Paper to be presented at DRUID21
Copenhagen Business School, Copenhagen, Denmark
October 18-20, 2021

Complementarity between R&D collaborations, firm's product innovation and the moderating role of absorptive capacity

Enrique Acebo
University of León
Department of Management
e.acebo@unileon.es

José-Ángel Miguel-Dávila
University of León
Department of Management
jam.davila@unileon.es

MARIANO Nieto
Universidad de Leon
Direccion y Economia de la Empresa
mariano.nieto@unileon.es

Abstract

Using a marginal effects approach and insights from innovation management theory, we investigate the existence of a complementary effect in R&D collaboration between scientific and supply-chain partners. Previous studies encourage firms to collaborate with external organizations to access different innovation modes. However, others claim the existence of diminishing effects as the number of collaborators grows. In this paper, we theorize that rather than be mutually excluding, both frameworks are the two sides of the same coin, moderated by the firm's ability to deal with different types of R&D collaboration. Specifically, we argue that firms' absorptive capacity determines the existence of a complementary or substitutive effect. This framework is tested against an unbalanced panel sample of 11,703 innovative firms over a decade on product innovation, new-to-market product innovation, and share of turnover from new products. Our results show that firms that have a strong absorptive capacity reach complementary effects collaborating with scientific and supply-chain partners simultaneously. And, firms that do not have enough absorptive capacity suffer substitutive effects. Finally, these results demonstrate the importance of analysing the interaction between firms' capabilities and the external partners to increase the firm's innovation output.

Complementarity between R&D collaborations, firm's product innovation and the moderating role of absorptive capacity

ABSTRACT

Using a marginal effects approach and insights from innovation management theory, we investigate the existence of a complementary effect in R&D collaboration between scientific and supply-chain partners. Previous studies encourage firms to collaborate with external organizations to access different innovation modes. However, others claim the existence of diminishing effects as the number of collaborators grows. In this paper, we theorize that rather than be mutually excluding, both frameworks are the two sides of the same coin, moderated by the firm's ability to deal with different types of R&D collaboration. Specifically, we argue that firms' absorptive capacity determines the existence of a complementary or substitutive effect. This framework is tested against an unbalanced panel sample of 11,703 innovative firms over a decade on product innovation, new-to-market product innovation, and share of turnover from new products. Our results show that firms that have a strong absorptive capacity reach complementary effects collaborating with scientific and supply-chain partners simultaneously. And, firms that do not have enough absorptive capacity suffer substitutive effects. Finally, these results demonstrate the importance of analysing the interaction between firms' capabilities and the external partners to increase the firm's innovation output.

Keywords: R&D collaboration; Absorptive Capacity; Complementarity; Product Innovation;

JEL Classification: M10; D83

Complementarity between R&D collaborations, firm's product innovation and the moderating role of absorptive capacity

1. INTRODUCTION

Access to external knowledge is vital for firms' innovative and overall performance (Chesbrough et al., 2006; Johnson, 2002; March, 1991). Firms can source new knowledge from individuals (Von Hippel, 2005) and organisations (Nieto and Santamaría, 2007) within and beyond the supply chain (Belderbos et al., 2004; Tether, 2002). One central mechanism to do it and access to different innovation modes is R&D collaboration (Jensen et al., 2007). Empirical evidence suggests that this mechanism offers firms the best way to share and access to knowledge, ideas, and resources from external partners (Martínez-Noya and Narula, 2018). Specifically, R&D collaboration with scientific partners offers the opportunity to access new technologies and infrastructures (Caloghirou et al., 2004; Perkmann and Walsh, 2007); collaboration with suppliers let to access tactical knowledge increasing firm efficiency (Liker et al., 1996; Song and Di Benedetto, 2008); and, with customers to discover market opportunities (Mustak et al., 2013; Von Hippel, 1978).

As a result, several authors have theorized that the multiple R&D collaborations with different types of external partners enrich innovative processes more than any other innovation strategy (Belderbos et al., 2015; Faems et al., 2010; Jensen et al., 2007). From this perspective, R&D collaboration with different types of partners produces a complementary effect that helps companies reach the highest innovative performance levels. However, these conclusions collide with those claiming the existence of substitutive effects and diminishing results as external partners increase in number (Fu, 2012; Laursen and Salter, 2006; Leiponen and Helfat, 2010). These authors argue that the excess of information and the complexity introduced by multiple partners negatively affect firms' innovation performance.

To solve the conflict between both relevant literature directions, several scholars have searched variables that could shed light on the existence of complementary and substitutive effects. On the one hand, some authors have focused on the nature of external knowledge and have determined that the existence of opposite effects are caused by the increasing complexity of combining external knowledge linked to different innovation modes (González-Pernía et al., 2015; Haus-Reve et al., 2019). On the other hand, several authors have focused on firms' internal resources and capabilities to absorb and process external knowledge and have shown that this internal dimension mitigates the negative effect of an excessive openness to external knowledge search (Hagedoorn and Wang, 2012; Kafouros et al., 2020).

Despite these contributions stressing the role of internal and external dimensions on innovation performance, studies taking both into account as well as their interaction on innovation outcomes have been few and far between (Asimakopoulos et al., 2020; Carmona-Lavado et al., 2021; Escribano et al., 2009; Gkypali et al., 2017). Therefore, recent literature reviews have pointed out the need to take into account the nature of different knowledge sources and their interaction with the firms' capabilities (Agostini et al., 2020; Bogers et al., 2017). This study is an attempt to analyse how the complementarity or substitutability between different R&D collaboration partners depends on firms' absorptive capacity.

Using a marginal effects analysis, we can quantify and compare the firms' likelihood to innovate based on the different combination of R&D collaborations at different absorptive capacity levels. We suggest that the existence of a complementary or substitutive effect between knowledge from scientific partners and supply-chain collaborations relies on the firm's ability to internalise and exploit them simultaneously. This hypothesis led us to contrast the theoretical proposition that collaboration with different types of partners is beneficial for firms' innovation (Jensen et al., 2007), without denying the existence of adverse effects if firms cannot manage multiple sources of knowledge (Laursen and Salter, 2006). Since some authors have claimed the substitutability of scientific and supply-chain partner collaboration without analysing firms' internal aspects interaction (Haus-Reve et al., 2019; Kobarg et al., 2019), our findings are crucial to managers and policymakers because they offer an extensive analysis of the interaction between the internal and external determinants of firms' product innovation. Our conclusions prevent them from making a U-turn in the promotion of open innovation strategies with their stakeholders (West and Bogers, 2014).

Relying on an unbalanced panel sample of 11,703 Spanish firms, extracted from the Spanish version of the Community Innovation Survey (PITEC) during the period 2006-2016, we examine whether firms' absorptive capacity positively moderates the simultaneous R&D collaboration with scientific partners and supply-chain partners with respect to the firms' likelihood to innovate. To validate our analysis, we test our hypothesis on product innovation, new-to-market products and the share of turnover from new products. Our results show that, without considering the firm's absorptive capacity, firms that collaborate only with one type of partner are more innovative than firms that collaborate with scientific and supply-chain partners. However, if firm's absorptive capacity is analysed, the combination of both R&D collaborations is revealed as complementary in those firms which have the highest level of absorptive capacity. These results are robust on three measured of innovation (product innovation, new-to-market, share of turnover of innovative product) and reach its greatest effect on the new-to-market products. Thus, we conclude the interaction between internal and external dimension is what really matters to determine the existence of a complementary or substitutive effect.

The scheme we follow to present our results reflects how the research was structured and carried out. In section 2, we review the role of R&D collaboration, its connexion with different innovation modes and the moderating role of absorptive capacity. In section 3, we present the sample, and the methodology applied. In section 4, we offer the results from our regression and marginal analysis. In section 5, we discuss our results. Finally, in the last section, we present the main conclusions and suggestions for future research.

2. THEORETICAL FRAMEWORK

2.1. R&D collaborations and innovation

Innovation management literature considers external knowledge a critical determinant for firm innovation (Chesbrough et al., 2006). Firms can source external knowledge from individuals or organisations through technological alliances, strategic technology partnering and joint R&D projects (Un et al., 2010). R&D collaboration with external partners offers firms an opportunity to learn different types of knowledge along all the value chain (Johnson, 2002; Love et al., 2014).

Scholars have analysed the effect of each type of external collaboration to firm's likelihood to innovate in depth. For example, Faems et al. (2005) and Nieto and Santamaría (2010) showed how collaboration with scientific partners is typically more explorative – aiming to create new knowledge rather than commercial ends. Also, Song and Di Benedetto (2008) and Vega-Jurado et al. (2009) have shown how collaboration with suppliers and customers tends to optimize core competencies, helping firms exploit technological and market opportunities. This literature concentrating on the effects of external knowledge sources on firms' innovation can be linked to a broader literature on modes of innovation (Fitjar and Rodríguez-Pose, 2013; Jensen et al., 2007; Parrilli and Alcalde Heras, 2016).

Jensen et al. (2007) were the first who pointed out that collaboration with specific partners leads firms to access different types of external knowledge and, via this, to different innovation modes (Johnson, 2002). Jensen et al. (2007) differentiated between two innovation modes: the 'Science, Technology, and Innovation' (STI), and the 'Doing, Using, and Interacting' (DUI). The STI innovation mode promotes firms' innovation based on advanced scientific and technological knowledge from universities and research institutes. In contrast, the DUI innovation mode is based on informal knowledge from supply-chain partners such as suppliers and customers. Each innovation mode can be applied to all firms; however, STI mode is preferred in high technology sectors (Vivas and Barge-Gil, 2015), while, the DUI mode is preferred in traditional manufacturing sectors (Rodriguez et al., 2017).

