Managing Knowledge Spillovers: The Impact of Absorptive Capacity on Innovation Performance[§]

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Abstract

This paper evaluates how firm absorptive capacity moderates the impact of knowledge spillovers on innovation performance. We would expect that those firms with higher levels of absorptive capacity are able to manage knowledge spillovers more efficiently, and are therefore more likely to transform them into innovative outcomes. Additionally, we seek to understand how key contingencies of the external knowledge environment do influence the relationship between absorptive capacity, knowledge spillovers and innovation performance. We introduce a new index of absorptive capacity based on the first principal component of four key elements: fully staff R&D department, the stock of patents, training activity for its R&D personal and the share of scientist and researchers over the total number of employees of the firm. Our empirical analysis on innovation performance is based on a sample of 2265 Spanish innovative firms drawn from the 2000 and 2002 Community Innovation Surveys (CIS) administered by the Spanish National Statistics Institute (INE). Our main results show that absorptive capacity is indeed an important source of competitive advantage for the firm and is even more critical in turbulent knowledge sectors and in sectors with tighter intellectual property rights (IPR). Those results are robust to sample selection issues and to the correlation between knowledge spillovers and other variables like absorptive capacity.

Keywords: Absorptive capacity, innovation, knowledge spillovers.

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"Ninety-nine percent of everything exciting that happens will happen outside your own research labs" Tom McKillop, CEO of Astra Zeneca.

1/ Introduction

One of the most important changes in the organization of the innovation process within corporations in the last two decades has been the increasing recognition of the importance of external knowledge flows (Rigby and Zook, 2002). Firms are gradually abandoning the idea that the generation of new knowledge is mostly an internal process (Arora et al., 2001; Gans and Stern, 2003). In some industries, the boundaries between the knowledge stock of the organization and the external knowledge stock have been blurring (Teece, 1998).

Cohen and Levinthal's seminal contributions highlight that firms cannot benefit from external knowledge flows by simply being exposed to them (Cohen and Levintal, 1989, 1990). Firms need instead to develop the ability to recognize the value of new external knowledge, assimilate it, and apply it to commercial ends. In other words, firms must possess "absorptive capacity". Given the increasing role of external knowledge flows in recent years, absorptive capacity has gradually become a key driver of firm competitive advantage (Barney, 1991; Cockburn and Henderson, 1998).

This paper follows in this tradition and attempts to empirically isolate the impact of absorptive capacity on innovation performance. We do so by arguing that absorptive capacity, rather than conditioning innovation performance directly, acts as a moderator of the impact of external knowledge flows. This assumption allows us to empirically disentangle the role of absorptive capacity from that of innovation ability and other inputs of the innovation process. Specifically, this research focuses on involuntary knowledge flows, *i.e.* knowledge spillovers, which arise when part of the knowledge generated by an organization spills over its boundaries and becomes available to other organizations (Nelson, 1959; Arrow, 1962).[1]

How do knowledge spillovers affect firm innovation performance? What is the role of absorptive capacity, and how does it interact with knowledge spillovers and innovation performance? We argue that absorptive capacity has a twofold role in the relationship between knowledge spillovers and innovation performance. First, firms endowed with higher levels of absorptive capacity will be more aware of the existence of knowledge spillovers. For instance, a firm, whose R&D employees have never published in scientific journals, might

[1] After the seminal work of d'Aspremont and Jaquemin (1989), spillovers have been mostly modeled as exogenous in the theoretical literature of industrial organization. Recently, some authors have incorporated the important role of absorptive capacity as a necessary condition for benefiting from the spillovers (Kamien and Zang, 2000).

ignore the existence of specialized journals where a great deal of publicly available knowledge could be sourced. Similarly, a firm actively investigating the possibility of improving its own product can better understand the knowledge embodied in the products launched by its rivals by reverse engineering them. Second, the benefits of the knowledge spillovers that each firm can identify and recognize also depend on its absorptive capacity. Firms with higher levels of absorptive capacity will be able to manage more efficiently external knowledge flows and better integrate them with internally generated flows, such as to advance innovation performance. In other words, we posit that firms with higher levels of absorptive capacity extract more value from otherwise similar stocks of knowledge spillovers. This latter effect is what we refer to as "the moderating role of absorptive capacity".

As a further refinement of our theory and using the insights from the literature, we explore how some key contingencies in the external knowledge environment influence the relationship between absorptive capacity, knowledge spillovers and innovation performance. In particular, we focus on two types of contingencies: the degree of turbulence and the level of legal appropriability.

To perform our empirical analysis we employ a sample of 2265 Spanish innovative firms drawn from the 2000 and 2002 Community Innovation Survey (CIS) administered by the Spanish National Statistics Institute. We find evidence that firms endowed with more absorptive capacity both enjoy more knowledge spillovers, and turn them more efficiently into innovative outcomes. Our data also suggest that the role of absorptive capacity strongly depends on the contingencies of the external knowledge environment. Our findings remain qualitatively unchanged after we carefully control for sample selection and for the potential correlation between knowledge spillovers and other variables like for instance absorptive capacity and innovation performance.

Our paper contributes to the empirical literature on absorptive capacity and its impact on different innovation outcomes. Cohen and Levinthal (1989) argue that the desire to assimilate external know-how creates a positive incentive to invest in R&D. They offer indirect evidence of the relationship between innovation performance and absorptive capacity by showing that knowledge spillovers encourage, rather than diminish, the investment in R&D. Gambardella (1992), based on several case studies of large US drug manufacturers, concludes that firms with better in-house scientific research programs have exploited more efficiently outside scientific information. Focusing on collaborative linkages in the biotechnology industry, Arora and Gambardella (1994) find that a firm's absorptive capacity plays a crucial role in explaining the number of alliances that each firm is establishing. Cockburn and Henderson (1998) show that connectedness to the scientific community is a key factor in driving a firms' ability to recognize and use upstream research and findings. Moreover, connectedness is significantly correlated with performance in drug discovery. Veugelers (1997) using a dataset similar to ours on 290 Flemish firms shows that firms with greater absorptive capacity present greater complementarity between external sources of R&D (e.g., from alliance partner) and internal R&D spending. Related, Cassiman and Veulegers (2005) have shown that reliance on more basic R&D, which might proxy firm absorptive capacity, is a contextual variable positively affecting the complementarity between internal and external innovation activities. Summarizing, direct evidence of the impact of absorptive capacity on innovation performance is still scarce. Most of the available evidence does not yet convincingly separate the "two faces of R&D" (Cohen and Levinthal, 1989), i.e. whether successful innovators are better at capturing knowledge spillovers, or they are simply more productive in R&D. Our empirical strategy to disentangle the two effects is by positing that absorptive capacity, rather than conditioning innovation performance directly, moderates the impact of knowledge spillovers once we have controlled for other drivers of innovation performance, like for instance inputs of the innovation process and firm innovation ability. This, we believe, constitutes our contribution to the related literature.

The remainder of the paper is organized as follows. Section 2 develops the theoretical underpinnings drawing on the related literature on knowledge spillovers and absorptive capacity. In Section 3, we conduct the empirical analysis. The paper ends with some final remarks.

2/ Background theory: knowledge spillovers and absorptive capacity

Innovation is a complex activity in which new knowledge is applied to commercial ends. New knowledge is generated through a cumulative process in which knowledge is added, deleted, transformed, modified or simply reinterpreted. Part of this knowledge reaches the firm from external sources (Cassiman and Veulegers, 2002). To be sure, the role of external knowledge flows for the success of firm innovation activity has long been recognized (Rosenberg, 1982). Inward looking firms have been accused to suffer from the so-called "not-invented here" syndrome (Katz and Allen, 1982). However, the importance of knowledge generated outside the firm's boundaries has increased dramatically in the last few years (see our initial quotation).

The increasing availability of external knowledge does not imply that firms can simply rely on outside knowledge flows. In fact, mere exposure to external knowledge is not sufficient to internalize it successfully. As discussed in the introduction, Cohen and Levinthal (1990) have highlighted the key role played by "absorptive capacity".[2] Absorptive capacity is defined as the ability to recognize the value of new external knowledge, assimilate it, and apply it to commercial ends. Recent developments of the literature have addressed absorptive capacity as a multidimensional construct. For instance, Arora and Gambardella (1994) distinguish between the ability to evaluate external knowledge and the ability to exploit it. Zahra and George (2002) introduce a similar distinction between what they call potential and realized absorptive capacity. Potential absorptive capacity enables a firm's receptiveness to external knowledge; realized absorptive capacity reflects a firm's capacity to leverage absorbed knowledge.

