientation of innovations of industrial and service firms (Miles, 2007; Van de Vrande et al., 2009; Leiponen, 2012), it seems fair to think that the factors driving the firms' decision to engage in R&D cooperation may vary depending on the sector in which the firm operates. Roper and Hewitt-Dundass (2004) stresses the idea that there are a variety of modes of innovation, one based on firms' internal capabilities and another based on interactivity, and some are more commonly found among manufacturers while others are more commonly found among services. In fact, following Tether (2005) services do innovate differently from manufacturers in the sense that the latter "are more likely to source advanced technologies through in-house R&D, the acquisition of advanced machinery and equipment and through collaborations with universities and research institutes whereas services, and particularly those with an organisational orientation to their innovation activities, are more likely to source new technologies through collaborations with customers and suppliers, or through the acquisition of external intellectual property". However, most of the previous empirical literature on the determinants of R&D cooperation rarely considers the service sector in their analyses, either because of lack of data or because services have long been considered to innovate scarcely. Therefore, as an additional exercise, we will look at the manufacturing and service sectors separately to see to what extent the determinants in the choice of R&D partner may be different between both sectors.

In this study we use the Technological Innovation Panel (PITEC), a comprehensive database of Spanish companies which mainly provides information on innovative activities of industrial and service firms. Most previous studies have been limited by their use of cross-sectional databases, whereas the longitudinal structure of the PITEC database allows us to address some of the problems that these previous studies encountered, mainly endogeneity issues. This way, we perform a cross-section analysis taking into account the simultaneity bias inherent in this kind of analysis via the inclusion of lagged explanatory variables as well as via corrections for endogeneity through a control function approach.

Therefore, the value added of this chapter is threefold. First of all, our study considers that firms make simultaneous R&D agreements with different types of partners and consequently the decisions regarding the type of cooperation partner are not independent from each other, a fact that should be considered explicitly. Second, thanks to the availability of a longitudinal database, the time dimension is taken into account by the use of lagged explanatory variables at the same time that instrumental variables are used in order to minimize endogeneity problems present in this kind of analysis. And thirdly, it tries to disentangle the differences between service and manufacturing sectors when choosing partners for cooperating in their R&D activities. Most empirical studies are based on the manufacturing sector and do not include analyses on the service sector, which has its own innovation dynamics and should, therefore, be considered separately.

After this introduction, Section 2.2 in this chapter proceeds with the literature review. Section 2.3 describes the database and shows some descriptive statistics. Section 2.4 details the estimation methodology and Section 2.5 presents the empirical results. Finally, we present the major conclusions.

2.2 Literature Review

We present now the main factors that the literature has considered to influence the decision of firms to participate in R&D cooperation, and discuss how their impact may vary with the type of partner of such collaboration.

Among the main determinants of R&D cooperation, the literature of industrial organization emphasizes knowledge spillovers (see Katz, 1986; D'Aspremont and Jacquemin, 1988; Kamien et al., 1992). It is possible to distinguish two kinds of spillovers: incoming and outgoing spillovers. *Incoming spillovers* refer to the flows of external knowledge that a firm is able to capture, and the information sources for them are usually situated in the public domain. This way, firms that place a higher value on incoming spillovers and externally generated knowledge in their innovative activity might have a greater scope for learning and gaining from knowledge exchange through cooperative agreements. By and large, the empirical literature has supported this positive impact of a firm placing a higher value on income spillovers on the probability of R&D cooperation (Cassiman and Veugelers, 2002; Kaiser, 2002; Belderbos et al., 2004b; Veugelers and Cassiman, 2005; López, 2008; Abramovsky et al., 2009; Serrano-Bedia et al., 2010; Chun and Mun, 2012). However, if taking into account the type of partner, this relationship would be expected to be stronger in collaborations with research institutions and universities. As signalled by Abramovsky et al. (2009), it might be expected that firms which are able to get more benefits from external knowledge might be more likely to engage in cooperation agreements with the research base or, at least, with firms outside their own industry. Confirming this reasoning, Cassiman and Veugelers (2002) obtained a positive but non-significant impact of incoming spillovers in vertical cooperation, that is, with suppliers or clients.

Outgoing spillovers reflect the firm's inability to control the knowledge that flows outside it, the converse of which can be thought of as the extent of *appropriability*. In the literature, the effect of appropriability problems on firms' probability to engage in R&D cooperation agreements is ambiguous. On the one hand, a better appropriability of the results of innovation through protection may have a positive effect on cooperation in R&D, as firms can control outgoing information flows and there are less incentives for others to become a free-rider on other firms' investments (Cassiman and Veugelers, 2002). However, excessive legal protection may hinder the internalization of the flows shared by the partners and may thus have a negative effect on R&D cooperation (Hernán et al., 2003; López, 2008). This result must be smoothed according to the partner, since Cassiman and Veugelers (2002) obtained that a better appropriability would increase the probability of cooperating with customers or suppliers whereas it is unrelated with research institutes. Among other reasons, it is sensible to think that the information which is commercially sensitive, result of more applied research projects, often leaks out to competitors through common suppliers or customers. Therefore, only those firms with enough protection of their information would be willing to engage in cooperation agreements at the vertical level. In other words, we might expect firms facing appropriability problems be less likely to engage in collaborative arrangements with competitor firms compared to agreements with more dissimilar partners, for instance with research institutes, where free-riding may be less feasible and the incentives to do it are lower given they are not competing in the same market.

Another determinant of R&D cooperation strategies, which is related to the flows of knowledge, is the firm's *absorptive capacity*. Absorptive capacity has been identified in many studies as an important feature of the firms since it makes them more likely to be successful innovators, which could make them more attractive cooperation partners for other firms (Bayona et al., 2001; Fritsch and Lukas, 2001; Miotti and Sachwald, 2003; Hernán et al., 2003; Belderbos et al., 2004b; Röller et al., 2007; Arranz and Arroyave, 2008). However, how a firm's absorptive capacity affects its own incentives to cooperate is not so clear. As pointed out by Cohen and Levinthal (1989) a certain absorptive capacity is required to assimilate and exploit knowledge in the environment; a company with more absorptive capacity is able to access a greater amount of knowledge than another with lower capacity, and will obtain greater benefits from cooperation agreements in R&D with the subsequent greater incentive to cooperation agreements. However, a greater absorptive capacity allows the firm to easily access external knowledge as well as getting benefit from it for free, thus having a lower incentive to cooperate. These arguments would be equally valid for any type of partner.

According to the strategic management literature, companies use research alliances with the idea of accessing complementary knowledge such as *market knowledge or qualified personnel*, or in order to *share the risks and the costs of R&D activities* (see Pisano, 1990; Hagedoorn, 1993; Sakakibara, 1997; Das and Teng, 2000; Hagedoorn et al., 2000). This line of thinking postulates that by combining their efforts, firms can alleviate the barriers to innovation or at least share the risks inherent to innovation. Among others, Bayona et al. (2001), Tether (2002), Miotti and Sachwald (2003), Belderbos et al. (2004b), Röller et al. (2007) and López (2008) provide evidence supporting this argument. Taking into consideration the type of partner, and since basic research projects, such as the ones carried out by universities and research centers, tend to be riskier than applied and more commercially oriented projects, on the one hand, one would expect cost- and risk- sharing motivations to be more important for collaborative agreements with research institutions (Cassiman and Veugelers, 2002; Abramovsky et al., 2009). However, although this higher risk of basic research would induce risk sharing benefits from cooperation, at the same time it invokes higher transaction costs for cooperation, in the sense that enforcing partner compliance in cooperative contracts will be more difficult when the technology is characterised by a large amount of uncertainty. In this sense, Veugelers and Cassiman (2005) find, for the Belgian case, that these cooperative agreements with research institutions tend to be formed whenever risk is not an important obstacle to innovation and typically serve to share costs. Similarly, Miotti and Sachwald (2003) find that risks do not influence the likelihood of cooperation with any type of partner. There are, therefore, reasons for an ambiguous effect of cost- and risk-sharing motivations on the probability of cooperating with science.

Other key determinants of the R&D cooperation strategies mentioned in most previous empirical studies are firm size and public funding. In general, *firm size* has been found positively related to the probability of engaging in R&D cooperation (Bayona et al., 2001; Fritsch and Lukas, 2001; Tether, 2002; Miotti and Sachwald, 2003). It is argued that firms need to have certain structure and resources to be able to face the commitment required in partnerships and to benefit from cooperation agreements. This is more probably available in large firms than in small firms. However, it can be thought that small firms may need cooperation with other firms or institutions in order to manage innovation activities which otherwise could not carry out because of their limited resources. Empirical evidence seems to give more support to the former argument, being big firms more likely to enter in R&D cooperation agreements, irrespectively of the type of partner.

As regards *public funding*, when firms obtain public R&D subsidies they may be more likely to establish cooperation agreements with another firm or with institutions given that this way they have the resources to do the research (Arranz and Arroyabe, 2008; Busom and Fernández-Ribas, 2008; Abramovsky et al., 2009). Also, many times public support programmes for R&D activities aim to ease cooperative innovation agreements by firms that would otherwise not engage in such activity. Additionally, there may be reasons to believe that public funding may have a greater impact on the likelihood to engage in university collaborations, since institutional incentives for university scientists to transfer knowledge and technology to firms might be weak. Similarly, we expect to find the weakest relationship between the receipt of public funding and cooperation with competitors.

Most empirical analyses have assumed that the strategies of cooperation with different types of partners in R&D activities are independent; however, the existence of simultaneous agreements with different partners may suggest that there are interrelations between such strategies which should be taken into account. Only Belderbos et al. (2004b) apply a multivariate probit model which accounts for possible systematic correlations between the different cooperation strategies (competitors, suppliers, customers and research institutions in their case). They supported the notion of interdependence between the different cooperation decisions, which may be due to complementarities in R&D cooperation strategies but also to omitted firm-specific factors affecting all types of cooperation.

In general, the review of the empirical literature does not offer evidence of sectoral differences in the determinants of R&D cooperation, since most of the applications refer to the manufacturing sector. However, the service sector has presented significant growth in recent decades and has an innovation dynamics on its own. This way, given that our database allows us to consider both sectors separately, we will additionally do so to see if any of the relationships commented above can differ across the two sectors. As far as we know, only Abramovsky et al. (2009) provides some evidence on the heterogeneity in the motivation for R&D collaboration agreements across sectors. They obtain that cooperation is less frequent in manufactures which could be related to the fact that in such sector *legal protection methods* are used more intensively. In other words, cooperative innovation may be used as a substitute to patenting in manufactures but not in services. As a direct consequence, one could think that a greater use of protection methods has a lower impact on R&D cooperation in the service sector than in manufacturing. However, Serrano-Bedia et al. (2010), who only analyse institutional cooperation for Spanish firms, find that legal protection is not statistically significant neither in the manufacturing nor in the service sector, so that certain ambiguity of the effect of appropriability seems to be there. Another interesting difference found in Abramovsky et al. (2009) refers to the impact of *internal R&D intensity* on cooperation which appears to be clearer in the service sector, implying that internal and external R&D might be substitutes in such sector, at a greater extent than in manufactures. However, Serrano-Bedia et al. (2010) provided evidence of a positive relationship between absorptive capacity and the incentives to cooperate both in manufactures and services in the Spanish case.

All in all, this chapter provides additional evidence and contributes to the analysis of differences in the motivations that lead to cooperation in innovation according to different types of partners while explicitly considering the interdependencies between them. The differences encountered between manufacturing and services are also highlighted. In addition, access to a longitudinal database will allow us to reduce the endogeneity bias that may arise in an analysis of this kind, overcoming an important limitation in most previous studies.

2.3 Data and Descriptive Analysis

The database used in this study is the Technological Innovation Panel (PITEC)[2]. As mentioned in previous section, this is a panel produced jointly by the Spanish National Statistics Institute (INE), the Spanish Foundation for Science and Technology (FECYT) and the Cotec Foundation, with information on innovative activity of Spanish companies. PITEC is a survey carried out yearly and the questions about cooperation are asked in a 3-year period. The advantage of using this database is that it allows partial control over potential endogeneity problems inherent in this kind of analysis by introducing lags in the explanatory variables. Specifically, the variables for R&D cooperation (dependent variables) are taken from the 2008 survey (wave 2006-2008), while the explanatory variables correspond to the 2006 survey (wave 2004-2006).[3]

The PITEC sample in 2008 contains information on 12813 businesses, but after a cleaning of the data[4] and selecting only the firms of manufacturing and services, the figure falls to 10443. Moreover, since the aim of this chapter is to

[2] This database is available to the public at http://sise.fecyt.es/

[3] Note that, although PITEC has a panel structure, we carried out a cross-section analysis because of the complexity of the estimation strategy, as discussed in Section 2.4.1.

[4] Firms that report confidentiality issues, mergers, closures, employment incidents and so on are eliminated, as are those observations that present anomalies such as firms with zero business levels or excessively high values of R&D intensity, measured as the ratio between R&D expenditure and turnover (the rule used was the mean plus twice the standard deviation).

study R&D cooperation, and since only firms engaged in innovation respond to the questions relevant to cooperation, the analysis is restricted to the group of innovative companies.[5] Finally, our sample comprises 7362 companies. Table A2.1 in the Appendix provides more information on the selection of the sample.

PITEC asks firms which kind of partner they cooperated with in their innovation processes. According to this question, we distinguish between three different types of cooperation agreements:[6]

- Horizontal cooperation: cooperation agreements with competitors or other enterprises of the same sector.
- Vertical cooperation: cooperation agreements with suppliers of equipment, materials, components or software or with customers or clients.
- Institutional cooperation: cooperation agreements with consultants, commercial labs, or private R&D institutes, universities or other higher education institutions, government or public research institutes, technological centres.

Table 2.1 shows the different strategies of cooperation chosen by innovative companies. Around 34% of innovative enterprises in the industrial and service sectors reported cooperating with at least one partner during the period 2006-2008. Research institutions are the main partners in innovation activities, accounting for 78% of all cooperation agreements, while only 24% of firms

[5] That is, firms that have introduced innovations in products or processes, or who were undertaking innovation activities during the analysed period or abandoned them.

[6] The survey also offers information on another type of cooperation: cooperation with firms in the same group. However, we do not consider such typology since only firms belonging to a group can cooperate within their group, while all the other types of partners can be chosen by all firms. However, in order to control for possible different behaviour of such firms, the regression analysis includes a dummy variable for firms belonging to a group. The same kinds of cooperation are used in López (2008) and Abramovsky et al. (2009).

cooperate with their competitors. Moreover, we see that 48% of companies maintain agreements simultaneously with at least two types of partners. For example, out of the 1954 companies that cooperate with institutions, 60% also have agreements with other type of partners. It seems, therefore, that companies find benefits in having different forms of cooperation simultaneously. Specifically, the data show that cooperation with research institutions tends to be most often complemented by vertical cooperation.

Table 2.1. R&D cooperation strategies among Spanish innovative firms

I	V	H	Strategies	# Firms	%
0	0	0	Non-cooperation	4842	**65.8**
		1	Only Horizontal	80	3.2
	1	0	Only Vertical	436	17.3
		1	Vertical + Horizontal	50	2.0
1	0	0	Only Institutional	788	31.3
		1	Institutional + Horizontal	132	5.2
	1	0	Institutional + Vertical	683	27.1
		1	All strategies	351	13.9
Total innovative firms with at least a cooperative agreement				2520	**34.2**
Horizontal R&D cooperation (H)*				613	24.3
Vertical R&D cooperation (V)*				1520	60.3
Institutional R&D cooperation (I)*				1954	77.5

* H: Competitors; V: Suppliers and/or Customers; I: Consultants, commercial labs or private R&D institutes; universities; government or public research institutes; technological centres.
Note: Except for the 2 values in bold, the rest of % are computed over the total number of firms cooperating.

The proportion of innovative companies with the diverse types of cooperation agreements and according to the two sectors under consideration is shown in Table 2.2. As it can be seen, there is a higher proportion of innovative companies in the industrial sector (80.9%) than in the service sector (61.3%). However, the propensity to cooperate is higher in the service sector: 40% of innovative companies in this sector have cooperation agreements with other partners, compared to 31% in the industrial sector. This may be related to the fact that manufacturing firms use legal protection methods more intensively and then, they do not need to cooperate to have a secure atmosphere where to carry out innovation activities. That is, cooperation may act as a substitute to legal protection through patenting. On the contrary, it seems that the formal protection methods used in the service sector, more relying in trademarks and copyright would not be working as a substitute to R&D cooperation activities.

Table 2.2. Percentage of innovative firms by type of cooperation and sector

Sector	Innovative Firms	Cooperation	Horizontal	Vertical	Institutional
Industrial	80.93	31.07	5.38	18.92	23.81
Service	61.30	39.57	13.30	23.57	31.17
Total	72.32	34.23	8.33	20.65	26.54

Table 2.2 also shows that innovative companies in both sectors prefer to cooperate with research institutions (31% in services versus 24% in manufactures) followed by suppliers or customers (24% versus 19%). In turn, the least frequent partner is that of competitors, with the highest difference among sectors found in such a case (13% in services and 5% in manufactures). This low level of horizontal cooperation may be just because firms do not find it profitable to do so either because of anticompetitive or procompetitive reasons. According to the former, cooperation with rivals offer firms an opportunity to coordinate behaviour, which can facilitate collusions. However, in many cases collusive arrangements are not attractive because of free-riding behaviour or anti-trust concerns and hence make firms less likely to form R&D collaborations with competitors (Goeree and Helland, 2010). We might expect incentives to cheat to be stronger within cooperation agreements with competitor firms, leading to horizontal cooperation being less frequent and even less in the manufacturing sector, where competition tends to be higher (Abramovsky et al., 2009). On the other hand, procompetitive benefits from R&D collaborations, such as shared risks, alleviated financial constraints and shared costs could not be achieved large enough to compensate anticompetitive effects of collusion (Gugler and Siebert, 2007).

Table 2.3 presents statistics on the characteristics of the companies engaged in cooperation and according to the types of agreement involved. It appears that innovative firms that engage in cooperation agreements are more likely to place higher importance on incoming spillovers and to receive public funding than those which do not cooperate; they also tend to have a higher mean of internal R&D intensity, and use some form of legal protection at a higher rate.A conclusion which is consistent in both sectors.

Table 2.3. Characteristics of innovative firms and their strategies of cooperation [a]

Sector	Variables	Innovative Firms	Cooperative	Non-cooperative	Type of cooperation		
					Horizontal	Vertical	Institutional
Industrial	N	4625	1437	3188	249	875	1101
	Incoming Spillovers	0.356	0.420	0.327	0.489	0.436	0.430
	Legal Protection	36%	43%	33%	46%	44%	45%
	R&D Intensity	0.053	0.072	0.044	0.109	0.071	0.083
	Risks	0.533	0.554	0.524	0.553	0.555	0.556
	Costs	0.588	0.602	0.582	0.616	0.596	0.608
	Lack of HK	0.471	0.481	0.466	0.477	0.473	0.476
	Public funding	42%	62%	34%	70%	61%	67%
	Belonging to a Group	37%	47%	33%	55%	51%	48%
	Less than 50 emp	48%	42%	51%	35%	37%	42%
	50 - 249 emp	37%	37%	37%	38%	38%	36%
	250 - 499 emp	9%	12%	8%	15%	14%	12%
	500 or more emp	6%	9%	5%	12%	11%	10%
Service	N	2737	1083	1654	364	645	853
	Incoming Spillovers	0.365	0.439	0.316	0.485	0.454	0.460
	Legal Protection	33%	41%	28%	45%	42%	43%
	R&D Intensity	0.274	0.420	0.178	0.468	0.451	0.476
	Risks	0.497	0.528	0.477	0.565	0.514	0.543
	Costs	0.589	0.629	0.562	0.639	0.613	0.643
	Lack of HK	0.442	0.472	0.422	0.497	0.476	0.481
	Public funding	45%	65%	33%	72%	64%	72%
	Belonging to a Group	36%	36%	35%	37%	42%	34%
	Less than 50 emp	59%	59%	59%	52%	51%	61%
	50 - 249 emp	21%	21%	21%	28%	25%	22%
	250 - 499 emp	8%	6%	9%	6%	7%	5%
	500 or more emp	12%	13%	11%	14%	17%	11%

Note: Mean values are presented as absolute values and % indicates the share of firms with the described characteristic.
[a] The definition of the variables is presented in Table 2.4.

Related to size, smaller firms in both sectors show a greater propensity to cooperate than big firms. But if we focus on SMEs (i.e. the group of firms with less than 50 employees), while in the service sector the percentage of firms cooperating and not cooperating is exactly the same, in the case of manufactures there are nine percentage points of difference in favour of noncooperative firms. This suggests that SMEs in the industrial sector are not so motivated to cooperate as in the case of services.

Finally, Table 2.3 shows that the differences in the characteristics of cooperative firms are minimal according to the type of cooperation partner, except that companies involved in horizontal cooperation have higher mean of internal R&D intensity and are more likely to have received some public financial support for their innovation activities in the case of the industrial sector.

2.4 Estimation Procedure

2.4.1 Method of estimation

We define three binary dependent variables for each of our three types of cooperation: horizontal, vertical and institutional cooperation. In order to identify the determinants of the decisions to participate in the different forms of cooperation, we specify and estimate a multivariate probit model that accounts for systematic correlation among the different decisions to cooperate. As noted in the previous section, the different cooperation strategies chosen by the firms are not mutually exclusive, which may imply that the choice of diverse types of partners is not independent from each other. Additionally, such systematic correlation may account for unobserved factors affecting all equations, so that estimating separate (probit) equations would lead to inefficient estimations (Zellner and Haung, 1962).

Although we had other estimation alternatives, we considered them not to be suitable. For instance, Kaiser (2002) estimates a nested logit model which assumes a sequential process in which firms initially decide whether to cooperate or not and, in a second step, they decide the type of cooperation partner. However, this approach does not take into account that firms can simultaneously engage multiple types of cooperation agreements. Additionally, a multinomial logit approach should consider all the potential excluding alternatives of cooperation, which are the eight alternatives shown in Table 2.1. This type of multinomial choice modelling has several weaknesses: it has too many parameters and it is difficult to interpret, and the Independence of Irrelevant Alternatives (IIA) assumption is likely to be violated given that the decisions of cooperation between the different types of partners are interdependent (McFadden, 1974).

We have three latent variables, $y_{i1}^*, y_{i2}^*, y_{i3}^*$ which measure the difference between benefits and costs that company i obtains by cooperating in R&D with competitors, with suppliers and/or customers, and with research institutions, respectively. Assuming that these differences depend linearly on a set of firm and sectoral characteristics, contained in x, we have:

$$y_{ij}^* = x_{ij}^{'}\beta_j + \varepsilon_{ij}, \qquad j = 1, 2, 3 \tag{2.1}$$

where β_j is a vector of parameters including the constant term and ε_{ij} are error terms distributed as a normal multivariate, each with mean zero and a variance-covariance matrix V, where V has values of 1 on the leading diagonal and correlations $\rho_{jk} = \rho_{kj}$ $(k = 1, 2, 3)$ as off-diagonal elements.

Since the latent variables are not directly observable and only their signs can be accounted for, binary variables are defined that summarize the signs as the choice made by firms for each type of partner. Thus, the multivariate probit model specifies the binary variables as follows:[7]

[7] Note that firms can choose not to cooperate in all cases.

$$y_{ij} = \begin{cases} 1 & if \quad y_{ij}^* > 0 \\ 0 & if \quad y_{ij}^* \leq 0 \end{cases} \qquad j = 1, 2, 3 \tag{2.2}$$

In this case, with three equations, there are eight joint probabilities corresponding to the eight combinations of different types of partners for cooperation and non-cooperation (as given in Table 2.1). The possible probabilities are determined by (Wooldridge, 2010; Cappellari and Jenkins, 2003; Cameron and Trivedi, 2005; Greene, 2008):

$$\begin{aligned} p_{hkl} &= \Pr\left[y_1 = h, y_2 = k, y_3 = l \right] \\ &= \Phi\left(q_1 x_{i1}^{'} \beta_1, q_2 x_{i2}^{'} \beta_2, q_3 x_{i3}^{'} \beta_3, \rho_{21}, \rho_{31}, \rho_{32} \right) \end{aligned} \tag{2.3}$$

where $\Phi(.)$ is the normal trivariate distribution function, $q_n = 1$ if $y_{in} = 1$ and $q_n = -1$ if $y_{in} = 0$ for $n = 1, 2, 3$. These probabilities are the basis for the maximum likelihood estimation, which is carried out using the routine developed by Cappellari and Jenkins (2003) who use simulation methods of the maximum likelihood function, specifically the GHK (Geweke-Hajivassiliou-Keane) simulator to calculate the probabilities.

2.4.2 Variables

Bearing in mind the literature review presented above, among the reasons leading firms to engage in collaborative innovative activity, in this chapter we focus on the roles of incoming spillovers and legal protection, cooperation as a means of overcoming constraints (i.e. risks, costs and lack of qualified personnel), the absorptive capacity of the firm and the receipt of public funding for innovation. We also control for some firm's characteristics such as firm size, belonging to a group of enterprises and sectoral dummy variables indicating the sector to which the firm belongs to. Although all these variables are listed and defined in Table 2.4, we make here some clarifications.

Incoming spillovers are measured by the importance that the firm attributed, on a four-point scale, to publicly available information for the innovation process of the firm. The information sources were conferences, trade fairs, exhibitions, scientific journals and trade/technical publications, professional and industry associations. To generate a firm-specific measure of incoming spillovers, we aggregated these answers by summing the scores on each of these questions and then the variable was rescaled from 0 (unimportant) to 1 (crucial). Firms that rate generally available external information sources as more important inputs to their innovation process are expected to be more likely to be actively engaged in cooperative R&D agreements. With the same survey data, we also computed the variable proxying for *legal protection*, which considers whether the firm used at least one legal method for protecting inventions or innovations (patents, registered an industrial design, trademark or copyright), taking a value of 1 if used, and 0 otherwise. There is not a consensus on the impact of such variable on cooperation, as surveyed in Section 2.2. Although we could have considered other proxies for these spillover variables, we have followed Cassiman and Veugelers (2002) who pointed that the advantage of the ones suggested here is that they are direct and firm-specific, allowing for heterogeneity among firms.

Other motives for engaging in cooperative R&D, such as cost- and risk-sharing and access to qualified personnel, have been proxied through the rates the firm attributed to the different obstacles to innovation: the uncertain demand for innovative goods or services (*Risks*), the lack of funds within the enterprise or lack of finance from sources outside the enterprise or the consideration that innovation costs are too high (*Costs*) and the lack of qualified personnel (*Lack of HK*). In the three cases, the variables were rescaled from 0 (unimportant) to 1 (crucial). This way, when costs, risks or lack of personnel are an important obstacle to innovation, we expect to observe more cooperative R&D agreements for the purpose of cost-, risk- and personnel-sharing.

Absorptive capacity as well as the firm's internal innovative activity is captured through the ratio between the intramural R&D expenditure and turnover (*R&D intensity*). *Firm size* (<50 employees, 50-249, 250-499 and >500), *public funding for innovation* and *belonging to a group* are binary dummy variables, taking the value 1 if the firm belongs to the corresponding size range, has received any kind of public funding (local, regional or national) and belongs to a group of companies, respectively, and zero otherwise. Finally, we included dummy variables for the sector, which we assume will pick up unobserved sectoral-specific attributes that contribute to the decision of a firm to enter into an R&D cooperative agreement.[8]

As the coefficients of multivariate probit models cannot be directly interpreted, we calculated the marginal effects on the unconditional expectations of the dependent variables. The marginal effect of an explanatory variable, x_{ij}, on the unconditional expectation of a dependent variable, y_{ij}, shows the impact of such explanatory variable on the propensity to engage in any kind of cooperation unconditional to another cooperation adopted by the firm. We present the marginal effects calculated as the average partial effects.[9]

[8] We include a binary sector variable (1=manufactures and 0=services) in the model for the whole sample and industry dummies at 2-digit level according to NACE-93 in the separate models for manufactures and services.
[9] A more detailed explanation of several types of marginal effects can be found in Sodjinou and Henningsen (2012).

Table 2.4. Definition of the variables included in the empirical analysis

Variables	Definitions
Dependent	
Cooperation with competitors (Horizontal)	= 1 if the firm cooperated in some of its innovation activities with competitors or other enterprises of the same sector in the period 2006-2008 = 0 otherwise
Cooperation with suppliers or customers (Vertical)	= 1 if the firm cooperated in some of its innovation activities with clients or customers; suppliers of equipment, materials, components or software in the period 2006-2008 = 0 otherwise
Cooperation with research institutions (Institutional)	= 1 if the firm cooperated in some of its innovation activities with consultants, commercial labs or private R&D institutes; universities or other higher education institutions; government or public research institutes; technological centres in the period 2006-2008 = 0 otherwise
Independent	
Incoming Spillovers	= 1 - sum of the scores of importance that the firm attributed [number between 1 (high) and 4 (not used)] to the following information sources for undertaking its innovation activities: conferences, trade fairs, exhibitions; scientific journals and trade/technical publications; professional and industry associations. Rescaled from 0 (unimportant) to 1 (crucial)
Legal Protection	= 1 if the firm used at least one of the following legal methods for protecting inventions or innovations: applied for a patent; registered an industrial design; registered a trademark; claimed copyright = 0 otherwise
R&D Intensity	Ratio between intramural R&D expenditure and turnover
Firm Size	<50 employees=1 if the firm has less than 50 employees; =0 otherwise 50 – 249 employees=1 if the firm has between 50 and 249 employees; =0 otherwise 250 – 499 employees=1 if the firm has between 250 and 499 employees; =0 otherwise 500 or more employees=1 if the firm has 500 or more employees; =0 otherwise
Risks	= 1 - the score of importance that the firm attributed [number between 1 (high) and 4 (not used)] to the uncertain demand for innovative goods or services as a factor that hampered its innovation activities. Rescaled from 0 (unimportant) to 1 (crucial)
Costs	= 1 - sum of the scores of importance that the firm attributed [number between 1 (high) and 4 (not used)] to the following factors that hampered its innovation activities: lack of funds within the enterprise or enterprise group; lack of finance from sources outside the enterprise; innovation costs too high. Rescaled from 0 (unimportant) to 1 (crucial)
Lack of qualified personnel (Lack of HK)	= 1 - the score of importance that the firm attributed [number between 1 (high) and 4 (not used)] to the lack of qualified personnel as a factor that hampered its innovation activities. Rescaled from 0 (unimportant) to 1 (crucial)
Public funding of innovation	= 1 if the firm received funding from local or regional authorities; or from central government to carry out its innovation activities = 0 otherwise
Belonging to a Group	= 1 if the firm belongs to a group of companies = 0 otherwise
Dummy of sector (Sector)	= 1 if the firm belongs to industrial sector = 0 if the firm belongs to service sector

Table 2.4. Definition of the variables included in the empirical analysis (Continued)

Variables	Definitions
Instrumental	
Basicness of R&D	= 1 - sum of the scores of importance that the firm attributed [number between 1 (high) and 4 (not used)] to the following information sources to carry out its innovation activities: universities or other higher education institutions, government or public research institutions and technological centres. Rescaled from 0 (unimportant) to 1 (crucial)
Export Intensity (Export)	Ratio between amount of export and turnover
Industry level of Incoming Spillovers (SpillSECT)	Mean of incoming spillovers at the industry level according to 2-digit NACE-93
Industry level of Legal Protection (LegalProtSECT)	Mean of legal protection at the industry level according to 2-digit NACE-93
Industry level of R&D Intensity (IntensSECT)	Mean of R&D intensity at the industry level according to 2-digit NACE-93

Note: Independent variables come from PITEC 2006. In table A2.2 of Appendix we show the matrix of correlation between explanatory variables

2.4.3 Addressing the problem of endogeneity

One problem in our estimation procedure refers to the possible endogeneity of some explanatory variables mainly due to simultaneity in the decision to engage in R&D cooperation agreements. In fact, both theoretical literature on Industrial Organization and most empirical literature have signalled that the extent to which firms benefit from incoming spillovers, the extent to which they can appropriate the returns to their innovative activity and the amount of resources devoted to R&D can themselves depend on whether or not firms engage in cooperation agreements (Cassiman and Veugelers, 2002; Belderbos et al., 2004b; López, 2008). We next explain the potential endogeneity of these three variables.