However, while Jensen et al. (2007, p. 690) claimed "what really improves the performance of innovation is the use of mixed strategies that combine strong versions of the two modes", the literature on R&D collaboration and innovation modes has mostly not addressed the existence of complementary or substitute effects. The few studies which did so offered contradictory results and used inadequate methodological approaches until recently. For example, some studies support the view that both innovation modes contribute positively to firms' innovation (Belderbos et al., 2015; González-Pernía et al., 2015), but other studies present more nuanced outcomes (Carrillo-Hermosilla et al., 2010; Fitjar and Rodríguez-Pose, 2013). Recently, Haus-Reve et al. (2019) claimed that rather than being complementary, scientific and supply-chain collaboration are substitutive on firms' product innovation.

Haus-Reve et al. (2019)'s study can be connected to a stream of strategic management literature that has pointed out how the excess of external R&D collaborations produced diminishing firms' performance (Fu, 2012; Laursen and Salter, 2006; Leiponen and Helfat, 2010). Laursen & Salter (2006) were the first who pointed out clearly how as the number of external partners increases, the firms' likelihood to innovate follows an inverted U-curve. Thus, Leiponen & Helfat (2010) showed that excessive reliance on different external partners could divert firms' critical resources away from its core business and disrupt current innovation routines. Recently, Dong et al. (2017) and Asimakopoulos et al. (2020) argued that this negative effect exists because firms do not get full use of all the potential learning opportunities each of the external partner types provides and suffer substitutive effects produced by information overload and escalating complexity (Ahuja and Morris Lampert, 2001; Fu, 2012).

Taking the above literature together, it can be expected that when firms have to determine their degree of openness to external collaboration (Laursen and Salter, 2006), they can choose between a specialized collaboration with partners linked to a specific innovation mode and collaborate with partners linked to different innovation modes (Jensen et al., 2007). For instance, firms can collaborate only with customers rather than cooperate with scientific supply-chain partners. Thus, we propose that substitutive effects and the diminishing effect on firms' innovation outcomes are not caused by the number of external partners but by the complexity that the combination of different external partners associated with specific innovation modes implies (Asimakopoulos et al., 2020; Gkypali et al., 2017; Haus-Reve et al., 2019). Collaboration with one type of partner will be less complicated than simultaneous collaboration with scientific and supply-chain partners.

We hypothesize that while access to as much external knowledge as possible is crucial for business innovation, collaboration with scientific and supply-chain partners linked to a specific innovation mode (STI or DUI) lets firms explore and exploit new knowledge easier than a combination of multiple external partners linked to different innovation modes (STI and DUI).

This model can be described as follow:

H1a: Firms that collaborate with scientific partners are more likely to introduce product innovation than those that do not.

H1b: Firms that collaborate with supply-chain partners are more likely to introduce product innovation than those that do not.

H2: Firms that cooperate simultaneously with scientific and supply-chain partners are less likely to introduce product innovation than those that cooperate with only one type of partner

.

2.2. The moderating role of absorptive capacity

Prior scholarly work has elucidated that tapping into external knowledge has differential effects on firm innovation outputs. Cohen and Levinthal (1990, 1989) pointed out the role played by a firms' absorptive capacity to internalise external knowledge and apply it to commercial ends. As Zahra & George (2002) and Todorova & Durisin (2007) explained, this ability is linked to a set of organisational routines and strategic processes through which firms acquire, assimilate, transform and apply knowledge to innovate. Cohen and Levinthal's seminal work placed the combination of internal and external knowledge in the centre of innovation processes (Escribano et al., 2009; Nieto & Quevedo, 2005), since then the relationship between the internal and external dimension of knowledge is not disassociated (Harris and Yan, 2019).

Escribano et al. (2009) were one of the first to point out how firms absorptive positively moderates the inverted U-shaped effect of external knowledge on firms' innovation outcomes. Today, the methodological scope has been expanded to analyse in-depth the interactions between external knowledge and absorptive capacity on firms' innovation outcome. For example, Hagedoorn & Wang (2012) studied the existence of a complementary or substitutive effect between internal and external R&D activities. They found that in-house R&D investment is a contingency variable that critically influences the association between them. Martínez-Costa et al. (2019) have found that the effect of external collaboration on innovation outcome is mediated by organisational learning, suggesting the importance of acquiring, distributing and interpreting the external knowledge correctly. And, recently, Asimakopoulos et al. (2020) have discovered that the relationship between external knowledge and firms' innovation efficiency is negatively moderated by internal organisational constraints such as high innovation costs and lack of information related to technology.

Whereas these studies have advanced our understanding of the effect of some absorptive capacity's dimensions on the effect produced by the number of external partners, the question of how firm internal R&D resources moderate the relationship between different types of knowledge remains unaddressed, even though Jensen et al. (2007, p. 681) define innovation as a process in which firms interact with external knowledge from different types of partners. None of the studies which analyse the impact of modes of innovation consider the possibility of an interactive effect between them and the firm's internal resources. All of them consider it as an independent variable (Fitjar and Rodríguez-Pose, 2013; González-Pernía et al., 2015; Haus-Reve et al., 2019).

The positive effect of absorptive capacity as a moderator variable in firm innovation process has been widely analysed. Like Escribano et al. (2009), Hagedoorn & Wang (2012), Asimakopoulos et al. (2020) and Gkypali (2017) show, firms with superior internal R&D resources are better at effectively screening, assimilating, internalising and capitalizing knowledge from external partners for business innovation. Thus, absorptive capacity would be a crucial variable in understanding the existence of complementarity or substitutive effects between partners linked to different modes of innovation (Agostini et al., 2020; Bogers et al., 2017; Hagedoorn and Wang, 2012).

Combining what authors from both literature directions have concluded (Asimakopoulos et al., 2020; González-Pernía et al., 2015; Haus-Reve et al., 2019), we suggest that the existence of a complementary or substitutive effect on firms' innovation does not depend only on the type or the number of partners but also on the firms' ability to internalise different types of knowledge and apply them to commercial ends. Firms with higher levels of absorptive capacity can reach higher levels of innovation outcomes combining knowledge from scientific and supply-chain collaborations. In contrast, firms which do not have enough level of absorptive capacity will suffer disappointing results due to not being able to deal with those sources of knowledge simoultaneously.

This hypothesis can be summarized as follows:

H3: Absorptive capacity positively moderates the effect of simultaneous collaboration with scientific and supply-chain partners.

3. METHODOLOGY

3.1. Data

The data used to test our hypotheses is extracted from the Spanish Technological Innovation Panel (PITEC), which Spanish version of the Community Innovation Survey (CIS). We use all the available waves of the survey to create an unbalanced panel of firms covering the period 2006-2016. During the assembly of this dataset, we excluded observations from firms that had gone through sudden employment changes resulting from a merger or acquisition, high labour turnover or a layoff (González-Pernía et al., 2015; Haus-Reve et al., 2019; Radicic and Pinto, 2019). As a result, we obtained a sample composed of 11,703 firms, which, over an average period of 7.7 years, yields a total sample of 105,118 observations.

3.2. Variables

To make our analysis most comparable to previous literature (González-Pernía et al., 2015; Haus-Reve et al., 2019; Rodriguez et al., 2017), we use three measures of innovation outcomes as dependent variables: *product innovation*, *new-to-market product innovation*, and the *share of turnover from new products*.

Product innovation is coded as a binary variable which takes a positive value if the firm has introduced new or significantly-improved goods or services to the market in the preceding three years. *New-to-market product innovation* is coded as a binary variable which only counts as a positive value if the product innovation was new to the firm's market, but excludes products that were new to a firm but already existing in the market. Tracking the *share of turnover from new products* allows for more variance across observed firms. It enables us to distinguish between innovative firms with ~~a~~ higher and lower share of innovative products in their turnover.

On average, 54.29 per cent of all firm observations, and 75.36 per cent of those with strong absorptive capacity report product innovation. On average, 26.45 per cent of all firms observed, and 81.20 per cent of those with strong absorptive capacity, report new-to-market product innovation.

Secondly, to set our independent variables, we distinguish between scientific collaboration (*STI* mode of innovation) and supply-chain collaboration *(DUI* mode of innovation). The former includes collaboration with, universities, research institutes, consultancy firms or other research organisations. The latter, collaboration with suppliers and customers. Both are based on surveys questions coded as a binary, positive value if firms cooperate with each type of partner, negative otherwise. This approach allows us to compare our results with previous studies (Fitjar and Rodríguez-Pose, 2013; González-Pernía et al., 2015; Haus-Reve et al., 2019; Parrilli and Alcalde Heras, 2016). Throughout the period, scientific collaboration was used by 38.10 per cent of firms, while supply-chain collaboration was used by 36.50 per cent of firms.

