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# Corporate scientists as triggers of transitions in firms' R&D strategies

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## Abstract

The long term success and viability of firms are largely contingent on their capacity to develop radical innovations and moving up the quality ladder of product development. In such a competitive environment, the design of an R&D strategy is a critical factor for the firm's innovation performance and long term survival. In this research we contend that the availability of personnel with PhD qualifications in R&D units is a triggering factor for two critical transitions in firms' R&D strategies: i) the shift from sporadic to persistent R&D efforts (R&D deepening); and ii) the initiation and persistence of exploration-oriented R&D activities (R&D broadening). We conduct our analysis drawing on a large sample of Spanish manufacturing firms covering the period 2006-2012. We address endogeneity concerns by using the exogenous supply of PhD graduates as an instrumental variable. Our results show that firms enrolling PhDs in their R&D units increase the chances of both R&D deepening and broadening.

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**Abstract**

The long term success and viability of firms are largely contingent on their capacity to develop radical innovations and moving up the quality ladder of product development. In such a competitive environment, the design of an R&D strategy is a critical factor for the firm's innovation performance and long term survival. In this research we contend that the availability of personnel with PhD qualifications in R&D units is a triggering factor for two critical transitions in firms' R&D strategies: i) the shift from sporadic to persistent R&D efforts (*R&D deepening*); and ii) the initiation and persistence of exploration-oriented R&D activities (*R&D broadening*). We conduct our analysis drawing on a large sample of Spanish manufacturing firms covering the period 2006-2012. We address endogeneity concerns by using the exogenous supply of PhD graduates as an instrumental variable. Our results show that firms enrolling PhDs in their R&D units increase the chances of both R&D deepening and broadening.


## 1. Introduction

In this research we contend that the availability of highly qualified scientists in R&D units is a triggering factor for critical transitions in firms' R&D strategies. More specifically, we investigate whether, and to what extent, the proportion of PhDs (relative to the number of employees within firms' R&D units) contributes to initiate the firm's transition towards a strategy of R&D *deepening* (i.e. shifting from sporadic to persistent R&D efforts) and towards a strategy of R&D *broadening* (i.e. shift towards a more explorative-orientation of R&D).

We test our propositions in a large sample of Spanish manufacturing and R&D performing firms, covering the period 2006-2012. We find that the availability of PhDs in an organization's R&D unit does not only contribute to increase the persistence in R&D efforts, but it also increases the proportion of resources devoted to R&D over time. Therefore, we show that it has a large positive contribution to facilitate the transition towards a more persistent and intense R&D commitments. Moreover, our results show that firms with a larger proportion of PhDs in their R&D activities are far more likely to start exploration activities. We also find that a larger proportion of PhDs contribute to intensify the efforts towards exploration compared to firms with a lower proportion of PhDs. These results are robust to alternative explanatory factors, such as the industry-level appropriability regimes in which firms operate. We address reverse causality problems by adopting an instrumental variable approach. More precisely, we build an indicator of the exogenous supply of PhDs faced by each firm, using data of graduated PhDs from each university and scientific area, and a correspondence matrix of scientific areas and industries already tested by Abramovsky et al. (2007). In addition, we build a second instrument based on the PhDs already working in the industry to which each firm belongs.

The rest of the document is organized as follows. Section 2 develops the conceptual background. Section 3 explains data and methodology. Section 4 shows some descriptive statistics. Section 5 presents the results and, finally, section 6 develops the discussion and conclusions.

## 2. Conceptual Background

The long term success and viability of firms are largely contingent on their capacity to develop radical innovations and moving up the quality ladder of product development (Klette and Grilliches, 2000). Leading firms need to continuously reinvent themselves with regards to their product portfolio, while followers and new entrants aim at challenging existing products and markets (Bessant, 2005; Cabral, 2003). In such a competitive environment, the design and implementation of an appropriate R&D strategy is a critical factor for the firm’s innovation performance and long term survival.

Designing an R&D strategy, however, is a complex problem that goes well beyond deciding the amount of R&D or the R&D intensity of the organization. In fact, one of the stylized facts from existing research is that, in most industries, R&D expenditures vary proportionally with firm size, and that a firm's R&D investment remains quite persistent over time, at least beyond a minimum threshold of R&D investment (Cohen et al., 1987; Cohen and Klepper, 1996; Klette and Grilliches, 2000).

Despite these stable patterns associated to R&D investments, firms' performance is extremely fluid and heterogeneous in terms of both growth and innovation rates. This inter-firm heterogeneity in innovation performance has been often attributed to the capacity to upgrade the quality and range of the product portfolio (Aghion and Howitt, 1992; Klette and Grilliches, 2000). Thus, pointing out to the claim that rather than the amount of R&D effort, the crucial decision is about the type of R&D chosen (Cabral, 2003).

In this sense, we argue that, in order to build the technological capabilities that contribute to moving up the quality ladder, firms' face a number of critical challenges in their R&D strategies. On the one hand, firms need to set in motion persistent efforts oriented to R&D. Many firms struggle with the transition from a sporadic approach on R&D activities towards a more continuous, permanent commitment on R&D efforts. This is particularly the case among small and medium firms (SMEs), and firms within non-R&D intensive industries (Mañez et al., 2015). Ahlin et al. (2013) have examined how, in the absence of previous R&D experience, firms confront important challenges when facing a transition towards persistent R&D. Indeed, a large proportion of firms engage only sporadically in formal R&D activities, often relying on the acquisition of external services to specialized R&D partners. This often limits their capacity to build an internal knowledge-base to support their product and process upgrading.

On the other hand, firms need to broadening their search space by expanding their R&D orientation, adopting more exploration-oriented strategies in their research activities. Exploratory search involves processes of experimentation and discovery, and a deliberate effort to move away from current organizational routines and knowledge bases (March, 1991; Levinthal and March, 1993). However, a radical transition towards an exploratory R&D strategy is not straightforward since the outcomes of this strategy are highly uncertain, and it often involves high-risk choices which may lead to innovation failure (D'Este et al., 2015).

Much of the research looking at the drivers of firms' transitions in R&D strategies has focused on the market and institutional features of the competitive environment in which companies operate. For instance, prior work has looked at the governance of appropriability regimes and the incentives to undertake high-risk R&D strategies in the presence of knowledge leakages from R&D (Conti, 2014). Prior research has also pointed out the influence of the relative position of companies along the technological performance ladder, suggesting the presence of higher incentives to undertake exploratory research among laggard firms. According to this research, laggard firms have a favorable disposition to undertake highly uncertain R&D projects compared to leading companies, which tend to choose safer technologies and more incremental R&D strategies (Cabral, 2003).