Incoming spillovers may be affected by R&D cooperation activities because firms may use these agreements to manage external knowledge flows and because the ability to create incoming spillovers from the general pool of knowledge can be a function of other innovation activities of the firm such as participation in cooperative agreements. Also, cooperating firms may try to maximize incoming spillovers among partners through information sharing, which will enhance the stability of cooperation. At the same time, firms that cooperate tend to protect their proprietary knowledge. In other words, we expect that firms engaged in cooperation agreements have an incentive to become more successful at controlling information sharing with their partners, as well as limiting free-riding by nonpartners. On the other hand, since R&D cooperation agreements may make internal expenditures more effective, R&D intensity can be influenced by such agreements.

Following the reasoning above and thanks to the availability of two different waves from our database, we lagged explanatory variables in order to limit the simultaneity bias inherent to this kind of studies, enabling us to overcome an important limitation in most previous studies. However, this approach only reduces the bias but does not correct for it.[10] Therefore, we attempt to deal with this potential endogeneity through a two-stage residual inclusion (2SRI) estimator (Terza et al., 2008) or control function approach (Rivers and Vuong, 1988; Wooldridge, 2010) which has been shown to be consistent in non-linear models. In practice, therefore, in the first stage we obtain the predicted residuals from the regression of the potential endogenous variables on all the assumed exogenous explanatory variables and the instruments. Then, in the second stage we include these predicted residuals into our main model as additional regressors (without excluding the potential endogenous variables). According to the Rivers and Vuong (1988) procedure, the usual t-statistic on the coefficients of such residuals is a valid test of the null hypothesis of exogeneity.

[10] Despite lagging the explanatory variables, as pointed out by Belderbos et al. (2004b), if cooperation is persistent, the factors determining this cooperation are still partly affected by those R&D agreements that were formed in the past and still in existence in the current period.

As instruments we use those commonly considered in the literature (Cassiman and Veugelers, 2002; López, 2008; Abramovsky et al., 2009; Chun and Mun, 2012): basicness of R&D, export intensity and the industry averages for each of the potentially endogenous variables at the two-digit industry level. With respect to the basic idea behind these instruments, *basicness of R&D* represents the extent to which the firm's R&D activity is directed towards basic research. According to Kamien and Zang (2000) firms for which the sources of basic R&D are more important for their innovation process are more likely to benefit from incoming spillovers. Therefore, we proxy the basicness of R&D performed by the firms through the variable measuring the importance given to sources of information from universities or research institutes for the innovation processes. We expect this variable to be positively correlated not only with the score on incoming spillovers, but also with the firm's absorptive capacity.

Turning to *export intensity*, this variable attempts to measure the extent of competition that firms face and we expect that it has a positive correlation with the use of protection methods. The idea is that exporting firms protect more their innovation since they face a more competitive environment (Arundel and Kabla, 1998; Cassiman and Veugelers, 2002). Finally, *industry level averages of incoming spillovers*, *legal protection* and *R&D intensity* are included in order to pick up the effect of unobserved industry-specific characteristics related to the respective potentially firm-specific endogenous variable (Pakes, 1983; López, 2008). It must be admitted that it is likely that some of these instruments are not truly exogenous. Nonetheless, given the difficulty to find completely suitable instruments in the kind of database used for this research, we will assume that our instruments are valid. What we can do, as we will see in the next section, is providing empirical evidence on such validity.[11]

2.5 Results

With the aim of analysing the determinants of R&D cooperative agreements with different types of partners and seeing the differences between the industrial and service sectors, in a first stage we estimate a model for all firms in both sectors and include a sectoral dummy variable to control for unobserved determinants common to the sector. Afterwards, we perform the same estimation for the subsamples of industrial and service firms separately. In the latter, we also include industry dummies at the 2-digit level according to NACE-93.

2.5.1 Considering endogeneity

The endogeneity of the variables proxying for incoming spillovers, legal protection and R&D intensity is confirmed by applying the Rivers-Vuong test (see Table 2.5) and calculating the Durbin-Wu-Hausman endogeneity test (see Table A2.3 in Appendix 2.B). In this approach the instruments must satisfy two conditions: relevance and exogeneity. The first condition can be tested on the basis of the first stage regressions shown in Table A2.4 of the Appendix, through the computation of two tests: the Angrist-Pischke test of underidentification and the F test for weak instruments (Wooldridge, 2010; Angrist and Pischke, 2009). The first checks whether the model is identified, identification requiring the instruments to be correlated with the potentially endogenous variables. The second tests weak identification which arises when

[11] In addition, following Pakes (1983)'s study and some recent literature (Arvanitis and Bolli, 2013), we also estimated our models using the industry averages for each of the potentially endogenous variables as the only instruments; that is, excluding export intensity and basicness of R&D variables of the set of instrumental variables. The results –available upon request– do not modify the general conclusions.

the instruments are correlated with the potentially endogenous variables, but only weakly. The values for both tests (Table A2.4 in the Appendix) show that the null hypothesis of underidentification is rejected, the same as for weak instruments, concluding in favour of the relevance of the instruments.[12]

The second condition, the exogeneity of the instruments, is more complicated to test in the context of a multivariate probit model.[13] Nevertheless, in order to provide some evidence about such exogeneity, we compute a version of the Sargan's test of overidentifying restrictions but in the framework of separate univariate probit models (Newey, 1987; Lee, 1992). The results (Table A2.5 in the Appendix) reveal that the joint null hypothesis that the instruments are uncorrelated with the error term and, therefore, correctly excluded from the estimated equation, cannot be rejected neither for the whole sample nor for the manufacturing and service samples separately. These results point to the exogeneity of the instruments used, although the results are conditional on the assumption that univariate probit models do not take into account the correlations between the error terms of the different equations, each one corresponding to one type of cooperation partner.

[12] Note that the partial R^2 of the first stage are very low and the value of the F-tests statistics are well above 10, which is usually considered a good threshold, and so the instruments cannot be judged as weak.

[13] As far as we know, exogeneity tests have not yet been implemented for multivariate nonlinear models.

Table 2.5. Estimates of multivariate probit models for R&D cooperation corrected by endogeneity

	Total Firms			Industrial Firms			Service Firms		
	Horizontal Cooperation	Vertical Cooperation	Institutional Cooperation	Horizontal Cooperation	Vertical Cooperation	Institutional Cooperation	Horizontal Cooperation	Vertical Cooperation	Institutional Cooperation
Incoming Spillovers/	1.980***	1.573***	3.276***	2.385***	1.768***	3.729***	1.685***	1.312***	2.591***
	(0.180)	(0.165)	(0.178)	(0.331)	(0.253)	(0.283)	(0.276)	(0.216)	(0.230)
Legal Protection/	-0.172	-0.515**	-0.383	-0.717	-0.670**	-0.449	0.055	-0.204	-0.439
	(0.290)	(0.220)	(0.233)	(0.468)	(0.294)	(0.336)	(0.439)	(0.389)	(0.401)
R&D Intensity/	0.307***	0.397***	0.370***	0.800	0.538	0.178	0.173	0.337***	0.422***
	(0.099)	(0.094)	(0.088)	(0.646)	(0.389)	(0.374)	(0.117)	(0.110)	(0.099)
Risks	-0.049	-0.056	-0.191***	-0.130	0.034	-0.192**	0.029	-0.186*	-0.174*
	(0.080)	(0.060)	(0.063)	(0.115)	(0.085)	(0.075)	(0.123)	(0.102)	(0.097)
Costs	-0.036	-0.038	-0.099	-0.004	-0.045	-0.093	-0.141	-0.049	-0.099
	(0.084)	(0.082)	(0.073)	(0.134)	(0.080)	(0.086)	(0.134)	(0.132)	(0.100)
Lack of HK	0.080	0.080	-0.003	0.032	-0.012	-0.117	0.202*	0.226**	0.188**
	(0.077)	(0.063)	(0.064)	(0.113)	(0.075)	(0.074)	(0.117)	(0.108)	(0.092)
Public funding	0.444***	0.444***	0.674***	0.454***	0.440***	0.667***	0.440***	0.452***	0.699***
	(0.048)	(0.041)	(0.039)	(0.067)	(0.050)	(0.043)	(0.089)	(0.073)	(0.083)
Belonging to a Group	0.141***	0.211***	0.134***	0.228***	0.227***	0.168***	0.018	0.159**	0.025
	(0.049)	(0.041)	(0.043)	(0.080)	(0.048)	(0.053)	(0.073)	(0.066)	(0.068)
Firm Size (base <50 employees)									
50 - 249 emp	0.145**	0.162***	0.003	0.137	0.134**	-0.018	0.207***	0.233***	0.048
	(0.060)	(0.042)	(0.045)	(0.085)	(0.055)	(0.055)	(0.078)	(0.070)	(0.071)
250 - 499 emp	0.144	0.277***	0.012	0.170	0.306***	0.007	0.078	0.235**	-0.027
	(0.097)	(0.068)	(0.073)	(0.121)	(0.087)	(0.099)	(0.143)	(0.110)	(0.113)
500 or more emp	0.356***	0.532***	0.317***	0.293**	0.510***	0.359***	0.421***	0.587***	0.322***
	(0.091)	(0.068)	(0.073)	(0.146)	(0.113)	(0.114)	(0.115)	(0.091)	(0.091)
Sector (=1 industrial)	-0.419***	-0.034	-0.083**						
	(0.053)	(0.043)	(0.040)						

$\hat{u}_1$	-1.703***	-1.210***	-3.296***	-2.017***	-1.360***	-3.789***	-1.493***	-0.987***	-2.524***
	(0.182)	(0.187)	(0.188)	(0.348)	(0.267)	(0.306)	(0.322)	(0.257)	(0.251)
$\hat{u}_2$	0.275	0.658***	0.573**	0.781	0.784**	0.598*	0.088	0.398	0.694*
	(0.287)	(0.221)	(0.241)	(0.478)	(0.296)	(0.333)	(0.434)	(0.404)	(0.402)
$\hat{u}_3$	-0.298***	-0.352***	-0.345***	-0.757	-0.506	-0.122	-0.177	-0.287**	-0.406***
	(0.106)	(0.098)	(0.096)	(0.660)	(0.398)	(0.388)	(0.117)	(0.113)	(0.103)
Constant	-2.315***	-1.679***	-1.987***	-2.797***	-1.809***	-2.247***	-2.358***	-1.676***	-1.787***
	(0.107)	(0.072)	(0.076)	(0.168)	(0.090)	(0.099)	(0.142)	(0.109)	(0.090)
ρ21		0.537***			0.515***			0.558***	
		(0.023)			(0.033)			(0.033)	
ρ31		0.566***			0.528***			0.605***	
		(0.023)			(0.034)			(0.031)	
ρ32		0.668***			0.664***			0.679***	
		(0.015)			(0.020)			(0.024)	
N		7362			4625			2737	
LogL		-7928.36			-4590.45			-3304.20	
Wald Test		Chi-sq(45) = 3204.54			Chi-sq(129) = 1617.80			Chi-sq(102) = 2205.63	
Ho: The coefficients are jointly = 0		Pval = 0.000			Pval = 0.000			Pval = 0.000	
Likelihood Test		Chi-sq(3) = 1593.5			Chi-sq(3) = 853.5			Chi-sq(3) = 740.2	
Ho: ρ21= ρ31= ρ32=0		Pval = 0.000			Pval = 0.000			Pval = 0.000	

Bootstrapped standard errors are presented in parentheses. / indicates instrumented. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

Estimations of the industrial and service samples include industry dummies at 2-digit level according to NACE-93. $\hat{u}_1$, $\hat{u}_2$ and $\hat{u}_3$ are respectively the predicted residuals of the incoming spillovers, legal protection and R&D intensity regressions in the first stage.

The estimated coefficients and their corresponding marginal effects of the second-stage are presented in Tables 2.5 and 2.6, respectively.[14] Comparing the results in Table 2.6 with those without instrumenting, as reported in Table A2.6 in Appendix 2.C, we must admit that there are differences in some of the marginal effects, although the main results are maintained. For instance, the marginal effects of incoming spillovers and R&D intensity are higher in the estimations corrected by endogeneity problems, probably due to endogeneity biases or alternatively to measurement errors. As pointed out by Cassiman and Veugelers (2002) in the case of incoming spillovers, the problem may arise from the use of qualitative measures for which the estimates without correcting for endogeneity are biased towards zero. The downward bias can also reflect the impact of past cooperation on the importance to publicly available information for innovation since once the firm has engaged in cooperation agreements, it could place more importance to knowledge flows shared among partners than to other external sources of information. After instrumenting, we also find that the marginal effects of the legal protection variable are not significant any more, with the exception of the cases of vertical cooperation for the whole and the manufacturing samples, in which this variable presents a negative effect. Overall, our analysis on the endogeneity problem shows that it can affect the results on the determinants of R&D cooperation strategies and hence, our procedure, not only considering lagged explanatory variables but also performing a two-step estimation, allows us to mitigate the potential bias.

[14] In order to adjust the coefficients' standard errors for the use of generated regressors we have obtained them through bootstrapping.

Table 2.6. Marginal effects on R&D cooperation corrected by endogeneity

	Total Firms			Industrial Firms			Service Firms		
	Horizontal Cooperation	Vertical Cooperation	Institutional Cooperation	Horizontal Cooperation	Vertical Cooperation	Institutional Cooperation	Horizontal Cooperation	Vertical Cooperation	Institutional Cooperation
Incoming Spillovers/	0.265***	0.396***	0.844***	0.231***	0.422***	0.920***	0.322***	0.360***	0.716***
	(0.027)	(0.040)	(0.038)	(0.035)	(0.059)	(0.056)	(0.049)	(0.059)	(0.055)
Legal Protection/	-0.022	-0.118**	-0.094	-0.065	-0.140**	-0.098	0.012	-0.049	-0.107
	(0.040)	(0.050)	(0.057)	(0.049)	(0.065)	(0.072)	(0.099)	(0.101)	(0.095)
R&D Intensity/	0.040***	0.100***	0.095***	0.078	0.125	0.036	0.032	0.088***	0.114***
	(0.013)	(0.022)	(0.023)	(0.050)	(0.097)	(0.101)	(0.023)	(0.030)	(0.030)
Risks	-0.007	-0.013	-0.049***	-0.013	0.006	-0.048**	0.005	-0.045*	-0.043*
	(0.011)	(0.015)	(0.015)	(0.011)	(0.018)	(0.019)	(0.022)	(0.026)	(0.025)
Costs	-0.005	-0.009	-0.025	0.001	-0.010	-0.022	-0.026	-0.015	-0.028
	(0.012)	(0.017)	(0.017)	(0.013)	(0.020)	(0.021)	(0.027)	(0.031)	(0.032)
Lack of HK	0.010	0.020	-0.001	0.003	-0.004	-0.030	0.038*	0.061**	0.050**
	(0.011)	(0.015)	(0.016)	(0.012)	(0.020)	(0.021)	(0.023)	(0.027)	(0.025)
Public funding	0.060***	0.115***	0.187***	0.044***	0.109***	0.176***	0.085***	0.126***	0.209***
	(0.008)	(0.011)	(0.011)	(0.008)	(0.013)	(0.014)	(0.018)	(0.022)	(0.023)
Belonging to a Group	0.019***	0.053***	0.034***	0.023***	0.055***	0.042***	0.003	0.043**	0.007
	(0.007)	(0.010)	(0.010)	(0.008)	(0.013)	(0.014)	(0.014)	(0.017)	(0.018)
Firm Size (base <50 employees)									
50 - 249 emp	0.019**	0.041***	0.001	0.013	0.032**	-0.005	0.041**	0.066***	0.015
	(0.008)	(0.011)	(0.011)	(0.009)	(0.014)	(0.014)	(0.020)	(0.023)	(0.023)
250 - 499 emp	0.020	0.074***	0.003	0.017	0.077***	-0.002	0.013	0.065*	-0.007
	(0.014)	(0.020)	(0.018)	(0.015)	(0.026)	(0.023)	(0.029)	(0.034)	(0.033)
500 or more emp	0.055***	0.154***	0.088***	0.032**	0.140***	0.095***	0.091***	0.175***	0.091***
	(0.016)	(0.023)	(0.021)	(0.016)	(0.034)	(0.032)	(0.029)	(0.032)	(0.030)
Sector (=1 industrial)	-0.059***	-0.011	-0.024**						
	(0.008)	(0.010)	(0.011)						

Bootstrapped standard errors are presented in parentheses. / indicates instrumented. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

2.5.2 Determinants of cooperation strategies for innovation

The results of the estimations on the determinants of cooperation strategies for the whole sample, and for industrial and service sectors separately, reported in Table 2.5, show that the error terms are positively and significantly correlated (ρ) across the different types of cooperation partners indicating the superiority of the multivariate probit model to the estimation of separated univariate probit models. In order to ease the analysis of the determinants of the different R&D cooperation strategies as well as the differences between the industrial and service sectors, we computed the marginal effects of each one of the explanatory variables (Table 2.6).

In general terms, we can observe that the determinants of R&D cooperation differ among the different types of cooperation partners. This finding shows the heterogeneity in the motivations for carrying out the different types of cooperation, and points to the need of studying them separately. We also note a significant effect of the sector on the probability of cooperating with any partner. We calculated a likelihood ratio test (LR) comparing the coefficients obtained for the full sample of firms with the ones obtained in the two separate subsamples (manufacturing and service firms). We obtained a test statistic of 67.42 which is above the critical value of the chi-squared with 89 degrees of freedom. So, we can conclude that there are significant differences between sectors in the sets of marginal effects. The negative sign of the sector variable in Table 2.6 shows that the probability of cooperating is lower for manufactures than for services, with much more pronounced differences in the case of horizontal cooperation (with competitors), while no significant differences are found between the two sectors in the case of vertical cooperation. These results are consistent with the descriptive statistics shown in Section 2.3.

With respect to the main drivers of R&D cooperation, results show a positive and significant relationship between incoming spillovers and the likelihood of the three types of cooperation. The higher the importance attributed by the firm to external sources of information, the more likely it is to obtain benefits through cooperation agreements (Cassiman and Veugelers, 2002; López, 2008). This impact is significantly higher in the case of partnerships with research institutions, particularly in industrial firms: a higher importance given to publicly available information increases the probability of institutional cooperation by approximately 92 and 72 percentage points in the industrial and service sector, respectively. This result is in line with the theoretical argument given by Abramovsky et al. (2009) that firms which are able to get more benefits from external knowledge might be more likely to engage in cooperation agreements with the research base or, at least, with firms outside their own industry. So, it seems fair to conclude that industrial firms benefit the most from the information coming from external sources, especially with regard to cooperating with research institutions. This probably has to do with the basicness of the research carried out by research institutions and universities, which is more likely to be of direct relevance to manufacturing firms.

The results for the legal protection variable, proxying for appropriability, show that it has a negative and significant effect on cooperation with suppliers or customers at the level of the whole sample and for industrial firms, but not in the rest of partnerships. This suggests that a higher use of legal protection methods may hamper the internalization of knowledge flows shared between manufacturing firms, in particular with suppliers or customers, and may thus decrease the probability of this kind of R&D cooperation agreements. In the case of the service sector we do not observe any significant effect. As mentioned by Abramovsky et al. (2009), cooperation might be perceived as a substitute to protection methods such as patenting innovations in the industrial sector, whereas it may not be used as a substitute to formal protection methods such as trademarks and copyright in service firms. That is, a higher use of protection methods has a lower impact on R&D cooperation in the service sector than in manufacturing. In any case, we may highlight that this result is only valid for vertical cooperation, since in all other cases, there is not a significant effect, probably due to the ambiguity of the impact of appropriability.

Regarding R&D intensity, we observe that the higher internal R&D intensity, the higher likelihood of cooperation with suppliers or customers and research institutions, but only in the service sector. This positive result is consistent with the literature highlighting the fact that a higher absorptive capacity of a firm may allow it to derive greater benefits from cooperation with other partners (Cohen and Levinthal, 1989). However, we do not find internal R&D intensity to affect significantly such decisions in the industrial sector. A possible explanation for this might be that the magnitude of internal R&D expenditure over turnover (as shown in Table 2.3) is much lower in manufactures than in services.

As far as factors hampering innovation activities are concerned, the results show that cost-sharing is not a significant motivation for cooperation in the Spanish case. Additionally, when a higher importance is attributed to risk, we obtain a lower probability of institutional cooperation, with no significant impact in the case of the other two types of partners (vertical and horizontal cooperation) for manufactures. This negative effect is also found in Veugelers and Cassiman (2005) for Belgian industrial firms. These authors claim that given the specific characteristics of scientific knowledge, the relation between research institutions and industrial firms is characterized by a large amount of uncertainty and therefore a higher risk makes it more difficult to enforce partner compliance in cooperation agreements.

Another difference between the industrial and service sectors lies in the importance of the limitations related to the lack of qualified personnel (lack of HK). No significant effects are found for the whole sample, but when it is split into industrial and services the impacts are notable in the latter. A higher importance attributed by service firms to the lack of human capital increases the probability of any kind of cooperation by approximately 5 percentage points. This positive effect implies that firms see the possibility of accessing additional human resources through partnerships with other companies or institutions. In contrast, decisions on R&D cooperation in the industrial sector do not seem to be driven by a shortage of human resources. This result is probably related to the fact that innovation is more closely involved with worker skills in the service sector than in manufactures, where machine and equipment play a more important role in the innovation process (Baldwin, 1999).

Public financial support from local, regional and national administrations is one of the main determinants of cooperation in the Spanish case in all its forms. The highest positive effect is found in the case of cooperation with research institutions, especially in the service sector. As shown in Table 2.6, the probability of engaging in institutional cooperation in the service sector is around 21 percentage points higher among firms that receive public funding for innovation compared to non-receivers of such funding. This effect is notably greater than for the other types of partnership (the marginal effects are approximately 10 percentage points lower in the horizontal and vertical cooperation). This positive effect of public funding in institutional cooperation may be due to the fact that subsidies are often designed to encourage the interaction between businesses and research institutions. Moreover, companies that can alleviate financial problems by means of public funding are keener to cooperate with their competitors, perhaps because public funding is a factor that is outside the realm of competition (Tether, 2002). In other words, there are reasons to believe that public support programs for R&D activities may ease cooperative innovation agreements by firms that otherwise would not engage in such activity.

Finally, the results show that, in general, large companies are more likely to establish agreements for innovation without striking differences neither among types of partnerships nor between sectors. In both sectors, companies with more than 500 employees are the most likely to cooperate with suppliers or customers (14 and 18 percentage points higher than SMEs in the industrial and the service sector, respectively), followed by cooperation with research institutions (10 and 9 percentage points higher in the industrial and the service sector, respectively). The ability of large firms to better reap the returns of cooperation agreements, thanks to the availability of a greater structure and resources to be able to face the commitment required in partnerships, would explain this higher probability of cooperating. And therefore, the argument that small firms may cooperate more intensively because they may need such cooperation in order to manage innovation activities which otherwise could not carry out because of their limited resources seems not to be applicable for the Spanish case.

2.5.3 Interrelations between cooperation strategies

As mentioned in the previous section, the perturbation terms of the different equations, each one for one type of cooperation partner, were positively and significantly correlated, indicating that analysing all cooperation decisions simultaneously is much more efficient that analysing each one separately. In other words, the results of our multivariate probit model are more precise than the results from separate traditional probit models. The positive sign of such correlations may be due to the existence of certain unobserved factors influencing the choice of several types of cooperation in the same direction (e.g. managerial ability or the stock of tacit knowledge) and/or that the cooperation with one partner may drive the cooperation with another type.[15]

In this sense, in Table 2.7 we present the correlations between the R&D cooperation decisions in the data, between the disturbance terms of the different partnerships and between the unconditional probabilities predicted by our multivariate probit model. While the correlation coefficients of the perturbation terms provide evidence in favour of the existence of interrelations between cooperation decisions due to common unobserved factors or complementarities, the correlations between the unconditional probabilities indicate that such interrelations are due to common observed factors.[16] As seen from Table 2.7, all these coefficients of correlation are statistically significant and positive, with higher values in the case of the correlations between the unconditional probabilities, which indicate that the interrelations between the cooperation strategies decisions are mainly driven by common observed factors.

[15] As pointed out by Belderbos et al. (2004b), the multivariate probit model takes these correlations into account, without being able to distinguish between the two sources of correlation. In this regard, a formal test of complementarity as in Mohnen and Röller (2005) would be necessary but it is beyond the scope of this piece of research.

[16] See Sodjinou and Henningsen (2012) for an application in the case of the interrelations between different technology adoption decisions.

Table 2.7. Correlation between the R&D cooperation decisions in the data (a), between the perturbation terms in the R&D cooperation model (b) and between the unconditional probabilities in the Multivariate Probit Model (c)

		Total Firms		Industrial Firms		Service Firms	
		Horizontal Cooperation	Vertical Cooperation	Horizontal Cooperation	Vertical Cooperation	Horizontal Cooperation	Vertical Cooperation
Vertical Cooperation	(a)	0.333		0.286		0.383	
	(b)	0.537		0.515		0.558	
	(c)	0.873		0.862		0.909	
Institutional Cooperation	(a)	0.357	0.479	0.301	0.466	0.410	0.493
	(b)	0.566	0.668	0.528	0.664	0.605	0.679
	(c)	0.880	0.891	0.914	0.864	0.900	0.884

All coefficients of correlation are statistically significant at 5 percent level.

Finally, our model allows us to obtain the predicted conditional probabilities of engaging in a certain type of cooperation partnership given that another cooperation decision is made. The values of such probabilities are reported in Table 2.8. The most striking conclusion from these results is that, on average, the probability of engaging in one type of cooperation is higher when another cooperation partnership is also been carried out simultaneously. For example, for industrial firms, the predicted probability of engaging in vertical cooperation, column P(V=1), if the firm also participates in institutional and horizontal cooperation projects is 79%, while this probability is only 13% when the firm does not participate in any other kind of cooperation agreement. Additionally, it is also important to point out that the predicted probability of carrying out cooperation with competitors (horizontal cooperation) when at least one other type of cooperation has been chosen is notably higher for service than industrial firms. That is, carrying out at least one type of cooperation facilitates the existence of cooperation with competitors in the service sector, whereas this relationship is less likely to occur among manufactures. This can be related to the lower competition present in services, leading them to cooperate more with competitors, and with a higher rate in the case of having the experience and the expertise provided by the fact of being also working cooperately in R&D projects with other types of partners.

Table 2.8. Conditional probabilities predicted by the Multivariate Probit Model

	Total Firms			Industrial Firms			Service Firms		
Strategies	**P(H=1)**	**P(V=1)**	**P(I=1)**	**P(H=1)**	**P(V=1)**	**P(I=1)**	**P(H=1)**	**P(V=1)**	**P(I=1)**
Only Horizontal	0.026	0.422	0.386	0.015	0.428	0.364	0.048	0.401	0.392
Only Vertical	0.100	0.137	0.443	0.064	0.133	0.441	0.161	0.141	0.442
Only Institutional	0.120	0.533	0.116	0.071	0.536	0.114	0.208	0.530	0.114
Vertical + Horizontal			0.740			0.723			0.749
Institutional + Horizontal		0.783			0.792			0.768	
Institutional + Vertical	0.278			0.189			0.412		

P(H=1), P(V=1) and P(I=1) indicate the probability of engaging in horizontal, vertical and institutional cooperation, respectively.

2.6 Conclusions

This chapter analysed the determinants in the choice of the different strategies of R&D cooperation (horizontal, vertical and institutional cooperation), with particular emphasis on the heterogeneity of their impact across the different strategies while explicitly considering the interrelations between them. Additionally, we tried to disentangle the differences between firms in the service and manufacturing sectors when choosing partners for R&D cooperation. The analysis was performed with data from the Technological Innovation Panel (PITEC) using the waves 2006 and 2008 for Spanish innovative firms. The availability of two waves as well as the use of a control function approach allowed us to address the problem of endogeneity.

Spanish firms tended to choose simultaneously several types of partners to carry out their innovation activities. Around 48% of the enterprises that decided to cooperate did so with at least two types of partners, and almost 14% cooperated with the three types of partners at a time. The most common partner was research institutions, and it was most frequently matched with partnerships with suppliers and/or customers. Statistical tests suggested that the choice of the type of partner is not independent one from another, pointing to the need for a multi-equation estimation that considers the interdependences between the three cooperation strategies. In fact, the econometric estimates obtained using a multivariate probit model corroborated the validity of this method compared with univariate estimations.

Related to the drivers of R&D cooperation we confirmed that, in the case of Spanish firms, incoming spillovers were an important determinant of the choice of cooperating with any type of partner, regardless of the sector, but this impact was significantly higher in the case of partnerships with research institutions and universities. This result is consistent with the notion that firms which are able to get more benefits from external knowledge might be more likely to engage in cooperation agreements with the research base or, at least, with firms outside their own industry. Similarly, public funding also played a key role in the firms' decisions to cooperate, especially when the partners are research institutions. This may be related to the fact that much of the public funding for innovation aims to encourage and promote knowledge transfer from research institutions to companies. Results also show that large firms are more likely to cooperate with all types of partner than small firms, highlighting the fact that large firms are more likely to face the commitment required in partnerships and better reap the returns of cooperation agreements.