Following the seminal work by Escribano et al. (2009) we measure absorptive capacity as a principal component of four variables: internal R&D expenses, R&D department, training for R&D personnel, and the ratio of scientists and researchers to total employees. This composite proxy has two main advantages (Kostopoulos et al., 2011). First, it is based on R&D activities that are considered critical for the conceptualisation and measurement of absorptive capacity (Bayona-Saez et al., 2017; García-Romero et al., 2017). Second, it offers a combinative and more objective operationalisation of absorptive capacity, which is often regarded as a necessity for unbiased estimation (Zahra and Hayton, 2008).

To improve understanding of the moderating role we coded firms' absorptive capacity as a binary variable (*ACAP*). We code it with a positive value if the firm's absorptive capacity is in the upper half of the construct distribution, and with a negative value if it is in the lower half (Escribano et al., 2009). To assess the scale reliability of the absorptive capacity construct, we found that Cronbach's alpha for every factor was more significant than the suggested threshold value of acceptable reliability of 0.7 (Hair, 2018). The instruments for the constructs were then validated by exploratory factor analysis (principal components analysis with varimax orthogonal rotation), and the results supported the structure of the construct.

Finally, to do the most reproducible and comparable study, we check for other factors that may influence a firm's innovation and have been commonly used in previous studies at the firm, at industrial and regional levels (Fitjar and Rodríguez-Pose, 2013; González-Pernía et al., 2015; Haus-Reve et al., 2019; Jensen et al., 2007).

At firm level, we check for firms' R&D expenditures, collaboration with competitors, share of educated employees, share of exports in turnover, size and age. Expenditure on internal R&D in the previous year (*R&D expenditure)* is assumed to increase a firms' internal knowledge stock (Montresor and Vezzani, 2016; Rodriguez et al., 2017). *Collaboration with competitors* has been found to have a mixed effect on a firm's likelihood to innovate (Belderbos et al., 2015; Fitjar and Rodríguez-Pose, 2013; Segarra-Blasco and Arauzo-Carod, 2008). The *share of educated employees* has been found positively related to firms' innovation output (Herrera and Nieto, 2016; Hervas-Oliver et al., 2011). Firms operating in the international market increased their likelihood to innovate (Cirera et al., 2015; Guisado-González et al., 2018). It was measured by the *share of exports in turnover.* Finally, we also controlled for firm *size* and *age*. Large and well-established firms receive scale benefits because of the indivisibility of the innovation activities (Nieto and Santamaría, 2010). Still, they may also have drawbacks, such as a rigid organisational structure (Baumann and Kritikos, 2016).

To control for industrial differences, firms were classified as belonging to a high or medium-high technology level. We established a dummy based on NACE Rev.2 classification: *High-technology manufacturing*, *Medium-high technology manufacturing*, and *High technology services*. Finally, regional characteristics were coded as a dummy variable (*Innovative Region*) taking the value 1 if the firm is established in the Spanish regions of Madrid, Basque Country or Catalonia. These regions are considered the most innovative areas in Spain because they have better regional innovation systems, leading to greater development of resources and innovation(Barajas and Huergo, 2010; Buesa et al., 2010; Herrera and Nieto, 2008).

Table 1 shows the description and the descriptive statistics for all the variables. For comparison, in the first column, we show the mean values and standard errors for the full sample. In the second column, the statistics are from firms with strong absorptive capacity, while those in the third column correspond to those with the weakest absorptive capacity. The correlation matrix (see Appendix) shows that there is a positive correlation between both innovation modes and absorptive capacity. Besides, an analysis based on correlation suggests that severe multicollinearity is not a problem (VIF = 1.80).

Insert Table 1 about here

3.3. Empirical model

To test our hypotheses, we established a panel regression model consistent with previous studies of firms' innovation modes (Caloghirou et al., 2004; González-Pernía et al., 2015; Haus-Reve et al., 2019; Jensen et al., 2007; Parrilli and Alcalde Heras, 2016; Rodriguez et al., 2017). Figure 1 shows the conceptual model.

Insert Figure 1 about here

Eq. 1. $$logit\left(P\left(Inno_{i,t}\right)\right) = \beta_0 + \beta_1 Inno_{i,t-1} + \beta_2 (ACAP_{i,t} * External\ Knowledge_{i,t}\big) + \beta_3 Z_{i,t} + \varepsilon_{i,t} + \alpha_i$$

$P(Inno_{i,t})$ is the probability of product innovation or new-to-market innovation for firm *i* at time *t*. We dealt with unobserved heterogeneity, controlling for firm innovation in the last period (*t-1*).

$ACAP_{i,t}$ captured firm *i* absorptive capacity at time *t*. The moderating role of absorptive capacity was measured by a binary variable which takes a positive value if the firm has strong absorptive capacity, and 0 otherwise. The vector $Ext.Knowledge_{i,t} = \left(STI_{i,t}, DUI_{i,t}\right)$ captured firm *i* collaboration with external partners linked to different innovation modes at time *t*. *STI* refers to scientific collaboration, while *DUI* refers to a supply-chain partnership. Both are coded as dummies that take a positive value if firm i is using one of the collaboration types at time *t*, and negative otherwise. The $Z_{i,t}$ vector refers to firms' control variables, including industrial and regional effects.

For the model using the share of turnover from new products as the dependent variable, $InnoSales_{i,t}$, we fit an equivalent Tobit model:

$$\text{Eq. 2. } tobit\big(P\big(InnoSales_{i,t}\big)\big) = \beta_0 + \beta_1 InnoSales_{i,t-1} + \beta_2\big(ACAP_{i,t} * External\ Knowledge_{i,t}\big) + \beta_3 Z_{i,t} + \varepsilon_{i,t} + \alpha_i$$

As in previous studies (González-Pernía et al., 2015; Haus-Reve et al., 2019), due to the unobservable influences of endogeneity, we validate our results using a fixed-effects model (also known as a *within panel data* model).

4. EMPIRICAL RESULTS

Table 2 and Table 3 present the results of the logit estimations. The former shows the estimates for product innovation and the latter, new-to-market product innovation. Table 4 shows the Tobit estimation for the share of product innovation in total turnover. Each table is composed of four columns following a general-to-specific model approach.

In Column 1, firm innovation is a general function of innovation in the previous period and control variables. As is thought, innovating in the preceding period makes firms significantly more likely to innovate in the analysed period as well. In addition, in this general model, the results for the controls are in line with expectations, and they are consistent in the following specifications. Specifically, R&D expenditure has a positive effect on firms' likelihood to introduce product innovations, as do firm size, collaboration with competitors, employees' education level, medium-high technology manufacturing sector, and being located in more innovative regions. However, firm age and exports are not statistically related to any of the innovation outcomes.

The estimates in columns 2 confirm that firms which only cooperate with partners linked to a specific mode of innovation are more likely to innovate than those that do not cooperate independently in the all measures of product innovation. Collaboration with supply-chain partner produces greater effects on the likelihood of introducing product innovation (0.543***) and new-to-market products (0.448***) than collaboration with scientific partners (0.356*** and 0.392***, respectively). However, this positive effect has different values in the analysis of the share of turnover. Collaboration with scientific partners (1.824***) has a greater effect than with supply-chain ones (1.341***).

Insert Table 2, 3, 4 about here

Next, we tested whether a firms' absorptive capacity moderates the combined effect of scientific and supply-chain collaboration. We analysed the estimated coefficient of the interaction between collaboration with partners linked to both modes of innovation (column 3). This interaction term indicated how firms' innovation output is affected when they simultaneously use different types of external knowledge. The interaction term suggests that combining different types of innovation modes reduces firms' likelihood of product innovation (-0.447***) and new-to-market products (-0.248***), and has a non-significant effect on the product-innovation share of turnover. There exists a substitutive effect in the likelihood to innovate in those firms which combine collaboration with multiple partners linked to different innovation modes.

To find whether firms' absorptive capacity does, or does not moderate the effect produced by the combination of different modes of innovation, we analysed how external and internal dimension interact. The final models of each table (column 4) show how the absorptive capacity influences the different combinations of scientific and supply-chain partners. First, an analysis of the regression coefficient between absorptive capacity and each specific R&D collaboration partner shows us that in all the specifications, collaboration with external partners reduces the effect of internal capacities on a firm's likelihood to innovate. Second, an analysis of the complementarity between scientific and supply-chain partners shows us that absorptive capacity positively influences their combination. This effect is greater in product innovation (1.094***) than in new-to-market products (0.878***). The effect produced in the product innovation share of turnover cannot be compared with the previous estimations but it also shows a positive effect (3.688***).

An analysis of the control variables throughout our models and specifications, show consistent results with only minor changes from the baseline models to the final specifications. First, the Schumpeterian control variables related to firm size and age show interesting results. In new-to-market product neither of them shows significant effects in the likelihood to innovate, in the share of turnover; both show statistically significant negative effects and in the product innovation model only firm size has a small significant effect, but not in new-to-market product, which depends more on new external knowledge rather than on the existence of internal routines associated with the size. Moreover, at industrial and regional level control variables show consistent result between them, firms in manufacturing medium-high technology industries and firms placed in innovative regions are more innovative in all the models.

Although some previous studies concluded their analyses with the coefficient estimation (González-Pernía et al., 2015), statisticians have pointed out that when we are fitting a nonlinear model with interactions, the interpretation of the regression coefficients is not sufficient. We also need to compute marginal effect (Baum, 2010; Buis, 2010; Mitchell, 2012). The marginal effect is an approximation of how much the dependent variable is expected to increase or decrease for an interaction between a group of explanatory variables.