Knowledge spillovers constitute a prototypical example of external knowledge sources that the firm can potentially exploit to enhance innovation performance. The concept of knowledge spillovers was pioneered by Nelson (1959) and Arrow (1962) who characterized knowledge as having the feature of a durable public good. The knowledge produced by an innovator is easily "borrowed" by another party, without compensating the former. Several authors have documented the importance of knowledge spillovers for strategic decisions at the firm level (Jaffe, 1986; Cohen and Levinthal, 1990; Cassiman and Veugelers, 2002). The amount of knowledge spillovers available to a firm depends on the density of firms' clustering in a given geographical area, the sector, the nature of knowledge, and the legal protection of intellectual property, among other things (Jaffe et al., 1993; Teece, 1986; Saxenian, 1996).

Although all firms located in a given geographical area and belonging to a given sector might equally benefit from the presence of knowledge spillovers, in practice, they differ in their ability to identify and exploit such spillovers and, therefore, both the amount and the effect of knowledge spillovers is unequally distributed across the population of firms. Put differently, absorptive capacity can be a source of a firm's competitive advantage (Barney, 1991).

Our objective in this paper is to empirically isolate the impact of absorptive capacity on innovation performance. This task is not straightforward since as Cohen and Levinthal (1989) have suggested, the drivers of absorptive capacity are highly correlated with the inputs of the innovation process and firm innovation ability, and it is possibly not easy to estimate their separate effect on innovation performance. For instance, consider R&D experience.

[2] Gans and Stern (2001) argue that firms invest in internal R&D to enhance their bargaining power in technology acquisitions. Arora et al. (2005) find only mild empirical evidence to support such a theory.

Greater R&D experience is both correlated with absorptive capacity and innovation ability, and in turn both capabilities affect innovation performance. Specifically, we would like to convincingly show that if a positive impact of absorptive capacity on innovation performance exists, this is not due to the misspecification of controls for innovation ability, innovation productivity, and inputs of the innovation process.

More precisely, our empirical approach is the following.

First, we posit that absorptive capacity has an impact on innovation performance only when there are external knowledge flows to identify, integrate and exploit. Put differently, a firm that leaves in a vacuum would not benefit from absorptive capacity. Hence, the way in which we isolate the role of absorptive capacity is through its moderating effect of the impact of knowledge spillovers on innovation performance. Firms with more absorptive capacity benefit more, or loose less, from the presence of knowledge spillovers.[3] Notice that the literature suggests two separate roles played by absorptive capacity with respect to external knowledge (Cohen and Levinthal, 1989; Arora and Gambardella, 1994; Zahra and George, 2002). First, absorptive capacity helps the firm to identify more knowledge spillovers. In other words, the amount of knowledge spillovers that the firm perceives is an increasing function of its absorptive capacity. Second, given the amount of knowledge spillovers identified by the firm, how much it can benefit from them also depends on its absorptive capacity. The former effect is what other scholars have called ability to identify, ability to evaluate or potential absorptive capacity, the latter effect is typically labeled as ability to use, ability to exploit or realized absorptive capacity. Overall, we can conclude that heterogeneity in the level of absorptive capacity translates into differences in the benefits from otherwise similar stocks of external knowledge both because the firm can identify more of them and because it can exploit them more efficiently.

Second, we need to control as well as we can for all other drivers of innovation performance, that is, inputs of the innovation process, ability to innovate, and efficiency of the innovation production function. As we mentioned above, many of these drivers of innovation performance are also drivers of firm absorptive capacity. Thus, it would be unviable to isolate the impact of absorptive capacity on innovation performance if one would have posited a direct effect, like for instance Cockburn and Henderson (1998). In such a case the only available option is to impose ex-ante a different set of proxies that explain absorptive

[3] We do not know whether knowledge spillovers have a positive or negative direct effect on innovation performance. For instance, Cassiman and Veugelers (2002) argue that spillovers might have a double role. Incoming spillovers might be beneficial, whereas outgoing spillovers might benefit competitors and thereby reducing the firm's competitive advantage in innovation.

capacity. We believe that absorptive capacity is so intertwined with innovation ability and several inputs of the innovation process that it would be meaningless to proceed in that way.

The relationship between absorptive capacity, knowledge spillovers and innovation performance crucially depends on some key contingencies in the external knowledge environment, which make of absorptive capacity a more or a less critical strategic dimension. We focus here on two contingencies: the degree of turbulence and the level of legal appropriability.

Degree of turbulence. March (1991) has proposed two broad types of qualitatively different learning activities through which firms divide their attention and resources: exploration and exploitation. Exploration implies search, discovery, experimentation, risk taking and innovation, while exploitation implies refinement, implementation, efficiency of production and selection. The role of outside knowledge is rather different across these two activities. While local search processes that characterize exploitation might not need external feedback, exploration activity more heavily relies on outside knowledge for idea generating, fundamental understanding of the phenomena, basic knowledge and market feedback. This implies that absorptive capacity is a more important ability for firms involved in exploration rather than in exploitation.

In stable knowledge environments, firms have a strong focus on the exploitation of knowledge since the knowledge domain firms wish to exploit is closely related to their current knowledge base. Differently, in turbulent knowledge environments, firms engage more actively in exploration since the relevant knowledge might be distant from their existing stock of knowledge. Hence, in turbulent knowledge environments it becomes far more important to monitor external knowledge development and an inward looking attitude is highly penalized. In turn, this consideration implies that the role of absorptive capacity is more important in turbulent knowledge environments. Because a great deal of the relevant knowledge for innovation activity is outside the firm's boundaries, knowledge spillovers become more important, and the ability to benefit from them plays a crucial role in securing competitive advantage.

Degree of legal appropriability. Another important characteristic of the knowledge environment is the strength of the appropriability regime (Zahra and George, 2002). Appropriability refers to the ability of the firm to protect the advantages of (and benefit from) new products or processes (Teece, 1986). Appropriability depends among other things on the strength of the legal protection of intellectual property rights (IPRs). Under a regime of strict protection of IPRs, firms patent their intellectual property to protect revenue streams arising from innovations. Imitation is more difficult and imitating firms need to incur higher costs to circumvent valid patents. By contrast, under a regime of weak protection of IPRs, firms can preserve their innovation advantages only by resorting to different means of protection like secrecy, lead time, complexity of routines, control of complementary assets (Teece, 1986). Secrecy, in particular, has been identified as the preferred mode for protecting both product and process innovations by Cohen et al. (2000) in a large survey of manufacturing firms. Patenting is considered a risky strategy because if the regime of protection is not too strong, a patent may provide enabling information for other firms to circumvent the process and yet achieve the desired output. Put differently, if one of the crucial task of a patent system is to disclose information that can be socially and efficiently used by other players, the risk of imitation when legal protection is weak makes this goal unattainable. In turn, this implies that firms will try to develop mechanisms to protect their innovation which tend to reduce the amount of disclosed information. By contrast, in regimes of tight legal protection of IPRs, firms patent extensively thereby contributing to generate comprehensive and accessible sources of scientific and technological information (Granstrand, 1999). For instance, Arora, Ceccagnoli and Cohen (2005) empirically show that firm propensity to patent and the patent premium (i.e. the extra profit that a patent confers to an innovation) are positively correlated. This means that the amount of external knowledge available to the firm is larger as well as more relevant under a strong IPRs regime. Hence, in sectors with tight legal appropriability, the role of absorptive capacity for assimilating, integrating and transforming such external information should be greater.