The differences found among the main determinants of R&D cooperation across sectors are also of great interest. In the case of Spanish firms, there was a greater propensity to cooperate in the service sector (40%) than in manufactures (31%). Additionally, this lower probability of R&D cooperation for manufactures was more pronounced in the case of horizontal cooperation (with competitors). This can be related with previous findings suggesting that in the manufacturing sector, for which legal protection methods are in general more important than for the service sector, cooperation may act as a substitute to legal protection through patenting. With respect to the effects of factors hampering innovations activities, a higher importance attributed to risk makes manufactures less likely to enter cooperation agreements with research institutions while in the service sector this factor is less important in influencing this type of cooperation. On the other hand, the need to address shortfalls of human resources to carry out innovations activities via cooperation agreements with different kinds of partners is an important factor for service firms but not for manufactures. Firms in the service sector see cooperation agreements as an effective way to enhance and complement their human resources for carrying out R&D activities. These differences are presumably due to sectoral differences in the orientation of innovations in industrial and services firms, since, for instance, innovation is more closely involved with worker skills in the service sector than in manufactures, where machine and equipment play a more important role in the innovation process (Baldwin, 1999). Finally, using legal protection methods reduces the probability of cooperating with suppliers and customers in the case of manufactures. This can be due to the fact that legal protection methods may hamper the internalization of knowledge flows shared between firms.

All in all, this research has given evidence on the differences observed in the determinants of R&D cooperation agreements among the different types of partnership and also across different sectors, which should be taken into account when designing policies that aim to encourage R&D cooperation as a means of increasing innovation in firms. In other words, the extent to which the motives for cooperation vary with different partners, which has been observed to be especially different in the case of R&D cooperation agreements with research institutes or universities, should be considered when policy makers decide the targets of their R&D policies, if they aim to maximise the impact of public funding. In this sense, it seems sensible for public administrations to seek ways of directing a higher proportion of their funding towards firms that have the potential to gain significant benefits from working cooperatively in R&D projects.

References

Abramovsky, L., Kremp, E., López, A., Schmidt, T. and Simpson, H. (2009) Understanding co-operative innovative activity: Evidence from four European countries, *Economics of Innovation and New Technology*, 18(3), 243-265.

Angrist, J.D. and Pischke, J.-S. (2009) *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton: Princeton University Press.

Arranz, N. and Arroyabe, J.C.F. (2008) The choice of partners in R&D cooperation: An empirical analysis of Spanish firms, *Technovation*, 28(1/2), 88-100.

Arundel, A. and Kabla, I. (1998) What percentage of innovations are patented? Empirical estimates for European firms, *Research Policy*, 27(2), 127-141.

Arvanitis, S. and Bolli, T. (2013) A comparison of national and international innovation cooperation in five European countries, *Review of Industrial Organization*, 43, 163–191.

Aschhoff, B. and Schmidt, T. (2008) Empirical evidence on the success of R&D cooperation -- Happy together? *Review of Industrial Organization*, 33(1), 41-62.

Baldwin, J.R. (1999) Innovation, training and success, *Research paper* No. 137, Analytical Studies Branch, Statistics Canada, Ottawa.

Bayona, C., García-Marco, T. and Huerta, E. (2001) Firms' motivation for cooperative R&D: An empirical analysis of Spanish firms, *Research Policy*, 30(8), 1289–1307.

Belderbos, R., Carree, M.A. and Lokshin, B. (2004a) Cooperative R&D and firm performance, *Research Policy*, 33(10), 1477-92.

Belderbos, R., Carree, M.A., Diederen, B., Lokshin, B. and Veugelers, R. (2004b) Heterogeneity in R&D co-operation strategies, *International Journal of Industrial Organization*, 22(8/9), 1237–63.

Busom, I. and Fernández-Ribas, A. (2008) The impact of firm participation in R&D programmes on R&D partnerships, *Research Policy*, 37(2), 240-257.

Cameron, C. and Trivedi, P. (2005) *Microeconometrics: Methods and Applications*. New York: Cambridge University Press.

Cappellari, L. and Jenkins, S.P. (2003) Multivariate probit regression using simulated maximum likelihood, *Stata Journal*, 3(3), 221– 235.

Cassiman, B. and Veugelers, R. (2002) R&D cooperation and spillovers: Some empirical evidence from Belgium, *The American Economic Review*, 92(4), 1169-84.

Chun, H. and Mun, S.-B. (2012) Determinants of R&D cooperation in small and medium-sized enterprises, *Small Business Economics*, 39(2), 419-436.

Cohen, W.M. and Levinthal, D. A. (1989) Innovation and learning: The two faces of R&D, *Economic Journal*, 99, 569–596.

D'Aspremont, C. and Jacquemin, A. (1988) Cooperative and noncooperative R&D in duopoly with spillovers, *The American Economic Review*, 78(5), 1133-7.

Das, T. and Teng, B.-S. (2000) A resource-based theory of strategic alliances, *Journal of Management*, 26, 31–60.

Faems, D., Van Looy, B. and Debackere, K. (2005) Interorganizational collaboration and innovation: Toward a portfolio approach, *Journal of Product Innovation Management*, 22(3), 238-250.

Fritsch, M. and Lukas, R. (2001) Who cooperates on R&D? *Research Policy*, 30(2), 297-312.

Goeree, M.S. and Helland, E. (2010) Do Research Joint Ventures serve a collusive function? *Working Paper* No 448, University of Zurich.

Greene, W. (2008) *Econometric Analysis*. Prentice Hall, 7th Edition.

Greenlee, P. and Cassiman, B. (1999) Product market objectives and the formation of Research Joint Ventures, *Managerial Decision Economics*, 20, 115-130.

Gugler, K. and Siebert, R. (2007) Market power versus efficiency effects of mergers and Research Joint Ventures: Evidence from the semiconductor industry, *Review of Economics and Statistics*, 89(4), 645-659.

Hagedoorn, J. (1993) Understanding the rationale of strategic technology partnering: Interorganizational modes of co-operation and sectoral differences, *Strategic Management Journal*, 14(5), 371–385.

Hagedoorn, J., Link, A.N. and Vonortas, N.S. (2000) Research partnerships, *Research Policy*, 29(4), 567-586.

Hernán, R., Marin, P. and Siotis, G. (2003) An empirical analysis of the determinants of Research Joint Venture formation, *Journal of Industrial Economics*, 51, 75-89.

Kaiser, U. (2002) An empirical test of models explaining research expenditures and research co-operating: Evidence from the German service sector, *International Journal of Industrial Organization*, 20(6), 747-774.

Kamien, M. and Zang, I. (2000) Meet me halfway: Research joint ventures and absorptive capacity, *International Journal of Industrial Organization*, 18(7), 995–1012.

Kamien, M., Muller, E. and Zang, I. (1992) Research Joint Ventures and R&D cartels, *The American Economic Review*, 82(5), 1293-1306.

Katz, M. (1986) An analysis of cooperative research and development, *The RAND Journal of Economics*, 17(4), 527–543.

Lee, L. (1992) Amemiya's Generalized Least Squares and tests of overidentification in simultaneous equation models with qualitative or limited dependent variables, *Econometric Reviews*, 11(3), 319-328.

Leiponen, A. (2012) The benefits of R&D and breadth in innovation strategies: A comparison of Finnish service and manufacturing firms, *Industrial and Corporate Change*, 21(5), 1255–81.

Lööf, H. and Broström, A. (2008) Does knowledge diffusion between university and industry increase innovativeness? *The Journal of Technology Transfer*, 33(1), 73-90.

López, A. (2008) Determinants of R&D cooperation: Evidence from Spanish manufacturing firms, *International Journal of Industrial Organization*, 26(1), 113-136.

McFadden, D. (1974) Conditional logit analysis of qualitative choice behaviour. In: Zarembka, P. (Ed), *Frontiers in Econometrics*. Academic Press, New York, 105-142.

Miles, I. (2007) Research and development (R&D) beyond manufacturing: The strange case of services R&D, *R&D Management*, 37(3), 249–268.

Miotti, L. and Sachwald, F. (2003) Cooperative R&D: Why and with whom? An integrated framework of analysis, *Research Policy*, 32(8), 1481–1499.

Mohnen, P. and Röller, L. (2005) Complementarities in innovation policy, *European Economic Review*, 49(6), 1431–50.

Newey, W.K. (1987) Efficient estimation of limited dependent variable models with endogenous explanatory variables, *Journal of Econometrics*, 36, 231-250.

Pakes, A. (1983) On group effects and errors in variables aggregation, *Review of Economics and Statistics*, 65(1), 168–173.

Pisano, G.P. (1990) The R&D boundaries of the firm: An empirical analysis, *Administrative Science Quarterly*, 35(1), 153–176.

Rivers, D. and Vuong, Q.H. (1988) Limited information estimators and exogeneity tests for simultaneous probit models, *Journal of Econometrics*, 39, 347–366.

Röller, L., Siebert, R. and Tombak, M. (2007) Why firms form (or do not form) RJVS, *The Economic Journal*, 117(522), 1122-44.

Roper, S. and Hewitt-Dundass, N. (2004) Innovation in services sector in Ireland – Scoping Study, for *Forfás by InnovationLab Ireland Ltd*, Belfast.

Sakakibara, M. (1997) Heterogeneity of firm capabilities and cooperative research and development: An empirical examination of motives, *Strategic Management Journal*, 18(S1), 143-164.

Segarra-Blasco, A. and Arauzo-Carod, J.M. (2008) Sources of innovation and industry-university interaction: Evidence from Spanish firms, *Research Policy*, 37(8), 1283-95.

Serrano-Bedia, A.M., López-Fernández, M.C. and García-Piqueres, G. (2010) Decision of institutional cooperation on R&D: Determinants and sectoral differences, *European Journal of Innovation Management*, 13(4), 439-465.

Sodjinou, E. and Henningsen, A. (2012) Community-Based management and interrelations between different technology adoption decisions: Innovations in Village Poultry Farming in Western Africa. *FOI Working Paper* 2012/11, University of Copenhagen, Institute of Food and Resource Economics.

Terza, J.V., Basu, A. and Rathouz, P.J. (2008) Two-Stage residual inclusion estimation: Addressing endogeneity in health econometric modelling, *Journal of Health Economics*, 27, 531–543.

Tether, B.S. (2002) Who co-operates for innovation, and why: An empirical analysis, *Research Policy*, 31(6), 947-967.

Tether, B.S. (2005) Do services innovate (differently)? Insights from the European innobarometer survey, *Industry and Innovation*, 12, 153–184.

Van de Vrande, V., De Jong, J.P.J., Vanhaverbeke, W. and De Rochemont, M. (2009) Open innovation in SME's: Trends, motives and management challenges, *Technovation*, 29, 423–437.

Veugelers, R. and Cassiman, B. (2005) R&D cooperation between firms and universities, some empirical evidence from Belgian manufacturing, *International Journal of Industrial Organization*, 23(5/6), 355–379.

Wooldridge, J.M. (2010) *Econometric Analysis of Cross Section and Panel Data.* Third Edition. Cambridge, MA: MIT Press.

Zellner, A. and Haung, D. (1962) Further properties of efficient estimators for seemingly unrelated regression equations, *International Economic Review*, 3, 300-313.

Appendix 2.A: Some additional results

Table A2.1. Sample selection

Total firms 2008	12813
Firms with some incident and primary and construction sector	2370
Non-innovative firms	2532
Firms with some incident or anomaly in 2006	549
Final sample	7362

Table A2.2. Correlation between explanatory variables

	Incoming Spillovers	Legal Protection	R&D Intensity	Risks	Costs	Lack of HK	Public funding	Belonging to a Group
Incoming Spillovers	1							
Legal Protection	0.1483	1						
R&D Intensity	0.0628	0.0455	1					
Risks	0.1626	0.0726	0.0118	1				
Costs	0.1512	0.0646	0.0528	0.3968	1			
Lack of HK	0.1059	0.0446	-0.0027	0.3420	0.4052	1		
Public funding	0.1387	0.1089	0.1472	0.0910	0.1256	0.0485	1	
Belonging to a Group	0.0277	0.0102	-0.0621	-0.0699	-0.1566	-0.083	-0.0222	1
Firm Size	0.0047	0.0202	-0.0341	-0.0626	-0.0858	-0.0403	-0.0289	0.1681

Appendix 2.B: Tests for endogeneity and results for first stage regresions

Table A2.3. Durbin-Wu-Hausman Test for endogeneity

	Total Firms	Industrial Firms	Service Firms
Ho: coefficients on the residuals = 0	Chi-sq(9) = 493.67 Pval = 0.000	Chi-sq(9) = 311.45 Pval = 0.000	Chi-sq(9) = 161.05 Pval = 0.000

Table A2.4. OLS first-stage regressions to control for endogeneity

	Total Firms			Industrial Firms			Service Firms		
	Incoming Spillovers	Legal Protection	R&D Intensity	Incoming Spillovers	Legal Protection	R&D Intensity	Incoming Spillovers	Legal Protection	R&D Intensity
Basicness of R&D	0.456***	0.131***	0.124***	0.438***	0.165***	0.063**	0.492***	0.067*	0.199***
	(0.012)	(0.022)	(0.031)	(0.015)	(0.029)	(0.025)	(0.02)	(0.035)	(0.069)
Export	0.001	0.001***	0.001	0.001	0.001***	0.001	0.001	0.001	0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
SpillSECT	0.602***	-0.168	-0.141	0.686***	-0.216	-0.100	0.387***	-0.478*	-0.582
	(0.077)	(0.148)	(0.187)	(0.111)	(0.223)	(0.212)	(0.135)	(0.252)	(0.48)
LegalProtSECT	-0.004	1.001***	0.004	-0.011	1.068***	-0.001	-0.024	0.883***	-0.108
	(0.044)	(0.077)	(0.092)	(0.065)	(0.118)	(0.136)	(0.063)	(0.11)	(0.154)
IntensSECT	-0.048***	-0.031	0.918***	0.067	0.048	0.864***	-0.034	0.013	0.919***
	(0.016)	(0.033)	(0.094)	(0.048)	(0.124)	(0.255)	(0.024)	(0.047)	(0.125)
Risks	0.069***	0.048***	-0.011	0.069***	0.052**	-0.007	0.068***	0.035	-0.031
	(0.010)	(0.018)	(0.024)	(0.012)	(0.023)	(0.023)	(0.016)	(0.029)	(0.049)
Costs	0.042***	0.048**	0.009	0.029**	0.011	0.015	0.063***	0.105***	-0.012
	(0.011)	(0.021)	(0.028)	(0.013)	(0.026)	(0.023)	(0.018)	(0.033)	(0.066)
Lack of HK	0.033***	0.018	-0.023	0.045***	0.028	-0.032	0.011	0.014	0.001
	(0.01)	(0.02)	(0.024)	(0.013)	(0.025)	(0.021)	(0.017)	(0.032)	(0.053)
Public funding	-0.015**	0.069***	0.081***	-0.018**	0.050***	0.027**	-0.006	0.100***	0.178***
	(0.006)	(0.012)	(0.014)	(0.007)	(0.015)	(0.011)	(0.011)	(0.02)	(0.036)
Belonging to a Group	-0.002	-0.009	-0.010	0.001	-0.007	-0.007	0.001	-0.016	-0.010
	(0.007)	(0.013)	(0.016)	(0.009)	(0.017)	(0.017)	(0.011)	(0.02)	(0.034)
Firm Size (base <50 employees)									
50 - 249 emp	0.016**	0.022	-0.089***	0.007	0.021	-0.058***	0.033**	0.029	-0.149***
	(0.007)	(0.013)	(0.015)	(0.008)	(0.016)	(0.014)	(0.013)	(0.023)	(0.035)
250 - 499 emp	0.027**	0.043**	-0.112***	0.018	0.057**	-0.066***	0.043**	0.009	-0.156***
	(0.011)	(0.021)	(0.017)	(0.014)	(0.028)	(0.021)	(0.019)	(0.033)	(0.027)

500 or more emp	0.022**	0.076***	-0.102***	-0.005	0.112***	-0.044	0.048***	0.045	-0.135***
	(0.011)	(0.022)	(0.024)	(0.015)	(0.033)	(0.041)	(0.016)	(0.031)	(0.029)
Constant	-0.033	-0.075	0.060	-0.058	-0.083	0.061	0.016	0.047	0.196
	(0.024)	(0.047)	(0.057)	(0.036)	(0.073)	(0.061)	(0.047)	(0.088)	(0.177)
N		7362			4625			2737	
R^2	0.251	0.051	0.162	0.229	0.048	0.037	0.290	0.061	0.178
Underidentification Test (Angrist and Pischke, 2009)									
		Chi-sq(3)			Chi-sq(3)			Chi-sq(3)	
	1313.32	168.38	741.55	601.66	87.03	81.71	649.32	62.53	260.68
	Pval = 0.000	Pval = 0.000	Pval = 0.000	Pval = 0.000	Pval = 0.000	Pval = 0.000	Pval = 0.000	Pval = 0.000	Pval = 0.000
Weak Instrument Test (Wooldridge, 2010, pp. 90 - 92; Angrist and Pischke, 2009)									
		F(3,7347)			F(3,4582)			F(5,2703)	
	F = 436.88	F = 56.01	F = 246.68	F = 199.82	F = 28.90	F = 27.14	F = 215.25	F = 20.73	F = 86.42

Heteroskedasticity-Robust standard errors are presented in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1
Estimations for total sample include a binary sector variable (1=industrial and 0=service), and for the industrial and services samples include sector dummies at 2-digit level according to NACE-93.

Table A2.5. A version of the Sargan's test of overidentifying restrictions in a framework of univariate probit models

Total Firms			Industrial Firms			Service Firms		
Horizontal Cooperation	**Vertical Cooperation**	**Institutional Cooperation**	**Horizontal Cooperation**	**Vertical Cooperation**	**Institutional Cooperation**	**Horizontal Cooperation**	**Vertical Cooperation**	**Institutional Cooperation**
	Chi-sq(2)			Chi-sq(2)			Chi-sq(2)	
Chi2 =0.001	Chi2 =2.080	Chi2 =1.137	Chi2 = 0.663	Chi2 = 3.345	Chi2 = 3.314	Chi2 =0.698	Chi2 = 1.038	Chi2 = 4.875
Pval = 0.999	Pval = 0.353	Pval = 0.567	Pval = 0.718	Pval = 0.188	Pval = 0.191	Pval = 0.705	Pval = 0.595	Pval = 0.087

Appendix 2.C: Results without correcting for endogeneity

Table A2.6. Marginal effects on R&D cooperation without correcting for endogeneity

	Total Firms			Industrial Firms			Service Firms		
	Horizontal C	**Vertical C**	**Institutional C**	**Horizontal C**	**Vertical C**	**Institutional C**	**Horizontal C**	**Vertical C**	**Institutional C**
Incoming Spillovers	0.090***	0.154***	0.183***	0.070***	0.147***	0.160***	0.111***	0.162***	0.203***
	(0.012)	(0.016)	(0.017)	(0.013)	(0.021)	(0.022)	(0.023)	(0.027)	(0.027)
Legal Protection	0.016**	0.036***	0.055***	0.007	0.026**	0.043***	0.029**	0.052***	0.068***
	(0.007)	(0.009)	(0.010)	(0.007)	(0.011)	(0.012)	(0.014)	(0.017)	(0.017)
R&D Intensity	0.010**	0.024***	0.029***	0.008	0.013	0.023*	0.008	0.025***	0.026***
	(0.004)	(0.006)	(0.006)	(0.010)	(0.017)	(0.012)	(0.007)	(0.007)	(0.008)
Risks	0.007	-0.003	0.004	-0.002	0.02	0.014	0.021	-0.038	-0.012
	(0.010)	(0.014)	(0.015)	(0.011)	(0.017)	(0.019)	(0.022)	(0.025)	(0.025)
Costs	0.011	0.006	0.029	0.011	0.007	0.029	-0.003	-0.003	0.010
	(0.012)	(0.017)	(0.018)	(0.013)	(0.02)	(0.022)	(0.024)	(0.029)	(0.03)
Lack of HK	0.013	0.021	0.011	0.002	-0.003	-0.013	0.047**	0.066**	0.067**
	(0.011)	(0.015)	(0.017)	(0.012)	(0.019)	(0.021)	(0.023)	(0.027)	(0.028)
Public funding	0.077***	0.130***	0.237***	0.051***	0.113***	0.206***	0.116***	0.158***	0.279***
	(0.007)	(0.009)	(0.01)	(0.007)	(0.011)	(0.012)	(0.014)	(0.017)	(0.018)
Belonging to a Group	0.022***	0.057***	0.047***	0.027***	0.062***	0.063***	0.004	0.044**	0.010
	(0.007)	(0.010)	(0.011)	(0.008)	(0.013)	(0.014)	(0.014)	(0.018)	(0.018)
Firm Size (base <50 employees)									
50 - 249 emp	0.020**	0.036***	0.006	0.009	0.024*	0.007	0.048***	0.062***	0.016
	(0.008)	(0.011)	(0.011)	(0.008)	(0.013)	(0.013)	(0.019)	(0.021)	(0.022)
250 - 499 emp	0.022	0.066***	0.017	0.013	0.067***	0.028	0.016	0.058*	-0.009
	(0.014)	(0.019)	(0.018)	(0.014)	(0.023)	(0.023)	(0.03)	(0.032)	(0.033)
500 or more emp	0.051***	0.133***	0.084***	0.021	0.113***	0.101***	0.093***	0.164***	0.085***
	(0.015)	(0.021)	(0.020)	(0.017)	(0.03)	(0.03)	(0.028)	(0.031)	(0.029)
Sector (=1 industrial)	-0.072***	-0.037***	-0.055***						
	(0.007)	(0.009)	(0.01)						

Bootstrapped standard errors are presented in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

Chapter 3:

Are R&D collaborative agreements persistent at the firm level? Empirical evidence for the Spanish case

Are R&D collaborative agreements persistent at the firm level? Empirical evidence for the Spanish case

3.1 Introduction

R&D cooperation with other firms or institutions has been shown in previous studies to have a positive and significant effect on firms' innovation performance (Miotti and Sachwald, 2003; Belderbos et al., 2004a; Lööf and Broström, 2008; Aschhoff and Schmidt, 2008; Barajas et al., 2012).[17] Innovation performance, however, may not be simply influenced by the simple occurrence or existence of R&D cooperation, but also by the persistence with which this strategy is carried out. Firms cooperating continuously are more likely to enjoy better alliances and accumulate knowledge compared to firms having a one-off collaboration, which in turn could have positive implications for innovation outputs (Nieto and Santamaría, 2007). In this sense, empirical contributions on the study of R&D cooperation have expanded significantly in the last decades, however, understanding the persistence with which these agreements are carried out remains an important and under-researched topic in the literature and this chapter aims to provide empirical evidence on this issue.

According to Jacob et al. (2013), persistent utilization of cooperation agreements may allow firms to maintain their focus on their core domains through in-house specialisation, while external collaboration may provide them with a window of newly emerging technological opportunities that fall beyond

[17] According to the theoretical work of D'Aspremont and Jacquemin (1988), cooperation may even have a positive effect on social welfare. Nonetheless, it has also been pointed that welfare could be reduced if firms collude in output and hence, alliance strategies should not be supported if they involve product market collusion (Greenlee and Cassiman, 1999; Goeree and Helland, 2010).

their main areas of expertise. The collaboration will be so much more fruitful if the firm has a partner with resources that complement its own and that are relevant to the innovation being sought (Nieto and Santamaría, 2007). In addition, from a management perspective, cooperating in a persistent way allows firms obtaining know-how knowledge, which involves information about who knows what and who knows what to do, as well as the social ability to co-operate and communicate with different partners (Lundvall, 2004).

In this chapter we aim at providing evidence on the dynamics in firms' R&D cooperation behaviour. The main objective is, therefore, to analyse if R&D collaborative agreements are persistent at the firm level, and in such a case, to study what are the main drivers of this phenomenon. Knowing which determinants of persistence are prevalent has important policy implications. If carrying out R&D collaboration activities is state dependent, collaboration-stimulating policy measures, such as government support programmes, are supposed to have a deeper effect because they do not only affect current collaboration agreements but are also likely to induce a permanent change in favour of cooperation. If, on the contrary, persistence is driven by individual characteristics, temporary shocks to technological collaboration will rapidly dissipate, and support programmes are unlikely to have long-lasting effects and policy should focus more on policies trying to improve the specific factors that drive R&D cooperation.

Thus, understanding the determinants of the persistence of firms when undertaking agreements of collaboration would allow policy makers to focus resources on "survival-winners", that is, those firms that have acquired experience in cooperation relationships or with characteristics that make them be potential persistent cooperative firms. The present research contributes to this issue. In particular, we follow a dynamic approach in the analysis of cooperation persistence, taking into account the unobserved individual heterogeneity and handling the initial conditions problem. We use a representative sample of Spanish firms for the period 2002-2010.

In addition, following with the well-documented idea that cooperative experience can be considered as an incremental learning process in terms of the management of collaborative agreements (Powell et al., 1996), we aim at providing evidence on the extent to which having participated in technological collaborations with one type of partner in the past may be a significant dimension when it comes to analysing current collaborative agreements not only with the same but also with other type of partners. The literature on organizational learning (Levitt and March, 1988) discusses how firms recurrently cooperating learn how to manage cooperation agreements by repeatedly engaging in them. This gives us arguments to state that this experience of cooperation activities is not restricted to the fact of cooperating with the same partner or even with the same type of partner (i.e. competitors, clients, suppliers or universities and research centers). Firms with experience in technological cooperation agreements gained through long-standing relationships are likely to join other partners, even if they are of a different nature that the previous ones, just because they have learnt to develop and establish routines, policies and procedures based on their previous experiences (Nieto and Santamaría, 2007). Therefore, a second contribution of the present research deals with the differentiated persistence pattern of collaboration agreements for three different types of partners: customers and/or suppliers, competitors and institutions. We specifically explore the degree of the persistence in R&D collaborative activities when considering them separately as well as the possibility of finding crossed-persistence across these different partner types.

After this introduction, Section 3.2 proceeds with the literature review on the topic of the persistence in R&D cooperation activities. Section 3.3 describes the database used and the methodological issues. In Section 3.4 we present and discuss the results obtained and finally, the main conclusions of this study are presented in Section 3.5.

3.2 Literature review

The degree of cooperation persistence of a firm could be defined as the positive impact of past collaborations on present cooperation agreements. In principle, there are several potential sources for persistent behaviour (Heckman, 1981). Firstly, it might be caused by true state dependence, this meaning that the decision to innovate through cooperation in one period in itself enhances the probability to cooperate in the subsequent period. Secondly, firms may have some specific characteristics which make them mostly prone to cooperate. To the extent that these characteristics persist over time, they will inevitably induce persistence in cooperation agreements as well. Such features can be classified into observable attributes, such as firm size or firm's absorptive capacity, and unobservable ones, like managerial abilities or the stock of tacit knowledge, that are typically not observed. If these unobserved features present correlation over time, and are not properly controlled for in the estimation, past cooperation activities may appear to affect future cooperation simply because it picks up the effect of these persistent unobservable characteristics. It is known in the literature as spurious state dependence. As a consequence, the unobserved individual heterogeneity and the well-known initial conditions problem have to be addressed rigorously.

The literature suggests the existence of real true state dependence in cooperation activities through various mechanisms and processes. Firms tend to establish routines that are associated with positive performances, and are, therefore, replicated and perpetuated without drastic changes, leading to path dependency in their behaviour and strategy (Cyert and March, 1963; Nelson and Winter, 1982; Levitt and March, 1988; Belderbos et al., 2012). Thereby, experience of collaboration has a positive effect on subsequent alliance performance mainly because firms develop and establish routines, policies and procedures based on their experiences (Hoang and Rothaermel, 2005; Nieto and Santamaría, 2007).

In the same vein, cooperation experience should be considered as an incremental learning process. On the one hand, by cooperating firms acquire a set of capabilities and knowledge stocks that allow them to benefit by learning from specific areas of specialisation of their partners (Dyer and Singh, 1998; Gulati, 1999; Eisenhardt and Martin, 2000). The ability to successfully leverage the complementary resources of its partners depends on the firm's level of prior-related knowledge which is partly made up thanks to previous experience of collaboration. On the other hand, experience in networking will also have an effect on the management of collaborative agreements. The literature on organizational learning (Levitt and March, 1988; Powell et al., 1996) shows that firms continuously engaged in alliances learn from previous experience as firms learn how to manage these hybrid organizational forms by repeatedly engaging in them. In addition, the more alliance experience a firm has, the more it becomes structurally embedded in an alliance network, providing it with network-level information on new partnering opportunities (Granovetter, 1985). It also brings information with respect to a firm's reputation to potential partners, enhancing their ability to assess the firm's attractiveness. In such a scenario a greater degree of trust between firms cooperating continuously may be reached, which is a basic requisite for a successful partnership (Gulati, 1995; Nooteboom, 2004).

As a consequence of the whole process, experience in cooperation allows firms not only to obtain quite specialised competences but also to find the most reliable experts, forming a source of information on potential partners over time. This learning is also related to the concept of "learning by interacting" which points to how interaction in innovation enhances the relationship with external partners (Lundvall, 1988; Lundvall, 2004; Jensen et al., 2007). Since a firm's ability to recognise the value of new external information as well as to assimilate and apply it to commercial ends, is a function of the level of knowledge, learning in one period will allow for a more efficient accumulation of external knowledge in subsequent periods (Cohen and Levinthal, 1990). This cumulative nature of knowledge would induce state dependence in cooperative behaviour.

Another reason why some firms are expected to be persistent R&D co-operators lies in the fact that cooperation agreements involve costs that may not be recoverable. Firms need to incur start-up costs for establishing cooperation agreements (for instance, costs related to searching, training and adapting to the partner of cooperation) and sometimes require a relatively large initial investment. This kind of costs can be considered, at least partly, as sunk costs (Sutton, 1991; Cohen and Klepper, 1996) and entail barriers to entry into and exit from cooperation projects. Firms involved in cooperation agreements should better not stop cooperating in order to increase the probability of recovering their initial investments and gain from positive results from such agreements. The presence of important sunk costs represents an essential motive for entering and staying in a specific regime of R&D activity (Le Bas et al., 2011). As pointed by Clausen et al. (2012), technological alliances in which knowledge is jointly developed between firms, interactions between customers and suppliers or cooperation with research institutions may have important sunk costs and may, therefore, be more durable.

Likewise, different forms of cooperation may exhibit different degrees of persistence depending on the resource deficiency of the firm (Belderbos et al., 2012). Firms may consider the specialised resources and capabilities owned by suppliers and customers, competitors and research institutions and how they may differentially contribute in providing complementarity. According to the alliance portfolio view, having a diversity of partnership is positive for the firm, since the potential complementarities between different types of partners may bring in different sets of knowledge or complementary capabilities (Vassolo et al., 2004). On the other hand, because partner types differ in their risk profiles, differences in cooperation persistence may arise. For instance, collaboration with competitors may be less persistence because the fear of helping a rival and the lack of trust—given the increased risk of opportunistic behaviour— (Nieto and Santamaría, 2007) may lead this strategy to stop; whereas cooperation with universities and research institutes allows inexpensive and low-risk access to specialist knowledge generally focused on the most generic or basic R&D so that it would be easier to find long-term strategic research collaboration (Archibugi and Coco, 2004; Veugelers and Cassiman, 2005; Arranz and Arroyabe, 2008; Woerter, 2012).