So as to be able to compare and correctly interpret the interactive effect that different types of collaboration and absorptive capacity have on the likelihood of firm innovation, we have to take marginal analysis into account. These effects are evidence by means of the cross-partial derivation of the interaction term. Table 5 presents the marginal effects of the combination of both innovation modes and firms' absorptive capacity at average levels of the control variables in the model for product innovation and new-to-market product innovation.

Insert Table 5 about here

In Table 5, the marginal effects of the combination of scientific and supply-chain collaboration on innovation output are shown to be positively moderated by firms' absorptive capacity. Firms which do not cooperate with any partner and have the weakest absorptive capacity (blue circle marker (DUI=0, STI=0)) are those which innovate the least. Specifically, the probability of product innovation is 25.5 per cent for firms that do not cooperate formally with any external organisation, in comparison with 50.9 per cent for firms that do not cooperate but have strong absorptive capacity. The differences in the probability of new-to-market product innovations are very similar, 8.0 per cent for firms that do not cooperate with any partners and 18.3 per cent for firms which do not collaborate but have strong absorptive capacity.

Firms which only use one type of R&D collaboration and do not have the strongest absorptive capacity (green square marker (DUI=1, STI=0) or maroon diamond marker (DUI=0, STI=1) are more innovative than firms which combined different types of external partners (orange triangle marker (DUI=1, STI=1)). However, these effects are widely overridden when the firm's absorptive capacity is strong. In this case, the combination of scientific and supply-chain collaborations enhanced product innovation to 62.4 per cent. In comparison, scientific collaboration remains at 51.8 per cent and supply-chain collaboration at 60.3 per cent. These effects are more significant in new-to-market product innovation, where the complementary effect is positively moderated by firms' absorptive capacity to reach 29.0 per cent. In comparison, scientific collaboration remains at 21.5 per cent and supply-chain collaboration mode at 24.1 per cent. Based on these results, we can claim that absorptive capacity positively moderates the effect of simultaneous collaboration with scientific and supply-chain partners.

These results can be illustrated more clearly by examining the estimated marginal effects in graphical representation. The marginal effects of each R&D collaboration partner on the probability of firm innovation conditional on firms' absorptive capacity are shown in Figures 2 and 3. Figure 2 shows the marginal effect on product innovation and Figure 3 on new-to-market product innovation. Firms' absorptive capacity and its moderating role on the complementary effect between scientific and supply-chain collaboration on firms' probability of innovation is crucial.

Insert Figure 2 and 3 here

Finally, Table 6 shows the effects of fixed-effect estimation (using a balanced panel data and in our full equation specification) on firms' likelihood of introducing product innovation and new-to-market product innovation. Overall, the effects of both R&D collaborations are positive and significant, also in this model. As in the random effect model, the interaction term of the combination of these two types of external knowledge is negative, and absorptive capacity positively moderates this, generating a complementary effect. The estimated coefficients of control variables are consistent with the results of our previous analyses.

Insert Table 6 about here

----

5. DISCUSSION

We used data of 11,703 Spanish firms to examine whether firms' absorptive capacity positively moderates the effect of combining different knowledge sources on the likelihood of firms' to innovate. We distinguished two types of external R&D collaborations linked to different innovation modes: scientific partners such as universities and research institutes are linked to STI mode and collaboration with supply-chain partners and customers are linked to DUI mode. We examined the moderation effect of absorptive capacity on the existence of a complementary effect on firms' product innovation, new-to-market product innovation, and share of turnover from new products. We analysed the data using a regression model and marginal effects analysis to control the effect of other variables and to be able to draw conclusions regarding complementary or substitutive effects on firms' innovation.

Our results suggest that firms achieve greater product innovation when they collaborate with different types of external partners and have the ability to properly explore and exploit this combination of knowledge. Collaboration with one type of partner, by contrast, offers the best likelihood of innovation if firms do not have enough absorptive capacity. Specifically, firms which try to deal simultaneously with types of knowledge and do not have absorptive capacity suffer substitutive effects on their likelihood to innovate.

Taken together, the results suggest that the existence of complementary effects among different R&D collaborations partners depends on firms' absorption capacity. Firms which can invest in in-house R&D and scientific personnel are prepared to deal with the cost and complexity of collaboration with more than one type of partner. In doing so, logic requires that extra-organisational collaboration and open innovation strategies take into account the internal and external perspectives. Not all external collaboration partners widely analysed under the concept of "external search breadth" (Laursen and Salter, 2006) are associated with the same innovation mode and the firms' internal capability to deal with different internal knowledge (Cohen and Levinthal, 1990). Only a few past studies simultaneously consider this dual-dimension. Moreover, and even recent works have studied the effect of external knowledge following this bias analysis point of view (Carrillo-Carrillo and Alcalde-Heras, 2020; Haus-Reve et al., 2019; Kobarg et al., 2019). R&D collaboration strategies work if firms have internal resources and competences necessary to deal with different external knowledge sources (Asimakopoulos et al., 2020; Gkypali et al., 2017).

In addition, our results show that an open innovation strategy is one of the two most important factors for the attainment of product innovation. However, the importance of this external dimension cannot hide the relevance of the internal firm absorptive capacity. While this result calls for further research to investigate other methods of measurement of absorption capacity and other forms of R&D collaboration, we believe that the implementation of a broad search of external knowledge has to be associated with the development of higher degrees of absorptive capacity if firms want to reach the highest levels of product innovation independent of other characteristics of the firms.

6. CONCLUSIONS

To address questions regarding the complementary effect of R&D collaborations linked to different innovation modes, this study set out to understand whether and how the firms' absorptive capacity determines the existence of a positive or negative effect on a firms' innovation. We proposed that only firms which have higher levels of absorptive capacity can achieve complementarity effects. In contrast, firms which do not have this internal capacity suffer substitutive effects when combining both innovation modes, be-cause of the complexity of coordination and dealing with a variety of partners. We contrast our hypotheses empirically, relying on data from 11,703 Spanish firms. Our result suggests the existence of a complementary effect moderated by the absorptive capacity independent of firm size, age and regional effect, among other firm's characteristics. By shaping the nature of the interaction between these internal and external influences, we can conclude that an open innovation strategy positively influences firms with a strong absorptive capacity. These results provide two main contributions to the literature.

First, they contribute to open innovation theory and strategic management literature by extending prior analysis of the effect of external knowledge on the benefits firms reap from wide external collaboration relationships. We move beyond considering that each type of partner is linked to an innovation mode. Thus, we propose that different external partners provide access to other new knowledge and technologies, which are the basis of different innovation modes (Nieto & Santamaría, 2007). This introduces a new aspect into an open innovation strategy that tries to deal with the risk of 'over-searching', warned about by Caloghirou et al. (2004), Escribano et al. (2009) and Laursen & Salter (2006).

Second, by testing whether the existence of a complementary effect depends on firms' absorptive capacity, we contribute to the literature on innovation management, finding the critical factor that determines the complementarity between external partners. Applying a panel regression method and marginal analysis, we were able to measure the interaction between both innovation modes and the moderating role of firms' absorptive capacity (on average) of other factors. Specifically, our research shows that those firms cooperate with a different type of partners linked to different innovation modes, and simultaneously do not increase their likelihood to innovate unless they have enough absorptive capacity to manage the excess of ideas as well as new information.

In addition, our findings suggest some policy and management implications, reinforcing views about the crucial role of absorptive capacity in the managing of different innovative modes (Asimakopoulos et al., 2020). Since the seminal work by Jensen et al. (2007), governments have been fostering the creation of robust collaboration within and beyond the supply-chain, following the notion that the more knowledge sources firms use, the more they will innovate. These views have stimulated public innovation policies, generating positive effects in several countries (Borrás and Laatsit, 2019). Our findings show the importance of not underestimating firms' absorptive capacity in the innovation system. Not only do firms need to cooperate with several agents, but they also need to manage and be able to take advantage of such collaboration.

Our analysis also suffers from certain limitations which may address and open new research directions. First, some limitations related to the usage of a CIS-based survey (Hong et al., 2012). The structure of the dependent variables limits our understanding of the quality or complexity of innovation and only relies on formal agreements. An exploration of informal relationship at an organizational level and between individual partners. Second, this analysis is based on product innovation. In the future, process innovation and eco-innovation should also be taken into account (Acebo et al., 2021; Ritala and Almpanopoulou, 2017). Moreover, due to the nature of our sample, comprising only Spanish firms, we cannot be sure that these results will be generalizable to other countries, and more research has to be done in this direction.

In summary, our results reoriented the analysis of collaborative innovation to take into account the crucial role played by firms' absorptive capacity; both are needed to increase innovation. These findings show how theoretical innovation literature had understood the main foundations for successful firms' innovation: a virtuous combination of firm capabilities and open innovation environments.