3/ Empirical Analysis

3.1/ Data

The dataset used in this study is assembled from the Community Innovation Survey (CIS) conducted in Spain in 2000 and administered by the Spanish National Statistics Institute (INE), and a fully comparable survey conducted by the same Institute in 2002 (*Encuesta de Innovación Tecnológica, EIT).* The purpose of the survey is to collect detailed information about innovation activities of Spanish firms belonging to all sectors of the economy. The database for each year is a stratified sample according to the number of employees and the sector. In particular, the number of employees has been divided into three intervals (from 10 to 49; from 50 to 249 and more than 250). INE has only sent the questionnaire to firms with more than 10 employees. Firms are assigned to 55 different 2-digit sectors (grouped in 10 broad 1-digit sectors) following a Spanish classification called CNAE. Questionnaires were sent to the CEOs. The response rate has been quite large (92%). This is not surprising given that Spanish firms have a legal obligation to fulfil questionnaires administered by the INE. The final database, after removing observations with missing values, is a panel of about 4000 firms that have answered the questionnaire in both periods. Some diagnostic checks have been performed to assure that the sample we employ does not suffer any serious selection bias.[4] Slightly more than 55% of the firms of our sample have indicated that they have spent a positive amount of resources in innovation activities. We consider that the problem we want to analyze is rather meaningless for those firms that have not devoted resources to innovation activities.[5] However, for completeness we also report our results using the full sample, and correcting the estimated coefficients through the Heckman's two-stage selection model (see Table 6).

3.2/ Variable definition

Innovation performance.

We consider two different measures of innovation performance. NEWPROD is the percentage of total annual sales (by the year 2002) that consist of new or substantially improved products introduced over the period 2000-2002. The natural log has been used to compensate for skewness.[6] INNOV is a dummy that equals 1 if the firm has introduced a product or a process innovation during the period 2000-2002 and 0 otherwise.

Knowledge spillovers.

In the questionnaire, firms rated the importance of different information sources for innovation on a four-point scale from 1 (high) to 4 (not at all). We focus on 7 sources: suppliers, clients, competitors, universities, other research institutions, specialized journals and meetings.[7] We build an index (SPILLOVER) by computing the principal component of the variables that capture the role of the aforementioned sources of external knowledge.[8] Notice that this is a firm-specific measure of knowledge spillovers, and therefore it is likely to be a function of the ability of the firm to identify and recognize external knowledge flows, i.e. its absorptive capacity. Indeed, if a firm cannot identify the presence of external useful

[4] Specifically, we have checked that the records we removed for missing values were not different in some observable dimensions from the sample we finally used.
[5] In addition, such firms are allowed to skip to fill in most parts of the questionnaire. So, we would not be able to measure some key variables, like a firm's absorptive capacity, for instance.
[6] For all variables, V, that display observations with zero values, we define the transformed variable as log(1+V).
[7] Cassiman and Veugelers (2002) in their study of R&D cooperation and spillovers discuss the virtues of a measure of knowledge spillovers based on the importance of different information sources for innovation vis-à-vis alternative measures proposed in the literature.
[8] As a robustness check, we have also used in unreported estimations (available upon request) a measure based on the normalized sum of the 7 variables capturing the aforementioned sources of external knowledge. Results remain qualitatively unchanged.

information it will naturally tend to classify it as not important. Moreover, to classify anything one has to have the ability to understand the object under scrutiny and compare it to some reference object (March, 1991; Levinthal and March, 1993). In subsection 3.4, we specifically address this issue in two ways: first, by using the 2-digit sector average level of knowledge spillovers and, second, by factoring out the effect of absorptive capacity from our measure of knowledge spillovers. Additionally, we also recognize the possibility that knowledge spillovers may be correlated with innovation performance, even if this latter variable is lead by one period. The reason is the existence of some inertia in innovation performance due to the presence of unobservable heterogeneity (firm fixed-effects). We address this econometric issue in Table 8.

Absorptive capacity.

The literature has proposed several different measures of absorptive capacity, and none seems to be superior to all others in all circumstances. In their seminal paper Cohen and Levinthal (1990) used R&D intensity, although they argued that the process of building absorptive capacity is cumulative. So, rather than to the actual flow of R&D investment, absorptive capacity more closely relates to the depreciated sum of past investments in R&D. To capture this cumulativeness aspect of absorptive capacity Veugelers (1997) and Cassiman and Veugelers (2002), among others, use the fact that the firm has an R&D department fully staffed. Alternatively, other authors have used the stock of granted and not expired patents as a natural proxy of the stock of knowledge accumulated by the firm in the past (Cockburn and Henderson, 1993). On a theoretical level, patent stock is an attractive construct for firm absorptive capacity (Silverman, 1999). Each dollar spent on internal R&D may not generate the same amount of knowledge stock. Some research is likely to be unproductive and should not be weighed equally to that which is successful (Hall, Jaffe, and Trajtenberg, 2001). Other papers that have used a similar construct are Stuart (2000) and Cockburn and Henderson (1994). Finally, since absorptive capacity has to do with the ability of the individuals of the organization to assimilate, process and transform external knowledge flows, scholars have also used measures of the firm human capital. For instance, Mowery and Oxley (1995) and Keller (1996) employ investment in scientific and technical training and the number of scientists and engineers. Similarly, Veugelers (1999) uses the number of doctorates within the R&D department. Following the different suggestions of the literature, we have operationalized our measure of absorptive capacity by constructing an indicator, ABSCAP, which is the principal component of 1) a dummy which is equal to 1 if the firm has a fully staffed R&D department, 2) the stock of patents (entered in logarithms), 3) a dummy which is equal to 1 if the firm undertakes training activity for its R&D personnel, and 4) the share of scientists and researchers over total employees.

In order to capture empirically the moderating role of absorptive capacity, we cross our indicator of firm absorptive capacity with our measure of knowledge spillovers (ABSCAP*SPILLOVER). In addition, we also control for a direct effect of knowledge spillovers, SPILLOVER, on innovation performance.

Innovation ability and inputs of the innovation process.

We need to control as well as we can for other possible drivers of innovation performance. To correctly predict the outcome of the innovation process, one needs to measure the inputs entering the innovation production function and the properties of such a function (i.e. the ability to innovate). A standard input of the innovation process is the amount - in this case, the flow - of investment in R&D (INTERNAL R&D, which is measured in a log scale). Innovation performance will also depend on the skills and abilities of the researchers. We proxy these dimensions through the same two variables we employed in our indicator of absorptive capacity, that is, a dummy (TRAINING) which is equal to 1 if the firm undertakes training activity for its R&D personnel, and the share of researchers and scientists over total employees (R&D SKILL). Finally, for the sake of completeness we also control for the stock of patents (NUMPATENT). Although we argued that the stock of patents is a valid construct for absorptive capacity, it might also capture firm innovation ability since firms with greater innovation ability might have obtained more patents.[9]

Turbulent knowledge sectors.

Turbulent knowledge environments are those environments where the underlying knowledge base is under a process of continuous evolution and change. By identifying the degree of knowledge turbulence at the sector level, we attempt to address the fact that some industries may experience greater technological ferment that may drive both the importance of absorptive capacity and the opportunities to benefit from knowledge spillovers. We define as turbulent sectors those in which the rate of increase in the share of sales due to new or improved products is higher than the economy average rate of increase (TURBULENT).

Sectors with strong IPRs.

Firms rated on a four-point scale the effectiveness of four different legal methods for protecting IPRs: patents, utility models, trademarks and copyrights. We summed up the four scores, and standardized such as the resulting index varies between 0 (minimum protection)

[9] Among the possible drivers of innovation performance, we have omitted the variable PERMANENT_R&D, i.e. a dummy capturing the presence of a fully staffed permanent R&D department, because it shows a correlation of 0.76 with INTERNAL R&D.

and 1 (maximum protection). Finally, we average the firm level index at the sector level. For a similar methodology, see Cassiman and Veulegers (2002). Sectors with strong IPRs are those having a score higher than the average of the economy (APPROPRIABILITY).

Control variables.

We use the number of employees in a log scale (SIZE) as a control for firm size. We control for firm size because previous research has found that innovation performance might benefit from economies of scale and scope (Henderson and Cockburn, 1994). We use a dummy (NEW) that signals whether a firm is of new creation or not. Indeed, several authors have suggested that new ventures might have stronger incentives to innovate under certain technological regimes (Henderson, 1993; Christensen, 1997). We also control for the existence of factors that hinder innovation performance (INN_OBSTACLES). Firms rated on a four-point scale the importance of the following obstacles to innovation activity: a) excessive risk, b) large sunk investment, and c) short pocket. We normalize the sum to vary between 0 and 1. Following Cassiman and Veugelers (2002), we control for the ability of the firm to protect its innovation using strategic tools like lead time, design complexity and secrecy (STRATEGIC PROTECTION). This is again a normalized sum of three scores (for the importance of lead time, design complexity, and secrecy) that varies between 0 and 1. Finally, to control for sector- and location-specific sources of heterogeneity in innovation performance we introduce a set of 1-digit sector dummies and a set of dummies for Spanish regions.