While most studies on R&D cooperation strategies have examined the determinants of carrying out this strategy and their consequences on the firm's performance in a single point in time, the dynamics of R&D cooperation behaviour has been relatively ignored. From our knowledge, Belderbos et al. (2012) and Jacob et al. (2013) are the only ones to explore the persistent character of alliance strategies although with very specific objectives. Whereas the first one uses a data set on innovative Dutch firms to analyse the persistence of, and interrelation between horizontal and vertical technology alliances, the second one examines to what extent prior engagement in international alliances with partners from developed countries increases the propensity to form technology alliances with partners based in emerging economies and vice versa. In our research, we study the extent of the phenomenon of persistence in the firms' decisions to engage in cooperation agreements as a way to carry out innovation activities, attempting to control for the presence of unobserved individual heterogeneity and the initial condition problem. In this sense, we consider that the issue of persistence in R&D cooperation activities is relevant and merits further research since it determines how systematically firms access external knowledge and resources to carry out innovation activities, which can be behind the traditional issue of whether or not, and to what extent, innovation is persistent.

3.3 Empirical model

Our empirical approach follows the definition of cooperation persistence as "state dependence" presented in the previous section, basically that having engaged in R&D cooperation activities increases the probability to engage in such arrangements currently. So, the study considers a dynamic random effects probit model[18] which allows for state dependence and unobserved individual heterogeneity to analyse the discussed causal relationship.[19]

[18] A fixed effects model, in which the individual specific effect is correlated with the independent variables, suffers from the so-called "incidental parameter problem" making it unfeasible to estimate. For this reason, the literature generally assumes a random effects specification in this kind of analysis (Hsiao, 2003; Wooldridge, 2010).

[19] A similar type of analysis has been applied in an important amount of literature on the persistence of innovation (and R&D), see e.g. Peters (2009), Raymond et al. (2010), Triguero and Córcoles (2013) and Arqué-Castells (2013).

The latent variable model is specified as follows:

$$y_{it}^{*} = \gamma\, y_{it-1} + x_{it}^{'}\, \beta + \alpha_i + \varepsilon_{it}\,, \qquad y_{it} = 1\left[\, y_{it}^{*} > 0 \right] \qquad (3.1)$$

$$i = 1,\, \ldots,\, N;\; t = 2,\, \ldots,\, T$$

where y_{it}^{*} is the latent dependent variable which measures the difference between benefits and costs that firm *i* obtains during the current period *t* by cooperating in R&D with other firms or institutions. Instead of observing y_{it}^{*} we observe only a binary variable y_{it} indicating the sign of y_{it}^{*}. Thus, $1[.]$ is an indicator function that takes on the value 1 whenever the statement in brackets is true, and zero otherwise. y_{it-1} is an indicator for cooperation during the previous period and captures the previous cooperation experience; γ is the parameter of interest which indicates the level of persistence in the dependent variable. As $\gamma > 0$, the higher the value of γ, the higher the level of persistence. x_{it} is a vector of observable characteristics of the firm that may be associated with the persistence in cooperation and β the corresponding vector of parameters to be estimated; α_i are unobserved individual-specific random effects which are assumed to be uncorrelated with the independent variables; and ε_{it} is a time and individual-specific error term that is assumed to be distributed as $N(0,1)$.

The correlation between the compound error terms in equation (3.1) in any two periods is $\rho = \sigma_{\alpha}^{2} / \left(\sigma_{\alpha}^{2} + 1\right)$. In this context, ρ represents the percentage of the variance of the compound error term $(\alpha_i + \varepsilon_{it})$ explained by unobserved heterogeneity. Testing the statistical significance of this coefficient leads to an easy test for the presence of the unobserved effect, that is, the relevance of the random effects estimator over the pooled one.

As pointed out by Raymond et al. (2010), the existence of true persistence can be ascertained only after accounting for unobserved individual effects and handling properly the initial conditions problem. The simplest assumption is to take the initial conditions to be exogenous, but it is not expected so because the start of the observation period for each firm could be correlated with the unobserved characteristics of the firms (Heckman, 1981; Wooldridge, 2005). In our context, if the initial conditions are taken to be exogenous, the coefficient of the lagged dependent variable would be overestimated. In other words, it will lead to an overstatement of the true state dependence in R&D cooperation decisions. Since for most firms the cooperation process did not start at the same time of this study's observation timeframe, we assume the initial conditions to correlate with the unobserved effect.

Thus, to consistently estimate our parameter of interest (γ) we account for both unobserved heterogeneity and the initial conditions using the Wooldridge (2005) approach. Specifically, it assumes that the unobserved individual heterogeneity depends on the initial conditions (y_{i0}) and the time-varying exogenous variables, namely:

$$\alpha_i = \delta_0 + \delta_1 y_{i0} + \delta_2 \overline{x}_i + u_i \tag{3.2}$$

where $\overline{x}_i$ represents the means of time-variant exogenous variables; u_i is assumed to be distributed $N(0, \sigma_u^2)$ and independently of the explanatory variables, the initial conditions (y_{i0}), and the idiosyncratic error term (ε_{it}).[20]

[20] Since the regressors exhibit too little time variation (within variation) and given the high correlation between the variables and their within means (see Table 3.2 and Table A3.2 in Appendix 3.B), we are not able to identify δ_2 and hence, we followed the strategy adopted by Raymond et al. (2010) assuming that the unobserved individual effects are correlated only with the initial values of y_{it}.

Substituting equation (3.2) into equation (3.1) gives:

$$y_{it}^{*} = \gamma\, y_{it-1} + x_{it}^{'}\beta + \delta_0 + \delta_1\, y_{i0} + \delta_2\, \overline{x}_i + u_i + \varepsilon_{it} \qquad (3.3)$$

In this case, the relative importance of the unobserved effect is measured as $\rho = \sigma_u^2 / \left(\sigma_u^2 + 1\right)$.

3.4 Dataset, variables and descriptive analysis

3.4.1 Dataset and variables

We use the Technological Innovation Panel (PITEC)[21] with data from different successive waves of the Spanish Innovation Survey conducted every year by the INE, which in turn is based on the Community Innovation Survey (CIS). An important advantage of using this database is that it allows us to study different issues related to innovation activities of Spanish manufacturing and service firms over time as it is specifically designed to analyse technological activities. Given the specific aim of this study and because the questions about cooperation are asked in a three-year period (i.e. the survey asks whether or not the firm cooperated in the period between t-2 and t), we consider four waves of the PITEC: 2004 (wave 2002-2004), 2006 (wave 2004-2006), 2008 (wave 2006-2008) and 2010 (wave 2008-2010), covering the period 2002-2010.

A cleaning process has been carried out and only those firms belonging to the industrial and service sectors, with at least ten employees and positive sales have been taken into account.[22] In addition, since we are interested in the

[21] This database is available at http://icono.fecyt.es/PITEC/Paginas/por_que.aspx
[22] Firms that report confidentiality issues, mergers, closures and employment incidents are eliminated.

persistence of R&D cooperation activities, our analysis is restricted to firms engaging in innovative activities for which technology collaboration is relevant.[23] We distinguish two panel data sets. The first one is an unbalanced panel comprising all firms that are present in at least two consecutive waves;[24] and the second one is a balanced sub-sample, so that only firms which are present in all the waves are included. In Table 3.1 we show some characteristics of the two data sets.

Table 3.1. Characteristics of the panel data sets

	Unbalanced panel	Balanced panel
Number of observations	25,364	16,016
Number of firms	7,566	4,004
Number of consecutive obs. per firm	>=2	4
Average number of consecutive obs.	3.4	4

In each PITEC survey, for a three-year period, the firm is asked if it had any cooperation agreement with other firms or institutions on its innovation activities. Based on this question, we define our dependent variable of cooperation as an indicator variable which takes the value 1 if the firm decided to cooperate and zero otherwise.[25] PITEC also asks firms which kind of partner they cooperated with in their innovation processes. According to this question, we distinguish between three different types of cooperation agreements in order to analyse to what extent the experience in cooperating with one type of partner influences the probability of cooperating with the same or with other types of partners:[26] Horizontal cooperation (with

[23] That is, firms that have introduced innovations in products or processes, or who were undertaking innovation activities during the analysed period or abandoned them.
[24] Using the unbalanced panel allows us to obtain more precise estimates as a higher number of observations and for a greater variety of firms are considered. Additionally, we control partly for survival biases as firms are allowed to enter and exit the sample at any period.
[25] Note that a lag of this variable refers to two to four years, two lags refer to four to six years and so on.
[26] The survey also offers information on another type of cooperation: cooperation with firms in the same group. However, as done in Chapter 2, we do not consider such typology since only firms belonging to a group can cooperate within their group, while all the other types of

competitors or other enterprises of the same sector), Vertical cooperation (with suppliers of equipment, materials, components or software or with customers or clients) and Institutional cooperation (with consultants, commercial labs, or private R&D institutes, universities or other higher education institutions, government or public research institutes and technological centres).

The explanatory variable of interest is the lag of the dependent variable. Notice that we cannot observe individual collaborative agreements between firms, but rather the general collaboration behaviour; therefore, persistence is understood as continuously collaborating, irrespective of whether it is with the same firm or different firms in each period.[27]

We also control for other factors that have been traditionally considered in the literature as influencing the decisions to engage in R&D cooperation activities as outlined below. Not considering them explicitly in the regression analysis would bias the results concerning the true state dependence in the innovative cooperation strategy. Following previous theoretical and empirical papers, as well as our research done in Chapter 2, among the factors leading firms to engage in collaborative innovative activity, we focus on incoming spillovers, appropriability conditions, the firm's absorptive capacity and the receipt of public funding for innovation. We also control for some firms' characteristics such as firm size, belonging to a group of enterprises and sectoral dummy variables at the 2-digit level according to NACE-93. Since the variables proxying for the determinants of cooperation are the same as those in Chapter

partners can be chosen by all firms. However, in order to control for the possible different behaviour of such firms, the regression analysis includes a dummy variable for firms belonging to a group.

[27] We are assuming that a firm collaborating with a different firm in each period generates the same observed pattern than a firm cooperating with only a single firm over the whole period.

2, we refer the reader to Section 2.4.2 for a detailed explanation on the construction of the variables as well as the expected impact according to the arguments found in previous literature.

See Table A3.1 in Appendix 3.A for a more detailed explanation of the definitions of the variables. To avoid problems of simultaneity with the decision of engaging in R&D cooperative agreements, all the independent variables are one-wave lagged.

3.4.2 Descriptive analysis

Some descriptive statistics of the variables used in our empirical analysis are shown in Table 3.2. Although all of them can vary across firms and time we can see that in all cases the variation across firms (between variation) is much higher compared to the time variation (within variation).

Table 3.2. Descriptive statistics of variables in the empirical analysis

	Unbalanced						Balanced					
	mean	std. dev.			min	max	mean	std. dev.			min	max
		overall	between	within				overall	between	within		
Cooperation_t-1	0.382	0.486	0.414	0.268	0	1	0.409	0.492	0.395	0.293	0	1
Incoming spillovers	0.363	0.277	0.240	0.151	0	1	0.380	0.275	0.223	0.161	0	1
Legal protection	0.357	0.479	0.408	0.266	0	1	0.377	0.485	0.387	0.291	0	1
R&D intensity	0.075	0.245	0.240	0.083	0	2	0.071	0.233	0.216	0.086	0	2
Firm size	314.24	1430.17	1440.76	280.15	10	41168	334.36	1305.78	1277.71	269.81	10	37274
Local funding	0.300	0.458	0.390	0.252	0	1	0.321	0.467	0.379	0.273	0	1
National funding	0.269	0.444	0.370	0.250	0	1	0.296	0.456	0.366	0.273	0	1
European funding	0.074	0.261	0.220	0.139	0	1	0.083	0.276	0.228	0.155	0	1
Belonging to a group	0.416	0.493	0.472	0.147	0	1	0.442	0.497	0.470	0.160	0	1

Table 3.3 reports the transition probabilities of engaging in R&D cooperation agreements between periods t-1 and t, t-2 and t and t-3 and t for both the unbalanced and the balanced panels. In the unbalanced panel, nearly 71% of the cooperators in one wave persisted in cooperation in the subsequent wave, that is, after two to four years, while 29% stopped their arrangements. In a

similar vein, about 84% of the non-cooperators remained in this status in the following wave and 16% changed it engaging into agreements of cooperation in the subsequent period. The corresponding figures are very similar in the balanced panel. Therefore, it turns out that the probability of cooperating in period t was about 55 percentage points higher for previous co-operators than for previous non-cooperators, showing the considerably high persistence in cooperation activities from period to period. In addition, although the probability of permanence in the same state decreases as the period of observation extends, the last transition matrices (t-3 and t) still show a high level of persistence in the decisions to engage in R&D cooperation: almost 57% of co-operators and 73% of non-cooperators remain in their initial state after six to eight years, with very similar figures for the balanced panel.

Table 3.3. Transition probabilities matrix

		Cooperation in t			
		Unbalanced panel		Balanced panel	
Cooperation in		Non-cooperation	Cooperation	Non-cooperation	Cooperation
t-1	Non-cooperation	83.70	16.30	82.50	17.50
	Cooperation	29.24	**70.76**	27.39	**72.61**
t-2	Non-cooperation	78.22	21.78	77.63	22.37
	Cooperation	39.01	**60.99**	36.99	**63.01**
t-3	Non-cooperation	73.35	26.65	73.35	26.65
	Cooperation	43.43	**56.57**	42.89	**57.11**

In any case, the probability of persisting in cooperation agreements in the case of Spanish firms seems not to be as high as the one observed in R&D activities reported in previous studies. Also for a panel of Spanish manufacturing firms observed during the period 1998-2009, Arqué-Castells (2013) report that 89% of R&D performers in one year persisted in R&D the subsequent year, while 11% ceased their R&D activities. Similarly, 95% of non R&D performers maintained their status the next period while only 5% entered into R&D. Thus, compared with R&D, neither persistence is as high in cooperation activities, nor transitions are so infrequent. The firm may decide to carry cooperation activities as a strategy to innovate, however, there are several ways to develop innovation, so that according to different objectives, it may not always be necessary to follow cooperative agreements with other firms and/or institutions. Besides, the continuity of a cooperation agreement does not only depend on the firm itself, but also on the decision from the other counterpart of continuing with such alliance, which can make this type of activities of a less-continuous nature in themselves.

Table 3.4 shows the transition probabilities of cooperation agreements for the three types of partners. First of all, it turns out that there are hardly any differences between the unbalanced panel and the smaller balanced panel. We also observe that persistence in cooperation at the firm-level is larger in the case of research institutions and universities, with more that 68% of firms that cooperated in one period that persisted in cooperation activities in the subsequent period, followed by co-operators with clients or suppliers, that presented a persistence rate of 63%. In the case of cooperating with competitors, about 52% of them persisted in t+1, l6 percentage points lower than with institutions. Among other reasons, one could point to the fact that cooperating with competitors may follow strategic reasons that can vary substantially over time depending on the market conditions, economic cycle and the situation of the two firms. Also, it could be that as a consequence of their bilateral nature, in which two competitors have to be in accordance to follow the alliance, this type of agreements suffers from relatively important fluctuations. On the contrary, cooperation agreements with institutions may follow structural objectives of the firm cooperating, which tend to be of a long-term nature. In any case, transitions are relatively frequent in all the cases. For instance, nearly 32% of co-operators with institutions in one wave ceased such cooperative activities in the following, which is the lowest share (this probability increases in the case of vertical cooperation until 37%, and sums up to nearly 48% in horizontal cooperation). This higher stability for the case of technological cooperation with research institutions and universities, can be due to the fact those firms do not look for merely short-term alliances but for a way to carry out a long-term innovation strategy.

Table 3.4. Transition probabilities matrix – Type of cooperation

		Unbalanced panel		Balanced panel	
		Non-cooperation	Cooperation	Non-cooperation	Cooperation
		Vertical cooperation in t			
Vertical cooperation in t-1	Non-cooperation	89.10	10.90	88.19	11.81
	Cooperation	37.24	**62.76**	34.86	**65.14**
		Horizontal cooperation in t			
Horizontal cooperation in t-1	Non-cooperation	95.32	4.68	95.01	4.99
	Cooperation	47.65	**52.35**	45.84	**54.16**
		Institutional cooperation in t			
Institutional cooperation in t-1	Non-cooperation	88.63	11.37	87.68	12.32
	Cooperation	31.59	**68.41**	30.17	**69.83**

3.5 Results

3.5.1 Persistence in collaborative behaviour

The results on the regression estimation are given in Table 3.5. As it is observed, the statistical significance of the panel-level variance component over the total variance (ρ) indicates that the random effects estimator is preferred over the pooled probit estimator, indicating the accuracy of considering the former. In the first column we report the marginal effects from the estimation of the dynamic random effects probit model taking into account the unobserved individual heterogeneity and assuming the initial conditions as being exogenous. As mentioned before, since the persistence of engaging in R&D cooperation may be spurious when the individual effects and the initial conditions are not addressed, these results can be contrasted with the estimates obtained assuming that the initial conditions are correlated with the individual effects, as presented in the second column. The two additional columns report the same regressions as before for the balanced panel. By and large, the results of the two datasets are very similar. Therefore, it can be taken as a robustness check confirming our results about the persistence in R&D cooperation activities.

The estimates in column (1) that allow for individual-specific effects but take initial conditions to be exogenous, give an average marginal effect of the lagged dependent variable of 0.47, positive and highly significant. This result indicates that firms are persistent in carrying out cooperation activities as a strategy to undertake their innovation activities. The Wooldridge estimates that are shown in the second column, after taking into account the assumption of the initial conditions correlated with the unobserved individual effects, yield an average marginal effect of 0.34, that is, firms that performed cooperation agreements at t-1 have a probability of cooperating at t around 34 percentage points higher than firms which did not cooperate at t-1. Two main conclusions arise. First, there is evidence of the existence of a behavioural effect in the sense that the decision to cooperate in a period enhances the probability of being co-operator in subsequent periods. That is, our results suggest a significant state dependence effect for cooperation activities. Second, in line with previous findings in the literature, the hypothesis of exogenous initial conditions leads to overestimation of the degree of persistence.[28]

[28] Because in the PITEC surveys the cooperation variable is related to a 3-year period, part of this persistence may be due to a one-year overlap. However, we carried out the same analysis using a sample without any overlap in the measurement period (i.e. considering three waves: 2004 (2002-2004), 2007 (2005-2007) and 2010 (2008-2010)) and the resulting conclusions were virtually unchanged. The results are reported in Table A3.3 in Appendix 3.B. The reason why we did not opt for this last sample was that this would imply losing observations. For the case of innovation persistence, Raymond et al. (2010) found that the effect of the overlapping year is not important.

Table 3.5. Marginal effects from dynamic random effects probit model

	Unbalanced panel			Balanced panel		
	Random effects probit	Wooldridge correction		Random effects probit	Wooldridge correction	
	(1)	(2)	(3)	(4)	(5)	(6)
Cooperation $_{i,t-1}$ (*persistence*)	0.473***	0.337***	0.318***	0.470***	0.329***	0.311***
	(0.008)	(0.018)	(0.029)	(0.011)	(0.020)	(0.037)
Cooperation $_{i,t0}$ (*initial conditions*)		0.188***	0.187***		0.204***	0.204***
		(0.021)	(0.021)		(0.024)	(0.024)
R&D activities $_{i,t-1}$			0.076***			0.085***
			(0.018)			(0.023)
R&D activities $_{i,t0}$ (*initial conditions*)			0.036*			0.028
			(0.021)			(0.033)
Cooperation $_{i,t-1}$*R&D activities $_{i,t-1}$			0.017			0.016
			(0.027)			(0.037)
Incoming spillovers	0.095***	0.106***	0.090***	0.090***	0.099***	0.086***
	(0.016)	(0.018)	(0.018)	(0.020)	(0.024)	(0.024)
Legal protection	0.035***	0.040***	0.036***	0.036***	0.041***	0.037***
	(0.009)	(0.010)	(0.010)	(0.011)	(0.013)	(0.013)
R&D intensity	0.088***	0.107***	0.092***	0.096***	0.123***	0.110***
	(0.024)	(0.028)	(0.028)	(0.035)	(0.042)	(0.042)
Firm size (base <50 employees)						
50 – 249 emp	0.039***	0.046***	0.045***	0.038***	0.047***	0.045***
	(0.010)	(0.012)	(0.012)	(0.013)	(0.016)	(0.016)
250 – 499 emp	0.056***	0.067***	0.075***	0.056***	0.070***	0.075***
	(0.016)	(0.020)	(0.020)	(0.020)	(0.025)	(0.025)
500 or more emp	0.102***	0.119***	0.126***	0.097***	0.115***	0.118***
	(0.018)	(0.022)	(0.022)	(0.023)	(0.028)	(0.029)
Public funding for innovation						
Local funding	0.096***	0.099***	0.092***	0.103***	0.103***	0.097***
	(0.010)	(0.011)	(0.011)	(0.013)	(0.015)	(0.015)
National funding	0.099***	0.104***	0.096***	0.098***	0.101***	0.094***
	(0.011)	(0.012)	(0.012)	(0.013)	(0.015)	(0.015)
European funding	0.119***	0.124***	0.121***	0.133***	0.134***	0.132***
	(0.019)	(0.022)	(0.022)	(0.023)	(0.027)	(0.027)
Belonging to a group	0.062***	0.071***	0.071***	0.077***	0.091***	0.090***
	(0.010)	(0.012)	(0.012)	(0.013)	(0.015)	(0.015)
Industry dummies	Included	Included	Included	Included	Included	Included
Time dummies	Included	Included	Included	Included	Included	Included
Observations	17,568	17,568	17,568	12,012	12,012	12,012
Number of firms	7,566	7,566	7,566	4,004	4,004	4,004
Log L	-8418.381	-8370.928	-8393.193	-5852.373	-5809.207	-5795.298
Wald test (χ^2)	5007.341	3605.362	5011.80	3256.116	2339.050	2349.590
	Pval = 0.000	Pval = 0.000	Pval = 0.000	Pval = 0.000	Pval = 0.000	Pval = 0.000
σ_α	0.226	0.635	0.233	0.294	0.686	0.687
	(0.057)	(0.046)	(0.056)	(0.059)	(0.051)	(0.051)
Rho (ρ)	0.049	0.288	0.051	0.080	0.320	0.321
	(0.023)	(0.030)	(0.024)	(0.029)	(0.032)	(0.032)
Likelihood test (H_0: $\rho=0$)	4.375	78.444	4.825	7.681	77.860	78.135
	Pval = 0.018	Pval = 0.000	Pval = 0.014	Pval = 0.003	Pval = 0.000	Pval = 0.000

Standard errors are presented in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1
Note: The marginal effects are calculated as the average partial effects.

Nevertheless, we may wonder whether the true state dependence found here is genuine and specific of cooperative agreements and not just caused by state dependence in R&D; in other words, if it is not just caused because firms carrying out R&D persistently are likely to show persistence in all those activities within their R&D domains, such as collaborative agreements. The point addressed here is therefore to provide evidence on whether firms i) cooperate persistently because they carry out R&D persistently and R&D is organised in a persistence way over time or whether firms ii) cooperate persistently on top of the persistence found in R&D.

In order to be sure that we are not omitting the effect of carrying out R&D activities persistently and picking it up as persistence in cooperation, we consider another specification which includes not only the lagged cooperation dummy variable but also a lagged R&D dummy variable (with the corresponding initial conditions), plus an interaction term between them in order to show how persistence in cooperation relates to persistence in R&D.[29] The R&D dummy variable picks up whether or not the firm engaged in internal and/or external R&D activities. This way, if both parameters accompanying the R&D and the cooperation variables are significant, we could conclude that firms do cooperate persistently after taking into account persistence in R&D.

The results are shown in column 3 and 6 of Table 3.5 for the unbalanced and balanced panel, respectively. We observe that after accounting for persistence in R&D activities, which reports a significant parameter, the one on cooperation persistence is still significant. This points to the conclusion that the true state dependence in cooperation we find in this study is different from persistence in R&D and is maintained on top of the latter. With respect to the

[29] We thank an anonymous referee for pointing this point out.

interaction effect, the results do not show any significant additional impact on cooperation in t for those firms that simultaneously carried out R&D and cooperation in t-1. Thus, our results allow us to conclude that the cooperation persistence is genuine and firms cooperate persistently on top of the persistence in R&D.[30]

While taking into account the dynamic behaviour of cooperation, we also observe that the importance attributed to sources of information publicly accessible, the use of protection methods, firm size, and the fact of belonging to a group of enterprises affect positive and significantly the probability to cooperate. Furthermore, it is worth noting that the firm's decision to cooperate in R&D activities depends significantly on public funding (local, national and European). This result is in accordance with many studies analysing the relationship between R&D cooperation and subsidies (Busom and Fernández-Ribas, 2008; Arranz and Arroyabe, 2008; Abramovsky et al., 2009) and evidence that R&D subsidies designed to encourage innovation activities could alleviate barriers to cooperation. Of course this dependence of R&D cooperation on public funding can be a problem for the long-term R&D strategy of the firm, since not receiving public funds because of government budget cuts could force the firm stopping their cooperation agreements.

With the aim of analysing the strength of this persistence found in cooperation activities, the first two columns in Table 3.6 refer to the same estimations as those given in Table 3.5, but now including an additional variable that takes the value 1 if the firm decided to cooperate two periods before (t-2),

[30] Alternatively, with the aim of studying whether the state dependence found in this research is genuine, we could have considered another specification which includes the lagged cooperation dummy variable and a variable measuring whether or not the firm performed R&D continuously during the previous period (*Permanent R&D*), which is also available in the dataset. The conclusions are maintained, since we observe that after accounting for R&D activities carried out continuously, the parameters on cooperation persistence are still significant. The results are provided in Table A3.4 in Appendix 3.B.

irrespectively of what was done in period t-1. As observed, true state dependence is also observed in the case of a longer time span, which in our case corresponds to four to six years, although with a much lower intensity. This result is in line with the evolutionary perspective that sees innovation as a dynamic process that develops over time. In this process, having participated in cooperation activities in the past may allow firms to accumulate technological knowledge which increases their absorptive capability, allowing them to engage in further innovation projects carried out jointly with other partners. That is, it enables firms to strengthen their resource endowment which last over time. However, what happens when a firm that has been cooperating in innovation activities stops doing it? Can it re-start cooperating with more feasibility than those which did not cooperate before? Columns (3) and (4) include an explanatory variable, namely $Coop_{t-2/t-1=0}$, that takes the value 1 if the firm cooperated in t-2, restricted to the fact of not having carried out cooperation activities in t-1. Under the same scenario of non-cooperators in t-1, the value of such variable is 0 if the firm did not cooperate either in t-2. According to the literature on organizational learning (Levitt and March, 1988; Powell et al., 1996), firms repeatedly engaged in an activity such as innovation cooperation learn how to manage these organizational forms by engaging in them repeatedly, as they develop and establish routines, policies and procedures based on their experiences. According to our estimates, firms not engaged in cooperation activities in t-1 but with previous experience in t-2 have a significantly higher probability of engaging in cooperation agreements in t, if compared with those that did not carried out cooperation activities in the past (at least the time periods that fall under control in our sample). This past dependence is much lower than in the case of cooperating continuously, but still points to the fact that once a firm begins to collaborate, it will gain experience and develop a reputation as a partner which keeps in time. This "learning by doing" seems to be maintained in time, at least in short periods of time.

Table 3.6. Marginal effects from dynamic random effects probit model (unbalanced panel)

	Random effects probit	Wooldridge correction	Random effects probit	Wooldridge correction
	(1)	(2)	(3)	(4)
Cooperation $_{i,t-1}$	0.483***	0.482***		
	(0.011)	(0.011)		
Cooperation $_{i,t-2}$	0.138***	0.121***		
	(0.014)	(0.020)		
Coop $_{i,t-2/t-1=0}$			0.082***	0.057***
			(0.012)	(0.021)
Cooperation $_{i,t0}$		0.022		0.026
		(0.018)		(0.017)
Incoming spillovers	0.106***	0.106***	0.030*	0.030*
	(0.022)	(0.022)	(0.016)	(0.016)
Legal protection	0.050***	0.050***	0.033***	0.034***
	(0.013)	(0.013)	(0.010)	(0.010)
R&D intensity	0.048	0.047	0.012	0.012
	(0.035)	(0.035)	(0.033)	(0.033)
Firm size (base <50 employees)				
50 – 249 emp	0.041***	0.041***	0.025**	0.025**
	(0.014)	(0.014)	(0.011)	(0.011)
250 – 499 emp	0.065***	0.065***	0.040**	0.041**
	(0.022)	(0.022)	(0.019)	(0.019)
500 or more emp	0.109***	0.109***	0.075***	0.076***
	(0.024)	(0.024)	(0.023)	(0.024)
Public funding for innovation				
Local funding	0.102***	0.101***	0.051***	0.050***
	(0.014)	(0.014)	(0.012)	(0.013)
National funding	0.099***	0.099***	0.066***	0.067***
	(0.015)	(0.015)	(0.014)	(0.014)
European funding	0.079***	0.079***	0.051	0.051
	(0.028)	(0.028)	(0.031)	(0.032)
Belonging to a group	0.042***	0.042***	0.013	0.013
	(0.013)	(0.013)	(0.010)	(0.010)
Industry dummies	Included	Included	Included	Included
Time dummies	Included	Included	Included	Included
Observations	10,002	10,002	6,104	6,104
Number of firms	5,998	5,998	4,133	4,133
Log L	-4441.680	-4440.926	-2369.920	-2368.611
Wald test (χ^2)	2438.253	2438.502	298.691	125.828
	Pval = 0.000	Pval = 0.000	Pval = 0.000	Pval = 0.000
σ_α	0.267	0.268	0.010	0.294
	(0.082)	(0.067)	(0.044)	(0.371)
Rho (ρ)	0.066	0.067	0.001	0.080
	(0.038)	(0.038)	(0.009)	(0.185)
Likelihood test (H_0: $\rho=0$)	2.995	3.008	0.001	0.173
	Pval = 0.042	Pval = 0.041	Pval = 0.491	Pval = 0.339

Standard errors are presented in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1
Note: The marginal effects are calculated as the average partial effects.

3.5.2 Persistence pattern of collaboration for different types of partners

We turn now to the analysis of the differentiated persistence pattern of collaboration agreements for three types of partners: customers and/or suppliers, competitors and research institutions. We specifically explore the degree of persistence in R&D collaborative activities when considering them separately as well as the possibility of finding such effect across the different partnerships.

