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Exploring and Yet Failing Less:

Learning from Exploration, Exploitation and Human Capital in R&D

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Abstract

Exploration is both a risky activity and a key ingredient in the strategy of firms that strive for radical innovations. This paper investigates a dual facet of the exploratory component of R&D activities with regards to innovation failures: while exploration increases firms' exposure to failure, it also provides learning opportunities to curve down innovation failures. This paper contributes to organizational learning and innovation management research by proposing that firms' valuable learning does not automatically follow from exploration, but instead, it is conditional on reaching a threshold level of exploratory R&D activities. It is also proposed that valuable learning from exploration is enhanced when exploration is combined with other complementary sources of learning: exploitation and human capital. Our baseline results point to an inverted U-shaped relation: investment in exploratory activities increases the rate of failure in innovation up to a point beyond which exploration is found to decrease the rate of failure. We observe this inverted U-shaped relationship both at the conception and development phases of the innovation process. We also show that firms' commitments to exploitative R&D activities and the availability of human capital act as relevant moderators: they contribute to speed the organisational learning process enhanced by exploration and result in lowering the probability of innovation failure at the downstream and conception phases, respectively.

Keywords: *innovation failure; exploration; exploitation; human capital; learning*

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1. INTRODUCTION

Exploration is a key ingredient in the strategy of firms that strive for radical innovations. Since disruptive innovations entail the promise of large revenue opportunities and contribute to build resources that are difficult to imitate by competitors, exploration strategies become fundamental for building a firm's sustained competitive advantage (Bower & Christensen, 1995; Christensen, 1998). However, exploration also increases the exposure of firms to failure. Thus, while firms need to explore in order to build and retain a competitive edge, they also need to learn how to manage the greater uncertainty and risk involved in highly explorative innovation activities (Edmondson, 2011).

This is not an easy balance. Firms want to minimise operational-based instances of failures and curve down failures to a minimum (Desai, 2010). At the same time, firms might be willing to tolerate some degree of failure so long as it provides valuable new knowledge and learning opportunities for their innovation strategies (Leonard-Barton, 1995; Edmondson, 2011). While there is a well-established literature examining the returns to research and development (R&D) on firms' innovation performance (Mansfield, 1980; Freeman, 1982; Rosenberg, 1990), and an increasing literature on the organisational learning opportunities from failure (Haunschild & Sullivan, 2002; Madsen & Desai, 2010), there is much less research about the relationship between firms' exploration activities within the R&D department and innovation failure.

This paper aims to contribute to the organisational learning and innovation management literatures by shedding new light on the mechanisms that govern the capacity of firms to generate valuable learning from R&D exploration. More specifically, we propose that valuable learning is not a mechanical outcome from accumulated exploration, as a traditional learning-curve perspective would assume (Zangwill & Kantor, 1998). Instead, we contend that fruitful learning from exploration is conditional on reaching a threshold level of exploratory R&D. This expected non-linearity is due to the complexity of the processes involved in exploration activities and to the fact that outcomes from exploration are inherently challenging to interpret, and are therefore susceptible to cause attribution errors about the precise underlying causal relationships and inferential errors from the restricted samples of experimentation results.

We also contend that effective learning opportunities from exploration can be enhanced when exploration is combined with other complementary sources of learning within organisations: exploitation activities and human capital. The underlying rationale is that R&D exploitation and availability of highly research-skilled employees enhance firms' capacity to obtain valuable knowledge from the learning opportunities generated by exploration activities. Both R&D exploitation activities and human capital provide firms with strategic assets to overcome cognitive biases derived from the inherently complex and causal ambiguous results from exploration activities.

Accordingly, we examine the following interrelated questions. First, we investigate whether, and to what extent, firms learn from the exploratory component of R&D by succeeding to reduce innovation failure at both the conception and downstream phases of the innovation process. And second, we investigate whether the firm's engagement in exploitation within the R&D activities and the availability of highly qualified human capital contribute to speed the organisational learning process from exploration with regards to lowering innovation failure.

To answer these questions we use a sample of 3,625 manufacturing firms from the Spanish Technological Innovation Panel (PITEC). We conduct an analysis that draws on information from the firms' expenditures in the exploratory (i.e. basic and applied research) and exploitative (product and process development) components of R&D activities. We find a curvilinear (inverted U-shape) relationship between investment in exploration and innovation failure at both the conception and downstream phases of the innovation process. Our results also provide evidence of a moderating role of both exploitation and human capital on the learning returns from exploration activities, at the downstream and conception phases of the innovation process, respectively.