A summary of the definition of all variables is shown in Table 1.

[INSERT TABLE 1 ABOUT HERE]

Descriptive statistics of the main variables are shown in Table 2. There, we also provide means and standard deviations for different sub-samples: a) Firms with a level of absorptive capacity in the upper third of the distribution (AC=1); b) Firms with a level of absorptive capacity in the lower third of the distribution (AC=0); c) Firms with AC=1 (0) that operate in turbulent sectors –columns 4 (5); d) Firms with AC=1 (0) that operate in sectors with strong IPRs –columns 6 (7).

[INSERT TABLE 2 ABOUT HERE]

Table 2 shows that those firms with a level of absorptive capacity in the upper third of the distribution display higher innovation performance than those in the lower third of the distribution (the difference in the conditional mean value of NEWPROD is 0.809). Interestingly, this difference is higher once we focus on those firms that belong to turbulent sectors (1.171) or belong to sectors with strong IPRs (1.182). Thus, it seems that the role of absorptive capacity for innovation performance is particularly important in turbulent sectors and/or sector with tight legal appropriability.

A second result that can be extracted from this table is that those firms with a level of absorptive capacity in the upper third of the distribution report higher knowledge spillovers than those in the lower third of the distribution (difference=0.122). This difference is larger once we focus on turbulent sectors (difference=0.182) or in sectors with strong IPRs (difference=0.158). Hence, it appears that absorptive capacity and knowledge spillovers are positively correlated, and in turn both are positively related to innovation performance. The econometric analysis below explores more carefully these relationships.

3.3/ Econometric Analysis

In this section we estimate the effect of several potentially interesting economic variables on the outcome of the innovation process or on innovation performance (NewProd and Innov). It is important to recall the reader that while our innovation performance measures (dependent right hand side variables in the regressions) are drawn from the 2002 survey, all other explanatory variables come from the 2000 survey. This time lag helps us reducing the potential endogeneity problems between innovation performance and the variables capturing knowledge spillovers and absorptive capacity, and constitutes an improvement vis-à-vis other related research based on cross-section CIS.

Specifically, the basic equation for the *introduction of new products*, measured by the log of the percentage of sales from new or substantially improved products, is the following:

$$\begin{aligned} NewProd_{it+1} = a &+ b_1 NumPatent_{it} + b_2 R\&DSkills_{it} + b_3 Training_{it} + b_4 InternalR\&D_{it} + b_5 Spillovers_{it} + \\ &+ b_6 AbsCap_{it}{*}Spillovers_{it} + b_7 StrategicProtection_{it} + b_8 InnObstacles_{it} + \\ &+ b_9 Size_{it} + b_{10} New_{it} + \sum_{S=1}^{9} b'_{10+S} Dum_{Si} + \sum_{L=1}^{16} b'_{19+L} Dum_{Li} + e_{it+1} \qquad (1) \end{aligned}$$

where Dum_{Si} is a set of 9 dummies capturing the sector of firm i's primary activity (1-digit classification) and Dum_{Li} is a set of 16 dummies capturing the localization of firm i within the 17 main regions of Spain. e_{it+1} is the error term of the regression and has a Normal distribution with zero mean and σ_ι^2 variance (heteroskedastic). We estimate the NewProd equation by least squares (OLS) with robust standard errors, and in order to make coefficients comparable across different estimations, we enter all variables in standardized form. This does not alter the significance of the coefficients, i.e. the p-values remain unchanged.

For the specification of the determinants of the i-*firm decision to innovate at time t+1*, we use a PROBIT regression model,

$$\begin{aligned} \mathrm{P}(Innovation_{it+1}=1/X) = \Phi(a + b_1 NumPatent_{it} + b_2 R\&DSkills_{it} + b_3 Training_{it} + b_4 InternalR\&D_{it} + \\ + b_5 Spillovers_{it} + b_6 AbsCap_{it}{*}Spillovers_{it} + b_7 Strategic\Pr otection_{it} + b_8 InnObstacles_{it} + \\ + b_9 Size_{it} + b_{10} New_{it} + \sum_{S=1}^{9} b'_{10+S} Dum_{Si} + \sum_{L=1}^{16} b'_{19+L} Dum_{Li}) \end{aligned} \quad (2)$$

where $\Phi(.)$ is the cumulative Normal distribution and the dependent variable Innovation_{it} is equal to one if the expected profits of the decisions to innovate are positive. That is

$$Innovation_{it} = \begin{Bmatrix} 1 \;\; if \;\; E(p_{it}^{Innov}) \succ p_{it}^{*Innov} \\ 0 \quad otherwise \end{Bmatrix}.$$

The estimation results of equations (1) and (2) are shown in Table 3. Notice that we have only focused on those firms that have invested a positive amount of resources in innovation activity. This is not the set of all innovative firms, since some firms might be unsuccessful in their innovation activity. However, we think that it makes sense to investigate the moderating role of absorptive capacity on innovation performance for only those firms that perform some R&D activity. Therefore, since we select our sample based on a threshold decision, i.e. whether the firms expend or not resources in innovation activity, our results might suffer a sample selection bias. We will address this econometric concern in the following section after the discussion of the main empirical results.

[INSERT TABLE 3 ABOUT HERE]

First of all, notice that knowledge spillovers have a positive and significant impact on innovation performance, especially on the probability to innovate. So, firms that enjoy more knowledge spillovers are more innovative. Second, firms with higher levels of absorptive capacity benefit more from knowledge spillovers. Indeed, our cross variable (ABSCAP*SPILLOVER) is positive and highly significant. Hence, one can conclude that other things equal, knowledge spillovers have a direct and positive impact on innovation performance, and the magnitude of this effect strongly depends on a firm's absorptive capacity. Put differently, firms with higher levels of absorptive capacity are more innovative because they exploit more efficiently the flow of external knowledge. Indeed, all variables held constant at their median values, a firm has a 19.02% probability to innovate in the next period. This probability rises to 22.62% when we change the value of absorptive capacity from the median (0.113) to the upper quartile of the distribution (0.228).[10]

The signs of the other variables seem plausible. A larger investment in R&D (flow) generates a higher chance to obtain an innovation. This effect is significant across all our specifications. Similarly, the stock of patents is positive and significantly correlated with innovation performance. Other measures of innovation ability, TRAINING and R&D SKILLS, do not show up stable (i.e. signs change across specifications) and significant coefficients. Strategic protection and firm size are positively and significantly related to innovation performance. Finally, start-up firms do not have an advantage in innovation activity vis-à-vis more established rivals.

As a second objective of this study we would like to understand if the importance of absorptive capacity depends on the contingencies of the knowledge environment. We have argued that absorptive capacity should play a more crucial role in those sectors with greater knowledge turbulence and those with stricter legal protection of IPRs. Table 4 specifically addresses this issue. We have added two additional variables to our previous list of regressors. The former is the product of ABSCAP, SPILLOVER and TURBULENT. If this term shows up positive it implies that absorptive capacity is more important to turn knowledge spillovers into innovative products in those sectors with a more turbulent knowledge environment. The latter is the product of ABSCAP, SPILLOVER and APPROPRIABILITY. If this term shows up positive it implies that absorptive capacity is more important to turn knowledge spillovers into innovative products in those sectors with stricter legal enforcement of IPRs.

[INSERT TABLE 4 ABOUT HERE]

Table 4 suggests that absorptive capacity is indeed a more important source of competitive advantage in those sectors characterized by higher degrees of knowledge turbulence and stricter legal enforcement of IPRs, respectively. The coefficients of the two additional regressors are positive and significant in all specifications.

3.4/ Robustness checks

We discuss here some of the econometric checks we have conducted in order to increase our confidence about the robustness of the findings.

First, since we have a sample with very heterogeneous firms - some have just few employees while others are large multinational corporations, there are sizable differences between mean and median values for different variables. This might suggest the presence of a

[10] We are using as specification the last column of Table 3.

significant amount of outliers and, in turn, potential problems in the estimations. To control for the effect of these outliers, we have re-estimated our specifications using the correction introduced by Huber (1964).[11] The results - shown in Table 5 - do not change qualitatively and are even stronger in comparison to those of Tables 3 and 4.