REFERENCES

Acebo, E., Miguel-Dávila, J.Á., Nieto, M., 2021. External stakeholder engagement: Complementary and substitutive effects on firms' eco-innovation. Bus. Strateg. Environ. 1–17. https://doi.org/10.1002/bse.2770

Agostini, L., Nosella, A., Sarala, R., Spender, J.-C., Wegner, D., 2020. Tracing the evolution of the literature on knowledge management in inter-organizational contexts: a bibliometric analysis. J. Knowl. Manag. 24, 463–490. https://doi.org/10.1108/JKM-07-2019-0382

Ahuja, G., Morris Lampert, C., 2001. Entrepreneurship in the large corporation: a longitudinal study of how established firms create breakthrough inventions. Strateg. Manag. J. 22, 521–543. https://doi.org/10.1002/smj.176

Asimakopoulos, G., Revilla, A.J., Slavova, K., 2020. External Knowledge Sourcing and Firm Innovation Efficiency. Br. J. Manag. 31, 123–140. https://doi.org/10.1111/1467-8551.12367

Barajas, A., Huergo, E., 2010. International R&D cooperation within the EU framework programme: Empirical evidence for Spanish firms. Econ. Innov. New Technol. 19, 87–111. https://doi.org/10.1080/10438590903016492

Baum, C.F., 2010. Stata Tip 88: Efficiently Evaluating Elasticities with the Margins Command. Stata J. Promot. Commun. Stat. Stata 10, 309–312. https://doi.org/10.1177/1536867X1001000212

Baumann, J., Kritikos, A.S., 2016. The link between R&D, innovation and productivity: Are micro firms different? Res. Policy 45, 1263–1274. https://doi.org/10.1016/j.respol.2016.03.008

Bayona-Saez, C., Cruz-Cázares, C., García-Marco, T., Sánchez García, M., 2017. Open innovation in the food and beverage industry, Management Decision. https://doi.org/10.1108/MD-04-2016-0213

Belderbos, R., Carree, M., Lokshin, B., 2004. Cooperative R&D and firm performance. Res. Policy 33, 1477–1492. https://doi.org/10.1016/j.respol.2004.07.003

Belderbos, R., Carree, M., Lokshin, B., Fernández Sastre, J., 2015. Inter-temporal patterns of R&D collaboration and innovative performance. J. Technol. Transf. 40, 123–137. https://doi.org/10.1007/s10961-014-9332-4

Bogers, M., Zobel, A.-K., Afuah, A., Almirall, E., Brunswicker, S., Dahlander, L., Frederiksen, L., Gawer, A., Gruber, M., Haefliger, S., Hagedoorn, J., Hilgers, D., Laursen, K., Magnusson, M.G., Majchrzak, A., McCarthy, I.P., Moeslein, K.M., Nambisan, S., Piller, F.T., Radziwon, A., Rossi-Lamastra, C., Sims, J., Ter Wal, A.L.J., 2017. The open innovation research landscape: established perspectives and emerging themes across different levels of analysis. Ind. Innov. 24, 8–40. https://doi.org/10.1080/13662716.2016.1240068

Borrás, S., Laatsit, M., 2019. Towards system oriented innovation policy evaluation? Evidence from EU28 member states. Res. Policy 48, 312–321. https://doi.org/10.1016/j.respol.2018.08.020

Buesa, M., Heijs, J., Baumert, T., 2010. The determinants of regional innovation in Europe: A combined factorial and regression knowledge production function approach. Res. Policy 39, 722–735. https://doi.org/10.1016/j.respol.2010.02.016

Buis, M.L., 2010. Stata Tip 87: Interpretation of Interactions in Nonlinear Models. Stata J. Promot. Commun. Stat. Stata 10, 305–308. https://doi.org/10.1177/1536867X1001000211

Caloghirou, Y., Kastelli, I., Tsakanikas, A., 2004. Internal capabilities and external knowledge sources: Complements or substitutes for innovative performance? Technovation 24, 29–39. https://doi.org/10.1016/S0166-4972(02)00051-2

Carmona-Lavado, A., Cuevas-Rodríguez, G., Cabello-Medina, C., Fedriani, E.M., 2021. Does open innovation always work? The role of complementary assets. Technol. Forecast. Soc. Change 162, 120316. https://doi.org/10.1016/j.techfore.2020.120316

Carrillo-Carrillo, F., Alcalde-Heras, H., 2020. Modes of innovation in an emerging economy: a firm-level analysis from Mexico. Innovation 22, 334–352. https://doi.org/10.1080/14479338.2020.1735395

Carrillo-Hermosilla, J., Del Río, P., Könnölä, T., 2010. Diversity of eco-innovations: Reflections from selected case studies. J. Clean. Prod. 18, 1073–1083. https://doi.org/10.1016/j.jclepro.2010.02.014

Chesbrough, H.W., Vanhaverbeke, W.&, West, J., 2006. Open innovation: Researching a new paradigm. Oxford University Press, New York (US).

Cirera, X., Marin, A., Markwald, R., 2015. Explaining export diversification through firm innovation decisions: The case of Brazil. Res. Policy 44, 1962–1973. https://doi.org/10.1016/j.respol.2015.06.004

Cohen, W.M., Levinthal, D.A., 1990. Absorptive Capacity: A New Perspective on Learning and Innovation. Adm. Sci. Q. 35, 128. https://doi.org/10.2307/2393553

Cohen, W.M., Levinthal, D.A., 1989. Innovation and Learning: The Two Faces of R & D. Econ. J. 99, 569. https://doi.org/10.2307/2233763

Dong, J.Q., McCarthy, K.J., Schoenmakers, W.W.M.E., 2017. How Central Is Too Central? Organizing Interorganizational Collaboration Networks for Breakthrough Innovation. J. Prod. Innov. Manag. 34, 526–542. https://doi.org/10.1111/jpim.12384

Escribano, A., Fosfuri, A., Tribó, J.A., 2009. Managing external knowledge flows: The moderating role of absorptive capacity. Res. Policy 38, 96–105. https://doi.org/10.1016/j.respol.2008.10.022

Faems, D., De Visser, M., Andries, P., Van Looy, B., 2010. Technology alliance portfolios and financial performance: Value-enhancing and cost-increasing effects of open innovation. J. Prod. Innov. Manag. 27, 785–796. https://doi.org/10.1111/j.1540-5885.2010.00752.x

Faems, D., Van Looy, B., Debackere, K., 2005. Interorganizational Collaboration and Innovation: Toward a Portfolio Approach*. J. Prod. Innov. Manag. 22, 238–250. https://doi.org/10.1111/j.0737-6782.2005.00120.x

Fitjar, R.D., Rodríguez-Pose, A., 2013. Firm collaboration and modes of innovation in Norway. Res. Policy 42, 128–138. https://doi.org/10.1016/j.respol.2012.05.009

Fu, X., 2012. How does openness affect the importance of incentives for innovation? Res. Policy 41, 512–523. https://doi.org/10.1016/j.respol.2011.12.011

García-Romero, A., Escribano, Á., Tribó, J.A., 2017. The impact of health research on length of stay in Spanish public hospitals. Res. Policy 46, 591–604. https://doi.org/10.1016/j.respol.2017.01.006

Gkypali, A., Filiou, D., Tsekouras, K., 2017. R&D collaborations: Is diversity enhancing innovation performance? Technol. Forecast. Soc. Change 118, 143–152. https://doi.org/10.1016/j.techfore.2017.02.015

González-Pernía, J.L., Parrilli, M.D., Peña-Legazkue, I., 2015. STI–DUI learning modes, firm–university collaboration and innovation. J. Technol. Transf. 40, 475–492.

https://doi.org/10.1007/s10961-014-9352-0

Guisado-González, M., González-Blanco, J., Coca-Pérez, J.L., Guisado-Tato, M., 2018. Assessing the relationship between R&D subsidy, R&D cooperation and absorptive capacity: an investigation on the manufacturing Spanish case. J. Technol. Transf. 43, 1647–1666. https://doi.org/10.1007/s10961-017-9579-7

Hagedoorn, J., Wang, N., 2012a. Is there complementarity or substitutability between internal and external R&D strategies? Res. Policy 41, 1072–1083. https://doi.org/10.1016/j.respol.2012.02.012

Hagedoorn, J., Wang, N., 2012b. Is there complementarity or substitutability between internal and external R&D strategies? Res. Policy 41, 1072–1083. https://doi.org/10.1016/j.respol.2012.02.012

Hair, J.F., 2018. Multivariate Data Analysis, 8th ed. Cengage Learning EMEA, London (UK).

Harris, R., Yan, J., 2019. The measurement of absorptive capacity from an economics perspective: definition, measurement and importance. J. Econ. Surv. 33, 729–756. https://doi.org/10.1111/joes.12296

Haus-Reve, S., Fitjar, R.D., Rodriguez-Pose, A., 2019. Does combining different types of collaboration always benefit firms? Collaboration, complementarity and product innovation in Norway. Res. Policy 48, 1476–1486. https://doi.org/10.1016/j.respol.2019.02.008

Herrera, L., Nieto, M., 2016. PhD careers in Spanish industry: Job determinants in manufacturing versus non-manufacturing firms. Technol. Forecast. Soc. Change 113, 341–351. https://doi.org/10.1016/j.techfore.2015.09.019

Herrera, L., Nieto, M., 2008. The national innovation policy effect according to firm location. Technovation 28, 540–550. https://doi.org/10.1016/j.technovation.2008.02.009

Hervas-Oliver, J.-L., Garrigos, J.A., Gil-Pechuan, I., 2011. Making sense of innovation by R&D and non-R&D innovators in low technology contexts: A forgotten lesson for policymakers. Technovation 31, 427–446. https://doi.org/10.1016/j.technovation.2011.06.006

Hong, S., Oxley, L., Mccann, P., 2012. A survey of the innovation surveys. J. Econ. Surv. 26, 420–444. https://doi.org/10.1111/j.1467-6419.2012.00724.x