In contrast to these approaches, this research investigates the antecedents of two types of transitions in R&D strategies, by looking at the scientific profile of individuals within firms' R&D functions. More specifically, we contend that the availability of highly qualified scientists in R&D units is a triggering factor for two critical transitions in R&D strategies: deepening and broadening of R&D strategies. The micro-foundations behind the connections between the recruitment of highly skilled R&D workers and the enforcement of these two types of R&D strategy transitions are discussed in the following sections.

### 2.1. From sporadic to persistent R&D: towards an R&D deepening strategy.

While current research highlights the innovation-related benefits from persistent R&D efforts, many firms exhibit a discontinuous engagement in R&D activities (Peters, 2009; Antonelli et al. 2012; Triguero and Córcoles, 2013). Moreover, while the literature has advanced a number of sources of innovation persistence, such as success-breeds-success, sunk costs in R&D

and increasing returns from learning (see: Cefis and Orsenigo, 2001; Peters, 2009; Antonelli et al. 2012; Clausen et al. 2012; Ganter and Hecker, 2013; Triguero and Córcoles, 2013), little is known about the precise mechanisms that enable this persistent behavior.

Maintaining persistent commitments with R&D activities is not easy and requires firms not only to increase their R&D expenditures but also to continuously renew their knowledge base. As the technological knowledge base ages quickly, firms need to build up capabilities in order to generate new knowledge and to recombine the existing bodies of knowledge (Kough and Zander, 1992). Several arguments support the idea that scientists play critical roles in these processes and contribute to the construction of the firm's capabilities to undertake more continuous R&D efforts.

One of these roles is related to the function of knowledge provider. Scientists provide firms with intellectual capital derived from their advanced education, training and experience in undertaking scientific and technological research (Luo et al., 2009; Subramaniam and Youndt, 2005). The contribution of this intellectual capital to R&D activities has been analyzed with special attention to the science-driven industries, such as biotechnology, where it has been demonstrated that the scientists' embodied knowledge is a determinant factor of firm growth (Zucker et al., 1998; 2002ab). Much of the knowledge arising from scientific breakthroughs is characterized by an excludable nature. The high complexity and the tacit dimension of this type of knowledge make its transfer difficult and requires the active participation of actors with particular knowledge backgrounds and skills (Zucker et al., 1998). As a result, hiring PhDs remains of major importance for companies seeking to profit from scientific knowledge. By hiring highly qualified scientists, firms can incorporate not only the most up-to-date scientific knowledge but also the skills needed to produce and exploit it (Lee et al., 2010).

Literature links this role of knowledge provider with a "learning by hiring" which assumes that the recruit's tacit knowledge diffuses internally and become part of firm's overall knowledge base (Singh and Agrawal, 2011). In general, studies have used productivity measures, such as patents, to reveal how this knowledge provider role conditions R&D activities. Strong evidences exist that firms recruiting scientists increase not only their patent propensity but also the number and quality of their patents (Tzabbar, 2009; Singh and Agrawal, 2011; Al-Laham et al., 2011; Subramanian et al., 2013). In addition, studies that have analyzed patent citations have shown that firms recruiting scientists not only increase their knowledge base but also draw heavily from their new scientists' ideas (Song et al., 2003; Sing and Agrawal, 2011).

Recent literature has gone even further and established that knowledge is not the only contribution of scientists to R&D activities. A shift from sporadic to continuous R&D effort may require access to other resources and the scientists' intellectual capital does not only include scientific knowledge, but also skills, experience and access to knowledge networks (Luo et al., 2009). During their doctoral and research training, scientists develop different skills useful to firms at different stages of the innovation process (Herrera and Nieto, 2015). Some of these skills go far beyond of their discipline's general background being directly related to the capability to formulate, structure and solve problems. Zellner (2003) pointed out that these wider set of skills could be of greater value to consolidate firms' R&D commitments and innovation performance, than those derived from their specific disciplinary knowledge background.

Since only few organizations can internally generate all the necessary knowledge to support ongoing R&D effort, firms seek for external knowledge sources through strategic innovation alliances. Scientists enrolled in firms' R&D activities are play a significant role in enabling these strategies since: 1) they are critical to integrate different and diffuse knowledge sources (Hess and Rothaermel, 2012); 2) they connect firms with scientific knowledge producers which are key to undertake R&D activity changes (Subramaniam and Youndt, 2005) and 3) they attract research partners as they can send an organizational legitimacy signal (expert personnel managing R&D) thus reducing potential partner's evaluative uncertainties (Luo et al., 2000). Along those lines, studies have pointed to scientists' influence on building R&D alliances. Luo et al. (2009) found that increasing the number of scientists in firms attracted more R&D partners, especially when the firms were located outside of the main industrial network.

In this context, highly qualified scientists can turn out to be critical when firms intend to build an internal knowledge base on which to support a persistent R&D effort. Thus, we put forward the following hypothesis:

Hypothesis 1: *Firms employing highly qualified scientists (i.e. PhDs) are more likely to undertake a transition towards a deepening R&D strategy. These firms are more likely to: a) shift from sporadic to continuous R&D activities; and b) intensify R&D resource commitments over time.*

### 2.2. Starting and sustaining exploration-oriented R&D activities: towards an R&D broadening strategy

In order to sustain their competitive position and respond to market demands, firms must focus on renewing their technological knowledge base. One way to do this is through the engagement in exploration research activities (Garcia et al. 2003). These activities are inherently risky, yet they substantially increase the likelihood of achieving high performance levels. Firms conducting exploratory research strategies increase the opportunities to identify and produce novel solutions (March 1991). However, in order to pursue exploratory search strategies firms must develop capabilities to manage unfamiliar knowledge and skills (Garcia-Granero et al. 2014). This is the reason why R&D orientation changes towards a more exploratory search of knowledge depend partly on the presence of highly qualified personnel.

Previous literature has associated the recruitment of scientific personnel with a higher probability to search beyond the firm's existing technological boundaries (Al-Laham et al. 2011). These highly skilled human resources are particularly well- positioned to take decisions regarding the course and orientation of R&D activities, since scientists are likely to perform gate-keeping and boundary spanning roles which enables the development of firm's capabilities with regard to collecting, assimilating, filtering and applying external knowledge (Rothaermel and Hess, 2007). Due to their exposure to breakthrough scientific knowledge and market needs, scientists provide firms with a substantial competitive advantage in order to assess accurately the implications of current research from a commercial point of view (Zellner, 2003).