Columns (1) to (3) in Table 3.7 show the estimates of our specification for the three types of partners separately. In other words, we want to analyse whether it is possible to observe different persistence trends according to the type and the diversity of partners. Again, after taking into account the assumption of the initial conditions correlated with the unobserved individual effects, we obtain lower parameters for persistence than with the hypothesis of exogenous initial conditions.[31] The Wooldridge estimates yield a marginal effect of 0.29 for institutions, that is, firms that performed cooperation agreements with research institutions at t-1 have a probability of cooperating at t around 29 percentage points higher than do firms that did not cooperate at t-1 with research centers. The same applies for the case of cooperation with clients or suppliers, with almost the same probability. In the case of cooperating with competitors, this probability is of 11 percentage points, much lower but still significant.

[31] For the sake of brevity, the results without the Wooldridge correction are not reported here, although they are available upon request.

Table 3.7. Marginal effects from dynamic random effects probit model – Type of cooperation (unbalanced panel)

	Univariate models			Trivariate model		
	Vertical cooperation	Horizontal cooperation	Institutional cooperation	Vertical cooperation	Horizontal cooperation	Institutional cooperation
	(1)	(2)	(3)	(4)	(5)	(6)
Vertical coop $_{i,t-1}$	0.288***			0.235***	0.006	0.013
	(0.022)			(0.016)	(0.006)	(0.012)
Horizontal coop $_{i,t-1}$		0.115***		0.015	0.106***	0.001
		(0.025)		(0.014)	(0.015)	(0.017)
Institutional coop $_{i,t-1}$			0.294***	0.032***	0.011**	0.232***
			(0.021)	(0.010)	(0.006)	(0.016)
Vertical coop $_{i,t0}$	0.135***			0.085***	0.015***	0.025**
	(0.018)			(0.010)	(0.005)	(0.011)
Horizontal coop $_{i,t0}$		0.057***		0.040***	0.037***	0.033**
		(0.011)		(0.013)	(0.006)	(0.015)
Institutional coop $_{i,t0}$			0.189***	0.039***	0.019***	0.123***
			(0.021)	(0.009)	(0.005)	(0.010)
Incoming spillovers	0.068***	0.028***	0.086***	0.041***	0.028***	0.056***
	(0.012)	(0.005)	(0.014)	(0.011)	(0.006)	(0.012)
Legal protection	0.021***	0.003	0.036***	0.012*	0.002	0.025***
	(0.007)	(0.003)	(0.008)	(0.006)	(0.003)	(0.007)
R&D intensity	0.046***	0.009*	0.077***	0.036**	0.011*	0.057***
	(0.016)	(0.005)	(0.020)	(0.015)	(0.007)	(0.016)
Firm size (base <50 employees)						
50 – 249 emp	0.036***	0.011***	0.030***	0.029***	0.012***	0.021***
	(0.009)	(0.003)	(0.010)	(0.007)	(0.004)	(0.008)
250 – 499 emp	0.053***	0.017***	0.052***	0.040***	0.013**	0.035***
	(0.015)	(0.006)	(0.017)	(0.011)	(0.006)	(0.012)
500 or more emp	0.104***	0.027***	0.099***	0.071***	0.019***	0.063***
	(0.017)	(0.008)	(0.020)	(0.011)	(0.006)	(0.012)
Public funding for innovation						
Local funding	0.054***	0.015***	0.087***	0.028***	0.012***	0.060***
	(0.008)	(0.003)	(0.009)	(0.007)	(0.004)	(0.007)
National funding	0.062***	0.020***	0.098***	0.038***	0.018***	0.066***
	(0.009)	(0.004)	(0.010)	(0.007)	(0.004)	(0.007)
European funding	0.045***	0.031***	0.106***	0.019*	0.025***	0.062***
	(0.015)	(0.007)	(0.019)	(0.012)	(0.005)	(0.012)
Belonging to a group	0.042***	0.007**	0.020**	0.033***	0.007**	0.013*
	(0.008)	(0.003)	(0.009)	(0.007)	(0.004)	(0.007)
Industry dummies	Included	Included	Included	Included	Included	Included
Time dummies	Included	Included	Included	Included	Included	Included
Observations	17,568	17,568	17,568		17,568	
Number of firms	7,566	7,566	7,566		7,566	
Log L	-6892.452	-3648.657	-7008.542		-16055.941	
Wald test (χ^2)	2966.723	1659.641	3450.835		4534.700	
	Pval = 0.000	Pval = 0.000	Pval = 0.000		Pval = 0.000	
σ_α	0.576	0.649	0.656	0.609	0.656	0.701
	(0.052)	(0.070)	(0.052)	(0.037)	(0.050)	(0.036)
Rho (ρ)	0.249	0.297	0.301	ρ_{12} = 0.436	ρ_{23} = 0. 526	ρ_{31} = 0. 573
	(0.034)	(0.045)	(0.033)	(0.031)	(0. 028)	(0. 020)
Likelihood test (H_0: ρ=0)	47.277	39.453	68.394			
	Pval = 0.000	Pval = 0.000	Pval = 0.000			

Standard errors are presented in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1
Note: The marginal effects are calculated as the average partial effects.

Several conclusions are worth pointing out. First, that irrespective of the type of partner, there exists a behavioural effect in the sense that the decision to cooperate with one type of partner in one period enhances the probability of being the same kind of co-operator in subsequent periods. These results suggest a significant state dependence effect for cooperation activities even once we consider separately the different types of alliances. Second, among the reasons of the highest persistence in the case of collaboration with customers, clients and research institutions one may think of the relatively limited risk of information spilling over if compared to the one in agreements with competitors, which may imply a higher persistence of the former alliance strategies. In the case of collaboration with competitors, due to the similar knowledge both firms share, the capacity for absorption of knowledge spillovers and, as a consequence, of creating free-ridership (Nooteboom, 2004) is particularly important. As a consequence, agreements of cooperation with competitors are not only scarcer but also less permanent.

It is also sensible to think that cooperation with one type of partner may be affected by the experience in cooperation with partners of a different nature. In order to account for this possible crossed-persistence, we augment our model by incorporating not only the past alliance engagement in the same type of partnership but also variables that consider if the firm was previously engaged in an alliance with each of the other two types of partners. This specification allows us to analyse whether firms with experience in technological cooperation agreements of one type are likely to form alliances with a different type of partner.

To allow for likely interdependencies between firm's decisions to engage in cooperation with a type of partner and avoid the possible bias resulting from modelling the decisions separately, we estimate a trivariate dynamic random effects probit model. We follow the empirical strategy adopted by Devicienti and Poggi (2011) which also assumes the Wooldridge initial conditions approach. The results are provided in Columns 4 to 6 in Table 3.7.

According to our results, once again the magnitude of persistence in alliances is significantly positive and of a similar magnitude than the ones obtained when the interrelations across types of partners were not included. That is, persistence in the case of institutional as well as vertical cooperation is higher than in the case of collaboration agreements with competitors, and in all cases, these persistences of the same kind of partnership are stronger than cross-persistence effects. However, only cooperation agreements with institutional partners significantly influence the likelihood of cooperating in the future with a different type of partner, although with a much lower intensity than in the case of the same partnership group. For instance, we find that firms that performed cooperation agreements with research institutions at t-1 have a probability of cooperating with clients or suppliers at t around 3 percentage points higher than do firms which did not cooperate at t-1 with such institutions. Among the reasons behind such influence of past alliances with institutions, we may think on the idea that relations with research centers or universities may allow the firm to obtain higher insights on future opportunities for innovation and the creation of a next-generation technology. Subsequent to this, the firm may need to start technological collaboration agreements with clients or suppliers so that they adapt their processes to this new technology. Additionally, as mentioned earlier, collaboration with research institutions is seen as an inexpensive and low-risk source of specialist knowledge, generally focused on the most generic or basic R&D and long-term strategic research (Archibugi and Coco, 2004; Veugelers and Cassiman, 2005; Arranz and Arroyabe, 2008; Woerter, 2012). Thus, this type of cooperation may provide the basis and tools for forming future agreements with any type of collaboration partner. On the other hand, since the objectives of vertical collaborations often differ from those of horizontal collaborations and there exists risk of undesirable knowledge spillovers and free-ridership, especially in case of collaboration with competitors (Ahuja, 2000), these types of agreements do not seem to influence significantly the future decisions to join partners of a different nature. All in all, it seems fair to think that research collaboration with clients, suppliers and competitors tends to be most often complemented by the knowledge gained through the collaboration with research institutions.

3.6 Conclusions

Our study is an attempt to analyse persistence in R&D cooperation activities and, as a consequence, understand innovation in a globalised environment. Initially, persistence in cooperation agreements is appealing, as it provides firms with a stream of information that becomes available thanks to being embedded in a network. The results show that there is a high persistence in R&D cooperation activities at the firm level. After discounting the impact of observed and unobserved firm characteristics, a firm cooperating in t-1 has a probability of cooperating in t which is around 33 percentage points higher than that of a firm not having cooperated in the previous period. It has been shown that such persistence is genuine in the sense that it is beyond the persistence observed in R&D. This could be explained by the accumulation of knowledge and capabilities that may be gained from past experiences in cooperation projects, the barriers to enter and exit which can arise due to sunk costs, and the success and reliability in past cooperation agreements. In addition, we observe that firms with higher incoming spillovers, higher R&D intensity, large firms and firms that belong to a group of enterprises as well as firms that use protection methods (such as patenting, registered an industrial design, trademark or copyright) are more persistent in their technological collaborative agreements.

When taking into account the different types of partnership, we conclude that the highest persistence is found in the case of collaboration with institutions, followed by customers and clients. One potential explanation may be related to the relatively limited risk of spillovers in those types of alliances if compared to the one in agreements with competitors, which may imply a higher persistence of the former alliances. Finally, we obtain that cooperation agreements with universities and research institutes increase the likelihood of cooperating in the future with a different type of partner, while collaboration with customers, suppliers and competitors in the past do not appear to influence such cooperation with other types of partners.

From a policy view, the fact that R&D cooperation is state dependent implies that collaboration-stimulating policy measures, such as government support programmes, are supposed to have a deeper effect because they do not only affect current collaboration agreements but are also likely to induce a permanent change in favour of cooperation. In addition, since persistence is also driven by certain individual characteristics of the firms, they could be taken into account when designing policies to stimulate cooperation in a persistent way. For instance, besides cooperation, policy makers should also stimulate the absorptive capacity of firms which would allow them to form long-term alliances.

References

Abramovsky, L., Kremp, E., López, A., Schmidt, T. and Simpson, H. (2009) Understanding co-operative innovative activity: Evidence from four European countries, *Economics of Innovation and New Technology*, 18(3), 243-265.

Ahuja, G. (2000) Collaboration networks, structural holes, and innovation: A longitudinal study, *Administrative Science Quarterly*, 45, 425-455.

Archibugi, D. and Coco, A. (2004) International partnerships for knowledge in business academia: A comparison between Europe and USA, *Technovation*, 24(7), 517–528.

Arqué-Castells, P. (2013) Persistence in R&D performance and its implications for the granting of subsidies, *Review of Industrial Organization*, 43, 193-220.

Arranz, N. and Arroyabe, J.C.F. (2008) The choice of partners in R&D cooperation: An empirical analysis of Spanish firms, *Technovation*, 28, 88-100.

Aschhoff, B. and Schmidt, T. (2008) Empirical evidence on the success of R&D cooperation -- Happy together? *Review of Industrial Organization*, 33(1), 41-62.

Barajas, A., Huergo, E. and Moreno, L. (2012) Measuring the economic impact of Research Joint Ventures supported by the EU Framework Programme, *Journal of Technology Transfer*, 37, 917-942.

Bayona, C., García-Marco, T. and Huerta, E. (2001) Firms' motivation for cooperative R&D: An empirical analysis of Spanish firms, *Research Policy*, 30(8), 1289–307.

Belderbos, R., Carree, M.A. and Lokshin, B. (2004a) Cooperative R&D and firm performance, *Research Policy*, 33(10), 1477-92.

Belderbos, R., Carree, M.A., Diederen, B., Lokshin, B. and Veugelers, R. (2004b) Heterogeneity in R&D co-operation strategies, *International Journal of Industrial Organization*, 22(8-9), 1237–63.

Belderbos, R., Gilsing, V. and Lokshin, B. (2012) Persistence of, and Interrelation Between, Horizontal and Vertical Technology Alliances, *Journal of Management*, 38(6), 1812-34.

Busom, I. and Fernández-Ribas, A. (2008) The impact of firm participation in R&D programmes on R&D partnerships, *Research Policy*, 37(2), 240-257.

Cassiman, B. and Veugelers, R. (2002) R&D cooperation and spillovers: Some empirical evidence from Belgium, *The American Economic Review*, 92(4), 1169-84.

Clausen, T., Pohjola, M., Sapprasert, K. and Verspagen, B. (2012) Innovation strategies as a source of persistent innovation, *Industrial and Corporate Change*, 21(3), 553–585.

Cohen, W.M. and Klepper, S. (1996) A reprise of size and R&D, *Economic Journal*, 106, 925-951.

Cohen, W.M. and Levinthal, D. A. (1989) Innovation and learning: The two faces of R&D, *Economic Journal*, 99, 569–596.

Cohen, W.M. and Levinthal, D.A. (1990) Absorptive capacity: A new perspective of learning and innovation, *Administrative Science Quarterly*, 35(1), 128–152.

Cyert, R.M. and March, J.G. (1963) *A behavioral theory of the firm*. Englewood Cliffs, NJ: Prentice Hall.

D'Aspremont, C. and Jacquemin, A. (1988) Cooperative and noncooperative R&D in duopoly with spillovers, *The American Economic Review*, 78(5), 1133-37.

Devicienti, F. and Poggi, A (2011) Poverty and social exclusion: two sides of the same coin or dynamically interrelated processes? *Applied Economics*, 43, 3549–71.

Dyer, J. H. and Singh, H. (1998) The relational view: cooperative strategy and sources of inter-organizational competitive advantage, *Academy of Management Review*, 23, 660-679.

Eisenhardt, K. M. and Martin, J. A. (2000) Dynamic capabilities: What are they? *Strategic Management Journal*, 21, 1105-21.

Fritsch, M. and Lukas, R. (2001) Who cooperates on R&D? *Research Policy*, 30(2), 297-312.

Goeree, M.S. and Helland, E. (2010) Do Research Joint Ventures serve a collusive function? *Working Paper* No 448, University of Zurich.

Granovetter, M. (1985) Economic action and social structure: the problem of embeddedness, *American Journal of Sociology*, 91, 481-510.

Greenlee, P. and Cassiman, B. (1999) Product market objectives and the formation of Research Joint Ventures, *Managerial and Decision Economics*, 20, 115-130.

Gulati, R. (1995) Social structure and alliance formation patterns: A longitudinal analysis, *Administrative Science Quarterly*, 40, 619–652.

Gulati, R. (1999) Network location and learning: The influence of network resources and firm capabilities on alliance formation, *Strategic Management Journal*, 20, 97-420.

Heckman, J.J. (1981) Heterogeneity and state dependence. In: Rosen, S. (Ed.), *Studies in labor markets*, 91-140. Chicago: Chicago University Press.

Hernán, R., Marin, P. and Siotis, G. (2003) An empirical analysis of the determinants of Research Joint Venture formation, *Journal of Industrial Economics*, 51, 75-89.

Hoang, H. and Rothaermel, F. (2005) The effect of general and partner specific alliance experience on joint R&D project performance, *Academy of Management Journal*, 48(2), 332–345.

Hsiao, C. (2003) *Analysis of Panel Data*. Cambridge University Press.

Jacob, J., Belderbos, R. and Gilsing, V. (2013) Technology alliances in emerging economies: Persistence and interrelation in European firms' alliance formation, *R&D Management*, 43(5), 447-460.

Jensen, M., Johnson, B., Lorenz, E. and Lundvall, B.-Å. (2007) Forms of knowledge and modes of innovation, *Research Policy*, 36(5), 680–693.

Le Bas, C., Mothe, C. and Nguyen-Thi, T.U. (2011) Technological innovation persistence: Literature survey and exploration of the role of organizational innovation, CEPS Instead, *Working Paper* 2011-54.

Levitt, B. and March, J.G. (1988) Organizational learning, *Annual Review of Sociology*, 14, 314-340.

Lööf, H. and Broström, A. (2008) Does knowledge diffusion between university and industry increase innovativeness? *The Journal of Technology Transfer*, 33(1), 73-90.

López, A. (2008) Determinants of R&D cooperation: Evidence from Spanish manufacturing firms, *International Journal of Industrial Organization*, 26, 113-136.

Lundvall, B.-Å. (1988) Innovation as an interactive process: from user–producer interaction to the national system of innovation. In: Dosi, G. Freeman, C., Nelson, R., Silverberg, G. and Soete, L. (Eds.), *Technical Change and Economic Theory*. Pinter, London, 349–369.

Lundvall, B.-Å. (2004) The economics of knowledge and learning. In: Christensen, J.L. and Lundvall, B.-Å. (Eds.), Product Innovation, Interactive Learning and Economic Performance (*Research on Technological Innovation and Management Policy*, vol 8). Emerald Group Publishing Ltd., 21-42.

Miotti, L. and Sachwald, F. (2003) Cooperative R&D: Why and with whom? An integrated framework of analysis, *Research Policy*, 32(8), 1481-1499.

Nelson, R.R. and Winter, S.G. (1982) *An evolutionary theory of economic change*. Cambridge, MA: Belknap.

Nieto, M.J. and Santamaría, L. (2007) The importance of diverse collaborative networks for the novelty of product innovation, *Technovation*, 27, 367-377.

Nooteboom, B. (2004) *Inter-firm collaboration, learning and networks: An integrated approach*. London: Routledge.

Peters, B. (2009) Persistence of innovation: Stylised facts and panel data evidence, *The Journal of Technology Transfer*, 34, 226-243.

Powell, W., Koput, K. and Smith-Doerr, L. (1996) Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology, *Administrative Science Quarterly*, 41(1), 116-146.

Raymond, W., Mohnen, P.A., Palm, F. and Van der Loeff, S.S. (2010) Persistence of innovation in Dutch manufacturing: Is it spurious? *The Review of Economics and Statistics*, 92, 495-504.

Röller, L., Siebert, R. and Tombak, M. (2007) Why firms form (or do not form) RJVS, *The Economic Journal*, 117(522), 1122-1144.

Sutton, J. (1991) *Sunk costs and market structure*. MIT Press, London.

Tether, B.S. (2002) Who co-operates for innovation, and why: An empirical analysis, *Research Policy*, 31(6), 947-967.

Triguero, Á. and Córcoles, D. (2013) Understanding innovation: an analysis of persistence for Spanish manufacturing firms, *Research Policy*, 42(2), 340-352.

Vassolo, R.S., Anand, J. and Folta, T.B. (2004) Non-additivity in portfolios of exploration activities: A real options based analysis of equity alliances in biotechnology, *Strategic Management Journal*, 25, 1045-61.

Veugelers, R. and Cassiman, B. (2005) R&D cooperation between firms and universities. Some empirical evidence from Belgian manufacturing, *International Journal of Industrial Organization*, 23(5–6), 355–379.

Woerter, M. (2012) Technological proximity between firms and universities and technology transfer, *Journal of Technology Transfer*, 37, 828–866.

Wooldridge, J.M. (2005) Simple solutions to the initial conditions problem in dynamic nonlinear panel data models with unobserved heterogeneity, *Journal of Applied Econometrics*, 20, 39–54.

Wooldridge, J.M. (2010) *Econometric Analysis of Cross Section and Panel Data*. Third Edition. Cambridge, MA: MIT Press.

Appendix 3.A: Variable definitions

Table A3.1. Definition of the variables included in the empirical analysis

Variables	Definitions
Dependent	
Cooperation $_t$	= 1 if the firm cooperated in some of its innovation activities with other enterprises or institutions in the period t = 0 otherwise
Type of Cooperation:	
Vertical Cooperation $_t$	= 1 if the firm cooperated in some of its innovation activities with clients or customers; suppliers of equipment, materials, components or software in the period t = 0 otherwise
Horizontal Cooperation $_t$	= 1 if the firm cooperated in some of its innovation activities with competitors or other enterprises of the same sector in the period t = 0 otherwise
Institutional Cooperation $_t$	= 1 if the firm cooperated in some of its innovation activities with consultants, commercial labs or private R&D institutes; universities or other higher education institutions; government or public research institutes; technological centres in the period t = 0 otherwise
Independent	
Cooperation $_{t-1}$	= 1 if the firm cooperated in some of its innovation activities with other enterprises or institutions in the period t-1 = 0 otherwise
Incoming spillovers	= 1 if firm gives high importance to the following information sources for undertaking its innovation activities: conferences, trade fairs, exhibitions; scientific journals and trade/technical publications; professional and industry associations. = 0 otherwise
Legal Protection	= 1 if the firm uses at least one of the following legal methods for protecting inventions or innovations: applied for a patent; registered an industrial design; registered a trademark; claimed copyright = 0 otherwise
R&D Intensity	Ratio between intramural R&D expenditure and turnover
Firm Size	<50 employees =1 if the firm has less than 50 employees; =0 otherwise 50 – 249 employees =1 if the firm has between 50 and 249 employees; =0 otherwise 250 – 499 employees =1 if the firm has between 250 and 499 employees; =0 otherwise 500 or more employees=1 if the firm has 500 or more employees; =0 otherwise
Local funding	= 1 if the firm receives funding from local or regional authorities to carry out its innovation activities = 0 otherwise
National funding	= 1 if the firm receives funding from central government to carry out its innovation activities = 0 otherwise
European funding	= 1 if the firm receives funding from European Union to carry out its innovation activities = 0 otherwise
Belonging to a group	= 1 if the firm belongs to a group of enterprises = 0 otherwise

Appendix 3.B: Some additional results

Table A3.2. Correlation between the explanatory variables and their corresponding within means

Incoming spillovers	0.839
Legal protection	0.832
R&D intensity	0.941
Firm size	0.981
Local funding	0.836
National funding	0.826
European funding	0.846
Belonging to a group	0.954

Table A3.3. Marginal effects from dynamic random effects probit model (Three waves)

	Unbalanced panel		Balanced panel	
	Random effects probit	Wooldridge correction	Random effects probit	Wooldridge correction
Cooperation $_{i,t-1}$ (*persistence*)	0.386***	0.260***	0.395***	0.265***
	(0.011)	(0.028)	(0.013)	(0.031)
Cooperation $_{i,t0}$ (*initial conditions*)		0.164***		0.168***
		(0.034)		(0.036)
Incoming spillovers	0.099***	0.107***	0.084***	0.089***
	(0.020)	(0.023)	(0.023)	(0.027)
Legal protection	0.029**	0.032**	0.023*	0.025*
	(0.011)	(0.013)	(0.013)	(0.015)
R&D intensity	0.065**	0.076**	0.055	0.067
	(0.030)	(0.034)	(0.038)	(0.045)
Firm size (base <50 employees)				
50 – 249 emp	0.045***	0.049***	0.035**	0.039**
	(0.013)	(0.015)	(0.015)	(0.018)
250 – 499 emp	0.065***	0.073***	0.055**	0.063**
	(0.021)	(0.024)	(0.023)	(0.028)
500 or more emp	0.109***	0.122***	0.104***	0.119***
	(0.023)	(0.027)	(0.026)	(0.031)
Public funding for innovation				
Local funding	0.087***	0.094***	0.099***	0.108***
	(0.013)	(0.015)	(0.015)	(0.017)
National funding	0.118***	0.130***	0.119***	0.133***
	(0.013)	(0.015)	(0.015)	(0.018)
European funding	0.163***	0.179***	0.157***	0.173***
	(0.024)	(0.027)	(0.027)	(0.031)
Belonging to a group	0.070***	0.081***	0.075***	0.089***
	(0.013)	(0.015)	(0.014)	(0.017)
Industry dummies	Included	Included	Included	Included
Time dummies	Included	Included	Included	Included
Observations	10,508	10,508	8,032	8,032
Number of firms	6,492	6,492	4,016	4,016
Log L	-5420.735	-5407.278	-4183.650	-4171.152
Wald test (χ^2)	2207.177	1643.576	1881.365	1368.202
	Pval = 0.000	Pval = 0.000	Pval = 0.000	Pval = 0.000
σ_α	0.283	0.665	0.245	0.668
	(0.073)	(0.077)	(0.091)	(0.084)
Rho (ρ)	0.074	0.306	0.057	0.309
Likelihood test (H_0: $\rho=0$)	4.281	29.720	2.047	24.757
	Pval = 0.019	Pval = 0.000	Pval = 0.076	Pval = 0.000

Standard errors are presented in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1
Note: The marginal effects are calculated as the average partial effects.

Table A3.4. Marginal effects from dynamic random effects probit model (Wooldridge correction)

	Unbalanced panel	Balanced panel
Cooperation $_{i,t-1}$ (*persistence*)	0.334***	0.326***
	(0.018)	(0.020)
Cooperation $_{i,t0}$ (*initial conditions*)	0.186***	0.204***
	(0.021)	(0.024)
Permanent R&D	0.080***	0.086***
	(0.011)	(0.014)
Incoming spillovers	0.086***	0.081***
	(0.018)	(0.024)
Legal protection	0.033***	0.035***
	(0.010)	(0.013)
R&D intensity	0.086***	0.102**
	(0.027)	(0.041)
Firm size (base <50 employees)		
50 – 249 emp	0.041***	0.041**
	(0.012)	(0.016)
250 – 499 emp	0.065***	0.067***
	(0.020)	(0.025)
500 or more emp	0.116***	0.109***
	(0.022)	(0.028)
Public funding for innovation		
Local funding	0.094***	0.097***
	(0.011)	(0.015)
National funding	0.094***	0.091***
	(0.012)	(0.015)
European funding	0.124***	0.134***
	(0.022)	(0.027)
Belonging to a group	0.069***	0.088***
	(0.012)	(0.015)
Industry dummies	Included	Included
Time dummies	Included	Included
Observations	17,568	12,012
Number of firms	7,566	4,004
Log L	-8342.705	-5790.394
Wald test (χ^2)	3637.883	2364.141
	Pval = 0.000	Pval = 0.000
σ_α	0.631	0.684
	(0.046)	(0.051)
Rho (ρ)	0.285	0.319
Likelihood test (H_0: $\rho=0$)	76.880	77.554
	Pval = 0.000	Pval = 0.000

Standard errors are presented in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1
Note: The marginal effects are calculated as the average partial effects.

Chapter 4:

Does absorptive capacity determine collaborative research returns to innovation? A geographical dimension

Does absorptive capacity determine collaborative research returns to innovation? A geographical dimension

4.1 Introduction

The literature on R&D cooperation and their impact on knowledge diffusion and innovation and consequently on growth, has expanded greatly in recent years (see e.g. Autant-Bernard et al. (2007) and Bergman (2009) for evidence at the macro level; and Vega-Jurado et al. (2009) and Arvanitis and Bolli (2013) at the micro level). The growing need for enhanced innovation capability through the use of new knowledge produced elsewhere is leading firms to expand technology interaction with different and increasingly geographically dispersed actors. Indeed, collaborative research with a broader range of external partners may enable innovating firms to acquire required information from a variety of sources which could lead to more synergies and intake of complementary knowledge, thus promoting innovation performance (Belderbos et al., 2006; Laursen and Salter, 2006; Nieto and Santamaría, 2007; Van Beers and Zand, 2014).

The present piece of research contributes to this literature. In particular, we focus on the geographical scope of research alliances and study their differentiated impact on innovation performance. A priori, R&D collaboration with partners abroad provides access to unique resources of foreign partners, which can produce complementary knowledge that may be in short supply in the firm's home country. This is because partners abroad are embedded in different national innovation systems than partners in the domestic market (Miotti and Sachwald, 2003; Lavie and Miller, 2008; Van Beers and Zand, 2014). Therefore, we expect collaborative research with partners from abroad to have higher impact on the firm's innovative performance than national research collaborations. In addition, the underlying logic would state that when the external knowledge is similar to existing competences in the country, it can be absorbed easily, but will not add much to the existing local knowledge (Boschma and Iammarino, 2009). In sum, distant knowledge sources should allow individuals in innovative firms to make novel associations and linkages which increase their innovativeness.

Despite the extensive literature on the relationship between collaborative research and innovation performance, little attention has been placed on the impact that the geographical scope of such research alliances may have on innovation performance. There are some papers with national studies on the differences between national and international research alliances with respect to the impact on innovation output (Miotti and Sachwald, 2003; Cincera et al., 2003; Lööf, 2009; Arvanitis and Bolli, 2013) which tend to conclude that innovation performance is positively and significantly influenced by international R&D cooperation, but remains unaffected or less affected by national cooperation. However, our research extends previous literature by disaggregating the geographical scope of the international alliances to explore the effect of collaborative research with partners in particular geographic areas. Specifically, for knowledge that comes from abroad, we differentiate among collaborations maintained with European partners and those further away (the US, China, India, or other countries). The latter are theorized to provide less redundant pieces of knowledge, which would allow enhancing creativity and innovation to a greater extent than in the intra-European case. Indeed, Miotti and Sachwald (2003) conclude that French firms resort to transatlantic R&D alliances in order to access specific and complementary R&D resources, whereas cooperation with European partners is mainly motivated by cost economising. This being true, it is sensible to think that both transoceanic and intra-European cooperation have a positive influence on the share of innovative products, although cooperation with transoceanic partners can have a higher influence whenever firms conduct research at the technological frontier. The reasoning is that this difference is due to the complementarity of the resources of extra-EU partners with those of European firms, making this type of cooperation more efficient in terms of innovation, especially for more radical innovation. We will check this hypothesis empirically.

The second issue in which this research extends the existing empirical literature addresses the fact that firms can form alliances from several geographical areas at a time. Previous literature has focused on the importance of diverse collaborative agreements in terms of the type of partner –supplier, client, competitor, or research organisation– in achieving product innovations. In general terms, it is concluded that firms that obtain the greatest positive impact maintain collaborative alliances with different types of partners. In other words, using a wide range of external actors helps the firm to achieve innovation since having a broader spectrum of experiences with diverse partners should allow for wider knowledge than collaboration with only one type of partner (Becker and Dietz, 2004; Laursen and Salter, 2006; Nieto and Santamaría, 2007). We extend this reasoning to the geographical dimension. In principle, we hypothesize that collaborating with partners from diverse geographical areas should substantially boost innovation thanks to the amount and variety of knowledge that can be shared, allowing the alliance partners to fill out their initial resources and enabling the firm to make novel association and linkages. In contrast, additional alliances with the same partner may provide only redundant information and could result in inertia (Hoang and Rothaermel, 2005), the same that additional alliances with partners in the same geographical area would imply information from the same regional or national innovation system. We can then argue that diverse geographical sources of knowledge provide opportunities for the firm to choose among different technological paths. Having a heterogeneous portfolio of partners enables access to diverse sources of information which facilitates firms to transfer and apply that knowledge. Thereby we will evaluate the impact of conducting research alliances with partners in at least two different geographical areas, which is assumed as providing greater diversity of the type of exchanged knowledge in the collaborative agreement.