Jensen, M.B., Johnson, B., Lorenz, E., Lundvall, B.-Å.Å., 2007. Forms of knowledge and modes of innovation. Res. Policy 36, 680–693. https://doi.org/10.1016/j.respol.2007.01.006

Johnson, B., 2002. Why all this fuss about codified and tacit knowledge? Ind. Corp. Chang. 11, 245–262. https://doi.org/10.1093/icc/11.2.245

Kafouros, M., Love, J.H., Ganotakis, P., Konara, P., 2020. Experience in R&D collaborations, innovative performance and the moderating effect of different dimensions of absorptive capacity. Technol. Forecast. Soc. Change 150, 14. https://doi.org/10.1016/j.techfore.2019.119757

Kobarg, S., Stumpf-Wollersheim, J., Welpe, I.M., 2019. More is not always better: Effects of collaboration breadth and depth on radical and incremental innovation performance at the project level. Res. Policy 48, 1–10. https://doi.org/10.1016/j.respol.2018.07.014

Kostopoulos, K., Papalexandris, A., Papachroni, M., Ioannou, G., 2011. Absorptive capacity, innovation, and financial performance. J. Bus. Res. 64, 1335–1343. https://doi.org/10.1016/j.jbusres.2010.12.005

Laursen, K., Salter, A., 2006. Open for innovation: The role of openness in explaining innovation performance among U.K. manufacturing firms. Strateg. Manag. J. 27, 131–150. https://doi.org/10.1002/smj.507

Leiponen, A., Helfat, C.E., 2010. Innovation objectives, knowledge sources, and the benefits of breadth. Strateg. Manag. J. 31, 224–236. https://doi.org/10.1002/smj.807

Liker, J.K., Kamath, R.R., Wasti, S.N., Nagamachi, M., 1996. Supplier involvement in automotive component design: Are there really large US Japan differences? Res. Policy 25, 59–89. https://doi.org/10.1016/0048-7333(95)00826-8

Love, J.H., Roper, S., Vahter, P., 2014. Learning from openness: The dynamics of breadth in external innovation linkages. Strateg. Manag. J. 35, 1703–1716. https://doi.org/10.1002/smj.2170

March, J.G., 1991. Exploration and Exploitation in Organizational Learning. Organ. Sci. 2, 71–87. https://doi.org/10.1287/orsc.2.1.71

Martínez-Costa, M., Jiménez-Jiménez, D., Dine Rabeh, H.A., 2019. The effect of organisational learning on interorganisational collaborations in innovation: an empirical study in SMEs. Knowl. Manag. Res. Pract. 17, 137–150. https://doi.org/10.1080/14778238.2018.1538601

Martínez-Noya, A., Narula, R., 2018. What more can we learn from R&D alliances? A review and research agenda. BRQ Bus. Res. Q. 21, 195–212. https://doi.org/10.1016/j.brq.2018.04.001

Mitchell, M., 2012. Interpreting and visualizing regression models using Stata. Stata Press books 558.

Montresor, S., Vezzani, A., 2016. Intangible investments and innovation propensity: Evidence from the Innobarometer 2013. Ind. Innov. 23, 331–352. https://doi.org/10.1080/13662716.2016.1151770

Mustak, M., Jaakkola, E., Halinen, A., 2013. Customer participation and value creation: A systematic review and research implications. Manag. Serv. Qual. 23, 341–359. https://doi.org/10.1108/MSQ-03-2013-0046

Nieto, M., Quevedo, P., 2005. Absorptive capacity, technological opportunity, knowledge spillovers, and innovative effort. Technovation 25, 1141–1157. https://doi.org/10.1016/j.technovation.2004.05.001

Nieto, M.J., Santamaría, L., 2010. Technological collaboration: Bridging the innovation gap between small and large firms. J. Small Bus. Manag. 48, 44–69. https://doi.org/10.1111/j.1540-627X.2009.00286.x

Nieto, M.J., Santamaría, L., 2007. The importance of diverse collaborative networks for the novelty of product innovation. Technovation 27, 367–377. https://doi.org/10.1016/j.technovation.2006.10.001

Parrilli, M.D., Alcalde Heras, H., 2016. STI and DUI innovation modes: Scientific-technological and context-specific nuances. Res. Policy 45, 747–756. https://doi.org/10.1016/j.respol.2016.01.001

Perkmann, M., Walsh, K., 2007. University-industry relationships and open innovation: Towards a research agenda. Int. J. Manag. Rev. 9, 259–280. https://doi.org/10.1111/j.1468-2370.2007.00225.x

Radicic, D., Pinto, J., 2019. Collaboration with external organizations and technological innovations: Evidence from Spanish manufacturing firms. Sustainability 11, 2479. https://doi.org/10.3390/su11092479

Ritala, P., Almpanopoulou, A., 2017. In defense of ‘eco’ in innovation ecosystem.

Technovation 60–61, 39–42. https://doi.org/10.1016/j.technovation.2017.01.004

Rodriguez, M., Doloreux, D., Shearmur, R., 2017. Variety in external knowledge sourcing and innovation novelty: Evidence from the KIBS sector in Spain. Technovation 68, 35–43. https://doi.org/10.1016/j.technovation.2017.06.003

Segarra-Blasco, A., Arauzo-Carod, J.-M., 2008. Sources of innovation and industry–university interaction: Evidence from Spanish firms. Res. Policy 37, 1283–1295. https://doi.org/10.1016/j.respol.2008.05.003

Song, M., Di Benedetto, C.A., 2008. Supplier's involvement and success of radical new product development in new ventures. J. Oper. Manag. 26, 1–22. https://doi.org/10.1016/j.jom.2007.06.001

Tether, B.S., 2002. Who co-operates for innovation, and why An empirical analysis. Res. Policy 31, 947–967. https://doi.org/10.1016/S0048-7333(01)00172-X

Todorova, G., Durisin, B., 2007. Absorptive capacity: Valuing a reconceptualization. Acad. Manag. Rev. 32, 774–786. https://doi.org/10.5465/AMR.2007.25275513

Un, C.A., Cuervo-Cazurra, A., Asakawa, K., 2010. R&D Collaborations and Product Innovation. J. Prod. Innov. Manag. 27, 673–689. https://doi.org/10.1111/j.1540-5885.2010.00744.x

Vivas, C., Barge-Gil, A., 2015. IMPACT ON FIRMS OF THE USE OF KNOWLEDGE EXTERNAL SOURCES: A SYSTEMATIC REVIEW OF THE LITERATURE. J. Econ. Surv. 29, 943–964. https://doi.org/10.1111/joes.12089

Von Hippel, E., 2005. Democratizing innovation: The evolving phenomenon of user innovation. J. fur Betriebswirtschaft 55, 63–78. https://doi.org/10.1007/s11301-004-0002-8

Von Hippel, E., 1978. A customer-active paradigm for industrial product idea generation. Res. Policy 7, 240–266. https://doi.org/10.1016/0048-7333(78)90019-7

West, J., Bogers, M., 2014. Leveraging External Sources of Innovation: A Review of Research on Open Innovation. J. Prod. Innov. Manag. 31, 814–831. https://doi.org/10.1111/jpim.12125

Zahra, S.A., George, G., 2002. Absorptive capacity: A review, reconceptualization, and extension. Acad. Manag. Rev. 27, 185–203. https://doi.org/10.5465/AMR.2002.6587995

Zahra, S.A., Hayton, J.C., 2008. The effect of international venturing on firm performance: The moderating influence of absorptive capacity. J. Bus. Ventur. 23, 195–220. https://doi.org/10.1016/j.jbusvent.2007.01.001