Several studies have shown how scientists can change the focus of R&D activities towards more exploratory activities. Lacetera et al. (2004) found that hiring start scientists (those with a high productivity in terms of publications) increased the firm's propensity to engage in science–driven R&D activities. They showed that star scientists act as magnets for other researchers into the firm, which leads to a sharp improvement of the firm's performance as a knowledge contributor, both in terms of generating publications and patents. This capacity to attract qualified researchers is largely due to the role of star scientist to ensuring the credibility and legitimacy of R&D strategies which are oriented to basic research and exploration. In the same line, Ding (2011) showed that the PhD presence in biotech firms is strongly related to the firms' adoptions of open science policies, which encourage personnel to carry out basic science research. PhDs can thus develop a more profound understanding of scientific knowledge and grasp better cutting-edge scientific research methods, consequently, placing more importance on research benefits.

Other authors have also established that scientists' knowledge backgrounds have an influence on firms' R&D orientation, as they are determinant when firms have to choose between exploration or exploitation knowledge strategies. Some studies have shown that firm recruitment of scientists with distant knowledge (scientists who possess knowledge outside of the firm's technological boundaries) leads to engagement in exploratory research activities, compared to firms which enroll scientists with a knowledge background similar to the recruiting firm. (Tzabbar et al., 2013). Scientists' research orientations contribute also differently to the firms' knowledge exploration activities, thereby having different impacts on the innovation performance. Toole and Czarnitzki (2009) showed that scientists whose human capital are oriented towards exploring scientific opportunities significantly improve the firms' research-oriented task performance whereas those scientists whose human capital is oriented towards exploring commercial opportunities significantly improve the firms' invention-oriented task performance.

Scientists' backgrounds have also been revealed to be a critical factor to explain firms' innovation strategies. Subramanian (2012) pointed out that a strong scientific background in applied research is a key competence for combinatory innovations (which are obtained by exploring new knowledge derived from different technology types in an attempt of recombining them into novel innovations). In this regard, Herrmman and Peine (2011) show that scientists can alter their R&D focus in order to pursue radical, incremental or imitative strategies of innovation product development, providing evidence that exploration research activities are facilitated by scientists with heterogeneous knowledge backgrounds (scientists stemming from many different disciplines, countries and universities).

In sum, the presence of highly qualified scientists in firms' R&D units is likely to play a critical role in enabling experimentation and discovery processes, favoring the adoption of exploration-oriented strategies in firms' research activities.. Thus, we put forward the following hypothesis:

Hypothesis 2: *Firms employing highly qualified scientists (i.e. PhDs) are more likely to undertake a transition towards a broadening R&D strategy. These firms are more likely to: a) initiate explorative R&D activities; and b) sustain and intensify their R&D resource commitments to exploration research over time.*

## 3. Data and methodology

Corporate scientists' contributions to R&D resources or strategies have not been analyzed exhaustively. There are a number of key antecedents for our research: Lacetera et al. (2004) have analyzed the effect of hiring star scientists on the movement towards science-driven drug discovery in the pharmaceutical industry; and Tzabbar (2009) has analyzed if the recruitment of technologically distant scientists results in a significant technological repositioning in the biotechnology industry. Our study differs from theirs in three important points. First, we do not restrict the analysis to specific types of scientist (stars or technologically distant), but generalize it to ‘mean’ scientists. Second, we do not restrict the analysis to a very specific, science-intensive industry, such as drugs or biotechnology, but cover all manufacturing industries and, third, as a consequence, we broaden the analysis to cover the transition from occasional to permanent R&D in addition to the transition to more explorative R&D.

### 3.1 Data

The empirical analysis employs information from the Spanish Technological Innovation Panel (PITEC). This statistical instrument is developed by the Spanish Institute of Statistics (with advice from a group of university researchers) to study the evolution of the innovation activities of Spanish firms over time. The database is at the disposal of researchers on the FECYT web site[1]. The information provided in PITEC is based on the Spanish Innovation Survey, which belongs to a European-wide project known as Community Innovation Survey (CIS). CIS-type surveys have been widely used to analyze innovation-related question in economics and managements literatures (Mairesse and Mohen, 2010).

PITEC has three main advantages that make it particularly suitable for this study. First and most important a distinctive feature of PITEC is that it provides information on the R&D survey thus allowing for a more detailed picture on firms’ R&D activities. For example, it provides information on the number of PhDs in the firms’ R&D units, which is the key information for developing our analysis. Second, PITEC provides information about the breakdown of firms’ R&D investment in three components: basic, applied and development research expenditures. And third, PITEC is designed as a panel data survey so that we can observe firms’ transitions over time. Actually, this study would not be feasible with a cross-sectional data approach. We use data for the period 2006-2012, since the number of R&D personnel was not defined in terms of full-time equivalent units, prior to 2006. Additionally, we restrict our analysis

[1] http://icono.fecyt.es/Paginas/home.aspx. To observe confidentiality, an anonymized version of the data is available on the web site. The anonymization procedure applied at the PITEC is described on the web page.

to manufacturing firms because the role played by R&D in services is quite different and because we aim at retaining those sectors which generally set up formal R&D units.

To test the hypotheses, we formulate the following model:

$$T_{it} = \beta_0 + \beta_1 PhD_{it} + x'_{it}\gamma + \varepsilon_{it}$$

Where T is an indicator of transition, PhD is an indicator of PhDs in the R&D function of the firm and x is a vector of covariates. Definitions for all variables are provided in Table 1.

*Dependent variables*

We measure transition 1 using two different indicators. The first one (HoldR&D) aims to capture the continuous vs. occasional R&D activity and is defined as a dummy variable that takes the value 1 if the firm still performs R&D in t+1 and zero otherwise. The second one (R&Dvariation) is a continuous variable and is defined as the variation of the R&D investment per employee (in logs) between t and t+1.[2]

On the other hand, transition 2 is represented using three different indicators: The first one (Startexploration) aims to analyze the decision to start exploration activities, and it is defined as a dummy variable that takes the value 1 if the firm performs exploration activities in t+1 (considering only those firms not performing exploration activities in t). By exploration research activities we refer to the firm's resource investments in the *basic* and *applied* components of R&D activities (as opposed to *development*). The second measure (Holdexploration) captures the continuous vs. occasional exploration activity and is defined as dummy variable that takes the value 1 if the firm maintains or increases the investment in exploration activities in t+1, and zero if they reduced their investment in exploration research

[2] It is important to note that we are analyzing the role played by PhDs in the R&D function o firm's R&D transitions. Actually, we only observe PhDs for those firms already performing R&D, so that it is not feasible to analyse the decision to start R&D (by definition we do not observe PhDs prior to this decision). Accordingly, our population of interest for transition 1 will be composed only of firms already performing R&D.

activities. The third one (Explorationvariation) is a continuous variable and is defined as the variation of the exploration orientation of each firm for those firms already doing exploration activities. It is computed as the variation, between t and t+1, in the proportion of R&D resources devoted to basic and applied research relative to total budget on R&D activities.