The paper is organised as follows. First, we review the literature on exploration and failure in organisational learning, and the conditions that may contribute to enhance learning from exploration, showing the line of reasoning that leads to our hypotheses. Second, we describe the data and methods to test the hypotheses. Third, we present our findings and test whether our results are sensitive to different empirical models. Finally, we discuss the implications of our findings for management and future research.

2. CONCEPTUAL BACKGROUND AND HYPOTHESES

2.1 Exploration and innovation failure in R&D

Involvement in formal R&D activities is a crucial mechanism through which firms implement their strategic commitments to continuous learning and innovation strategies. R&D contributes to nurture and maintain expertise in fields that can represent future opportunities, and to build in-house competencies to develop new products or processes (Tidd et al., 1997; Cohen & Levinthal, 1990; Dodgson et al., 2008). This holds particularly true for exploratory R&D activities, which radically depart from the current experience of the organisation and provide a buffer to myopic learning.

Firms may deliberately try to counterbalance the biases towards learning process that are focused on the short run and involve experimentation in the near neighbourhood of current experience, by committing to continuous exploration activities. Exploration contributes to build and compromise capabilities outside current competencies and niches (Katila & Ahuja, 2002; Nerkar, 2003; Rosenkopf & Nerkar, 2001), and it favours the appreciation of risk-taking and the awareness of learning opportunities from unanticipated events (Edmondson, 2011; Madsen & Desai, 2010). While exploitation is necessary to guarantee survival in the short run, exploration is essential to secure long-term survival, as it allows for deviation from average and the potential realisation of a position of primacy and leadership among competitors (Levinthal & March, 1993; March, 1991).

However, exploratory R&D also expands the opportunity-space for instances of innovation failure, due to the inherent complex nature of the activities involved and uncertainty about the outcomes. Following Cannon and Edmondson (2005), we define failures as deviations from expected and desired results that include “both avoidable errors and the unavoidable negative outcomes of experiments and risk taking” (: 300). In the context of R&D activities, there are two critical phases where failures are likely to emerge. On the one hand, failure can take place at early stages of the innovation process - i.e. the conception or upstream phase - when ideas for new products are proposed and tested, with the aim to establish an intended design or a proof-of-concept prototype. On the other hand, failures can occur at later stages of the innovation process - i.e. development or downstream phase - when R&D efforts are oriented to achieve a functional or working prototype that sets the standards for scaling up manufacture.

In sum, while exploratory R&D may contribute to expand the firms’ search space and identification of new opportunities, it also increases the exposure of firms to instances of innovation failure. This leads us to question about whether, and to what extent, firms can manage this tension by virtue of learning from R&D exploration in order to curve down innovation failures.

2.2 Learning from R&D exploration activities

Firms involved in exploration set up programmed procedures and routines, thus suggesting that experimentation is far from an unstructured activity (Cyert & March, 1963; Nelson & Winter, 1982). When organising their exploration activities, firms are likely to accept and understand that more radical experiments will inevitably lead to more spectacular failures. As Leonard-Barton (1995) and Edmondson (2011) have pointed out, there are some instances of innovation failure that are associated to deliberate actions of organisations towards experimentation and exploration, as this type of failures are expected to provide valuable opportunities to gain new knowledge, helping the organisation to lead ahead of competition and ensure firms' future growth and survival. These instances of failures have been labelled as good, intelligent or desirable failures, because they are an inherent component of the learning process associated to exploration.

Intelligent failures are likely to be particularly important at early conception stages of an innovation project when firms are willing to explore different routes of action and aim at screening out unfeasible alternatives at comparatively low costs, as few resources are generally committed to any of the conceptual designs at early stages of product development (Cannon & Edmondson, 2005). Fostering experimentation at the conception phase can elicit extremely valuable information from failed options, since this information will help companies to avoid problems further downstream in the innovation process, when correcting problems involve costs that are orders of magnitude higher than at earlier stages. Learning capacity from experimentation has been dramatically expanded with the emergence of new simulation technologies that have systematically reduced the costs for the generation of critical data and information on new virtual prototypes, as opposed to physical ones (Thomke, 2001). These learning opportunities, however, cannot be taken for granted and firms may succumb to an overload of information and to the inherent uncertainties and complexity of tasks involved in exploration. In these circumstances, innovation failures become an almost unavoidable feature of exploration activities. Indeed, complexity-related failures, however undesirable, have come to be considered as a concurrent feature of firms' exploration strategies (Edmondson, 2011; Leonard-Barton, 1995).