TABLES AND FIGURES

Table 1. Descriptive Statistics

VARIABLES	Description	Full Sample	ACAP	
			ACAP=0	ACAP=1
		Mean (S.D.)	Mean (S.D.)	Mean (S.D.)
Product innovation	Dummy variable taking the value 1 if firm introduced any new or significantly improved products in the preceding three years.	0.457 (0.498)	0.215 (0.411)	0.723 (0.448)
New-to-market product innovation	Dummy variable taking the value 1 if firm developed any product innovations that were new to firm's market.	0.265 (0.441)	0.095 (0.293)	0.451 (0.498)
Product innovation share of turnover (%)	Share of turnover in the survey year from new or significantly improved products developed in the preceding three years	7.897 (20.83)	2.882 (13.67)	13.41 (25.44)
Scientific collaboration, STI	Dummy variable taking the value 1 if firm cooperated with universities, research institutes or consultancy firms in the preceding three years.	0.196 (0.397)	0.049 (0.216)	0.358 (0.479)
Supply-chain collaboration, DUI	Dummy variables taking the value 1 if firm cooperated with suppliers or customers in the preceding three years.	0.161 (0.367)	0.0480 (0.214)	0.285 (0.451)
Absorptive capacity, ACAP	Dummy variables taking the value 1 if firm absorptive capacity (internal R&D expenses, R&D department, training for R&D personnel, and ratio of scientists to total employees) is in the upper half of the distribution.	0.476 (0.499)	0.000 (0.000)	1,000 (0,000)
Collaboration with competitors	Dummy variables taking the value 1 if firm cooperated with competitors in the preceding three years.	0.066 (0.248)	0.012 (0.108)	0.125 (0.331)
R&D expenditure (log) (t-1)	Total amount of expenditure on research and development activities in the preceding three years. Lagged one survey period.	6.966 (6.324)	1.820 (4.272)	12.62 (1.680)
Firm age (log)	Number of years since firm foundation in the year of the survey	2.145 (1.571)	2.232 (1.525)	2.049 (1.615)
Firm size (log)	Number of full-time employees in firm in the year of the survey.	4.122 (1.729)	4.054 (1.849)	4.196 (1.583)
Share of Exports (%)	Share of firm's sales in non-domestic market in the year of the survey.	0.002 (0.144)	0.002 (0.187)	0.001 (0.073)
Share of educated employees (%)	Share of firm's workers who have completed a higher education (university) degree	26.98 (28.76)	20.56 (26.62)	34.03 (29.38)
Manufacturing high technology	Dummy variables taking the value 1 if firm sector is: Pharmaceutical; Computing (Hardware), Optics and electronics and Aeronautics.	0.0331 (0.179)	0.014 (0.116)	0.0544 (0.227)
Manufacturing medium-high technology	Dummy variables taking the value 1 if firm sector is: Chemistry, Metallurgy; Electrical equipment and supplies; Other machinery; Motor vehicles; Other Transportation or Other Manufacturing Assets	0.183 (0.387)	0.145 (0.352)	0.225 (0.417)
Service high technology	Dummy variables taking the value 1 if firm sector is: Computing (Software) or R&D Services.	0.0367 (0.188)	0.021 (0.142)	0.0544 (0.227)
Innovative Region	Dummy variables taking the value 1 if firm is settled in Madrid, Basque Country or Catalonia.	0.259 (0.438	0.004 (0.064)	0.540 (0.498)
Observations	Number of observations	105,118	55,033	50,085
Firms	Number of firms	12,849	9,179	8,521

Table 2. Random effect model, Product innovation. Unbalanced panel, time-period 2006-2016

VARIABLES	(1) Coef. (S.E.)	(2) Coef. (S.E.)	(3) Coef. (S.E.)	(4) Coef. (S.E.)
Product innovation $_{t-1}$	3.876***	3.860***	3.865***	3.877***
	(0.024)	(0.245)	(0.025)	(0.026)
STI, Scientific collaboration		0.356***	0.482***	1.200***
		(0.348)	(0.041)	(0.083)
DUI, Supply-chain collaboration		0.543***	0.764***	1.205***
		(0.373)	(0.053)	(0.086)
STI × DUI			-0.447***	-1.042***
			(0.074)	(0.158)
ACAP, Absorptive capacity				1.109***
				(0.037)
ACAP × STI				-1.163***
				(0.094)
ACAP × DUI				-0.824***
				(0.108)
ACAP × STI × DUI				1.094***
				(0.180)
Collaboration with competitors	0.475***	0.067	0.0882*	0.117**
	(0.048)	(0.051)	(0.052)	(0.052)
R&D expenditure (log) $_{t-1}$	0.130***	0.117***	0.118***	0.025***
	(0.002)	(0.002)	(0.002)	(0.003)
Firm age (log)	0.001	-0.002	0.002	0.015
	(0.024)	(0.243)	(0.024)	(0.025)
Firm size (log)	0.032***	0.018**	0.0212***	0.030***
	(0.008)	(0.007)	(0.008)	(0.008)
Share of exports (%)	-0.219	0.002***	-0.206	-0.214
	(0.154)	(0.001)	(0.155)	(0.156)
Share of educated employees (%)	0.002***	0.001***	0.001***	0.001**
	(0.001)	(0.001)	(0.001)	(0.001)
Manufacturing high technology	-0.242***	0.742	-0.279***	-0.279***
	(0.058)	(0.006)	(0.058)	(0.059)
Manufacturing medium-high technology	0.307***	0.291***	0.320***	0.287***
	(0.030)	(0.308)	(0.030)	(0.031)
Service high technology	0.083	-0.285***	0.0991	0.085
	(0.061)	(0.058)	(0.061)	(0.062)
Innovative region	0.468***	0.445***	0.454***	0.0649**
	(0.029)	(0.029)	(0.020)	(0.032)
Constant	-3.569***	-3.493***	-3.529***	-3.714***
	(0.051)	(0.052)	(0.052)	(0.054)
Year	YES	YES	YES	YES
Log Likelihood	-26247.006	-25979.993	-25973.001	-25489.459
Observations	89,903	89,903	89,903	89,903
Firms	11,703	11,703	11,703	11,703

*Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

Table 3. Random effect model, New-to-market product innovation. Unbalanced panel, time-period 2006-2016

VARIABLES	(1) Coef. (S.E.)	(2) Coef. (S.E.)	(3) Coef. (S.E.)	(4) Coef. (S.E.)
New-to-market product innovation $_{t-1}$	3.369*** (0.028)	3.323*** (0.279)	3.327*** (0.028)	3.310*** (0.028)
STI, Scientific collaboration		0.392*** (0.033)	0.470*** (0.039)	1.034*** (0.086)
DUI, Supply-chain collaboration		0.448*** (0.035)	0.578*** (0.049)	0.993*** (0.091)
STI × DUI			-0.248*** (0.067)	-0.830*** (0.157)
ACAP, Absorptive capacity				0.944*** (0.040)
ACAP × STI				-0.828*** (0.096)
ACAP × DUI				-0.643*** (0.107)
ACAP × STI × DUI				0.878*** (0.174)
Collaboration with competitors	0.540*** (0.043)	0.189*** (0.046)	0.199*** (0.046)	0.215*** (0.046)
R&D expenditure (log) $_{t-1}$	0.120*** (0.003)	0.108*** (0.003)	0.108*** (0.003)	0.076*** (0.003)
Firm age (log)	-0.042 (0.025)	-0.042 (0.026)	-0.043* (0.026)	-0.035 (0.026)
Firm size (log)	-0.003 (0.009)	-0.020** (0.009)	-0.018** (0.009)	-0.008 (0.009)
Share of exports (%)	-0.151 (0.141)	-0.001 (0.001)	-0.131 (0.142)	-0.133 (0.142)
Share of educated employees (%)	0.004*** (0.001)	0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)
Manufacturing high technology	-0.082 (0.060)	0.119** (0.324)	-0.126** (0.062)	-0.136** (0.063)
Manufacturing medium-high technology	0.206*** (0.032)	0.217*** (0.323)	0.220*** (0.032)	0.191*** (0.033)
Service high technology	0.104* (0.059)	-0.134** (0.067)	0.122** (0.060)	0.117* (0.061)
Innovative Region	0.342*** (0.029)	0.341*** (0.030)	0.342*** (0.030)	0.052* (0.031)
Constant	-3.662*** (0.054)	-3.592*** (0.055)	-3.606*** (0.055)	-3.814*** (0.057)
Year	YES	YES	YES	YES
Log Likelihood	-26873.789	-26617.669	-26610.444	-26320.791
Observations	89,903	89,903	89,903	89,903
Firms	11,703	11,703	11,703	11,703

Note: $* p < 0.1$, $** p < 0.05$, $*** p < 0.01$

Table 4. Tobit model, Product innovation share of turnover. Unbalanced panel, time-period 2006-2016

VARIABLES	(1) Coef. (S.E.)	(2) Coef. (S.E.)	(3) Coef. (S.E.)	(4) Coef. (S.E.)
Product Innovation share of turnover $_{t-1}$	0.519*** (0.004)	0.516*** (0.004)	0.516*** (0.004)	0.515*** (0.004)
STI, Scientific collaboration		1.824*** (0.183)	1.678*** (0.216)	2.148*** (0.450)
DUI, Supply-chain collaboration		1.341*** (0.189)	1.104*** (0.266)	2.591*** (0.461)
STI × DUI			0.467 (0.366)	-2.033** (0.840)
ACAP, Absorptive capacity				2.716*** (0.195)
ACAP × STI				-1.107** (0.506)
ACAP × DUI				-2.485*** (0.558)
ACAP × STI × DUI				3.688*** (0.936)
Collaboration with competitors	1.705*** (0.237)	0.291 (0.253)	0.268 (0.254)	0.260 (0.254)
R&D expenditure (log) $_{t-1}$	0.322*** (0.011)	0.273*** (0.012)	0.274*** (0.011)	0.181*** (0.014)
Firm age (log)	-0.485*** (0.123)	-0.481*** (0.123)	-0.480*** (0.123)	-0.455*** (0.123)
Firm size (log)	-0.172*** (0.039)	-0.217*** (0.040)	-0.219*** (0.040)	-0.206*** (0.040)
Share of exports (%)	-0.109 (0.351)	-0.001 (0.002)	-0.102 (0.351)	-0.0950 (0.351)
Share of educated employees (%)	0.0191*** (0.002)	0.017*** (0.002)	0.017*** (0.002)	0.016*** (0.002)
Manufacturing high technology	2.112*** (0.313)	0.251 (0.323)	1.947*** (0.313)	1.879*** (0.313)
Manufacturing medium-high technology	0.491*** (0.160)	0.493*** (0.160)	0.489*** (0.160)	0.378** (0.160)
Service high technology	0.245 (0.325)	1.956*** (0.313)	0.247 (0.325)	0.202 (0.325)
Innovative Region	1.495*** (0.158)	1.402*** (0.158)	1.402*** (0.158)	0.347** (0.175)
Constant	1.450*** (0.242)	1.690*** (0.243)	1.707*** (0.243)	1.417*** (0.244)
Year	YES	YES	YES	YES
Sigma	3.138*** (0.132)	3.165*** (0.130)	3.160*** (0.131)	3.166*** (0.130)
Log Likelihood	-26873.789	-378423.89	-26610.444	-26320.791
Observations	89,903	89,903	89,903	89,903
Firms	11,703	11,703	11,703	11,703

*Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

Table 5. Average marginal effects of innovation cooperation at mean values of all other variables

	Product innovation		New-to-market product. inno.	
	ACAP=0	ACAP=1	ACAP=0	ACAP=1
STI=0, DUI=0	0.255***	0.509***	0.080***	0.183***
	(0.004)	(0.006)	(0.002)	(0.004)
STI=0, DUI=1	0.533***	0.603***	0.190***	0.241***
	(.021)	(0.016)	(0.014)	(0.010)
STI=1, DUI=0	0.531***	0.518***	0.196***	0.215***
	(.020)	(0.011)	(0.013)	(0.007)
STI=1, DUI=1	0.572***	0.624***	0.224***	0.290***
	(0.026)	(0.011)	(0.017)	(0.008)

*Note: * p < 0.1, ** p < 0.05, *** p < 0.01*

Table 6. Fixed-effect models, Product innovation and New-to-market product innovation. Balanced panel time-period 2006-2016.