*Explanatory variables and control variables*

Regarding PhDs, we use two different indicators. The first one is a dummy variable that take the value of 1 if a firm employs at least one PhD in its R&D unit and zero otherwise. The second one is the proportion of PhDs in the R&D unit defined as number of PhDs relative to the number of employees in the R&D unit.

Since firms undertaking these transitions may be different to those that do not undertake them in some characteristics related to the presence or proportion of PhDs in the R&D team, we consider a complete set of covariates based on the observables from the survey. If these variables were not included in the model, then they would be confounding factors leading to a biased estimation of the role played by PhDs. Covariates included are the following. Firm size (lsize), which we measure by the logarithm of a firms' employee count; firm's R&D intensity (RD_intensity), which we define by the logarithm of the firm's total R&D expenditures per employee; the size of the R&D unit (lsizeteam), which is a count of the full time equivalents working in that unit; exports (export) which is a dummy variable that takes value 1 if a firms sells products abroad and zero otherwise; parent and joint venture, which are dummy variables that takes value 1 if the firm is the parent inside a group or a joint venture, respectively, and zero otherwise; the age (lage) of the firm, which we define as the log of the number of years since birth; and an indicator of appropriability (appropriability) which we define following Czarnitzky et al. (2007) as the industry average of the answer to the following question: "how important are your competitors as a source of information for the innovation process". The original answers go from one to four, we rescale the total score to create an indicator that varies between zero and one. We also include two indicator related to innovation funding: pubfun which is a dummy variable that takes value 1 if the firm received public funding and zero otherwise; and obstacle_funds, which is a dummy variable that takes value 1if the firm reports that lack of internal or external funds were an obstacle to innovate of moderate or severe importance . Finally, we include year and industry dummies.

*Instrumental variables*

Despite controlling for a wide range of covariates, it may well be that not all the relevant confounding factors are observable. Additionally, even if they were observable, a complication would remain: the decisions to undertake an R&D transition and the decision to hire PhDs may be simultaneous. While the correlation between transitions and PhDs will still be of great interest, the causal effects would remain undetermined. To address this problem we adopt an instrumental variable approach. More precisely, we use two different instruments.

The first one is based on the idea of the existence of an exogenous supply of PhDs faced by firms. This exogenous supply should influence the hiring of PhDs in a way uncorrelated with the transition decisions made by firms. In other words, it should be a source of exogenous variation. We build an indicator for this supply based on the new PhDs having obtained their degree in scientific and technological fields relevant for the firm economic activity. To determine which scientific and technological fields are relevant for the firm economic activity, we use the matrix provided by Cohen et al. (2002) and follow the methodology employed by Abramovsky et al. (2007). To build this instrument we use information from the Statistics of the University System, provided by INE. The idea is to match the supply of PhDs to the different manufacturing industries and locations, so that an indicator of firm-specific supply of PhDs is developed (details of the construction of this indicator are provided in the Appendix).

Additionally, we use a second instrument: the industry average of the potentially endogenous variable; that is, a share of PhDs in the R&D unit. This kind of instrument has been widely used when conducting research based on CIS-surveys (see, for example, Cassiman and Veugelers, 2002; Veugelers and Cassiman, 2005). The idea is that, having controlled for the covariates, the industry average picks up the effect of the industry specific attributions that are uncorrelated with firm specific omitted factors (Veugelers and Cassiman, 2005; Barge-Gil and Conti, 2013).

*Estimation method*

Finally, regarding estimation techniques we have used both OLS and non-linear models (logit and probit) for the equation models with binary dependent variables and OLS for models with continuous dependent variables. When instrumental variable techniques are employed we used two stage least squares and two step probit with instrumental variables. We tried all specifications with clustered errors at the firm level and with generalized least squares or random effects panel data (this is due to the fact that within firm variation in the main variables is too low to run fixed effects regressions). In this version, we report the results from OLS models with standard errors clustered at the firm level. The reason is that, by using this strategy, marginal effects are easily interpreted and comparable across specifications. Results are robust to the utilization of the different estimation techniques previously described.

## 4. Descriptive statistics

We have 18,008 firm-year observations for firms performing internal R&D in t and still being in the sample in t+1. Descriptive statistics for all variables used in the analysis are provided in Table 2.

We observe that 18.21% of our firms have at least one PhD in the R&D team and the share of PhDs is 26.32% for those firms. Of those firms performing R&D in period t, 87.92% still perform R&D in t+1. As the period analyzed shows an economic crisis, we observe that R&D intensity decreased, on average, on 0.9 log points. The distribution is asymmetric to the left and the median firm only reduces R&D intensity by 0.016 log points.

Regarding exploration activities, an average of 45.3% of R&D investments are devoted to them[3]. 65.8% of firms perform some exploration activity and, among them, the average

[3] The high importance of exploration activities in Spanish firms when compared with other western countries has been documented by Barge-Gil and López (2015).

investment is 68.84% of total R&D. However, it is worth noting that these exploration investments are quite often occasional or discontinuous (33.4% of firms interrupt them in the following period). On the other hand, of those firms not performing exploration activities at a given period, 16.82% decided to start them the next period.

## 5. Results

### 5.1. Transition 1

Two indicators are analyzed for transition 1: firms consolidating R&D activities (HoldR&D) and variation in R&D intensity (R&Dvariation). As key variables we use two different indicators: whether the firm employs or not a PhD in the R&D team and the share of R&D employees in the R&D team. Results are reported in Tables 3 and 4.

For the probability of holding R&D activities, columns 1 and 2 show OLS results, while Columns 3 and 4 show IV results in Table 3[4]. Firms having a PhD increase the probability of holding R&D by 2 probability points according to OLS estimates and by 6.6 probability points in the IV estimation, while a 1 point increase in the proportion of PhDs increases the probability of holding R&D by 0.1 probability points in the OLS and by 0.2 probability point in the IV estimation.

Regarding results for the variation in R&D intensity, columns 1 and 2 show OLS results, while Columns 3 and 4 show IV results in Table 4[5]. Firms having a PhD show an increase in R&D intensity, compared to those firms without a PhD, of 0.24 log points in the OLS and 0.607 in the IV estimation, while a 1 point increase in the weight of PhDs increase R&D intensity by 0.007 log points in the OLS and by 0.019 log points in the IV estimation.

[4] Instruments satisfy inclusion restriction (F=828.336, p.value=0.000) and exclusion restriction (Sargan test p-value=0.686). Wu-Hausman test of endogeneity shows a p-value equal to 0.0254.
[5] Instruments satisfy inclusion restriction (F=489.03, p.value=0.000) and exclusion restriction (Sargan test p-value=0.772). Wu-Hausman test of endogeneity shows a p-value equal to 0.0275.