[INSERT TABLE 5 ABOUT HERE]

Second, in our regressions in Tables 3, 4 and 5 we have focused only on those firms that have expended some positive amount of resources in innovation activity. Since we select our sample on a threshold, i.e. whether the firms expend or not resources in innovation activity, our results might suffer from some sort of selection bias. To take care of this problem, we have run a Heckman's two-stage selection model where in the first stage the inverse Mills ratio was obtained from a probit regression (to predict whether a firm expends resources in innovation activity or not) using all available observations.[12] In the second stage, the inverse Mill ratio was included as an additional variable to explain the variation in innovation performance. The results of the second stage estimation are reported in Table 6. We have a total of 3986 firms of which only 2265 expend a positive amount of resources in innovation activity. Notice that the Mill ratio is not significant at the 10% level in any specification. This suggests that the sample selection bias is not a serious issue here. Indeed, all coefficients have the same sign and are comparable in magnitude to those obtained in Tables 3, 4 and 5.

[INSERT TABLE 6 ABOUT HERE]

A third, more serious concern comes from the measure of knowledge spillovers we have employed. In the questionnaire, firms were asked to rate the importance of different external sources of information for their innovation activity. We have exploited these answers to build a firm-specific index of knowledge spillovers. Such index accounts for the fact that not all firms are exposed to the same amount of knowledge spillovers even if they compete in the same sector and/or geographical area. However, this measure is likely to be a function of the ability of the firm to identify and recognize external knowledge flows, i.e. its absorptive

[11] The process is as follows: Initially there is a screening and all outliers with a Cook's distance larger than one are eliminated (Li, 1985). Then, some weights are calculated using absolute residuals. Using these weights, there is an iterative process that ends when the maximum change in the weights is lower than 1%. The weights that are used initially are the Huber's (1964) ones. After convergence is achieved with these weights, the biweights proposed by Beaton and Turkey (1974) are used until convergence (variation in the biweights are lower than 1%).

[12] The specification we have used to predict this probability includes the following variables (for definitions see Table 1): ABSCAP, STRATEGIC PROTECTION, INN_OBSTACLES, SIZE, NEW, and sector and regional dummies. Additionally, for identification purposes we have introduced controls for total export activity and total investment. Finally, we have not included our measure of knowledge spillovers because whenever the dependent variable is zero (no R&D expenses), SPILLOVER is not defined by construction of the questionnaire.

capacity. Indeed, if a firm cannot identify the presence of external useful information it will naturally tend to classify it as not important. Moreover, to classify anything one has to have the ability to understand the object under scrutiny and compare it with some reference object (March, 1991; Levinthal and March, 1993). Hence, such a firm-specific measure of knowledge spillovers is likely to be correlated to a firm's level of absorptive capacity. Firms with greater absorptive capacity will show up a larger amount of firm-specific knowledge spillovers. (This is in fact the case as Table 2 shows.)

To check for this possibility we have run a regression in which we used as dependent variable our measure of knowledge spillovers and as explanatory variable our construct for absorptive capacity. Moreover, we have controlled for sector and geographical location through a vector of dummy variables for 10 sectors (1-digit classification) and a vector of dummy variables for 17 Spanish regions. As suggested by the literature, knowledge spillovers tend to be localized and their importance decays with distance (Henderson et al., 1993). The results from such regression (not reported here) show that absorptive capacity has a positive, substantial effect on knowledge spillovers. Other things being equal, when the level of absorptive capacity increases from its median value (0.1138) to the upper quartile of the distribution (0.2208) knowledge spillovers move from 0.3843 to 0.4393

We address this econometric concern in two ways. Results are reported in Table 7. First, we have used the sector average of knowledge spillovers instead of our firm-specific measure. The implicit assumption is that all firms belonging to the same sector experiment the same level of knowledge spillovers. Second, we have used the results of the regression described above to factor out the impact of absorptive capacity from our measure of knowledge spillovers (orthogonalization). We then have used the orthogonalized measure of knowledge spillovers to run our regressions in Table 7. More precisely, our new measure of knowledge spillovers is equal to SPILLOVER – β*ABSCAP, where β (=0.11) is the coefficient estimated from the equation driving knowledge spillovers described above. Table 7 confirms that our main empirical finding, that is, absorptive capacity positively moderates the impact of knowledge spillovers on innovation performance, is pretty robust.

[INSERT TABLE 7 ABOUT HERE]

A forth concern is the possibility that our measure of knowledge spillovers is correlated with the dependent variable (recall, however, that this latter is lead by one period). This may be the case when there is sufficient persistence in innovation performance, and those firms that have been successfully innovating in period t are also those that are successful in period t+1.[13] Hence, it may perfectly be the case that the drivers of innovation performance may also explain a firm's rating of the importance of external knowledge flows (our proxy for knowledge spillovers). To tackle this issue, we have run a 2SLS estimation, where we used as instrument a correction of the predicted value of knowledge spillovers obtained from the same specification we have described above. The exogenous variables are absorptive capacity and the dummies for 1-digit sector and regions. The correction consists in factoring out the effect of absorptive capacity from knowledge spillovers, following the same procedure described above.[14] The results are show in Table 8 and conform to our theoretical contentions.

[INSERT TABLE 8 ABOUT HERE]

Finally, we have experimented with several other control variables, like for instance export intensity, a dummy for multinational firms, province instead of regional dummies, 2-digit sector dummies, a herfindahl index to control for the degree of competition. Results did not change. Lastly, we have also investigated whether the presence of technology parks has any effect on a firm's innovation performance as well as on the moderating effect of absorptive capacity. We did not find any significant result (available from the authors upon request).

4/ Conclusions

Cohen and Levinthal (1989) have opened up a rich research agenda by defining the concept of absorptive capacity and emphasizing its key role for understanding firms' performance in innovation. However, they have also pointed out that absorptive capacity and innovation ability are so intertwined that it is very difficult to estimate separately their impact on innovation performance. In this paper we do so by arguing that absorptive capacity moderates the impact of knowledge spillovers on innovation performance. Firms endowed with more absorptive capacity are better equipped at identifying the presence of knowledge spillovers and, more importantly, at exploiting them efficiently.

Our results suggest that absorptive capacity is indeed a source of competitive advantage. In other words, this paper shows that it pays dividends, in terms of innovation

[13] The point is that if SPILLOVER$_t$ is correlated with the error term e_{it} of the NEWPROD$_t$ (INNOV$_t$) equation, it may also be correlated with the error term e_{it+1} of the NEWPROD$_{t+1}$ (INNOV$_{t+1}$) equation. This possibility may occur when the error term has a firm-specific component ($e_{it} = h_i + n_{it}$).

[14] In the probit estimations, following Wolridge (????) and Berger *et al.* (2005) we introduce directly the instrument in the specifications in order to deal with the endogeneity problem.

performance, for firms to invest in enhancing their absorptive capacity. Moreover, we have found that absorptive capacity is even more critical in turbulent knowledge sectors and sectors with tighter IPRs. In the knowledge-based economy, where large part of the relevant knowledge resides outside the firm's boundaries, this is a particularly important message for managers who aim at building sustainable competitive advantage.

This study is subject to a number of limitations. First, most of our data were self-reported assessments of firms' CEOs. Although the institution that administered the questionnaire (INE) took different steps, both, in the design and testing phases to limit concerns regarding single-informant data, the issues of key informant bias and common method bias cannot be totally ruled out. Second, our research was conducted using a sample of Spanish firms. We do not have any specific reason to believe that nationality might bias our results in a predictable direction. However, only by extending this research to other countries one could prove this conjecture, and generalize our findings. Fortunately, this is a very feasible avenue for future research. The very same dataset we have used for Spanish firms is available for many other European countries (the so-called "Community Innovation Survey"). Finally, the data employed in this study were cross-section, although we have been able to lead our dependent variables by one period in order to minimize simultaneity problems. Having a panel would improve the strength of our findings and would allow us to control more carefully for firm-specific sources of variation through firm fixed effects. This limitation is likely to be solved in the near future. Indeed, a new wave of data (CIS4 database) will be soon available, and there is a strong commitment by INE to update the database on a year basis.