VARIABLES	(1) Product innovation	(2) New-to-market product innovation
	Coef. (S.E.)	Coef. (S.E.)
Product innovation $_{t-1}$	2.136***	
	(0.0318)	
New-to-market product innovation $_{t-1}$		1.645***
		(0.025)
STI, Scientific collaboration	1.551***	1.202***
	(0.111)	(0.135)
DUI, Supply-chain collaboration	1.477***	1.222***
	(0.143)	(0.149)
STI × DUI	-1.519***	-1.248***
	(0.255)	(0.231)
ACAP, Absorptive capacity	1.017***	0.831***
	(0.071)	(0.057)
ACAP × STI	-1.212***	-0.896***
	(0.117)	(0.132)
ACAP × DUI	-1.065***	-0.862***
	(0.171)	(0.160)
ACAP × STI × DUI	1.504***	1.192***
	(0.283)	(0.241)
Collaboration with competitors	0.244***	0.253***
	(0.095)	(0.068)
R&D expenditure (log) $_{t-1}$	0.095***	0.076***
	(0.004)	(0.005)
Firm age (log)	-0.154***	-0.162***
	(0.013)	(0.013)
Firm size (log)	0.465***	0.341***
	(0.052)	(0.067)
Share of exports (%)	-0.164	-0.145
	(0.586)	(0.574)
Share of educated employees (%)	0.000	-0.000
	(0.001)	(0.001)
Manufacturing high technology	-0.099	-0.064
	(0.194)	(0.154)
Manufacturing medium-high technology	0.239	0.150
	(0.202)	(0.203)
Service high technology	0.082	0.068
	(0.233)	(0.208)
Innovative Region	0.225**	0.201**
	(0.103)	(0.090)
Log Likelihood	-14754.57	-13639.685
Observations	47,125	41,160
Firms	5,513	4,715

*Note: * p < 0.1, ** p < 0.05, *** p < 0.01*

Figure 1. Conceptual Model

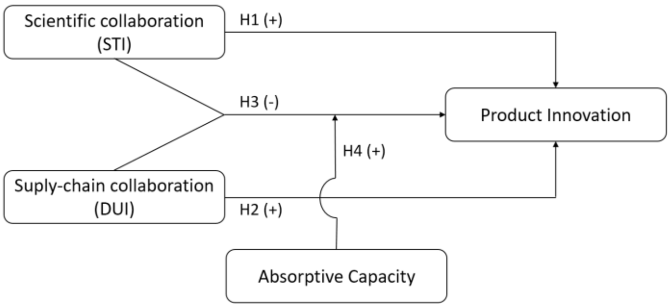


Figure 2. The moderating effects of absorptive capacity and scientific (STI) and supply-chain (DUI) collaboration on the probability of product innovation

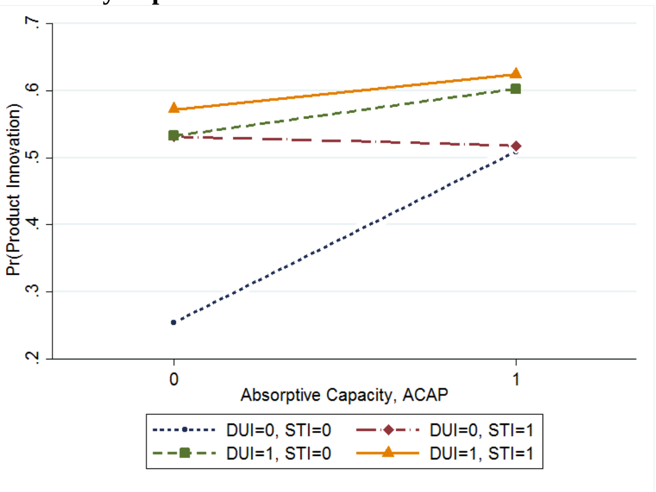
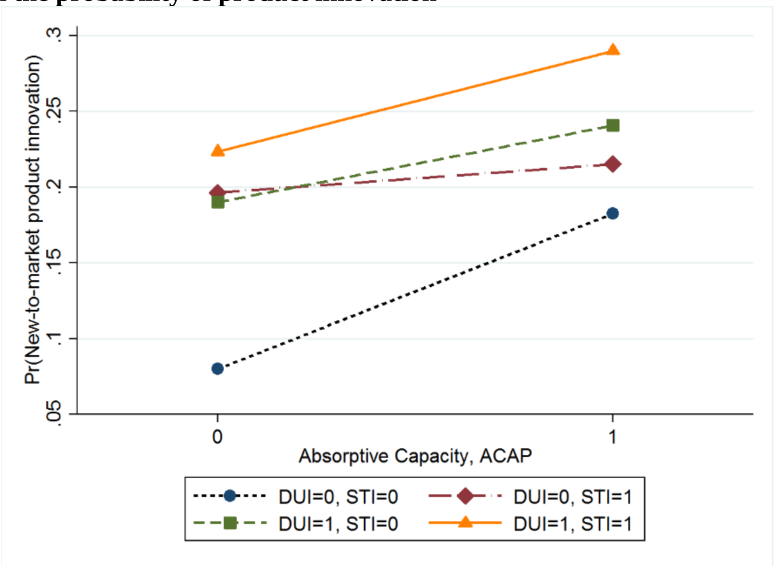


Figure 2. The moderating effects of absorptive capacity and scientific (STI) and supply-chain (DUI) collaboration on the probability of product innovation



APPENDIX

TABLE A. Correlation Matrix

	Product innovation	New-to-Market product innovation	Product innovation share of turnover (%)	STI	DUI	ACAP	Collaboration with competitors	R&D expend.
Product innovation	1.000							
New-to-Market product innovation	0.654***	1.000						
Product innovation share of turnover (%)	0.413***	0.632***	1.000					
STI, Scientific collaboration	0.304***	0.293***	0.181***	1.000				
DUI, Supply-chain collaboration	0.289***	0.276***	0.155***	0.547***	1.000			
ACAP, Absorptive capacity	0.509***	0.403***	0.252***	0.388***	0.322***	1.000		
Collaboration with competitors	0.174***	0.187***	0.111***	0.411***	0.370***	0.228***	1.000	
R&D expenditure (log)	0.556***	0.427***	0.264***	0.420***	0.373***	0.853***	0.255***	1.000
Firm age (log)	-0.062***	-0.055***	-0.056***	0.000	0.025***	-0.058***	0.009**	-0.063***
Firm size (log)	0.036***	0.028***	-0.041***	0.076***	0.127***	0.041***	0.075***	0.143***
Export (%)	0.003	-0.002	-0.001	-0.002	-0.001	-0.003	-0.001	-0.003
Share of educated employees (log)	0.146***	0.155***	0.144***	0.188***	0.137***	0.234***	0.159***	0.221***
Service high technology	0.038***	0.056***	0.082***	0.103***	0.089***	0.090***	0.106***	0.099***
Manufacturing medium-high technology	0.121***	0.062***	0.027***	0.009**	0.017***	0.102***	-0.034***	0.096***
Manufacturing high technology	0.085***	0.074***	0.043***	0.057***	0.045***	0.114***	0.038***	0.123***
Innovative Region	0.339***	0.274***	0.169***	0.227***	0.210***	0.610***	0.161***	0.552***

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Correlation Matrix (continued)

	Firm age	Firm size	Exports	Educated employees	Service	Manuf. M-H	Manuf. High	Innovative Region
Firm age (log)	1.000							
Firm size (log)	0.080***	1.000						
Export (%)	0.002	0.001	1.000					
Share of educated employees (log)	-0.018***	-0.265***	-0.003	1.000				
Service high technology	0.030***	-0.060***	-0.001	0.217***	1.000			
Manufacturing medium-high technology	0.213***	-0.058***	-0.001	-0.105***	-0.092***	1.000		
Manufacturing high technology	0.074***	-0.012***	-0.001	0.068***	-0.036***	-0.088***	1.000	
Innovative Region	-0.029***	0.039***	-0.002	0.200***	0.054***	0.085***	0.133***	1.000

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$