To sum up, regardless of the methodology employed and the indicators used for the dependent or the independent variables, the effect of PhDs on the transition 1 are positive, important in magnitude and statistically significant.

### 5.2. Transition 2

Three indicators are analyzed for transition 2. First, the decision to start exploration activities (Startexploration); second, the decision to consolidate exploration activities (Holdexploration); and third, the variation in the proportion of exploration activities (Explorationvariation). The results are shown in Tables 5, 6 and 7.

For the decision to start exploration activities, columns 1 and 2 show OLS results, while Columns 3 and 4 show IV results in Table 5.[6] The sample is smaller now because is composed only of firms not doing exploration in period t. Firms having a PhD increase the probability of starting exploration by 4 probability points in the OLS and by 43 probability points in the IV estimation, while a 1 point increase in the proportion of PhDs increases the probability of starting exploration by 0.1 probability points in the OLS and by 1.4 probability point in the IV estimation. The difference between OLS and IV estimations are much larger now. This result suggests that the biases from OLS estimations (i.e. underestimation) are much more severe when analyzing the second transition than when analyzing the first one, compared to estimates using instrumental variables.

For the decision to maintain exploration research activities (that is, avoid discontinuity in exploration activities), columns 1 and 2 show OLS results, while Columns 3 and 4 show IV results in Table 6.[7]. The sample is now composed of those firms doing exploration in period t. Firms having a PhD increase the probability of holding exploration by 3.9 probability points in the OLS and by 27.1 probability points in the IV estimation, while a 1 point increase in the weight of PhDs increases the probability of holding exploration by 0.1 probability points in the OLS and by 0.9

[6] Instruments satisfy inclusion restriction (F=89.827, p.value=0.000) and exclusion restriction (Sargan test p-value=0.1472). Wu-Hausman test of endogeneity shows a p-value equal to 0.0000.
[7] Instruments satisfy inclusion restriction (F=566.671, p.value=0.000) and exclusion restriction (Sargan test p-value=0.8592). Wu-Hausman test of endogeneity shows a p-value equal to 0.0000

probability points in the IV estimation. Again, the difference between OLS and IV estimations is quite large.

Finally, for the variation in exploration research activities, columns 1 and 2 show OLS results, while Columns 3 and 4 show IV results in Table 7.[8] The sample, as in the previous case, is composed of those firms doing exploration in period t. Firms having a PhD show an increase in exploration intensity, compared to those firms without a PhD, of 3.087 points in the OLS and 12.4 points in the IV, while a 1 point increase in the proportion of PhDs increase R&D intensity by 0.08 points in the OLS and by 0.395 points in the IV estimation.

To sum up, regardless of the methodology employed and the indicators used for the dependent or the independent variables, the effect of PhDs on transition 2 are positive, important in magnitude and statistically significant.

## 6. Discussion and conclusions

The purpose of this work has been to analyze the role played by PhD in R&D units as a triggering factor for two critical transitions in R&D strategies: R&D deepening (shifting from sporadic to persistent R&D efforts) and R&D broadening (shifting to more explorative-oriented R&D). While previous studies on this topic have focused on star scientists and on high tech sectors, we aimed to carry out a more general project, covering all manufacturing industries and every PhD in the R&D unit. To this aim, we test our propositions in a large sample of Spanish manufacturing and R&D performing firms, covering the period 2006-2012.

We find that the availability of PhDs in the organization R&D unit does not only contribute to increase the chances of persistence in R&D efforts, but it also increases the proportion of resources devoted to R&D over time. Thus, we show that it has a large positive contribution to facilitate the transition towards a continuous R&D commitment. Moreover, our

[8] Instruments satisfy inclusion restriction (F=566.671, p.value=0.000) and exclusion restriction (Sargan test p-value=0.4842). Wu-Hausman test of endogeneity shows a p-value equal to 0.0006.

results show that firms with a larger proportion of PhDs in their R&D activities are far more likely to start exploration activities, and to intensify the efforts towards exploration (relative to exploitation), compared to firms with a low proportion of PhDs.

We have included a large set of covariates to show that these results are robust to alternative explanatory factors (i.e. appropriability regimes, age and size of the firm, etc.) and we use an instrumental variable approach, building two indicators of the exogenous supply of PhD graduates that are used as instruments. We believe that the methodology used contributes to address endogeneity concerns.

This work has focused on average effects. Future research will be aimed at analyzing the heterogeneous effect of the role played by PhDs in R&D units in different types of firms, according to their size, internal R&D capabilities or manufacturing industry.

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**Appendix: Construction of the PhD supply**

To build our PhD supply measure we need to determine which scientific fields are relevant for a given industry. We follow Abramovsky et al. (2007) and match scientific fields to industries using data from the 1994 Carnegie Mellon Survey (CMS).This survey asks firms about the importance they attach to the following ten research fields: biology, chemistry, physics, computer science, material science, medical and health science, chemical engineering, electrical engineering, mechanical engineering and mathematics. Following Abramovsky et al. (2007) we establish that a research field is relevant for an industry if more than 50% of the CNS respondents in this industry had reported that the field is moderately or very important.

Data on the new PhD by fields and university are available at: http://www.ine.es/jaxi/menu.do?type=pcaxis&path=%2Ft13%2Fp405&file=inebase&L=0

We compute the new PhDs by year, university and scientific fields and match them with each firm using the region and industry of the firm, with the aim to develop a firm-specific measure of PhD supply. More precisely, we compute the number of new PhDs from universities in the same region and in scientific fields relevant for the firms' economic activity9. While the assumption of no mobility between regions may be quite strong, it looks like more reasonable than the assumption of perfect mobility. On the one hand, Spanish labor force is very immobile. On the other, data from the 2009 Survey of Human Resources for R&D (http://www.ine.es/jaxi/menu.do?type=pcaxis&path=%2Ft14%2Fp225&file=inebase&

[9] The indicator is normalized using the total number of R&D employees in each region.

L=0) shows that only 36.9% of PhDs work in a different region than the birth region[10]. We have tested the robustness of results to this assumption and they hold under the perfect mobility assumption, although the instrument, obviously, shows lower variation. Additionally, they also hold using a ‘neighbourhood’ assumption where people move to neighbour regions. Results of these checks are available upon request from the authors.7

[10] Ideally, we would like to know the percentage of PhDs working in the same region where they got the PhD but there are no public data of the region where they got the PhD. Presumably, the figure would be lower because some people move before doing the PhD.