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Wolridge

TABLE 1: Definition of the variables

	Definition
NEWPROD	The percentage (in logs) of 2002 total annual sales that consist of new or substantially improved products introduced over the period 2000-2002.
INNOV	A dummy that equals 1 if the firm has introduced a product or a process innovation during the period 2000-2002 and 0 otherwise.
NUMPATENT	The stock of non-expired patents entered in logarithms.
R&D SKILLS	The share of scientists and researchers over total employees.
TRAINING	A dummy that is equal to 1 if the firm undertakes training activity for its R&D personnel; and 0 otherwise.
PERMANENT R&D	A dummy that is equal to 1 if the firm has a fully staffed R&D department; and 0 otherwise.
ABSCAP	The principal component of four variables: a) NUMPATENT, b) R&D SKILLS, c) TRAINING, d) PERMANENT R&D.
INTERNAL R&D	The amount of internal R&D expenditures measured in a log scale.
SPILLOVER	The principal component of seven variables that capture the importance of 7 external knowledge sources: suppliers, clients, competitors, universities, other research institutions, specialized journals and meetings.
TURBULENT	A dummy that is equal to 1 if a firm operates in a sector where the rate of increase in the share of sales due to new or improved products is higher than the economy average rate of increase.
APPROPRIABILITY	A dummy that is equal to 1 if a firm competes in a sector that has a level of protection of IPRs greater than the economy level. Firms have rated the importance of four methods of protection: patents, utility models, trademarks and copyrights. We summed up the four scores at the firm level, and standardized such as the resulting index varies between 0 (minimum protection) and 1 (maximum protection). We then aggregate this variable at the sector level.
STRATEGIC PROTECTION	Measures the ability of the firm to protect its innovation using strategic tools like lead time, design complexity and secrecy. This is approached by the normalized sum of three scores (for the importance of lead time, design complexity, and secrecy).
INN_OBSTACLES	A variable that accounts for the existence of factors that hinder innovation performance. This is based upon the ratings on a four-point scale of the importance of the following obstacles to innovation activity: a) excessive risk, b) large sunk investment, and c) short pocket. We normalize the sum to vary between 0 and 1.
SIZE	The number of employees in a log scale.
NEW	A dummy that captures whether a firm is of new creation or not.
SECTOR DUMMIES	A set of dummy variables for our 10 1-digit sectors.
REGION DUMMIES	A set of dummy variables for the 17 main regions of Spain.

Table 2: Descriptive Statistics of the main variables

Table 2 presents the descriptive statistics of the variables that we use in the econometric analysis. The variables considered are defined in Table 1. In column 2, the statistics are from firms with an absorptive capacity in the upper third of the distribution (AC=1), while those of column 3 correspond to the lower third of the distribution (AC=0). The statistics of columns 4 and 5 are similar to those of columns 2 and 3 but focusing on firms in turbulent sectors (Turbulent=1). Finally, the last two columns follow the same logic as columns 2 and 3 but focusing on firms that operate in sectors with strong IPRs (Appropriability=1).

	All sample	AC=1	AC=0	AC=1& Turbulent=1	AC=0& Turbulent=1	AC=1& Approp.=1	AC=0& Approp.=1
NEWPROD	1.169	1.388***	0.579	1.973***	0.802	1.900***	0.718
	(1.531)	(1.574)	(1.213)	(1.586)	(1.437)	(1.591)	(1.329)
ABSCAP	0.143	0.199***	0.000	0.249***	0.000	0.256***	0.000
	(0.127)	(0.108)	(0.000)	(0.086)	(0.000)	(0.107)	(0.000)
NUMPATENT	0.446	0.600***	0.000	0.875***	0.000	0.976***	0.000
	(0.957)	(1.091)	(0.000)	(1.214)	(0.000)	(1.274)	(0.000)
R&D SKILLS	0.029	0.040***	0.000	0.049***	0.000	0.064***	0.000
	(0.089)	(0.103)	(0.000)	(0.078)	(0.000)	(0.123)	(0.000)
TRAINING	0.475	0.671***	0.000	0.704***	0.000	0.660***	0.000
	(0.500)	(0.470)	(0.000)	(0.457)	(0.000)	(0.474)	(0.000)
PERMANENT R&D	0.475	0.670***	0.000	0.910***	0.000	0.887***	0.000
	(0.499)	(0.470)	(0.000)	(0.286)	(0.000)	(0.317)	(0.000)
INTERNAL R&D	8.672	10.404***	3.086	12.637***	3.222	12.362***	4.420
	(5.596)	(4.773)	(4.731)	(2.270)	(4.927)	(2.682)	(5.182)
SPILLOVER	0.396	0.431***	0.309	0.466***	0.284	0.468***	0.310
	(0.214)	(0.210)	(0.205)	(0.203)	(0.208)	(0.206)	(0.209)
ABSCAP*SPILLOVER	0.217	0.303***	0.000	0.389***	0.000	0.407***	0.000
	(0.241)	(0.237)	(0.000)	(0.205)	(0.000)	(0.256)	(0.000)
STRATEGIC PROTECTION	0.222	0.268***	0.109	0.332***	0.151	0.344***	0.154
	(0.321)	(0.338)	(0.242)	(0.353)	(0.283)	(0.358)	(0.280)
INN_OBSTACLES	0.492	0.516***	0.424	0.541***	0.405	0.545***	0.436
	(0.306)	(0.296)	(0.325)	(0.288)	(0.334)	(0.291)	(0.332)
SIZE	4.892	5.021***	4.665	5.010***	4.487	4.874***	4.336
	(1.363)	(1.376)	(1.294)	(1.403)	(1.187)	(1.358)	(1.112)
NEW	0.030	0.034**	0.016	0.036	0.010	0.032	0.016
	(0.171)	(0.180)	(0.125)	(0.186)	(0.099)	(0.175)	(0.128)
Number of observations	2265	1606	504	334	102	821	243

Note. ***p-value 0.01, ** p-value 0.05, *p-value 0.10. Standard deviations are shown in parentheses. We have tested the differences between column 2 and column3; between column 4 and column 5; and between column 6 and column 7. The differences in the means are tested through the Mann-Whitney test.

TABLE 3: Moderating role of absorptive capacity

All variables are defined in Table 1. Both dependent variables are lead by one period to avoid simultaneity. The estimations include controls for sector and region fixed effects. All regressions are contingent on observing positive expenditures in innovation activity. In columns 1 and 3 we employ robust OLS regressions to control for heteroscedasticity. In columns 2 and 4 we estimate a Probit model.

	$NEWPROD_{t+1}$	$INNOV_{t+1}$	$NEWPROD_{t+1}$	$INNOV_{t+1}$
$NUMPATENT_t$	0.051***	0.032*	0.024	-0.010
	(3.420)	(1.740)	(1.190)	(-0.420)
$R\&D\ SKILLS_t$	0.072***	0.049**	0.023	-0.034
	(2.950)	(2.160)	(0.650)	(-0.960)
$TRAINING_t$	0.015	0.060***	-0.022	-0.003
	(0.830)	(2.670)	(-0.880)	(-0.100)
$INTERNAL\ R\&D_t$	0.264***	0.209***	0.232***	0.158***
	(9.260)	(4.950)	(7.450)	(3.540)
$SPILLOVER_t$			0.043*	0.112***
			(1.680)	(3.280)
$ABSCAP_t$ *$SPILLOVER_t$			0.120**	0.195***
			(1.820)	(2.480)
$STRATEGIC\ PROTECTION_t$	0.103***	0.101***	0.093***	0.080***
	(4.890)	(4.060)	(4.340)	(3.170)
$INN\_OBSTACLES_t$	0.004	0.003	-0.010	-0.026
	(0.150)	(0.100)	(-0.360)	(-0.790)
$SIZE_t$	0.047***	0.196***	0.032	0.171***
	(1.840)	(6.070)	(1.240)	(5.150)
NEW_t	-0.007	-0.015	-0.007	-0.014
	(-0.300)	(-0.510)	(-0.260)	(-0.450)
CONSTANT	-0.033	-1.172*	-0.050	-0.972
	(-1.08)	(-1.71)	(-1.07)	(-1.41)
Number of observations	2265	2265	2265	2265
R2	17.15	10.17	17.56	11.13
Test of fitness [1]	29.66	316.01	27.17	345.60
	(0.000)	(0.000)	(0.000)	(0.000)

Note. ***p-value 0.01, ** p-value 0.05, *p-value 0.10. In parentheses the t-values.

[1] For the OLS regressions we use the F-test and for the Probit models the LR test.

TABLE 4: Turbulent knowledge sectors and sectors with tight appropriability

All variables are defined in Table 1. Both dependent variables are lead by one period to avoid simultaneity. The estimations include controls for sector and region fixed effects. All regressions are contingent on observing positive expenditures in innovation activity. In columns 1 and 3 we employ robust OLS regressions to control for heteroscedasticity. In columns 2 and 4 we estimate a Probit model.