The third and main hypothesis of this chapter states that firms' absorptive capacity determines collaborative research returns to innovation. Innovation is an evolutionary and cumulative process. In consequence, only with the necessary capability to identify, assimilate, and develop useful external knowledge can the host firms and regions effectively benefit from incoming technology flows through research networks. As discussed by Cohen and Levinthal (1990), the differential impact of external incoming knowledge flows depends mainly on firms' absorptive capacity. In the present inquiry, we argue that absorptive capacity is needed to understand and transform inflows of knowledge into innovation. Those firms with higher levels of absorptive capacity can manage external knowledge flows more efficiently, and therefore, stimulate innovative outcomes (Escribano et al., 2009). Thus, even firms exposed to the same amount of external knowledge – within a cluster, for instance – might not enjoy the same benefits, because of their different endowments of absorptive capacity (Giuliani and Bell, 2005). However, we plan to give a step forward and analyse if this absorptive capacity is equally important for national and international sources of external knowledge. A priori, investing in internal R&D activities and training employees add to the absorptive capacity of the firm and increase its ability to understand and assimilate any knowledge from external sources. However, when these sources originate in very distant geographical areas, with different economic and social backgrounds, absorptive capacity may play a higher role than in the case of external knowledge originated within the same region or economic area.

We check the validity of these three hypotheses using data from the Spanish Technological Innovation Panel for the period 2004-2011, which contains detailed information on R&D and innovative behaviour of Spanish firms. Since innovation performance can only be observed for firms which report at least one innovation, the empirical strategy consists of a two-stage selection model, estimated using the Wooldridge's (1995) consistent estimator for panel data with sample selection. The first equation is a selection equation indicating whether or not the firm was innovative. The second stage of the analysis captures the impact of research collaboration with different and diverse geographical areas on innovative performance, taking into account how this impact may vary according to the absorptive capacity of the firm.

From a policy perspective, the results in this chapter confirm that not only investments in R&D are important to generate innovations, but also the degree to which connectivity with the outside world, which gives access to global knowledge hotspots, is useful for innovation. Such connectivity, among other ideas, is at the core of the 'smart specialisation' strategy recently launched by the European Commission (McCann and Ortega-Argilés, 2013). According to it, the "smart specialisation strategy" should include an analysis of potential partners in other regions and avoid unnecessary duplication. It also needs to be based on a strong partnership between businesses, public entities and knowledge institutions (European Commission, 2012). The empirical evidence presented in the present research goes in this direction. However, it also aims at showing to what extent the benefits of research collaboration are likely to differ across different geographic scales. Understanding such differentiated impact of research collaborations may help to identify the geographical areas from which the highest benefits can be obtained; which is critical to effectively promote regional economic growth and cohesion.

The outline of this chapter is as follows. Section 4.2 offers the empirical model. The dataset, variables and a descriptive analysis are given in Section 4.3 and Section 4.4 provides the main results. Section 4.5 concludes.

4.2 Empirical model

We aim to estimate the impact of research collaboration with partners in different geographical areas on innovative performance. Since innovative performance can only be observed for firms that report at least one innovation, we follow a two-stage approach to address the potential selection bias on the estimation of the innovation performance equation. The first stage of our analysis consists of a binary selection model using all available observations and considering as dependent variable whether or not the firm was innovative (*d*). In the second stage, we estimate the innovation performance equation taking account of the selection process. In this second stage model, the dependent variable that proxies for innovative performance (*y*) is a measure of the shares of sales due to new or significantly improved products.

The model has the following specification:

$$d_{it} = 1\left[z_{it}\gamma + \eta_i + u_{it} > 0\right], \tag{4.1}$$

$$y_{it} = \begin{cases} x_{it}\beta + \alpha_i + \varepsilon_{it} & \text{if} \quad d_{it} = 1 \\ 0 & \text{if} \quad d_{it} = 0, \end{cases} \tag{4.2}$$

where $i = 1, \ldots, N$, $t = 1, \ldots, T$, and 1[.] is an indicator function that takes on the value 1 if the expression between square brackets is true and 0 otherwise. In addition, γ and β are unknown parameter vectors to be estimated; z_{it} and x_{it} are vectors of explanatory variables with possibly common elements. In equation (4.2) we assume that there are valid exclusion restrictions. η_i and α_i are unobserved individual specific effects which may be correlated with z_{it} and x_{it}, respectively; and u_{it} and ε_{it} the idiosyncratic errors. The innovation performance variable (y_{it}) is only observable if the firm innovated ($d_{it} = 1$) and the parameter vector of interest to estimate is β.

We estimate the model using Wooldridge's (1995) consistent estimator for panel data with sample selection. This method consistently estimates β by first estimating a probit of d_i on z_i for each t and then saving the inverse Mills ratio, $\hat{\lambda}_{it}$. Next, we estimate by pooled OLS the equation of interest augmented by the inverse Mills ratio using the selected sample. The resulting equation is (Wooldridge, 2010):

$$y_{it} = x_{it}\beta + x_i\psi + \sum_{t=1}^{T}\rho_t D_t \hat{\lambda}_{it} + e_{it} \qquad \text{for all } d_{it} = 1 \tag{4.3}$$

where D_t is a time indicator variable and x_i represents a vector of means of the time-variant regressors.[32]

[32] We assume that the conditional mean of the individual effects are a linear projection on the within individual means of the time-variant regressors (Mundlak, 1978; Nijman and Verbeek, 1992; Zabel, 1992; Wooldridge, 1995).

4.3 Dataset, variables and descriptive analysis

4.3.1 Dataset

The data come from the Spanish Technological Innovation Panel (PITEC), as in the previous chapters, for the period 2004-2011. Our sample contains information on manufacturing and services firms with at least ten employees and positive sales. We use an unbalanced panel with 71,556 observations which represent about 10,902 firms for the whole period. In order to minimise potential endogeneity problems, all the explanatory variables are lagged. This results in a dataset covering 10,012 firms and 70,182 observations.

4.3.2 Variables

Dependent variables

The dependent variable in the first stage is binary, indicating whether the firm has been engaged in any innovation activity during the period t-2 and t. In the second stage, the measure of innovation performance, observed at period t, is defined as the share of sales due to new or significantly improved products. This is a quantitative measure of innovation performance often used in the literature and its logarithmic transformation benefits from being closer to a normal distribution and being symmetric[33] (Klomp and Van Leeuwen, 2001; Mohnen et al., 2006; Raymond et al., 2010; Robin and Schubert, 2013; Barge-Gil, 2013).

Explanatory variables

Based on previous literature, we explain the probability of being an innovator as a function of the firm size and its squared term (in order to take nonlinearities into account), market share, belonging to a group and industry

[33] $log[y/(1-y)]$ where the zero values are converted to 0.0001 and 100 per cent becomes 0.9999.

dummies (Veugelers and Cassiman, 1999; Vega-Jurado et al., 2009; Raymond et al., 2010). We also allow for factors perceived as barriers to innovation activities using four Likert-type constraint variables: cost obstacles, knowledge obstacles, market obstacles, and other obstacles (see Table A4.1 in Appendix 4.A for a detailed description of these variables). These variables are available for both innovative and non-innovative firms. Since the innovation indicator refers to the period between t-2 and t, we defined these explanatory variables in t-2. The variables market share, belonging to a group, and the four variables related to the obstacles to innovation presented above are considered as exclusion restrictions for the second stage. They are considered in the selection model as a likely influence on the decision to carry out innovation activities, but not as determinants of innovation performance.

In the second stage, to evaluate the impact of the geographical scope of research alliances on innovation performance, we constructed different sets of dummy variables indicating the geographic location of the collaboration partner. First, we distinguish between firms that collaborated in R&D activities exclusively with national partners (*National*) and those exclusively with international partners (*International*). Then, with the aim of disentangling the differential impact of international alliances, we distinguish among research collaborations maintained exclusively with European partners (*European*) and exclusively with partners in other areas including the US, China and India (*extra-European*). Finally, we further divide the extra-European alliances category into two different variables, namely US alliances (*US*) and alliances with partners in Asia and elsewhere (*Asian/Others*). We use these mutually exclusive variables to avoid potential problems of multicollinearity and also to capture the impact of each partnership area more clearly by separating it from the effects attributable to other partnership areas. In all cases, for firms that collaborate with partners in at least two different geographical areas, we constructed the variable *Multiple areas*, which takes the value 1 in such cases, and 0 otherwise.

The second independent variable of interest in our model is absorptive capacity. In this study we use the proportion of internal R&D expenditures over total sales as a proxy for a firm's absorptive capacity. This measure is the most common proxy for absorptive capacity in the literature and accounts for the effort of a firm to build a stock of knowledge (Jones et al., 2001; Belderbos et al., 2004; Faems et al., 2005; Schoenmakers and Duysters, 2006; Nieto and Santamaría, 2007; Van Beers and Zand, 2014). As discussed by Cohen and Levinthal (1989), the firm's stock of knowledge may play a dual role. First, it enables creation and assimilation of new knowledge which can be used for the development of new or enhanced products, thereby exerting a direct influence on innovation performance. A positive impact of this variable is therefore expected. Second, knowledge plays a role as a means to enhance the firm's ability to assimilate and exploit external sources of knowledge. Thus, those firms with greater R&D capacity have a developed technology base that allows them to manage external knowledge flows more efficiently, and therefore, stimulate innovative output (Escribano et al., 2009). In our research, this applies to knowledge acquired through research collaborations with partners in different geographic locations; to evaluate this we included a cross-product term between each collaboration variable and the proxy for absorptive capacity.

Control variables in the second stage include a set of 2-digit industry dummies as well as several other variables often used in studies on the innovative performance of firms. Among them, firm size is measured by the logarithm of the number of firm employees and its squared term is also included in order to consider the existence of non-linearities in this relationship. The sign for the impact of firm size is not clear a priori. According to the Schumpeterian hypothesis (Schumpeter, 1942) the size of the firm positively influences its innovative output. Large firms are more likely to have the necessary resources (infrastructure, financial resources, and production and marketing capabilities) to face the risks associated with innovation processes and hence, they are more likely than smaller firms to engage in innovative activities. While some empirical studies have supported the Schumpeterian hypothesis (Tsai, 2009; Raymond et al., 2010), this is not always the case. A number of studies have found that small firms are more innovation-intensive than larger firms. Among other reasons, this is due to a lower degree of rigidity when faced with innovations (Acs and Audretsch, 1988; Lööf, 2009; Arvanitis and Bolli, 2013).

A firm is considered a foreign-owned multinational if it has at least 50% of foreign capital and is headquartered outside Spain. Although the empirical evidence is not conclusive, previous studies suggest that the subsidiary of a foreign parent company may perform better in bringing new products to the market than a host company (Tsai, 2009). The idea is that foreign-owned firms have the advantage of accessing specific knowledge and resources of a group of firms and therefore can transfer technology at lower cost, which enables them to create new products and services in their host country more easily and enjoy a higher turnover from these innovations than a domestically owned firm (Reis, 2001; Dachs et al., 2008; Díaz-Díaz, 2008). In order to control for the experience and knowledge accumulated from past R&D, we also include a binary variable indicating whether the firm conducted internal R&D activities continuously (*Permanent R&D*), which is argued to have a positive influence on innovation output through learning effects (Aschhoff and Schmidt, 2008; Raymond et al., 2010; Van Beers and Zand, 2014). It is assumed that a firm that conducts R&D regularly has greater potential for detecting ideas for new products.

Further, recent literature considers that firms can better achieve and sustain innovation by adopting a diverse set of sources of information that are available and thus can be a proxy for unintentional externalities or spillovers. According to Duysters and Lokshin (2011) a greater access to external search channels allows firms to broaden the pool of technological opportunities and to draw on ideas from multiple external sources which can lead to a higher innovation performance. To measure the openness degree of a firm to these sources of information we follow a method similar to that of Laursen and Salter (2006) and Robin and Schubert (2013). We use the eight main sources of information available in the survey, each coded as a binary variable which is equal to 1 if the source was used and 0 otherwise. We exclude internal sources within the firm and university or public research institutes sources because, as in Laursen and Salter (2006) and Robin and Schubert (2013), most firms report no usage of these sources. These eight indicators are summed to construct a measure of openness which varies from 0 (no external sources used) and 8 (all external sources used); a higher value indicates a greater openness of a firm to external sources of information for innovation. However, this does not necessarily imply any formal cooperation, which in our case is measured through another set of variables. Finally, we include a demand-pull variable in the model. Following Raymond et al. (2010), we proxy it with a dummy variable that takes value 1 if at least one of the following objectives of innovation is scored as very important in the survey (where 1 is not used/not relevant and 4 is very important on a Likert scale), and 0 otherwise: extend product range, increase market or market share, and improve quality in goods and services. Most empirical studies find that firms that devote more effort to increasing demand for their products, and therefore to market expansion get higher sales of innovative products (Belderbos et al., 2004; Lööf and Broström, 2008; Raymond et al., 2010).

Table A4.1 in the Appendix provides more details on the definitions of the variables that are used in this study. Table A4.2 shows the correlations between the explanatory variables of the model. We do not observe any indication of multicollinearity in our regressions even when the cross terms between the collaboration variables and absorptive capacity are considered.

4.3.3 Descriptive analysis

Table 4.1 provides summary statistics for the dependent and explanatory variables used in the empirical analysis. Panel A offers figures only for innovate firms, while Panel B includes all firms in our sample, both innovative and non-innovative. We observe that 76% of Spanish firms are innovative and their average share of innovative sales is 27%. Additionally, within the innovative firms, the average size is 317 employees (median size is 63 employees) and R&D expenditures over turnover represent about 7.3%. On average, nearly 11% of innovative firms are foreign multinationals, while over half of them are firms conducting internal R&D continuously.

Table 4.1. Summary statistics on the variables used in the econometric analysis

	Mean	S.D. Overall	S.D. Between	S.D. Within
Dependent variables				
Innovation *(n=70,182)*	0.762	0.426	0.358	0.235
% of total innovative sales *(if innovation=1, n=53,502)*	27.11	36.08	26.38	25.45
Explanatory variables				
Panel A. Main equation (if innovation=1)				
RD	0.073	0.246	0.222	0.107
Size	317.1	1484.3	1495.1	366.0
Permanent R&D	0.537	0.498	0.404	0.301
Foreign multinational	0.110	0.313	0.285	0.120
Openness	5.083	2.744	2.157	1.855
Demand pull	0.628	0.483	0.365	0.338
Panel B. Selection equation (all obs., n = 70,182)				
Size	345.64	1533.0	1438.1	405.41
Cost obstacles	0.537	0.340	0.269	0.210
Knowledge obstacles	0.462	0.326	0.249	0.213
Market obstacles	0.631	0.266	0.203	0.172
Other obstacles	0.735	0.275	0.200	0.191
Market share (%)	0.570	2.287	1.998	0.987
Belonging to a group	0.418	0.493	0.458	0.179

Table 4.2 displays the distribution of the types of alliance by geographical areas and their temporal pattern. This table reveals interesting results. About one-third of innovative firms maintained some type of research alliances, which although not negligible, implies that only a minority of firms engage in collaborative agreements as part of their innovative process. Concerning the geographical scope of such collaborative agreements, research alliances with local partners are much higher than with foreign partners. On average, more than 60% of collaborative firms maintain research alliances exclusively with national partners with a decreasing pattern from 2005. The national nature of the majority of technological partnerships is not exclusive to the Spanish case. Previous studies with similar figures include Miotti and Sachwald (2003) and Monjon and Waelbroeck (2003) for the French case, and Van Beers and Zand (2014) for Dutch firms. The second most common type of alliance is that including both national and international partners which appears to be increasing over time, ranging from 27 to above 37 percent between 2005 and 2011. Within international alliances, research collaboration with European partners exclusively is the most common although with a slightly decreasing trend. Contrarily, the proportion of alliances with partners in more distant geographical areas tend to increase along the period, although are less frequent than European alliances. In particular, the share of collaborations with China, India, and others grew from 7.2% in 2005 to 12% in 2011. This is consistent with the idea that technological knowledge is becoming more and more dispersed over the world and firms are increasing their efforts to benefit from new hubs of knowledge such as the ones in Asia (Duysters and Lokshin, 2011). As stated by Bathelt et al. (2004) and Owen-Smith and Powell (2004), firms in regions build ‘pipelines’ in the form of alliances to benefit from knowledge hotspots around the world.

Table 4.2. Percentage of cooperative firms by type of alliance

	2005	2007	2009	2011
% Cooperative firms over innovative firms	0.358	0.339	0.353	0.378
Geographical areas of alliances (% of each category over cooperative firms)				
National exclusively	67.76	64.20	62.53	58.18
International exclusively	5.12	5.25	4.32	4.46
National & International	27.12	30.54	33.15	37.36
Total	100	100	100	100
International alliances				
European exclusively	79.86	71.09	75.49	69.57
US exclusively	3.60	7.03	6.86	6.52
Asian/Others exclusively	7.19	6.25	9.80	11.96
Multiple foreign areas (at least two)	9.35	15.63	7.84	11.96
Total	100	100	100	100

4.4 Results and discussion

4.4.1 Innovation performance and the geographical scope of research alliances

The first step in our empirical model is to estimate the selection equation (the propensity to innovate) for each year (see Table A4.3 in Appendix 4.B for the results of these regressions). From the estimation of these probit models we obtain the correction terms (the inverse Mill's ratio) which are included in the second stage, focused on the study of the impact of the geographical scope of research collaborations on the firms' innovative performance. Here the correction terms are included to account for the selection bias caused by the fact that we only observe the sales share of innovative products for firm that innovate. Through all the results presented below we perform two Wald tests: one on the joint significance of the six selection effects involved $(H_0 : \rho_{2006} = 0, ..., \rho_{2011} = 0)$ which can be interpreted as a test of selection bias; and the other for the joint significance of the coefficients on the within-individual means to check for the existence of correlated individual effects $(\mathrm{H}_0 : \psi = 0)$. As presented in Table 4.3, the values for these test statistics are significantly different from zero which points to the necessity of correcting for sample selection bias and suggesting the presence of correlated effects.

Table 4.3. Impact of the geographical scope of research alliances on innovation performance

	(1)	(2)	(3)	(4)
RD	1.502***	1.421***	1.420***	1.419***
	(0.183)	(0.184)	(0.184)	(0.184)
Size	-0.409***	-0.413***	-0.409***	-0.408***
	(0.107)	(0.107)	(0.107)	(0.107)
Size^2	0.032***	0.031***	0.030***	0.030***
	(0.010)	(0.010)	(0.010)	(0.010)
Permanent R&D	0.444***	0.435***	0.434***	0.434***
	(0.125)	(0.125)	(0.125)	(0.125)
Foreign multinational	0.061	0.084	0.087	0.091
	(0.235)	(0.235)	(0.235)	(0.236)
Openness	0.069***	0.059***	0.058***	0.058***
	(0.012)	(0.012)	(0.012)	(0.012)
Demand pull	0.445***	0.444***	0.446***	0.447***
	(0.092)	(0.092)	(0.092)	(0.093)
Research Collaborations				
National		0.344***	0.346***	0.346***
		(0.067)	(0.067)	(0.067)
International		0.946***		
		(0.242)		
European			0.422	0.423
			(0.263)	(0.263)
extra-European			3.132***	
			(0.669)	
US				3.912***
				(1.028)
Asian/Others				2.636***
				(0.997)
Multiple areas		0.494***	0.510***	0.511***
		(0.086)	(0.083)	(0.083)
Constant	-4.532***	-4.519***	-4.524***	-4.524***
	(0.296)	(0.295)	(0.297)	(0.297)
Industry dummies	Yes	Yes	Yes	Yes
Inverse Mills ratios	Yes	Yes	Yes	Yes
Means-fixed effects	Yes	Yes	Yes	Yes
Wald Test	χ^2 =95.63	χ^2 =94.41	χ^2 =95.33	χ^2 =95.08
(Selection)	*P-val=0.000*	*P-val=0.000*	*P-val=0.000*	*P-val=0.000*
Wald Test	χ^2 =410.23	χ^2 =392.87	χ^2 =391.97	χ^2 =391.94
(Means-fixed effects)	*P-val=0.000*	*P-val=0.000*	*P-val=0.000*	*P-val=0.000*
R-squared	0.095	0.096	0.096	0.096
Observations	35,865	35,865	35,865	35,865

Bootstrapped standard errors are presented in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

Table 4.3 shows the results for different specifications of our main model of innovation performance. Column 1 contains the control variables plus our proxy of absorptive capacity. As we observe, R&D expenses exert a significant and positive impact on innovation performance, a finding in line with the absorptive capacity literature, where it is argued that R&D expenditures stimulate firm's innovation output. Regarding the control variables, the results are robust through all our estimates. Our results indicate a negative and non-linear relationship between firm size and innovation performance. This finding is in consonance with other studies where the intensity of innovation is negatively related to size; probably once the firm has decided to innovate, small firms tend to benefit more from their innovations and experience greater impact on their sales. This can also be explained because innovative sales increase with the firm's size, that is, with additional employees, but less than the total sales of the firm (Lööf, 2009; Vega-Jurado et al., 2009; Robin and Schubert, 2013; Arvanitis and Bolli, 2013; Arvanitis et al., 2013). Also, the variable capturing the experience and knowledge accumulated from past R&D (*Permanent R&D*) has the expected positive sign. Thus, firms that undertook R&D continuously reach a larger share of innovative sales through learning mechanisms. In line with previous studies, the degree of openness of the firm and the demand pull indicator are positively associated with the intensity of product innovation (Belderbos et al., 2004; Duysters and Lokshin, 2011). In addition, we find that the variable capturing the foreign multinational nature of the firm is not significant, leading to the conclusion that foreign-owned firms are not necessarily different from their domestic counterparts when it comes to innovation output (in line with the results in Tsai, 2009 and Arvanitis and Bolli, 2013).

Column 2 of Table 4.3 presents the results when the collaboration variables are included. In a first instance, we are interested in assessing the difference in the impact of research collaboration with partners located in the firm's home country compared with partners abroad. As can be seen from Table 4.3, collaborations exclusively with national partners and those exclusively with international partners are found to be positive and statistically significant, pointing to a positive benefit from cooperation with external firms or institutions. Moreover, our results conclude that firms maintaining research collaborations with partners abroad increase the share of innovative sales more than those that collaborate only with partners located in the same geographical area. Indeed, we performed a Wald test for the equality of the coefficients to test if these effects are significantly different from each other. We reject the null hypothesis at a 5% significance level ($\chi^2 = 5.90$; $p\text{-}val = 0.015$). This can be explained by the fact that collaboration with partners abroad can improve access to new or complementary technologies and resources that provide less redundant pieces of knowledge, which would allow enhancing innovation. This is also consistent with two theoretical expectations: first, partners abroad are embedded in different national innovation systems than partners in the local market and therefore such international collaboration would allow firms to have access to complementary knowledge that is in short supply in their home region (Miotti and Sachwald, 2003); second, a firm maintaining collaborations with partners in remote countries is probably exposed to the needs of characteristic foreign markets and may therefore extend the scope of its accessible knowledge base (Lavie and Miller, 2008).

We now disaggregate the variable of international research alliances to distinguish the differentiated impact of collaborations maintained with European partners, with which, a priori, not only geographical distance is smaller but also cognitive and technological distance, than with partners in more remote areas (US, China, India, or other countries). The results are reported in Column 3. We obtain that collaborations exclusively with European partners do not significantly promote innovation sales, whereas when such alliances are formed exclusively with partners in very distant areas, the impact on innovation performance is found to be highly significant. Two main explanations can be found for this difference.

First, since technological specialisations are closer between European countries than European countries and the US, cooperation with US partners follow more knowledge-oriented motives, such as the utilization of technological synergies or access to specialised technologies where US firms tend to have strong competitive advantages. As Miotti and Sachwald (2003) obtain, French firms seek transatlantic rather than European partners whenever they conduct research at the technological frontier. On the contrary, intra-European partnerships seem to be used by French firms to share costs rather than access specific R&D resources. That is, the main drivers of international cooperation seem to differ for intra- and extra-European cases. Further, as Arvanitis (2012) found, resource motives seem to enhance innovation performance more strongly than cost-oriented motives (such as saving R&D costs). Thus it is straightforward that the impact of extra-European cooperation on innovation can be larger than that of national or European cooperation.

A second explanation of the different impact between intra- and extra-European cooperation may be found on the idea given by Lavie and Miller (2008) that the benefits and costs of cooperating in international contexts may vary according to the level of internationalization. Indeed, as commented above, international cooperation may provide new sources of attractive technologies and resources that are in short supply in the firm's home country, giving unique opportunities that domestic partners may not be able to offer. However, the national differences between the local firm and its foreign partner can also imply barriers to efficient resource exchange. These benefits and costs of cooperating in international contexts may vary according to the level of internationalization. Given the economic, social and institutional similarity between European firms, the resources and skills that can be gained thanks to cooperation agreements among them do not differ dramatically from those with domestic partners. However, at this low level of internationalization, the notion of psychic distance paradox may take place (O'Grady and Lane, 1996). That is, instead of identifying and understanding subtle but existing national differences with partners from other countries in Europe, a firm deciding to collaborate with a European partner may tend to implement managerial methods used when cooperating with national partners under the belief that these methods will also be applicable. In Lavie and Miller's (2008) words:

> Perceived similarities between the firm's home country and proximate countries reduce managers' uncertainty about the nature of the foreign environment and thus lead them to believe that conducting business in these countries would be relatively easy. Consequently, managers pay limited attention to latent yet critical national differences, which hinders their ability to fully understand the foreign countries from which their partners originate (pp. 626).

In sum, although cooperating with European partners may imply benefits for innovative output, the benefits are not as high as in the case of more distant partners and, more importantly for the Spanish case, they seem not to surpass the costs of cooperating in an international context. In contrast, having non-European partners, despite the high costs involved, gives firms access to non-redundant ties that provide access to new information and resources that are sufficiently distinctive from the firm's local knowledge base.

In any case, in relation to the impact of European cooperation, it should be taken into account that only around 4% of the firms in our sample cooperate exclusively with European partners (see Table 4.2). In most cases, those firms that cooperate with Europe also carry out some other type of cooperation (for instance, more than 17% of firms cooperate simultaneously with European and national partners). And in those cases of multiple cooperation, as we will see in next subsection, firms obtain a positive impact which is of a higher magnitude that cooperating with national partners exclusively. Therefore, the non-significant parameter of European cooperation should be mitigated, when having these figures in mind.

In Column 4 of Table 4.3, we observe that among firms with extra-European cooperative agreements, it is not only those linked with the US exclusively, but also with Asian/other partners that positively influence the innovative performance of Spanish firms, although it is of a higher magnitude for the US case. Firms with all kind of extra-European partners benefit from the higher difference in cultural, social, institutional and economic background of such collaborations. However, when cooperating with US firms, national and cultural differences are important but not as excessive as with Asia, so that firms can manage this internationalization by identifying and following opportunities. The firm and the US partners can communicate and engage in effective collaboration due to this cultural and social compatibility. In contrast, in the case of Asian or other partners, substantial national and cultural dissimilarities may imply an increase of the costs of cooperation. In any case, in light of the results, the benefits of such collaboration still far surpass the costs involved, yielding very fruitful relations for the generation of innovation.

4.4.2 Innovation performance and the diversity of research alliances

We account now for the fact the firms can establish relationships simultaneously with partners from different geographical areas. In Column 2 (Table 4.3), the *Multiple* variable indicates that firms have at least one national and one international partner, whereas in Columns 3 and 4, it implies that firms cooperate with at least two of the partnership categories in the respective estimation. Firms in the *Multiple* category do not cooperate exclusively with one geographical area, and the variable is therefore capturing the effect of geographical heterogeneity of the network. According to the results, it seems that in the Spanish case, establishing research collaboration agreements simultaneously with partners established in different geographical zones influences positively and significantly the firm's innovative performance. However, this diversity of partnership only leads to better innovation performance than that of innovating firms cooperating exclusively with national or exclusively with European partners. This suggests that collaborating with partners from several areas enhances innovation due to the amount and variety of knowledge to be shared, leading to more synergies and intake of complementary knowledge. Still, this effect is mainly due to the international nature of the collaboration agreements and thus, the access to non-local, non-redundant ties to achieve access to novel information, and not simply to their geographical diversity. This finding can be related to fact that while on the one hand, diversity facilitates learning and innovativeness, on the other hand, each firm has a certain management capacity to handle such diversity. A greater geographical diversity involves increased management costs and risk, resulting in lower benefits (Duysters and Lokshin, 2011). In turn, it seems that firms may reach a point after which marginal costs of managing more complex and heterogeneous networks are higher than the expected benefits from this increased heterogeneity. In any case, maintaining multiple partners enables firms to fill out their initial resources and skill endowments which definitely contribute to innovation performance in the Spanish case.

4.4.3 Geographical dimension in research cooperation and absorptive capacity

We now turn to the analysis of the role of firms' absorptive capacity in managing external knowledge flows derived from research alliances. Recall that, as argued by the economic literature, knowledge is absorbed more easily by firms that already have a relatively large pool of knowledge. Thus, the benefits of cooperation are not automatic but instead depend on the extent to which organizations can actively mobilize the potential capacity to acquire and assimilate new knowledge and the realized capacity to transform and exploit the new knowledge (Zahra and George, 2002). Hence, we hypothesize that those firms with large absorptive capacity, measured here as the share of R&D expenditures, obtain an innovation premium from alliances with other partners. The question is whether this premium is higher in the case of international alliances than for national ones. We account for this role of R&D by including interactions between R&D expenditures and the cooperation variables among the right hand side variables of our model. The direction and significance of the parameters of the cross-terms will indicate the extent to which firms' absorptive capacity is important to make the most of external knowledge flows conveyed by cooperation networks.

The results provided in Table 4.4 are broadly supportive of the general hypothesis above. The interaction term between R&D and the national cooperation variable is positive and significant at 10% level, whereas the estimated interaction with the international one is also positive and significant but now at 1% level. This evidence provides support to the proposition on the role of absorptive capacity in the assimilation of incoming knowledge flows stemming from cooperation. Firms with high absorptive capacity are more able to translate external knowledge coming from cooperative agreements into new, specific commercial applications more efficiently than in the absence of this feature. However, firms' absorptive capacity is especially efficient when the partner is from an international context, probably due to the fact that such absorptive capacity gives them the ability to understand and assimilate better the knowledge that comes from other national systems of innovation. A firm can learn more from its foreign partners, with their different cultures and environments and, therefore, different resources, values, norms, and beliefs. If the organization possesses the potential capacity to acquire and assimilate such new knowledge, the benefit from this international cooperation increases.