**Appendix: Tables**

Table 1. Variable definition

| Variable | Definition | Mean | Std Dev |
|---|---|---|---|
| HoldR&D | Dummy variable that takes the value of 1 if the firm still performs internal R&D in t+1 | 0.88 | 0.33 |
| R&Dvariation | $R\&Dintensity_{t+1}$ –$R\&Dintensity_{t}$ (both measured in logs) | -0.90 | 2.60 |
| Startexploration | Dummy variable that takes the value of 1 if the firm performs exploration activities in t+1 (defined only for those firms not performing exploration activities in t) | 0.09 | 0.28 |
| Holdexploration | Dummy variable that takes the value of 1 if the firm still performs exploration activities in t+1 (defined only for those firms already performing exploration activities in t) | 0.67 | 0.47 |
| Explorationvariation | $Exploration_{t+1}$-$Exploration_{t}$ (where research is the proportion of R&D resources related to research activities) | -14.22 | 36.80 |
| phd | Dummy variable that takes the value of 1 if the firm has at least one PhD in the R&D team | 0.18 | 0.39 |
| sphd | Percentage of PhDs in the R&D team | 4.79 | 14.5 |
| lsize | Total number of employees (in logs) | 4.24 | 1.33 |
| RD_intensity | Total R&D expenditures per employee (in logs) | 7.97 | 1.29 |
| export | Dummy variable that takes the value of 1 if the firm exports | 0.88 | 0.33 |
| lsizeteam | Total number of employees in the R&D team (in logs) | 1.33 | 1.15 |
| parent | Dummy that takes the value of 1 if the firm  is the parent company of a group | 0.09 | 0.28 |
| joint_venture | Dummy that takes the value of 1 if the firm is the result of a joint venture | 0.01 | 0.10 |
| obstacle_funds | Dummy variable that takes the value of 1if the firm reports that lack of funds internal or external funds were an obstacle to innovate of moderate or severe importance | 0.75 | 0.44 |
| appropriability | Industry average of the answers to the question: How important are your competitors as a source of information for the innovation process? | 2.78 | 0.16 |
| lage | Firm age (in logs) | 3.13 | 0.71 |
| pubfun | Dummy variable that takes the value of 1 if the firm received public funding | 0.49 | 0.50 |

Table 2. Correlation matrix

| | phd | sphd | lsize | RD_intensity | export | lsizeteam | parent | Joint_venture | Obstacle_funds | appropriability | lage | pubfun |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | | | | |
| Phd | 1 | | | | | | | | | | | |
| Sphd | 0.7013 | 1 | | | | | | | | | | |
| Lsize | 0.1929 | -0.0258 | 1 | | | | | | | | | |
| RD_intensity | 0.1806 | 0.082 | -0.3252 | 1 | | | | | | | | |
| Export | 0.0656 | 0.0129 | 0.1989 | -0.0023 | 1 | | | | | | | |
| lsizeteam | 0.3327 | 0.0282 | 0.5912 | 0.4306 | 0.1574 | 1 | | | | | | |
| Parent | 0.1093 | 0.0334 | 0.1943 | 0.0036 | 0.0686 | 0.1683 | 1 | | | | | |
| Joint_venture | 0.0003 | 0.0043 | 0.0142 | 0.009 | 0.0136 | 0.0185 | -0.0326 | 1 | | | | |
| obstacle_funds | -0.0258 | -0.0007 | -0.1365 | 0.0437 | -0.0307 | -0.0755 | -0.0073 | -0.0087 | 1 | | | |
| appropriability | -0.1225 | -0.0712 | 0.075 | -0.2485 | -0.019 | -0.1861 | 0.0023 | -0.0231 | 0.0012 | 1 | | |
| lage | 0.0666 | -0.0195 | 0.3373 | -0.1397 | 0.1734 | 0.1671 | 0.1052 | -0.0129 | -0.0879 | 0.0174 | 1 | |
| pubfun | 0.1201 | 0.0342 | 0.1253 | 0.2428 | 0.051 | 0.2717 | 0.0795 | -0.0062 | 0.0401 | -0.0109 | 0.0059 | 1 |

Table 3. Transition 1. Dependent variable HoldR&D

| | (1) Dummy OLS | (2) Share OLS | (3) Dummy IV | (4) Share IV |
|---|---|---|---|---|
| phd | 0.020*** | | 0.066*** | |
| | [0.006] | | [0.022] | |
| sphd | | 0.001*** | | 0.002*** |
| | | [0.000] | | [0.001] |
| lsize | 0.041*** | 0.041*** | 0.040*** | 0.041*** |
| | [0.004] | [0.004] | [0.004] | [0.004] |
| RD_intensity | 0.034*** | 0.034*** | 0.033*** | 0.033*** |
| | [0.004] | [0.004] | [0.004] | [0.004] |
| export | 0.057*** | 0.057*** | 0.056*** | 0.056*** |
| | [0.010] | [0.010] | [0.008] | [0.008] |
| lsizeteam | 0.006 | 0.008 | 0.003 | 0.009** |
| | [0.005] | [0.005] | [0.005] | [0.005] |
| parent | -0.004 | -0.003 | -0.008 | -0.007 |
| | [0.008] | [0.008] | [0.009] | [0.009] |
| joint_venture | -0.030 | -0.031 | -0.030 | -0.033 |
| | [0.025] | [0.025] | [0.024] | [0.024] |
| obstacle_funds | -0.002 | -0.002 | 0.001 | 0.001 |
| | [0.006] | [0.006] | [0.006] | [0.006] |
| appropriability | -0.009 | -0.010 | 0.010 | 0.008 |
| | [0.022] | [0.022] | [0.024] | [0.024] |
| mediumlow | 0.011 | 0.011 | 0.010 | 0.010 |
| | [0.008] | [0.008] | [0.007] | [0.007] |
| mediumhigh | 0.038*** | 0.038*** | 0.039*** | 0.038*** |
| | [0.008] | [0.008] | [0.008] | [0.008] |
| high | 0.049*** | 0.049*** | 0.047*** | 0.046*** |
| | [0.011] | [0.011] | [0.011] | [0.011] |
| lage | 0.007* | 0.007* | 0.005 | 0.007* |
| | [0.004] | [0.004] | [0.004] | [0.004] |
| pubfun | 0.006 | 0.006 | 0.002 | 0.002 |
| | [0.005] | [0.005] | [0.005] | [0.005] |
| year06 | 0.021*** | 0.021*** | 0.018** | 0.019** |
| | [0.008] | [0.008] | [0.009] | [0.009] |
| year07 | 0.007 | 0.007 | 0.005 | 0.006 |
| | [0.008] | [0.008] | [0.009] | [0.009] |
| year08 | -0.013 | -0.013 | -0.011 | -0.010 |
| | [0.008] | [0.008] | [0.009] | [0.009] |
| year09 | -0.015* | -0.015* | -0.018** | -0.018** |
| | [0.009] | [0.009] | [0.009] | [0.009] |
| year10 | -0.006 | -0.006 | -0.008 | -0.007 |
| | [0.009] | [0.009] | [0.009] | [0.009] |
| *N* | 17520 | 17520 | 16999 | 16999 |
| chi2 | | | 1094.374 | 1092.692 |
| r2 | 0.061 | 0.061 | 0.058 | 0.056 |