	$NEWPROD_{t+1}$	$INNOV_{t+1}$	$NEWPROD_{t+1}$	$INNOV_{t+1}$
$NUMPATENT_t$	0.022	-0.011	0.021	-0.014
	(1.130)	(-0.460)	(1.050)	(-0.590)
R&D $SKILLS_t$	0.046	-0.025	0.028	-0.034
	(1.280)	(-0.680)	(0.860)	(-0.930)
$TRAINING_t$	-0.013	-0.003	-0.001	0.005
	(-0.540)	(-0.110)	(-0.060)	(0.160)
INTERNAL $R\&D_t$	0.207***	0.157***	0.217***	0.163***
	(6.630)	(3.500)	(6.650)	(3.610)
$SPILLOVER_t$	0.047**	0.107***	0.046**	0.109***
	(1.820)	(3.120)	(1.800)	(3.180)
$ABSCAP_t$ *$SPILLOVER_t$	0.051	0.163**	-0.148***	0.028
	(0.760)	(2.030)	(-2.010)	(0.290)
$ABSCAP_t$ *$SPILLOVER_t$ *$TURBULENT_t$	0.088***	0.059*		
	(2.960)	(1.650)		
$ABSCAP_t$ *$SPILLOVER_t$ *$APPROPRIABILITY_t$			0.282***	0.200***
			(5.950)	(3.060)
STRATEGIC $PROTECTION_t$	0.087	0.080***	0.089***	0.080***
	(4.060)	(3.170)	(4.200)	(3.140)
$INN\_OBSTACLES_t$	-0.018	-0.025	-0.021	-0.031
	(-0.670)	(-0.760)	(-0.800)	(-0.930)
$SIZE_t$	0.058**	0.175***	0.050**	0.169***
	(2.200)	(5.260)	(1.900)	(5.100)
NEW_t	-0.005	-0.013	-0.003	-0.014
	(-0.210)	(-0.430)	(-0.130)	(-0.460)
CONSTANT	-0.307***	0.136	-0.084*	-1.002
	(-4.500)	(-0.978)	(-1.76)	(-1.45)
Number of observations	2265	2265	2265	2265
R2	19.02	11.21	19.35	11.44
Test of fitness [1]	23.33	347	28.84	355
	(0.000)	(0.000)	(0.000)	(0.000)

Note. ***p-value 0.01, ** p-value 0.05, *p-value 0.10. In parentheses the t-values.

[1] For the OLS regressions we use the F-test and for the Probit models the LR test.

TABLE 5: Robustness checks on the effect of outliers (Huber correction)

Estimations that control for the effect of outliers are performed using the algorithm of Huber (1964). All variables are defined in Table 1. The dependent variable is lead by one period to avoid simultaneity. The estimations include controls for sector and region fixed effects. All regressions are contingent on observing positive expenditures in innovation activity.

	NEWPROD $_{t+1}$	NEWPROD $_{t+1}$	NEWPROD $_{t+1}$	NEWPROD $_{t+1}$
NUMPATENT $_{t}$	0.056***	0.021	0.021	0.011
	(3.840)	(1.070)	(1.060)	(0.590)
R&D SKILLS $_{t}$	0.107***	0.042	0.053**	0.028
	(5.670)	(1.400)	(1.770)	(0.950)
TRAINING $_{t}$	0.030*	-0.019	-0.021	-0.007
	(1.560)	(-0.730)	(-0.810)	(-0.300)
INTERNAL R&D $_{t}$	0.195***	0.154***	0.154***	0.155***
	(5.470)	(4.120)	(4.140)	(4.250)
SPILLOVER $_{t}$		0.052**	0.048	0.048*
		(1.760)	(1.630)	(1.690)
ABSCAP*SPILLOVER $_{t}$		0.167***	0.110*	-0.124
		(2.570)	(1.660)	(-1.570)
ABSCAP*SPILLOVER*TURBULENT $_{t}$			0.117***	
			(4.360)	
ABSCAP*SPILLOVER*APPROPRIABILITY $_{t}$				0.382***
				(7.290)
STRATEGIC PROTECTION $_{t}$	0.128***	0.115***	0.113***	0.117***
	(6.110)	(5.490)	(5.420)	(5.690)
INN_OBSTACLES $_{t}$	-0.008	-0.021	-0.023	-0.024
	(-0.280)	(-0.740)	(-0.810)	(-0.880)
SIZE $_{t}$	0.103***	0.084***	0.083***	0.082***
	(3.760)	(3.050)	(3.000)	(3.050)
NEW $_{t}$	-0.007	-0.007	-0.007	-0.003
	(-0.260)	(-0.260)	(-0.260)	(-0.130)
CONSTANT	-0.204	-0.092	-0.845	-0.030
	(-0.96)	(-0.43)	(-1.490)	(-0.140)
Number of observations	2265	2265	2265	2265
R2	20.28	21.24	21.89	24.58
Test of fitness [1]	16.69	16.69	16.83	19.62
	(0.000)	(0.000)	(0.000)	(0.000)

Note. ***p-value 0.01, ** p-value 0.05, *p-value 0.10. In parentheses the t-values.

[1] We use the F-test.

TABLE 6: Robustness checks on sample selection bias (Heckman estimations)

All variables are defined in Table 1. Both dependent variables are lead by one period to avoid simultaneity. The estimations include controls for sector and region fixed effects. In columns 1, 3 and 5 we employ robust OLS regressions. In columns 2, 4 and 6 we estimate a Probit model. Table 6 only shows the results of the second stage estimation. In the first stage, we have estimated a probit model to predict positive innovation expenditures using the following variables: ABSCAP, STRATEGIC PROTECTION, INN_OBSTACLES, SIZE, NEW, and for identification purposes we have also introduced controls for total export activity and total investment as well as dummies for sectors and regions. We have not included knowledge spillovers because whenever the dependent variable is zero (no R&D expenditures), SPILLOVER is not defined by construction of the questionnaire. From these estimations we computed the Mills Ratio that was introduced in the second stage estimations shown in Table 6.

	$NEWPROD_{t+1}$	$INNOV_{t+1}$	$NEWPROD_{t+1}$	$INNOV_{t+1}$	$NEWPROD_{t+1}$	$INNOV_{t+1}$
$NUMPATENT_t$	0.020	-0.012	0.018	-0.014	0.008	-0.018
	(0.980)	(-0.510)	(0.910)	(-0.560)	(0.390)	(-0.730)
$R\&D\ SKILLS_t$	0.040	-0.034	0.051^{*}	-0.024	0.027	-0.034
	(1.340)	(-0.950)	(1.690)	(-0.670)	(0.910)	(-0.930)
$TRAINING_t$	-0.018	-0.011	-0.027	-0.012	-0.021	-0.009
	(-0.630)	(-0.310)	(-0.920)	(-0.360)	(-0.740)	(-0.260)
$INTERNAL\ R\&D_t$	0.149^{***}	0.143^{***}	0.144^{***}	0.140^{***}	0.139^{***}	0.139^{***}
	(3.620)	(2.930)	(3.510)	(2.870)	(3.460)	(2.850)
$SPILLOVER_t$	0.051^{*}	0.108^{***}	0.047^{*}	0.102^{***}	0.046^{*}	0.104^{***}
	(1.730)	(3.140)	(1.580)	(2.970)	(1.600)	(3.020)
$ABSCAP_t * SPILLOVER_t$	0.164^{***}	0.191^{***}	0.104^{*}	0.159^{**}	-0.137^{*}	0.013
	(2.530)	(2.430)	(1.580)	(1.970)	(-1.730)	(0.130)
$ABSCAP_t * SPILLOVER_t * TURBULENT_t$			0.117^{***}	0.060^{*}		
			(4.330)	(1.690)		
$ABSCAP_t * SPILLOVER_t * APPROPRIABILITY_t$					0.383^{***}	0.212^{***}
					(7.170)	(3.190)
$STRATEGIC\ PROTECTION_t$	0.119^{***}	0.081^{***}	0.114^{***}	0.081^{***}	0.114^{***}	0.079^{***}
	(5.560)	(3.150)	(5.370)	(3.140)	(5.470)	(3.050)
$INN\_OBSTACLES_t$	-0.024	-0.027	-0.028	-0.026	-0.033	-0.035
	(-0.840)	(-0.820)	(-0.990)	(-0.790)	(-1.190)	(-1.040)
$SIZE_t$	0.086^{***}	0.171^{***}	0.083^{***}	0.175^{***}	0.082^{***}	0.169^{***}
	(3.090)	(5.140)	(3.010)	(5.250)	(3.010)	(5.090)
NEW_t	-0.003	-0.015^{***}	-0.003	-0.014	0.000	-0.015
	(-0.110)	(-0.500)	(-0.110)	(-0.470)	(0.010)	(-0.490)
CONSTANT	-0.016	-0.060^{**}	-0.053	-0.068	-0.100	-0.101
	(-0.200)	(-0.650)	(-0.670)	(-0.730)	(-1.290)	(-1.070)
Mills ratio	-0.083	-0.916^{**}	-0.024	0.163	0.050	0.209
	(-0.370)	-1.310)	(-0.110)	(0.620)	(0.230)	(0.800)
Number of observations	3986	3986	3986	3986	3986	3986
R2	21.19	11.10	21.73	11.18	24.14	11.44
Test of fitness [1]	16.96	341.93	16.11	343.86	18.50	352.44
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note. ***p-value 0.01, ** p-value 0.05, *p-value 0.10. In parentheses the t-values.