Table 4.4. Impact of the geographical scope of research alliances on innovation performance: The role of absorptive capacity

	(1)	(2)	(3)
RD	0.796***	0.805***	0.805***
	(0.287)	(0.288)	(0.287)
Size	-0.432***	-0.428***	-0.428***
	(0.107)	(0.107)	(0.108)
Size^2	0.032***	0.032***	0.032***
	(0.010)	(0.010)	(0.010)
Permanent R&D	0.448***	0.446***	0.446***
	(0.126)	(0.126)	(0.125)
Foreign multinational	0.081	0.084	0.088
	(0.235)	(0.235)	(0.236)
Openness	0.059***	0.058***	0.058***
	(0.012)	(0.012)	(0.012)
Demand pull	0.442***	0.445***	0.446***
	(0.092)	(0.092)	(0.093)
Research Collaborations			
National	0.303***	0.305***	0.305***
	(0.070)	(0.070)	(0.071)
International	0.773***		
	(0.245)		
European		0.278	0.279
		(0.269)	(0.268)
extra-European		2.876***	
		(0.723)	
US			3.551***
			(1.126)
Asian/Others			2.577**
			(1.219)
Multiple areas	0.399***	0.416***	0.417***
	(0.088)	(0.087)	(0.087)
National * RD	0.753*	0.750*	0.750*
	(0.396)	(0.396)	(0.396)
International * RD	3.200***		
	(1.042)		
European * RD		2.908*	2.907*
		(1.568)	(1.569)

Table 4.4. Impact of the geographical scope of research alliances on innovation performance: The role of absorptive capacity (Continued)

	(1)	(2)	(3)
extra-European * RD		4.150	
		(5.138)	
US * RD			3.935
			(6.744)
Asian/Others * RD			1.231
			(19.053)
Multiple areas * RD	0.926***	0.924***	0.923***
	(0.338)	(0.340)	(0.340)
Constant	-4.460***	-4.464***	-4.463***
	(0.295)	(0.296)	(0.297)
Industry dummies	Yes	Yes	Yes
Inverse Mills ratios	Yes	Yes	Yes
Means-fixed effects	Yes	Yes	Yes
Wald Test	χ^2 =94.11	χ^2 =95.12	χ^2 =95.15
(Selection)	*P-val=0.000*	*P-val=0.000*	*P-val=0.000*
Wald Test	χ^2 =394.96	χ^2 =393.69	χ^2 =393.49
(Means-fixed effects)	*P-val=0.000*	*P-val=0.000*	*P-val=0.000*
R-squared	0.096	0.097	0.097
Observations	35,865	35,865	35,865

Bootstrapped standard errors are presented in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

Interestingly enough, when we go deeper in the disaggregation of the international area, (see columns 2 and 3, Table 4.4), interactions between R&D and cooperation are also positive and significant for the European case, but are neither for the US or the rest of the world. At first glance there is no clear explanation, but a closer look at the data for the measure of absorptive capacity, which is the share of internal R&D expenditure over sales, provides some insight. In the case of cooperating firms, the average value is 12%, whereas it is 4% for those cooperating exclusively within Europe and 14% in the case of doing it exclusively with US firms. In other words, absorptive capacity is lower for firms cooperating in Europa if compared with the average cooperative firm. These data, together with the non-significant parameter of European alliances, could lead us to think that although cooperating with European partners may imply benefits, they do not surpass the costs of this international cooperation, probably because the average firm cooperating in this context presents a relatively low average capacity. However, when the firm has sufficient absorptive capacity to reduce the barriers posed by the national differences, then the firms extract an innovation benefit from such alliances. On the contrary, firms that cooperate with US partners have, on average, a high absorptive capacity. Therefore, the representative Spanish firm cooperating with US partners already obtains a significant and high innovative premium from such cooperation agreements, so that a larger absorptive capacity does not signify an innovation premium. Most of those firms already have the capability to understand and exploit the non-redundant knowledge, information, and resources that can be provided by extra-European partners, so that an increase in this capacity does not make a difference. All in all, these results would point to the existence of a threshold R&D level for firms to absorb external knowledge. Innovative performance would increase with R&D intensity when the level of R&D is very low (as in our intra-European cooperation case) until it reaches an intermediary intensity where increments of R&D would not make a difference (extra-European cooperation).

As a robustness check to study the stability and significance of the estimated parameters and the results encountered so far with respect to the impact of cooperation, we estimated our main equation with the variable R&D computed as the proportion of R&D employees over total employment, which has also been used in the literature as a measure of absorptive capacity although not as commonly as the share of expenditures in R&D. The coefficients and resulting conclusions are virtually unchanged. These results are available upon request.

In sum, this section has provided evidence on the dual role of R&D and we have confirmed our third hypothesis that R&D of firms does not only contribute directly to innovation but also helps building up firms' absorptive capacity. This contributes to making innovative activities more productive, especially for firms that cooperate with European partners. The benefits of cooperation depend on the extent to which organizations possess the potential capacity to acquire and assimilate new knowledge and the realized capacity to transform and exploit this new knowledge.

4.5 Conclusions

This chapter examines the impact of the geographical scope of research alliances on innovative performance. Research alliances can be seen as a vehicle for voluntary knowledge exchanges and in this chapter we assume that partners geographically distant can provide firms with non-redundant information that gives access to new information and therefore stimulates innovation performance. Descriptive statistics, based on our sample of Spanish firms, show that the proportion of international alliances with partners in more distant geographical areas (US, China, India and other countries), although lower in number if compared to research alliances with geographically closest partners, has increased over the period 2004-2011. This suggests that firms are expanding technological interaction with different and increasingly geographically dispersed actors.

Empirical results show that maintaining collaborative agreements with partners outside the firm's home country borders exerts a significant and positive effect on innovative performance. This impact is found to be larger than that of national collaborative research. By and large, this supports the idea that firms benefit from interaction with international partners as a way to access new technologies and the specialised and novel knowledge they are unable to find locally. Our findings also showed that extra-European alliances, especially with US partners, impact on innovation more importantly probably due to the fact that in some sectors, the US conducts research at the technological frontier. Moreover, we provide evidence that in the Spanish case, although establishing simultaneous research collaboration agreements with partners located in different geographical areas positively and significantly influences the firm's innovative performance, it only improves innovation performance in comparison to firms cooperating exclusively with national or European partners. This can be related to the fact that a greater geographic diversity of partners involves increased management costs and risks, so that the benefits may not be as high as expected.

In addition, we confirm the role played by firms' absorptive capacity in determining collaborative research returns. Firms that have high absorptive capacity are more efficient at translating external knowledge from cooperative agreements into new, specific commercial applications. Further, this absorptive capacity seems especially efficient when the partner is international, probably due to the fact that such absorptive capacity gives the ability to better understand and assimilate the knowledge from a different national system of innovation. Interestingly enough, we obtain that although cooperating exclusively with European partners may imply benefits, they do not seem to surpass the costs of managing such international cooperation unless the firm combines it with a higher absorptive capacity to reduce the barriers posed by national differences.

All in all, these findings lead to conclude that although knowledge and innovation are well recognised as critical pillars of 'smart growth' in Europe, the right strategies to help move the continent in this direction are not so obvious. According to our results, a pivotal element to ensure the generation of new knowledge lies in accessing external sources of knowledge and facilitating interactive learning and interaction in innovation. This knowledge flow can take place through diffusion patterns based on knowledge externalities, relying on informal transmission channels that are relatively bounded in space, but also through intentional relations such as cooperation agreements. Hence, from a policy perspective, these results illustrate that although R&D and human capital efforts are of clear importance, the degree of connectivity of agents with the outside world and access to global knowledge hotspots is also useful for innovative outcomes. Such connectivity, among other ideas, is precisely at the core of the 'smart specialisation' strategy recently launched by the European Commission (McCann and Ortega-Argilés, 2013).

Finally, our results also align with the thinking that innovation policies which neglect the absorptive capacity of firms are problematic – or at least incomplete. They pinpoint that policies used in an undifferentiated manner for all kinds of firms may be misleading.

References

Acs, Z.J. and Audretsch, D.B. (1988) Innovation in large and small firms: An empirical analysis, *American Economic Review*, 78, 678–690.

Arvanitis, S. (2012) How do different motives for R&D cooperation affect firm performance? – An analysis based on Swiss micro data, *Journal of Evolutionary Economics*, 22(5), 981-1007.

Arvanitis, S. and Bolli, T. (2013) A comparison of national and international innovation cooperation in five European countries, *Review of Industrial Organization*, 43, 163–191.

Arvanitis, S., Lokshin, B., Mohnen, P. and Wörter, M. (2013) Impact of external knowledge acquisition strategies on innovation: A comparative study based on Dutch and Swiss panel data, *UNU-MERIT Working Papers*, 2013-003, 1-26.

Aschhoff, B. and Schmidt, T. (2008) Empirical evidence on the success of R&D cooperation -- happy together? *Review of Industrial Organization*, 33(1), 41-62.

Autant-Bernard, C., Billand, P., Frachisse, D. and Massard, N. (2007) Social distance versus spatial distance in R&D cooperation: Empirical evidence from European collaborations choices in micro and nanotechnologies, *Papers in Regional Science*, 86(3), 495-519.

Barge-Gil, A. (2013) Open Strategies and Innovation Performance, *Industry and Innovation*, 20(7), 585-610.

Bathelt, H., Malmberg, A. and Maskell, P. (2004) Clusters and knowledge: local buzz, global pipelines and the process of knowledge creation, *Progress in Human Geography*, 28, 31–56.

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

Belderbos, R., Carree, M.A. and Lokshin, B. (2004) Cooperative R&D and firm performance, *Research Policy*, 33(10), 1477-92.

Belderbos, R., Carree, M. and Lokshin, B. (2006) Complementarity in R&D cooperation strategies, *Review of Industrial Organization*, 28(4), 401–426.

Bergman, E. (2009) Embedding network analysis in spatial studies of innovation, *The Annals of Regional Science*, 43(3), 559-565.

Boschma, R.A. and Iammarino, S. (2009) Related variety, trade linkages and regional growth, *Economic Geography*, 85(3), 289-311.

Cincera, M., Kempen, L., Van Pottelsberghe, B., Veugelers, R. and Villegas, C. (2003) Productivity growth, R&D and the role of international collaborative agreements: some evidence for Belgian manufacturing companies, *Brussels Economic Review*, 46(3), 107-140.

Cohen, W.M. and Levinthal, D. A. (1989) Innovation and learning: The two faces of R&D, *Economic Journal*, 99, 569–596.

Cohen, W.M. and Levinthal, D.A. (1990) Absorptive capacity: A new perspective on learning and innovation, *Administrative Science Quarterly*, 35, 128–152.

Dachs, B., Ebersberger, B. and Lööf, H. (2008) The innovative performance of foreign-owned enterprises in small open economies, *The Journal of Technology Transfer*, 33, 393-406.

Díaz-Díaz, N.L., Aguiar-Díaz, I. and De Saá-Pérez, P. (2008) Impact of foreign ownership on innovation, *European Management Review*, 5, 253-263.

Duysters, G. and Lokshin, B. (2011) Determinants of alliance portfolio complexity and its effect on innovative performance of companies, *Journal of Product Innovation Management*, 28, 570–585.

Escribano, A., Fosfuri, A. and Tribó, J.A. (2009) Managing external knowledge flows: the moderating role of absorptive capacity, *Research Policy*, 38(1), 96–105.

European Commission (2012) Guide to Research and Innovation Strategies for Smart Specialisations (RIS 3). *Smart Specialisation Platform*.

Faems, D., Van Looy, B. and Debackere, K. (2005) Interorganizational collaboration and innovation: Toward a portfolio approach, *Journal of Product Innovation Management*, 22(3), 238–250.

Giuliani, E. and Bell, M. (2005) The micro-determinants of meso-level learning and innovation: evidence from a Chilean wine cluster, *Research Policy*, 34(1), 47–68.

Hoang, H.T. and Rothaermel, F.T. (2005) The effect of general and partner-specific alliance experience on joint R&D project performance, *Academy of Management Journal*, 48(2), 332-345.

Jones, G.K., Lanctot, Jr. A. and Teegen, H.J. (2001) Determinants and performance impacts of external technology acquisition, *Journal of Business Venturing*, 16(3), 255–283.

Klomp, L. and Van Leeuwen, (2001) Linking innovation and firm performance: a new approach, *International Journal of the Economics of Business*, 8(3), 343-364.

Laursen, K. and Salter, A. (2006) Open for innovation: The role of openness in explaining innovation performance among UK manufacturing firms, *Strategic Management Journal*, 27(2), 131–150.

Lavie, D. and Miller, S.R. (2008) Alliance portfolio internationalization and firm performance, *Organization Science*, 19(4), 623–646.

Lööf, H. (2009) Multinational enterprises and innovation: Firm level evidence on spillover via R&D collaboration, *Journal of Evolutionary Economics*, 19(1), 41–71.

Lööf, H. and Broström, A. (2008) Does knowledge diffusion between university and industry increase innovativeness? *The Journal of Technology Transfer,* 33(1), 73-90.

McCann, P. and Ortega-Argilés, R. (2013) Smart specialization, regional growth and applications to European Union cohesion policy, *Regional Studies*, DOI:10.1080/00343404.2013.799769.

Miotti, L. and Sachwald, F. (2003) Cooperative R&D: Why and with whom? An integrated framework of analysis, *Research Policy*, 32, 1481–99.

Mohnen, P., Mairesse, J. and Dagenais, M. (2006) Innovativity: a comparison across seven European countries, *Economics of Innovation and New Technology*, 15(4-5), 391–413.

Monjon, S. and Waelbroeck, P. (2003) Assessing spillovers from universities to firms: evidence from French firm-level data, *International Journal of Industrial Organization*, 21(9), 1255-1270.

Mundlak, Y. (1978) On the pooling of time series and cross-sectional data, *Econometrica*, 46, 69–86.

Nieto, M.J. and Santamaría, L. (2007) The importance of diverse collaborative networks for the novelty of product innovation, *Technovation*, 27, 367–377.

Nijman, T. and Verbeek, M. (1992) Nonresponse in panel data: the impact on estimates of a life cycle consumption function, *Journal of Applied Econometrics*, 7, 243–257.

OECD (2005) *Oslo Manual, Guidlines for collecting and interpreting innovation*, 3rd edition, OECD, Paris.

O'Grady, S. and Lane, H.W. (1996) The psychic distance paradox, *Journal of International Business Studies*, 27(2), 309–333.

Owen-Smith, J. and Powell, W.W. (2004) Knowledge networks as channels and conduits: the effects of spillovers in the Boston biotechnology community, *Organization Science*, 15, 5–21.

Raymond, W., Mohnen, P., Palm, F. and Van der Loeff, S.S. (2010) Persistence of innovation in Dutch manufacturing: is it spurious? *The Review of Economics and Statistics*, 92(3), 495-504.

Reis, A. (2001) On the welfare effects of foreign investment, *Journal of International Economics*, 54(2), 411-427.

Robin, S. and Schubert, T. (2013) Cooperation with public research institutions and success in innovation: Evidence from France and Germany, *Research Policy*, 42, 149–166.

Schoenmakers, W. and Duysters, G. (2006) Learning in strategic technology alliances, *Technology Analysis & Strategic Management*, 18(2), 245–264.

Schumpeter, J. (1942) Capitalism, Socialism and Democracy (New York: Harper).

Tsai, K.-H. (2009) Collaborative networks and product innovation performance: toward a contingency perspective, *Research Policy*, 38(5), 765-778.

Van Beers, C. and Zand, F. (2014) R&D cooperation, partner diversity, and innovation performance: an empirical analysis, *Journal of Product Innovation Management*, 31(2), 292–312.

Vega-Jurado, J., Gutiérrez-Gracia, A. and Fernández-de-Lucio, I. (2009) Does external knowledge sourcing matter for innovation? evidence from the Spanish manufacturing industry, *Industrial and Corporate Change*, 18(4), 637–670.

Veugelers, R. and Cassiman, B. (1999) Make and buy in innovation strategies: Evidence from Belgian manufacturing firms, *Research Policy*, 28, 63–80.

Wooldridge, J.M. (1995) Selection corrections for panel data models under conditional mean independence assumptions, *Journal of Econometrics*, 68, 115–232.

Wooldridge, J.M. (2010) *Econometric Analysis of Cross Section and Panel Data*. Third Edition. Cambridge, MA: MIT Press.

Zabel, J.E. (1992) Estimating fixed effects and random effects with selectivity, *Economics Letters*, 40, 269–272.

Zahra, S. and George, G. (2002) Absorptive capability: A review, reconceptualization, and extension, *Academy of Management Review*, 27(2), 185–203.

Appendix 4.A: Variable definitions

Table A4.1. Definition of the variables included in the empirical analysis

Variables	Definitions
Dependent	
Innovation	1 if the firm develop or introduced new or improved products or processes into the market; 0 otherwise
Innovation sales	Sales share of new or significantly improved products (log[new sales/(1-new sales)])
Independent	
RD	Ratio between intramural R&D expenditure and turnover
Size	Logarithm of number of employees (and its squared term)
Permanent R&D	1 if the firm reported that it performed internal R&D continuously; 0 otherwise
Foreign multinational	1 if the headquarter of the firm is outside Spain and it has at least a 50% of foreign capital; 0 otherwise
Openness	Number of information sources for innovations that a firm reported it had used (from within the firm or group, suppliers, clients, competitors, private R&D institutions, conferences, scientific reviews or professional associations)
Demand pull	1 if at least one of the following demand-enhancing objectives for the firm's innovations is given the highest score [number between 1 (not important) and 4 (very important)]; 0 otherwise: extend product range; increase market or market share; improve quality in goods and services
National	1 if the firm reported engagement in collaborative agreements exclusively with partners located in Spain; 0 otherwise
International	1 if the firm reported engagement in collaborative agreements exclusively with partners located outside Spain; 0 otherwise
European	1 if the firm reported engagement in collaborative agreements exclusively with partners located in the rest of Europe; 0 otherwise
extra-European	1 if the firm reported engagement in collaborative agreements exclusively with partners located in the US, China, India and other countries (not Spain, not the rest of Europe); 0 otherwise
US	1 if the firm reported engagement in collaborative agreements exclusively with partners located in the US; 0 otherwise
Asian/Others	1 if the firm reported engagement in collaborative agreements exclusively with partners located in China, India and other countries (not Spain, not the rest of Europe, not the US); 0 otherwise
Multiple areas	1 if the firm reported engagement in collaborative agreements with partners located in more than one area; 0 otherwise
Cost obstacles	Sum of the scores of importance that the firm attributed [number between 1 (not important) and 4 (very important)] to the following factors that hampered its innovation activities: lack of funds within the enterprise or enterprise group; lack of finance from sources outside the enterprise; innovation costs too high. Rescaled from 0 (unimportant) to 1 (crucial)
Knowledge obstacles	Sum of the scores of importance that the firm attributed [number between 1 (not important) and 4 (very important)] to the following factors that hampered its innovation activities: lack of qualified personnel; lack of information on technology; lack of information on markets; difficulty in finding cooperation partners for innovation. Rescaled from 0 (unimportant) to 1 (crucial)
Market obstacles	Sum of the scores of importance that the firm attributed [number between 1 (not important) and 4 (very important)] to the following factors that hampered its innovation activities: markets dominated by established enterprises; uncertain demand for innovative goods or services. Rescaled from 0 (unimportant) to 1 (crucial)
Other obstacles	Sum of the scores of importance that the firm attributed [number between 1 (not important) and 4 (very important)] to the following factors that hampered its innovation activities: not necessary due to previous innovations; not necessary due to the absence of demand. Rescaled from 0 (unimportant) to 1 (crucial)
Market share	Ratio of the sales of a firm over the total sales of the two-digit industry it belongs to
Belonging to a group	1 if the firm belongs to a group of enterprises; 0 otherwise

Appendix 4.B: Some additional results

Table A4.2. Correlation matrix of variables used in the second stage

		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
1	RD	1																			
2	Size	-0.146	1																		
3	Permanent R&D	0.219	0.013	1																	
4	Foreign multinational	-0.077	0.281	-0.003	1																
5	Openness	0.127	0.050	0.335	-0.021	1															
6	Demand pull	0.066	-0.029	0.264	-0.013	0.318	1														
7	National	0.031	0.002	0.080	-0.098	0.113	0.064	1													
8	International	-0.010	0.047	0.024	0.120	0.008	0.011	-0.071	1												
9	European	-0.012	0.038	0.015	0.111	0.003	0.015	-0.061	0.865	1											
10	extra-European	-0.002	0.021	0.013	0.019	0.004	-0.012	-0.027	0.381	-0.006	1										
11	US	0.003	0.024	0.005	0.014	0.005	-0.015	-0.017	0.239	-0.004	0.629	1									
12	Asian/Others	-0.005	0.008	0.013	0.014	0.002	-0.004	-0.021	0.293	-0.004	0.770	-0.001	1								
13	Multiple areas	0.205	0.151	0.225	0.113	0.212	0.129	-0.202	-0.008	-0.043	-0.017	-0.012	-0.015	1							
14	National * RD	0.267	-0.160	0.172	-0.074	0.116	0.084	0.502	-0.036	-0.031	-0.014	-0.009	-0.010	-0.101	1						
15	International * RD	0.044	-0.028	0.049	0.022	0.022	0.009	-0.036	0.502	0.377	0.294	0.148	0.260	-0.001	-0.018	1					
16	European * RD	0.035	-0.022	0.043	0.031	0.015	0.015	-0.032	0.451	0.522	-0.003	-0.002	-0.002	-0.023	-0.016	0.726	1				
17	extra-European * RD	0.017	-0.012	0.021	-0.004	0.011	-0.008	-0.014	0.192	-0.003	0.504	0.255	0.446	-0.010	-0.007	0.587	-0.002	1			
18	US * RD	0.031	-0.009	0.013	-0.001	0.012	-0.007	-0.009	0.121	-0.002	0.316	0.503	-0.001	-0.006	-0.004	0.298	-0.001	0.507	1		
19	Asian/Others * RD	0.002	-0.009	0.016	-0.004	0.006	-0.005	-0.011	0.152	-0.002	0.399	-0.001	0.518	-0.008	-0.005	0.506	-0.001	0.862	0.000	1	
20	Multiple areas * RD	0.513	-0.034	0.180	-0.021	0.152	0.088	-0.117	-0.015	-0.025	-0.011	-0.007	-0.009	0.580	-0.059	0.014	-0.013	-0.006	-0.004	-0.004	1

Table A4.3. Estimates of the first stage: selection equations

	T=2006	T=2007	T=2008	T=2009	T=2010	T=2011
Size	0.014	0.062	0.067	0.117*	0.036	0.077
	(0.069)	(0.067)	(0.064)	(0.069)	(0.067)	(0.065)
Size^2	0.002	-0.006	-0.004	-0.007	0.002	0.001
	(0.007)	(0.007)	(0.006)	(0.007)	(0.007)	(0.006)
Cost obstacles	0.353***	0.520***	0.594***	0.509***	0.573***	0.417***
	(0.073)	(0.069)	(0.069)	(0.073)	(0.071)	(0.065)
Market obstacles	0.540***	0.332***	0.178**	0.318***	0.415***	0.358***
	(0.077)	(0.071)	(0.071)	(0.075)	(0.074)	(0.069)
Knowledge obstacles	0.235**	0.363***	0.412***	0.536***	0.289***	0.415***
	(0.098)	(0.092)	(0.091)	(0.096)	(0.096)	(0.089)
Other obstacles	-1.152***	-1.243***	-1.211***	-1.210***	-1.218***	-1.231***
	(0.064)	(0.062)	(0.061)	(0.063)	(0.064)	(0.062)
Market share	1.039	0.710	2.736**	4.695***	2.886**	2.451**
	(0.891)	(1.035)	(1.088)	(1.267)	(1.183)	(1.006)
Belonging to a group	0.189***	0.165***	0.212***	0.184***	0.198***	0.219***
	(0.041)	(0.040)	(0.039)	(0.041)	(0.041)	(0.039)
Constant	0.468***	0.605***	0.470***	0.194	0.389**	-0.108
	(0.179)	(0.173)	(0.166)	(0.178)	(0.178)	(0.169)
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7764	8858	8805	8308	8065	7704
Log L	-3315.806	-3566.012	-3699.859	-3396.220	-3310.735	-3790.015
Pseudo R2	0.235	0.240	0.229	0.236	0.237	0.198

Standard errors are presented in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Chapter 5:

Conclusions

Conclusions

5.1 Summary and concluding thoughts

This doctoral thesis consists of three different empirical studies which represent new contributions to the empirical research of firms' R&D cooperation behaviour, one of the most relevant research issues in the field of Economics of Innovation. The three studies that constitute the dissertation focus on the Spanish case.

The first study, in Chapter 2, contributes to the understanding of the motivations for engaging in R&D cooperation agreements according to the type of partnership chosen. In this first piece of research we take into account several aspects which have previously been scarcely considered in the literature. Our findings provide evidence on the existence of simultaneous agreements with different partners, which suggests that the choice of the type of partner is not independent one from another. The evidence for Spanish firms suggests that research institutions are the main partners in innovation activities and this that type of cooperation tends to be most often complemented by vertical cooperation (cooperation with clients or suppliers). This may be related to the relatively limited risk of spillovers in those agreements if compared to the one in collaborations with competitors. In effect, the econometric estimates obtained corroborated the need for a multi-equation estimation that considers explicitly the interdependences between the different cooperation strategies.

The longitudinal structure of the PITEC database allows us to address some of the problems that these previous studies encountered, mainly endogeneity issues. This way, we perform a cross-section analysis taking into account the simultaneity bias inherent in this kind of analysis via the inclusion of lagged explanatory variables as well as via corrections for endogeneity through the control function approach. The results show the need of taking into account the endogeneity and that some of the estimated effects may vary when considering explicitly this endogeneity problem. Moreover, we look at the manufacturing and service sectors separately to make a more robust comparison and identify differences between them regarding the determinants in the choice of R&D partners which, to our knowledge, has received less attention to date.

On the whole, the findings of this chapter show that determinants of R&D cooperation differ between the different types of cooperation and between the two sectors under consideration. We find that placing a higher importance to publicly available information (incoming spillovers), receiving public funding and firm size increases the probability of cooperation with all kind of partners but the role is much stronger in the case of cooperative agreements with research institutions and universities. Our results also suggest that, for the Spanish case, R&D intensity and the importance attributed to the lack of qualified personnel as a factor hampering innovation are key factors influencing positively R&D cooperation activities in the service sector but not in manufactures.

The results of this chapter have important implications in terms of policy making. All in all, our results confirm that firms follow different paths in their innovation processes and have different needs concerning collaborative activities with other agents. Therefore, it seems fair that the differences found here should be borne in mind in the design of policies to encourage cooperation as a means of increasing innovation in firms. These policies should take account of the requirements of the sectors and firms being targeted. According to our results, the effectiveness of such policies, especially in the case of services firms, could be enhanced if complemented with policies that encourage their absorptive capacity. Indeed, we obtain that firms in the service sector are concerned about their lack of qualified personnel to undertake innovations and that cooperation plays a key role to overcome this obstacle.

Having in mind that innovation is a dynamic process which involves relationships both in the short and long term, and that network experiences are also considered as an incremental learning process that may influence positively the innovation capability of the firm, Chapter 3 aims at providing evidence on the persistence in firms' R&D cooperation behaviour. Firms with experience of collaboration acquired through long-standing relationships are likely to enjoy better alliances, which in turn could have positive implications for innovation outputs; however, the persistence of R&D cooperation behaviour has been relatively ignored. Thus, Chapter 3 investigates whether firms establish agreements of R&D cooperation persistently –with the same or different partners– as a strategy for carrying out innovation activities and the factors that lead to that persistence. In addition, it explored the degree of the persistence in R&D collaborative agreements considering the three different types of partners separately (customers and/or suppliers, competitors and research institutions and/or universities) as well as the possibility of finding crossed-persistence across these different partner types.

The findings in this study demonstrate true persistence in R&D cooperation activities at the firm level. After discounting the impact of observed and unobserved firm characteristics, the results suggests that firms follow a path of collaboration over time in the sense that the decision to cooperate in a period enhances the probability of being co-operator in subsequent periods. This result points to the fact that once a firm beings to cooperate, it will gain experience and develop a social ability to cooperate and communicate with different partners which keeps in time. Indeed, our results suggest a significant state dependence effect for cooperation activities even once we consider separately the different types of cooperation. While considering the possibility of crossed-persistence across the different partner types, we found that only in the case of institutional cooperation, previous experience in this type of agreements enhances the probability of cooperating in the future with all other partner types considered. Similar as in Chapter 2, it seems that research collaboration with clients, suppliers and competitors tends to be most often complemented by the knowledge gained through the collaboration with research institutions.

The results are of considerable interest for public policy in their efforts to promote R&D cooperation activities. As we already mentioned in Chapter 3, the fact that R&D cooperation is state dependent implies that collaboration-stimulating policy measures, such as government support programmes, are supposed to have a deeper effect because they do not only affect current collaboration agreements but are also likely to induce a permanent change in favour of cooperation. Thus, in order to induce sustained cooperation it would be necessary to stimulate cooperation. However, this policy should be accompanied by measures to enhance the firm's internal capabilities that are found to be important in contributing to the entry of firms to new and stable cooperative R&D projects.

Besides contributing to the study of the determinants influencing the decision to cooperate, this dissertation adds to the literature on the effect of cooperation on innovative performance. Chapter 4 examines the impact that the geographical scope of collaborative research may have on innovation performance. This study advances beyond the studies on the differences between national and international cooperation with respect to the impact on innovation output by disaggregating the geographical scope of the international alliances as well as analysing if absorptive capacity is equally important for national and international research alliances.

The results of this third chapter of the thesis allow us to conclude that the benefits of research collaboration differ across different dimensions of the geography. We found that the impact of extra-European cooperation on innovation is larger than that of national and European cooperation. This result suggests that firms benefit from interaction with international partners as a way to access new technologies, specialized knowledge from international sources or novel knowledge that they are unable to find locally. In addition, we found that research collaboration simultaneously with partners in different geographical areas leads to better innovation performance if compared to research collaborations exclusively with partners geographically closer. However, it does not seem to surpass the benefits of cooperating with extra-European partners, probably because a greater geographical diversity also implies increased management costs and risk, resulting in lower benefits. Regarding the role played by absorptive capacity on the relationship between collaboration research and innovation performance, we can conclude that a firm can learn more from its foreign partners, with different culture and environment, but if the firm possesses the potential capacity to acquire and assimilate such new knowledge, the benefit from cooperation increases.

These results have three main policy implications. First, establishing cooperation agreements appears to have a positive impact on firm innovation output, hence policy makers could promote R&D cooperation as a means of increasing innovation output in firms. Second, policy instruments should mostly target facilitating international cooperation, since it can provide with less redundant pieces of knowledge. Third, absorptive capacity is a key element to explain why some firms attain better innovation performance than others under the same strategy of collaboration; it aligns, therefore, with the thinking that innovation policies which neglect the firms' absorptive capacity are problematic – or at least incomplete.

5.2 Limitations and future research lines

Undoubtedly, the empirical exercises conducted in this thesis must be seen as a work in progress, rather than a closed research project. There are certain limitations that this thesis faced that are worth recognizing and which, at the same time, can serve to identify interesting lines for future research.