Marginal effects; Standard errors (clustered by firm) in brackets
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4. Transition 1. Dependent variable: R&Dvariation

| | (1)<br>Dummy OLS | (2)<br>Share OLS | (3)<br>Dummy IV | (4)<br>Share IV |
|---|---|---|---|---|
| phd | 0.244*** | | 0.607*** | |
| | [0.047] | | [0.178] | |
| sphd | | 0.007*** | | 0.019*** |
| | | [0.001] | | [0.006] |
| lsize | 0.100*** | 0.104*** | 0.097*** | 0.103*** |
| | [0.035] | [0.035] | [0.032] | [0.032] |
| RD_intensity | -0.210*** | -0.210*** | -0.209*** | -0.214*** |
| | [0.033] | [0.033] | [0.029] | [0.029] |
| export | 0.469*** | 0.468*** | 0.465*** | 0.463*** |
| | [0.078] | [0.078] | [0.061] | [0.061] |
| lsizeteam | 0.290*** | 0.312*** | 0.262*** | 0.321*** |
| | [0.040] | [0.040] | [0.039] | [0.038] |
| parent | 0.006 | 0.012 | -0.025 | -0.019 |
| | [0.060] | [0.060] | [0.071] | [0.070] |
| joint_venture | -0.179 | -0.187 | -0.176 | -0.200 |
| | [0.205] | [0.205] | [0.189] | [0.189] |
| obstacle_funds | -0.022 | -0.021 | -0.007 | -0.005 |
| | [0.044] | [0.044] | [0.045] | [0.045] |
| appropriability | 0.059 | 0.053 | 0.176 | 0.160 |
| | [0.178] | [0.178] | [0.190] | [0.190] |
| mediumlow | 0.132** | 0.131** | 0.125** | 0.128** |
| | [0.065] | [0.065] | [0.057] | [0.057] |
| mediumhigh | 0.410*** | 0.406*** | 0.410*** | 0.401*** |
| | [0.066] | [0.066] | [0.063] | [0.063] |
| high | 0.671*** | 0.671*** | 0.640*** | 0.635*** |
| | [0.090] | [0.090] | [0.091] | [0.092] |
| lage | 0.043 | 0.047 | 0.035 | 0.045 |
| | [0.030] | [0.030] | [0.030] | [0.030] |
| pubfun | 0.120*** | 0.121*** | 0.087** | 0.088** |
| | [0.043] | [0.043] | [0.041] | [0.041] |
| year06 | 0.145** | 0.146** | 0.121* | 0.127* |
| | [0.064] | [0.064] | [0.070] | [0.070] |
| year07 | 0.118* | 0.120* | 0.097 | 0.102 |
| | [0.065] | [0.065] | [0.070] | [0.070] |
| year08 | -0.072 | -0.069 | -0.057 | -0.047 |
| | [0.067] | [0.067] | [0.070] | [0.070] |
| year09 | -0.092 | -0.092 | -0.123* | -0.122* |
| | [0.069] | [0.069] | [0.072] | [0.072] |
| year10 | -0.026 | -0.025 | -0.045 | -0.039 |
| | [0.070] | [0.070] | [0.073] | [0.073] |
| *N* | 17520 | 17520 | 16999 | 16999 |
| chi2 | | | 904.873 | 903.101 |
| r2 | 0.052 | 0.053 | 0.048 | 0.047 |

Marginal effects; Standard errors (clustered by firm) in brackets
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5. Transition 2. Dependente variable: Startexploration

| | (1)<br>Dummy OLS | (2)<br>Share OLS | (3)<br>Dummy IV | (4)<br>Share IV |
|---|---|---|---|---|
| phd | 0.040** | | 0.438*** | |
| | [0.018] | | [0.076] | |
| sphd | | 0.001*** | | 0.014*** |
| | | [0.000] | | [0.003] |
| lsize | -0.004 | -0.004 | -0.006 | -0.002 |
| | [0.008] | [0.008] | [0.008] | [0.009] |
| RD_intensity | -0.007 | -0.007 | -0.011 | -0.011 |
| | [0.007] | [0.007] | [0.007] | [0.007] |
| export | 0.018 | 0.017 | 0.018 | 0.008 |
| | [0.016] | [0.016] | [0.016] | [0.016] |
| lsizeteam | -0.003 | -0.001 | -0.020* | 0.001 |
| | [0.010] | [0.010] | [0.010] | [0.010] |
| parent | 0.022 | 0.022 | 0.016 | 0.011 |
| | [0.021] | [0.021] | [0.021] | [0.022] |
| joint_venture | 0.079 | 0.080 | 0.069 | 0.077 |
| | [0.056] | [0.056] | [0.054] | [0.056] |
| obstacle_funds | 0.025** | 0.025** | 0.026** | 0.020 |
| | [0.012] | [0.012] | [0.012] | [0.012] |
| appropriability | -0.066 | -0.065 | -0.065 | -0.059 |
| | [0.043] | [0.043] | [0.049] | [0.050] |
| mediumlow | -0.023 | -0.022 | -0.022 | -0.019 |
| | [0.016] | [0.016] | [0.015] | [0.016] |
| mediumhigh | -0.026 | -0.026 | -0.032* | -0.033* |
| | [0.018] | [0.017] | [0.017] | [0.018] |
| high | -0.020 | -0.020 | -0.048* | -0.045* |
| | [0.025] | [0.025] | [0.025] | [0.026] |
| lage | -0.016* | -0.016* | -0.017** | -0.012 |
| | [0.009] | [0.009] | [0.008] | [0.009] |
| pubfun | 0.002 | 0.002 | -0.011 | -0.005 |
| | [0.011] | [0.011] | [0.011] | [0.011] |
| year06 | 0.008 | 0.008 | 0.003 | -0.004 |
| | [0.018] | [0.018] | [0.019] | [0.019] |
| year07 | 0.015 | 0.014 | 0.013 | 0.004 |
| | [0.018] | [0.018] | [0.019] | [0.020] |
| year08 | -0.019 | -0.019 | -0.023 | -0.023 |
| | [0.017] | [0.017] | [0.019] | [0.020] |
| year09 | -0.009 | -0.009 | -0.017 | -0.017 |
| | [0.018] | [0.018] | [0.019] | [0.020] |
| year10 | -0.028 | -0.027 | -0.029 | -0.025 |
| | [0.018] | [0.018] | [0.020] | [0.021] |
| *N* | 5997 | 5997 | 5815 | 5815 |
| chi2 | | | 69.951 | 66.344 |
| r2 | 0.007 | 0.008 | . | . |