[1] For the OLS regressions we use the F-test and for the Probit models the LR test.

TABLE 7: Robustness checks on the correlation between knowledge spillovers and absorptive capacity

All variables are defined in Table 1. Both dependent variables are lead by one period to avoid simultaneity. The estimations include controls for sector and region fixed effects. All regressions are contingent on observing positive expenditures in innovation activity. In columns 1 and 3 we employ robust OLS regressions to control for heteroscedasticity. In columns 2 and 4 we estimate a Probit model. In columns 1 and 2, we use a measure of knowledge spillovers computed at the 2 digit sector level (SECTOR_SPILLOVER) by averaging our firm level measure of knowledge spillovers (SPILLOVER). In columns 3 and 4 we use an orthogonalized measure of knowledge spillovers which factors out the effect of absorptive capacity on knowledge spillovers (RSPILLOVER). The exact methodology is explained in the text.

	$NEWPROD_{t+1}$	$INNOV_{t+1}$	$NEWPROD_{t+1}$	$INNOV_{t+1}$
$NUMPATENT_t$	-0.012	-0.018	0.030*	0.004
	(-0.730)	(-0.800)	(1.670)	(0.170)
R&D SKILLS $_t$	-0.031	-0.062**	0.041	0.001
	(-1.230)	(-1.810)	(1.380)	(0.030)
$TRAINING_t$	-0.038**	0.013	-0.015	0.008
	(-1.890)	(0.490)	(-0.600)	(0.270)
INTERNAL R&D$_t$	0.183***	0.164***	0.212***	0.162***
	(5.830)	(3.750)	(6.740)	(3.590)
SECTOR_SPILLOVER$_t$	0.015	0.092***		
	(0.570)	(2.650)		
ABSCAP$_t$*SECTOR_SPILLOVER$_t$	0.195***	0.173***		
	(5.810)	(3.910)		
RSPILLOVER$_t$			0.028	0.088***
			(1.180)	(2.780)
ABSCAP$_t$*RSPILLOVER$_t$			0.109**	0.176***
			(2.010)	(2.830)
STRATEGIC PROTECTION $_t$	0.091***	0.092***	0.090***	0.082***
	(4.340)	(3.650)	(4.220)	(3.260)
INN_OBSTACLES$_t$	-0.011	-0.002	-0.010	-0.023
	(-0.400	(-0.070)	(-0.390)	(-0.700)
SIZE $_t$	0.048**	0.180***	0.049**	0.177***
	(1.850)	(5.430)	(1.890)	(5.410)
NEW$_t$	-0.009	-0.021	-0.005	-0.014
	(-0.350)	(-0.670)	(-0.180)	(-0.450)
CONSTANT	-0.306	-1.096	0.092	-0.989
	(-5.520)	(-1.590)	(2.030)	(-1.430)
Number of obs.	2265	2265	2265	2265
R2	19.57	11.31	18.31	11.02
Test of fitness[1]	26.45	351.19	28.02	342.28
	(0.000)	(0.000)	(0.000)	(0.000)

Note. ***p-value 0.01, ** p-value 0.05, *p-value 0.10. In parentheses the t-values.

[1] For the OLS regressions we use the F-test and for the Probit models the LR test.

TABLE 8: Robustness checks on the endogeneity of knowledge spillovers

All variables are defined in Table 1. Both dependent variables are lead by one period to avoid simultaneity. The estimations include controls for sector and region fixed effects. All regressions are contingent on observing positive expenditures in innovation activity. The table only shows the second stage estimations where we used as an instrument the corrected predicted value of knowledge spillovers obtained from a specification that explains knowledge spillovers in terms of absorptive capacity and dummies for 1-digit sectors and regions. (see the text for the details of the construction of the instrument). In columns 1, 3 and 5 we estimate a 2SLS regression model that has NEWPROD as dependent variable. Columns 2, 4 and 6 explain INNOV through a Probit model that introduces the instruments directly in the specifications.

	$NEWPROD_{t+1}$	$INNOV_{t+1}$	$NEWPROD_{t+1}$	$INNOV_{t+1}$	$NEWPROD_{t+1}$	$INNOV_{t+1}$
$NUMPATENT_t$	-0.058*	-0.094***	-0.043	-0.093***	-0.053	-0.100***
	(-1.750)	(-3.340)	(-1.280)	(-3.320)	(-1.510)	(-3.540)
R&D SKILLS $_t$	-0.143***	-0.144***	-0.109**	-0.132***	-0.127**	-0.149***
	(-2.640)	(-3.660)	(-2.000)	(-3.350)	(-2.310)	(-3.710)
$TRAINING_t$	-0.150***	-0.122***	-0.138***	-0.121***	-0.129***	-0.114***
	(-4.120)	(-3.220)	(-3.660)	(-3.170)	(-3.350)	(-2.990)
INTERNAL R&D$_t$	0.103**	0.071	0.081*	0.071	0.085*	0.077*
	(2.170)	(1.450)	(1.600)	(1.450)	(1.610)	(1.570)
$SPILLOVER_t$	0.560	0.023	0.695*	0.025	0.747*	0.031
	(1.300)	(0.250)	(1.670)	(0.270)	(1.670)	(0.340)
$ABSCAP_t$ *$SPILLOVER_t$	0.431***	0.557***	0.300*	0.513***	0.127	0.398***
	(2.500)	(5.940)	(1.750)	(5.370)	(0.690)	(3.750)
$ABSCAP_t$ *$SPILLOVER_t$ *$TURBULENT_t$			0.080**	0.070**		
			(2.160)	(2.020)		
$ABSCAP_t$ *$SPILLOVER_t$ * APPROPRIABILITY $_t$					0.246***	0.195***
					(3.600)	(3.170)
STRATEGIC PROTECTION $_t$	0.025	0.086***	0.010	0.087***	0.003	0.086***
	(0.560)	(3.440)	(0.230)	(3.460)	(0.070)	(3.400)
INN_OBSTACLES$_t$	-0.128	0.002	-0.158**	0.002	-0.173**	-0.003
	(-1.450)	(0.050)	(-1.810)	(0.050)	(-1.870)	(-0.100)
SIZE $_t$	-0.033	0.144***	-0.028	0.148***	-0.027	0.141***
	(-0.860)	(4.290)	(-0.720)	(4.390)	(-0.700)	(4.190)
NEW_t	-0.001	-0.019***	0.000	-0.018	0.000	-0.02
	(-0.020)	(-0.610)	(-0.020)	(-0.580)	(0.000)	(-0.630)
CONSTANT	0.396***	-0.050	0.421**	-0.036	0.431***	0.014
	(5.030)	(-0.340)	(5.120)	(-0.240)	(5.150)	(0.090)
Number of observations	2265	2265	2265	2265	2265	2265
R2	18.68	11.32	19.29	11.46	20.07	11.65
Fitness test [1]	23.56	351.47	24.41	355.22	22.36	361.72
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note. ***p-value 0.01, ** p-value 0.05, *p-value 0.10. In parentheses the t-values.

[1] For the OLS regressions we use the F-test and for the Probit models the LR test.