First, we are aware of some limitations when searching for the best instruments for addressing endogeneity in Chapter 2. However, it is worth noting that the information in this research is obtained from a survey at the firm level, so that the information is limited. As pointed by López (2008), it is difficult to find perfectly exogenous instruments within a survey (CIS in his case, PITEC in ours) where every question is closely related. The instruments used in this study were used in previous empirical research on this issue (Cassiman and Veugelers, 2002; López, 2008; Abramovsky et al., 2009) and were chosen based on data availability. In this sense, we provide some evidence about the validity of our instruments as well as a comparison of the results without accounting for endogeneity and those after correcting for it. In any case, further research is required. Replicating our study with different dataset, also for various countries and with different sets of instruments, would be useful to confirm the generality of our findings.

On the other hand, given the relative importance of universities and research centers as cooperation partners for Spanish firms, a future study distinguishing between private and public sources (i.e., consultants, commercial labs, or private R&D institutes, versus universities or other higher education institutions, government or public research institutes or technology centres) would be very interesting. There is previous literature that suggests that different types of firms tend to draw on these different sources (Tether and Tajar, 2008; Barge-Gil et al., 2011). Similarly, an analysis which breaks up the service sector would allow us to account for the heterogeneity in this sector (Knowledge intensive business services versus Less knowledge intensive services).

Secondly, the main caveat of Chapter 3 was that, although we observe firm's R&D cooperation behavior over a relative long period (2002 to 2010), given the structure of the PITEC surveys we only have information for a limited number of periods (T=4). In addition, given the way the survey proceeds, there is a one-year overlap between two consecutive waves. Even though, as discussed in the chapter, it seems that the effect of the overlapping year is not important, further work would benefit from PITEC the years to come as it will allow carrying out the same analysis without any overlap in the measurement period, while having additional waves. Another important limitation was that the panel data set used does not allow us to identify individual collaborative agreements between firms, but rather the general collaboration behavior of the innovative firm in the PITEC. Thus, it would be desirable to have information about the specific collaborative partner in order to improve our understanding of persistence of collaborations. We expect further progress in the survey design taking into account these needs.

In addition, it would be interesting to provide empirical evidence on the reasons behind the state dependence found in the cooperation strategies of Spanish firms. Among other theoretical reasons explaining the state dependence process found in the Spanish case, the literature has stressed the hypothesis of "success-breeds-success", the presence of important sunk costs, which would represent an essential motive for entering and staying in a specific regime of R&D activity, and the consideration of cooperation as an incremental learning process of a cumulative nature which would induce state dependence. The aim is to provide evidence of which of these reasons are more relevant in the Spanish firms, and whether they are different according to the type of partner and the sector under consideration.

Regarding Chapter 4, it should be recognized that certain methodological limitations may affect our results, the most important one being inconsistent estimates due to endogeneity problems. Lagging variables of the right hand side of the models allowed us to reduce simultaneity bias inherent to this analysis. However, we are aware that further efforts should be done to completely eliminate such bias. One possible solution to the endogeneity problem is to use historic measures as instruments; however, since our observation units are firms, the panel data cover a relatively short number of time periods and PITEC cannot be matched with other sources, finding reliable instruments is a challenging task. Admittedly, suitable instruments still have to be found and so further research along these lines must be undertaken.

With respect to the impact of cooperation on innovative performance, it would be interesting to analyse the heterogeneity of such impact in terms of aspects such as the moment of the economic cycle as well as the levels of economic and institutional development of the territory in which the firms are located.

Related to the first idea, indeed, the globalization process and the consequences of the Great Recession have emphasized the importance of the competitiveness of Spanish firms. Among the drivers of such competitiveness there is one in which Spanish firms do not occupy any relevant position: innovation. In a context where resources devoted to R&D have diminished, technological collaboration could be an appropriate strategy for the adoption of knowledge and, consequently, for generating innovation. With this assumption, we aim to analyse to what extent firms that innovate, and specially those who do it through cooperative agreements, have suffered with less intensity the crisis. In other words, to know with precision if the innovative activity carried out by Spanish firms has changed as a consequence of the Great Recession and which are the characteristics of the most dynamic ones in this sense. We must be able to accomplish with this aim since we have information in PITEC from 2004 to 2012, so that we would cover four years of recession (2009-2012) with respect to five expansive ones (2004-2008).

Related to the second issue, the role of the territory, we follow the idea that locational effects and the socio-economic characteristics of the territory influence the processes of technological collaboration, as well as their impact on innovative capacity. The idea is that technological cooperation may not have a homogeneous impact in all the regions, giving place to territorial differences both in terms of generation of innovation and in terms of its impact on competitiveness and economic growth. This is an important political issue, since one fundamental of the European Research Area is to reduce the huge regional variation in the return to research and innovation. Traditionally, the EU policy, especially at the firm level, has focused on incentivizing the increase in R&D expenses, irrespectively of the characteristics of the firms and the areas in which they are localized. However, this policy could have been generating inequality among the territory if the returns to R&D investments, in terms of innovative outcome, were far from homogeneous spatially, and the biggest effects were obtained in the most technologically advanced economies. Therefore, we aim to provide further investigation on the heterogeneity of the impact of technological collaboration on innovative performance in terms of the level of economic and institutional development of the territory in which the firm is located. In order to follow this objective, it will be necessary to use some other database in which the regional dimension can be used, such as the Innovation Survey of the Spanish Statistical Institute.

Finally, given that firms also might benefit from other external knowledge sources, for instance, acquired through R&D outsourcing (as opposed to R&D collaboration) and it has become a phenomenon of increasing importance for firms (Nieto and Rodríguez, 2011; Dhont-Peltrault and Pfister, 2011), another line of research to which we will dedicate our efforts soon, is the analysis of potential complementarities or substitutabilities between R&D outsourcing and R&D cooperation and their impact on innovative performance while considering the geographical scope of these strategies. This issue holds a premise to better understand the impact of technology interaction with different geographically dispersed actors on innovation performance.

References

Abramovsky, L., Kremp, E., López, A., Schmidt, T. and Simpson, H. (2009) Understanding co-operative innovative activity: Evidence from four European countries, *Economics of Innovation and New Technology*, 18(3), 243-265.

Barge-Gil, A.; Santamaría, L. and Modrego, A. (2011) Complementarities between universities and technology institutes: New empirical lessons and perspectives, *European Planning Studies*, 19(2), 195-215.

Cassiman, B. and Veugelers, R. (2002) R&D cooperation and spillovers: Some empirical evidence from Belgium, *The American Economic Review*, 92(4), 1169-84.

Dhont-Peltrault, E. and Pfister, E. (2011) R&D cooperation versus R&D subcontracting: Empirical evidence from French survey data, *Economics of Innovation and New Technology*, 20(4), 309-341.

López, A. (2008) Determinants of R&D cooperation: Evidence from Spanish manufacturing firms, *International Journal of Industrial Organization*, 26, 113-136.

Nieto, M.J. and Rodríguez, A. (2011) Offshoring of R&D: Looking abroad to improve innovation performance, *Journal of International Business Studies*, 42, 345-361.

Tether, B.S. and Tajar, A. (2008) Beyond industry–university links: Sourcing knowledge for innovation from consultants, private research organisations and the public science-base, *Research Policy*, 37(6-7), 1079-95.

References[34]

Abramovsky, L., Kremp, E., López, A., Schmidt, T. and Simpson, H. (2009) Understanding co-operative innovative activity: Evidence from four European countries, *Economics of Innovation and New Technology*, 18(3), 243-265.

Acs, Z.J. and Audretsch, D.B. (1988) Innovation in large and small firms: An empirical analysis, *American Economic Review*, 78, 678–690.

Ahuja, G. (2000) Collaboration networks, structural holes, and innovation: A longitudinal study, *Administrative Science Quarterly*, 45, 425-455.

Angrist, J.D. and Pischke, J.-S. (2009) *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton: Princeton University Press.

Archibugi, D. and Coco, A. (2004) International partnerships for knowledge in business academia: A comparison between Europe and USA, *Technovation*, 24(7), 517–528.

Arqué-Castells, P. (2013) Persistence in R&D performance and its implications for the granting of subsidies, *Review of Industrial Organization*, 43, 193-220.

Arranz, N. and Arroyabe, J.C.F. (2008) The choice of partners in R&D cooperation: An empirical analysis of Spanish firms, *Technovation*, 28(1/2), 88-100.

Arundel, A. and Kabla, I. (1998) What percentage of innovations are patented? Empirical estimates for European firms, *Research Policy*, 27(2), 127-141.

Arvanitis, S. (2012) How do different motives for R&D cooperation affect firm performance? – An analysis based on Swiss micro data, *Journal of Evolutionary Economics*, 22(5), 981-1007.

Arvanitis, S. and Bolli, T. (2013) A comparison of national and international innovation cooperation in five European countries, *Review of Industrial Organization*, 43, 163–191.

Arvanitis, S., Lokshin, B., Mohnen, P. and Wörter, M. (2013) Impact of external knowledge acquisition strategies on innovation: A comparative study based on Dutch and Swiss panel data, *UNU-MERIT Working Papers*, 2013-003, 1-26.

Aschhoff, B. and Schmidt, T. (2008) Empirical evidence on the success of R&D cooperation -- happy together? *Review of Industrial Organization*, 33(1), 41-62.

Asheim, B. and Isaksen, A. (1997) Location, agglomeration and innovation: towards regional innovation systems in Norway, *European Planning Studies*, 5(3), 299–330.

[34] Complete list of references

Autant-Bernard, C., Billand, P., Frachisse, D. and Massard, N. (2007) Social distance versus spatial distance in R&D cooperation: Empirical evidence from European collaborations choices in micro and nanotechnologies, *Papers in Regional Science*, 86(3), 495-519.

Baldwin, J.R. (1999) Innovation, training and success, *Research paper* No. 137, Analytical Studies Branch, Statistics Canada, Ottawa.

Barajas, A., Huergo, E. and Moreno, L. (2012) Measuring the economic impact of Research Joint Ventures supported by the EU Framework Programme, *Journal of Technology Transfer*, 37, 917-942.

Barge-Gil, A. (2013) Open Strategies and Innovation Performance, *Industry and Innovation*, 20(7), 585-610.

Barge-Gil, A.; Santamaría, L. and Modrego, A. (2011) Complementarities between universities and technology institutes: New empirical lessons and perspectives, *European Planning Studies*, 19(2), 195-215.

Bathelt, H., Malmberg, A. and Maskell, P. (2004) Clusters and knowledge: local buzz, global pipelines and the process of knowledge creation, *Progress in Human Geography*, 28, 31–56.

Bayona, C., García-Marco, T. and Huerta, E. (2001) Firms' motivation for cooperative R&D: An empirical analysis of Spanish firms, *Research Policy*, 30(8), 1289–1307.

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

Belderbos, R., Carree, M. and Lokshin, B. (2006) Complementarity in R&D cooperation strategies, *Review of Industrial Organization*, 28(4), 401–426.

Belderbos, R., Carree, M.A. and Lokshin, B. (2004a) Cooperative R&D and firm performance, *Research Policy*, 33(10), 1477-92.

Belderbos, R., Carree, M.A., Diederen, B., Lokshin, B. and Veugelers, R. (2004b) Heterogeneity in R&D co-operation strategies, *International Journal of Industrial Organization*, 22(8/9), 1237–63.

Belderbos, R., Gilsing, V. and Lokshin, B. (2012) Persistence of, and Interrelation Between, Horizontal and Vertical Technology Alliances, *Journal of Management*, 38(6), 1812-34.

Bergman, E. (2009) Embedding network analysis in spatial studies of innovation, *The Annals of Regional Science*, 43(3), 559-565.

Boschma, R.A. and Iammarino, S. (2009) Related variety, trade linkages and regional growth, *Economic Geography*, 85(3), 289-311.

Busom, I. and Fernández-Ribas, A. (2008) The impact of firm participation in R&D programmes on R&D partnerships, *Research Policy*, 37(2), 240-257.

Cameron, C. and Trivedi, P. (2005) *Microeconometrics: Methods and Applications*. New York: Cambridge University Press.

Cappellari, L. and Jenkins, S.P. (2003) Multivariate probit regression using simulated maximum likelihood, *Stata Journal*, 3(3), 221– 235.

Cassiman, B. and Veugelers, R. (2002) R&D cooperation and spillovers: Some empirical evidence from Belgium, *The American Economic Review*, 92(4), 1169-84.

Chun, H. and Mun, S.-B. (2012) Determinants of R&D cooperation in small and medium-sized enterprises, *Small Business Economics*, 39(2), 419-436.

Cincera, M., Kempen, L., Van Pottelsberghe, B., Veugelers, R. and Villegas, C. (2003) Productivity growth, R&D and the role of international collaborative agreements: Some evidence for Belgian manufacturing companies, *Brussels Economic Review,* 46(3), 107-140.

Clausen, T., Pohjola, M., Sapprasert, K. and Verspagen, B. (2012) Innovation strategies as a source of persistent innovation, *Industrial and Corporate Change*, 21(3), 553–585.

Cohen, W.M. and Klepper, S. (1996) A reprise of size and R&D, *Economic Journal*, 106, 925-951.

Cohen, W.M. and Levinthal, D. A. (1989) Innovation and learning: The two faces of R&D, *Economic Journal*, 99, 569–596.

Cohen, W.M. and Levinthal, D.A. (1990) Absorptive capacity: A new perspective of learning and innovation, *Administrative Science Quarterly*, 35(1), 128–152.

Cyert, R.M. and March, J.G. (1963) *A behavioral theory of the firm*. Englewood Cliffs, NJ: Prentice Hall.

D'Aspremont, C. and Jacquemin, A. (1988) Cooperative and noncooperative R&D in duopoly with spillovers, *The American Economic Review*, 78(5), 1133-7.

Dachs, B., Ebersberger, B. and Lööf, H. (2008) The innovative performance of foreign-owned enterprises in small open economies, *Journal of Technology Transfer*, 33, 393-406.

Das, T. and Teng, B.-S. (2000) A resource-based theory of strategic alliances, *Journal of Management*, 26, 31–60.

Devicienti, F. and Poggi, A (2011) Poverty and social exclusion: two sides of the same coin or dynamically interrelated processes? *Applied Economics*, 43, 3549–71.

Dhont-Peltrault, E. and Pfister, E. (2011) R&D cooperation versus R&D subcontracting: Empirical evidence from French survey data, *Economics of Innovation and New Technology*, 20(4), 309-341.

Díaz-Díaz, N.L., Aguiar-Díaz, I. and De Saá-Pérez, P. (2008) Impact of foreign ownership on innovation, *European Management Review*, 5, 253-263.

Duysters, G. and Lokshin, B. (2011) Determinants of alliance portfolio complexity and its effect on innovative performance of companies, *Journal of Product Innovation Management*, 28, 570–585.

Dyer, J. H. and Singh, H. (1998) The relational view: cooperative strategy and sources of inter-organizational competitive advantage, *Academy of Management Review*, 23, 660-679.

Eisenhardt, K. M. and Martin, J. A. (2000) Dynamic capabilities: What are they? *Strategic Management Journal*, 21, 1105-21.

Escribano, A., Fosfuri, A. and Tribó, J.A. (2009) Managing external knowledge flows: the moderating role of absorptive capacity, *Research Policy*, 38(1), 96–105.

European Commission (2012) Guide to Research and Innovation Strategies for Smart Specialisations (RIS 3). *Smart Specialisation Platform*.

Faems, D., Van Looy, B. and Debackere, K. (2005) Interorganizational collaboration and innovation: Toward a portfolio approach, *Journal of Product Innovation Management*, 22(3), 238–250.

Fritsch, M. and Lukas, R. (2001) Who cooperates on R&D? *Research Policy*, 30(2), 297-312.

Giuliani, E. and Bell, M. (2005) The micro-determinants of meso-level learning and innovation: evidence from a Chilean wine cluster, *Research Policy*, 34(1), 47–68.

Goeree, M.S. and Helland, E. (2010) Do Research Joint Ventures serve a collusive function? *Working Paper* No 448, University of Zurich.

Granovetter, M. (1985) Economic action and social structure: the problem of embeddedness, *American Journal of Sociology*, 91, 481-510.

Greene, W. (2008) *Econometric Analysis*. Prentice Hall, 7th Edition.

Greenlee, P. and Cassiman, B. (1999) Product market objectives and the formation of Research Joint Ventures, *Managerial Decision Economics*, 20, 115-130.

Gugler, K. and Siebert, R. (2007) Market power versus efficiency effects of mergers and Research Joint Ventures: Evidence from the semiconductor industry, *Review of Economics and Statistics*, 89(4), 645-659.

Gulati, R. (1995) Social structure and alliance formation patterns: A longitudinal analysis, *Administrative Science Quarterly*, 40, 619–652.

Gulati, R. (1999) Network location and learning: The influence of network resources and firm capabilities on alliance formation, *Strategic Management Journal*, 20, 97-420.

Hagedoorn, J. (1993) Understanding the rationale of strategic technology partnering: Interorganizational modes of co-operation and sectoral differences, *Strategic Management Journal*, 14(5), 371–385.

Hagedoorn, J., Link, A.N. and Vonortas, N.S. (2000) Research partnerships, *Research Policy*, 29(4), 567-586.

Hamel, G. (1998) Strategy innovation and the quest for value, *Sloan Management Review*, 39(2), 7-14.

Heckman, J.J. (1981) Heterogeneity and state dependence. In: Rosen, S. (Ed.), *Studies in labor markets*, 91-140. Chicago: Chicago University Press.

Hernán, R., Marin, P. and Siotis, G. (2003) An empirical analysis of the determinants of Research Joint Venture formation, *Journal of Industrial Economics*, 51, 75-89.

Hoang, H. and Rothaermel, F. (2005) The effect of general and partner specific alliance experience on joint R&D project performance, *Academy of Management Journal*, 48(2), 332–345.

Hoffman, K., Milady, P., Bessant, J. and Perren, L. (1998) Small firms, R&D, technology and innovation in the UK: A literature review, *Technovation*, 18, 39–55.

Hsiao, C. (2003) *Analysis of Panel Data*. Cambridge University Press.

Jacob, J., Belderbos, R. and Gilsing, V. (2013) Technology alliances in emerging economies: Persistence and interrelation in European firms' alliance formation, *R&D Management*, 43(5), 447-460.

Jensen, M., Johnson, B., Lorenz, E. and Lundvall, B.-Å. (2007) Forms of knowledge and modes of innovation, *Research Policy*, 36(5), 680–693.

Jones, G.K., Lanctot, Jr. A. and Teegen, H.J. (2001) Determinants and performance impacts of external technology acquisition, *Journal of Business Venturing*, 16(3), 255–283.

Kaiser, U. (2002) An empirical test of models explaining research expenditures and research co-operating: Evidence from the German service sector, *International Journal of Industrial Organization*, 20(6), 747-774.

Kamien, M. and Zang, I. (2000) Meet me halfway: Research joint ventures and absorptive capacity, *International Journal of Industrial Organization*, 18(7), 995–1012.

Kamien, M., Muller, E. and Zang, I. (1992) Research Joint Ventures and R&D cartels, *The American Economic Review*, 82(5), 1293-1306.

Katz, M. (1986) An analysis of cooperative research and development, *The RAND Journal of Economics*, 17(4), 527–543.

Klomp, L. and Van Leeuwen, (2001) Linking innovation and firm performance: a new approach, *International Journal of the Economics of Business*, 8(3), 343-364.

Laursen, K. and Salter, A. (2006) Open for innovation: The role of openness in explaining innovation performance among UK manufacturing firms, *Strategic Management Journal*, 27(2), 131–150.

Lavie, D. and Miller, S.R. (2008) Alliance portfolio internationalization and firm performance, *Organization Science*, 19(4), 623–646.

Le Bas, C., Mothe, C. and Nguyen-Thi, T.U. (2011) Technological innovation persistence: Literature survey and exploration of the role of organizational innovation, CEPS Instead, *Working Paper* 2011-54.

Lee, L. (1992) Amemiya's Generalized Least Squares and tests of overidentification in simultaneous equation models with qualitative or limited dependent variables, *Econometric Reviews*, 11(3), 319-328.

Leiponen, A. (2012) The benefits of R&D and breadth in innovation strategies: A comparison of Finnish service and manufacturing firms, *Industrial and Corporate Change*, 21(5), 1255–81.

Levitt, B. and March, J.G. (1988) Organizational learning, *Annual Review of Sociology*, 14, 314-340.

Lööf, H. (2009) Multinational enterprises and innovation: Firm level evidence on spillover via R&D collaboration, *Journal of Evolutionary Economics*, 19(1), 41–71.

Lööf, H. and Broström, A. (2008) Does knowledge diffusion between university and industry increase innovativeness? *The Journal of Technology Transfer*, 33(1), 73-90.

López, A. (2008) Determinants of R&D cooperation: Evidence from Spanish manufacturing firms, *International Journal of Industrial Organization*, 26(1), 113-136.

López-Fernández, C., Serrano-Bedia, A.M. and García-Piqueres, G. (2008) Patterns of institutional cooperation in R&D for Spanish innovative firms in the manufacturing and service sectors, *Management Research News*, 31(11), 811-829.

Lundvall, B.-Å. (1988) Innovation as an interactive process: From user–producer interaction to the national system of innovation. In: Dosi, G. Freeman, C., Nelson, R., Silverberg, G., Soete, L. (Eds.), *Technical Change and Economic Theory*. Pinter, London, 349–369.

Lundvall, B.-Å. (2004) The economics of knowledge and learning. In: Christensen, J.L. and Lundvall, B.-Å. (Eds.), Product Innovation, Interactive Learning and Economic Performance (*Research on Technological Innovation and Management Policy*, vol 8). Emerald Group Publishing Ltd., 21-42.

Lundvall, B.-Å. (2007) National innovation system: analytical focusing device and policy learning tool, *Working Paper* R2007:004, ITPS – Swedish Institute for Growth Policy Studies.

McCann, P. and Ortega-Argilés, R. (2013) Smart specialization, regional growth and applications to European Union cohesion policy, *Regional Studies*, DOI:10.1080/00343404.2013.799769.

McFadden, D. (1974) Conditional logit analysis of qualitative choice behaviour. In: Zarembka, P. (Ed), *Frontiers in Econometrics*. Academic Press, New York, 105-142.

Miles, I. (2007) Research and development (R&D) beyond manufacturing: The strange case of services R&D, *R&D Management*, 37(3), 249–268.

Miotti, L. and Sachwald, F. (2003) Cooperative R&D: Why and with whom? An integrated framework of analysis, *Research Policy*, 32(8), 1481–99.

Mohnen, P. and Röller, L. (2005) Complementarities in innovation policy, *European Economic Review*, 49(6), 1431–50.

Mohnen, P., Mairesse, J. and Dagenais, M. (2006) Innovativity: a comparison across seven European countries, *Economics of Innovation and New Technology*, 15(4-5), 391–413.

Monjon, S. and Waelbroeck, P. (2003) Assessing spillovers from universities to firms: evidence from French firm-level data, *International Journal of Industrial Organization*, 21(9), 1255-70.

Mundlak, Y. (1978) On the pooling of time series and cross-sectional data, *Econometrica*, 46, 69–86.

Nelson, R.R. and Winter, S.G. (1982) *An evolutionary theory of economic change*. Cambridge, MA: Belknap.

Newey, W.K. (1987) Efficient estimation of limited dependent variable models with endogenous explanatory variables, *Journal of Econometrics*, 36, 231-250.

Nieto, M.J. and Rodríguez, A. (2011) Offshoring of R&D: Looking abroad to improve innovation performance, *Journal of International Business Studies*, 42, 345-361.

Nieto, M.J. and Santamaría, L. (2007) The importance of diverse collaborative networks for the novelty of product innovation, *Technovation*, 27, 367–377.

Nijman, T. and Verbeek, M. (1992) Nonresponse in panel data: the impact on estimates of a life cycle consumption function, *Journal of Applied Econometrics*, 7, 243–257.

Nooteboom, B. (2004) *Inter-firm collaboration, learning and networks: An integrated approach*. London: Routledge.

O'Grady, S. and Lane, H.W. (1996) The psychic distance paradox, *Journal of International Business Studies*, 27(2), 309–333.

OECD (2005) *Oslo Manual, Guidlines for collecting and interpreting innovation*, 3rd edition, OECD, Paris.

Owen-Smith, J. and Powell, W.W. (2004) Knowledge networks as channels and conduits: the effects of spillovers in the Boston biotechnology community, *Organization Science*, 15, 5–21.

Pakes, A. (1983) On group effects and errors in variables aggregation, *Review of Economics and Statistics*, 65(1), 168–173.

Peters, B. (2009) Persistence of innovation: Stylised facts and panel data evidence, *The Journal of Technology Transfer*, 34, 226-243.

Pisano, G.P. (1990) The R&D boundaries of the firm: An empirical analysis, *Administrative Science Quarterly*, 35(1), 153–176.

Powell, W., Koput, K. and Smith-Doerr, L. (1996) Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology, *Administrative Science Quarterly*, 41(1), 116-146.

Powell, W.W. and Grodal, S. (2005) Networks of innovators. In: Fagerberg, J., Mowery, D.C., Nelson, R.R. (Eds.), *The Oxford Handbook of Innovation*. Oxford University Press, Oxford, 56–85.

Raymond, W., Mohnen, P.A., Palm, F. and Van der Loeff, S.S. (2010) Persistence of innovation in Dutch manufacturing: Is it spurious? *The Review of Economics and Statistics*, 92, 495-504.

Reis, A. (2001) On the welfare effects of foreign investment, *Journal of International Economics*, 54(2), 411-427.

Rivers, D. and Vuong, Q.H. (1988) Limited information estimators and exogeneity tests for simultaneous probit models, *Journal of Econometrics*, 39, 347–366.

Roberts, R. (1998) Managing Innovation: The pursuit of competitive advantage and the design of intense environments, *Research Policy*, 27(2), 159-175.

Robin, S. and Schubert, T. (2013) Cooperation with public research institutions and success in innovation: Evidence from France and Germany, *Research Policy*, 42, 149–166.

Röller, L., Siebert, R. and Tombak, M. (2007) Why firms form (or do not form) RJVS, *The Economic Journal*, 117(522), 1122-44.

Romer, P.M. (1986) Increasing returns and long-run growth, *Journal of Political Economy*, 94(5), 1002-37.

Roper, S. and Hewitt-Dundass, N. (2004) Innovation in services sector in Ireland – Scoping Study, for *Forfás by InnovationLab Ireland Ltd*, Belfast.

Sakakibara, M. (1997) Heterogeneity of firm capabilities and cooperative research and development: An empirical examination of motives, *Strategic Management Journal*, 18(S1), 143-164.

Schilling, M.A. (2008) Understanding the alliance data, *Strategic Management Journal*, 30(3), 233-260.

Schoenmakers, W. and Duysters, G. (2006) Learning in strategic technology alliances, *Technology Analysis & Strategic Management*, 18(2), 245–264.

Schumpeter, J. (1942) Capitalism, Socialism and Democracy (New York: Harper).

Segarra-Blasco, A. and Arauzo-Carod, J.M. (2008) Sources of innovation and industry-university interaction: Evidence from Spanish firms, *Research Policy*, 37(8), 1283-95.

Serrano-Bedia, A.M., López-Fernández, M.C. and García-Piqueres, G. (2010) Decision of institutional cooperation on R&D: Determinants and sectoral differences, *European Journal of Innovation Management*, 13(4), 439-465.

Sodjinou, E. and Henningsen, A. (2012) Community-Based management and interrelations between different technology adoption decisions: Innovations in Village Poultry Farming in Western Africa. *FOI Working Paper* 2012/11, University of Copenhagen, Institute of Food and Resource Economics.

Sutton, J. (1991) *Sunk costs and market structure*. MIT Press, London.

Terza, J.V., Basu, A. and Rathouz, P.J. (2008) Two-Stage residual inclusion estimation: Addressing endogeneity in health econometric modelling, *Journal of Health Economics*, 27, 531–543.

Tether, B.S. (2002) Who co-operates for innovation, and why: An empirical analysis, *Research Policy*, 31(6), 947-967.

Tether, B.S. (2005) Do services innovate (differently)? Insights from the European innobarometer survey, *Industry and Innovation*, 12, 153–184.

Tether, B.S. and Tajar, A. (2008) Beyond industry–university links: Sourcing knowledge for innovation from consultants, private research organisations and the public science-base, *Research Policy*, 37(6-7), 1079-95.

Trigo, A. and Vence, X. (2011) Scope and patterns of innovation cooperation in Spanish service enterprises, *Research Policy*, 41(3), 602-613.

Triguero, Á. and Córcoles, D. (2013) Understanding innovation: an analysis of persistence for Spanish manufacturing firms, *Research Policy*, 42(2), 340-352.

Tsai, K.-H. (2009) Collaborative networks and product innovation performance: toward a contingency perspective, *Research Policy*, 38(5), 765-778.

Van Beers, C. and Zand, F. (2014) R&D cooperation, partner diversity, and innovation performance: an empirical analysis, *Journal of Product Innovation Management*, 31(2), 292–312.

Van de Vrande, V., De Jong, J.P.J., Vanhaverbeke, W. and De Rochemont, M. (2009) Open innovation in SME's: Trends, motives and management challenges, *Technovation*, 29, 423–437.

Vassolo, R.S., Anand, J. and Folta, T.B. (2004) Non-additivity in portfolios of exploration activities: A real options based analysis of equity alliances in biotechnology, *Strategic Management Journal*, 25, 1045-61.

Vega-Jurado, J., Gutiérrez-Gracia, A. and Fernández-de-Lucio, I. (2009) Does external knowledge sourcing matter for innovation? evidence from the Spanish manufacturing industry, *Industrial and Corporate Change*, 18(4), 637–670.

Veugelers, R. and Cassiman, B. (1999) Make and buy in innovation strategies: Evidence from Belgian manufacturing firms, *Research Policy*, 28, 63–80.

Veugelers, R. and Cassiman, B. (2005) R&D cooperation between firms and universities, some empirical evidence from Belgian manufacturing, *International Journal of Industrial Organization*, 23(5/6), 355–379.

Woerter, M. (2012) Technological proximity between firms and universities and technology transfer, *Journal of Technology Transfer*, 37, 828–866.

Wooldridge, J.M. (1995) Selection corrections for panel data models under conditional mean independence assumptions, *Journal of Econometrics*, 68, 115–232.

Wooldridge, J.M. (2005) Simple Solutions to the Initial Conditions Problem in Dynamic Nonlinear Panel Data Models with Unobserved Heterogeneity, *Journal of Applied Econometrics*, 20, 39–54.

Wooldridge, J.M. (2010) *Econometric Analysis of Cross Section and Panel Data*. Third Edition. Cambridge, MA: MIT Press.

Zabel, J.E. (1992) Estimating fixed effects and random effects with selectivity, *Economics Letters*, 40, 269–272.

Zahra, S. and George, G. (2002) Absorptive capability: A review, reconceptualization, and extension, *Academy of Management Review*, 27(2), 185–203.

Zellner, A. and Haung, D. (1962) Further properties of efficient estimators for seemingly unrelated regression equations, *International Economic Review*, 3, 300-313.