Marginal effects; Standard errors (clustered by firm) in brackets
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6. Transition 2. Dependent variable Holdexploration

| | (1)<br>Dummy OLS | (2)<br>Share OLS | (3)<br>Dummy IV | (4)<br>Share IV |
|---|---|---|---|---|
| phd | 0.039*** | | 0.271*** | |
| | [0.013] | | [0.039] | |
| sphd | | 0.001*** | | 0.009*** |
| | | [0.000] | | [0.001] |
| lsize | 0.041*** | 0.042*** | 0.031*** | 0.033*** |
| | [0.008] | [0.008] | [0.008] | [0.008] |
| RD_intensity | 0.031*** | 0.031*** | 0.020*** | 0.016** |
| | [0.007] | [0.007] | [0.007] | [0.007] |
| export | 0.025 | 0.025 | 0.018 | 0.020 |
| | [0.016] | [0.016] | [0.014] | [0.015] |
| lsizeteam | -0.008 | -0.004 | -0.021** | 0.011 |
| | [0.009] | [0.009] | [0.009] | [0.009] |
| parent | 0.034** | 0.035** | 0.016 | 0.019 |
| | [0.016] | [0.016] | [0.016] | [0.016] |
| joint_venture | 0.001 | -0.001 | 0.020 | 0.005 |
| | [0.043] | [0.043] | [0.043] | [0.043] |
| obstacle_funds | -0.019* | -0.019* | -0.015 | -0.013 |
| | [0.011] | [0.011] | [0.010] | [0.011] |
| appropriability | 0.016 | 0.014 | 0.044 | 0.032 |
| | [0.048] | [0.048] | [0.045] | [0.046] |
| mediumlow | -0.037** | -0.037** | -0.028** | -0.026* |
| | [0.015] | [0.015] | [0.013] | [0.014] |
| mediumhigh | 0.003 | 0.002 | 0.011 | 0.006 |
| | [0.016] | [0.016] | [0.015] | [0.015] |
| high | 0.020 | 0.020 | 0.007 | 0.001 |
| | [0.023] | [0.023] | [0.021] | [0.022] |
| lage | 0.016** | 0.016** | 0.016** | 0.021*** |
| | [0.007] | [0.007] | [0.007] | [0.007] |
| pubfun | -0.030*** | -0.030*** | -0.036*** | -0.037*** |
| | [0.010] | [0.010] | [0.010] | [0.010] |
| year06 | -0.040*** | -0.040*** | -0.031* | -0.026 |
| | [0.015] | [0.015] | [0.016] | [0.017] |
| year07 | -0.019 | -0.019 | -0.013 | -0.007 |
| | [0.015] | [0.015] | [0.016] | [0.017] |
| year08 | -0.030** | -0.030** | -0.023 | -0.018 |
| | [0.015] | [0.015] | [0.016] | [0.017] |
| year09 | -0.010 | -0.010 | -0.010 | -0.010 |
| | [0.015] | [0.015] | [0.017] | [0.017] |
| year10 | -0.007 | -0.007 | -0.005 | -0.002 |
| | [0.016] | [0.016] | [0.017] | [0.017] |
| *N* | 11523 | 11523 | 11184 | 11184 |
| chi2 | | | 296.143 | 288.941 |
| r2 | 0.023 | 0.023 | . | . |

Marginal effects; Standard errors (clustered by firm) in brackets
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7. Transition 2. Dependent variable: Explorationvariation

| | (1)<br>Dummy OLS | (2)<br>Share OLS | (3)<br>Dummy IV | (4)<br>Share IV |
|---|---|---|---|---|
| phd | 3.087*** | | 12.399*** | |
| | [0.789] | | [2.934] | |
| sphd | | 0.080*** | | 0.395*** |
| | | [0.023] | | [0.094] |
| lsize | 4.300*** | 4.355*** | 3.954*** | 4.055*** |
| | [0.597] | [0.596] | [0.584] | [0.581] |
| RD_intensity | 3.605*** | 3.606*** | 3.233*** | 3.065*** |
| | [0.552] | [0.552] | [0.540] | [0.553] |
| export | 3.880*** | 3.899*** | 3.476*** | 3.598*** |
| | [1.282] | [1.284] | [1.103] | [1.106] |
| lsizeteam | -0.277 | 0.042 | -0.894 | 0.568 |
| | [0.692] | [0.692] | [0.696] | [0.699] |
| parent | 1.419 | 1.504 | 0.544 | 0.703 |
| | [0.972] | [0.971] | [1.194] | [1.193] |
| joint_venture | 1.206 | 1.066 | 2.292 | 1.585 |
| | [2.923] | [2.918] | [3.264] | [3.278] |
| obstacle_funds | -1.002 | -0.981 | -0.786 | -0.673 |
| | [0.769] | [0.768] | [0.796] | [0.801] |
| appropriability | 1.263 | 1.110 | 2.316 | 1.804 |
| | [3.059] | [3.054] | [3.458] | [3.458] |
| mediumlow | -0.316 | -0.321 | 0.086 | 0.172 |
| | [1.077] | [1.077] | [1.014] | [1.019] |
| mediumhigh | 2.392** | 2.320** | 2.875** | 2.628** |
| | [1.136] | [1.133] | [1.127] | [1.128] |
| high | 3.929** | 3.905** | 3.368** | 3.096* |
| | [1.536] | [1.534] | [1.615] | [1.628] |
| lage | 0.969* | 1.011** | 0.926* | 1.126** |
| | [0.502] | [0.503] | [0.517] | [0.518] |
| Pubfun | -0.174 | -0.178 | -0.440 | -0.517 |
| | [0.718] | [0.717] | [0.732] | [0.736] |
| year06 | 1.286 | 1.306 | 1.632 | 1.875 |
| | [1.186] | [1.186] | [1.235] | [1.247] |
| year07 | 1.156 | 1.189 | 1.183 | 1.461 |
| | [1.177] | [1.176] | [1.244] | [1.255] |
| year08 | 0.164 | 0.196 | 0.382 | 0.641 |
| | [1.182] | [1.182] | [1.241] | [1.250] |
| year09 | 0.114 | 0.111 | 0.026 | 0.051 |
| | [1.183] | [1.183] | [1.279] | [1.284] |
| year10 | 1.480 | 1.497 | 1.602 | 1.719 |
| | [1.236] | [1.235] | [1.288] | [1.294] |
| *N* | 11523 | 11523 | 11184 | 11184 |
| chi2 | | | 504.407 | 500.562 |
| r2 | 0.043 | 0.043 | 0.033 | 0.025 |

Marginal effects; Standard errors (clustered by firm) in brackets
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$