In addition to intelligent and complexity-related failures, organisational learning research has also suggested the existence of 'failure traps' (Gupta et al., 2006), where engaging in exploration activities might lead to failure which in turn enhances further search, in an iterative self-reinforcing fashion. This argument goes in line with entrapment situations suggested in innovation management research, showing that it is often difficult for firms to stop unsuccessful ongoing innovation projects due to past organisational commitments (Balachandra et al., 1996; Jani, 2011). Innovation managers may find it difficult to disrupt and terminate ongoing unsuccessful projects if research teams have become highly emotionally involved, risking demoralising staff, or when continuation is required to justify previous investments, leading to a situation that is referred in the literature as 'escalation of commitment' (Jani, 2011; Scmidt and Calantone, 1998; Staw & Ross, 1987).

Despite the fact that 'intelligent' failures might be encouraged at conception phases of product development, and that 'entrapment' situations may lead to an escalation of commitments to projects that are identified as problematic at downstream stages of the innovation process, firms are expected to organise their exploration activities trying to keep operational innovation failures to a minimum, as failures reflect performance that falls below organisational targets (Desai, 2010), and often cause major disruptions in firms' competitive strategies (Kim & Miner, 2007; Madsen, 2009; Madsen & Desai, 2010).

Learning from programmed exploration to curve down failures can manifest in different ways. Sustained efforts on exploration contribute to develop intelligence, monitoring and surveillance capacities that enable firms to identify, analyze and act upon innovation failures (Edmondson, 2011; March, 1991). This programmed exploration can be particularly effective in curving down instances of "preventable" failure that are caused by deviance to rules, inattention or lack of abilities when conducting routine or predictable operations (Edmondson, 2011). Along similar lines, Thomke (2001) suggests that building experimentation capabilities implies avoiding two types of mistakes: those that result from badly conducted experiments and produce ambiguous or not valuable information, and those that involve repeating a prior failure. Thus, certain types of failures at both the conception and development phases are considered to be potentially avoidable as a result of operational-based learning: economies of scale in learning from exploration increase the possibility to develop effective monitoring and surveillance routine tasks that lower down the risks of failure both at the conception and development phases. At the same time, a sustained engagement in a exploration is expected to compensate for the flawed inference based on a small-scale experimentation (Kim et al., 2009).

According to the discussion above, we would expect a curvilinear, inverted U-shape relationship between exploration and the probability of experiencing failures at the conception and downstream phases. Regarding failures at the conception phase, it is argued that the probability of failure increases with exploration, not only as a result of the uncertain nature of exploration outcomes, but also because this stage prioritizes learning from 'intelligent' failures. However, this will happen only up to a point beyond which operational-based learning and accumulated intelligence from exploration lowers down the probability of failure, allowing the organisation to reach a faster and more effective screening of available alternatives. Accordingly, we put forward the following hypothesis:

H1: The degree of exploration in R&D has an inverted U-shaped relationship with the probability to experience an innovation failure at the conception phase.

Regarding failures at the downstream phase, it is argued that screening routines at early stages of product development are likely to be deficient or unsatisfactory and thus unlikely to prevent situations of 'entrapment' further downstream in the innovation process. However, we contend that once a certain scale of experimentation capabilities is reached, operational-based learning and accumulated intelligence from exploration should contribute to lower down the probability of failure at the development phase. This is a consequence of an improved capability for screening out poor alternatives at early stages, and a result of improved operational capabilities to deal with the complexity of product development downstream in the process. Accordingly we put forward that:

H2: The degree of exploration in R&D has an inverted U-shaped relationship with the probability to experience an innovation failure at the downstream phase.

2.3 Fastening learning from exploration: the role of exploitation and human capital

Learning from exploration is unlikely to be a straightforward process. Effective and faster learning demands some pre-conditions that should be satisfied by the organization (e.g. Edmondson, 2011; Gino & Pisano, 2011). Organisational learning and innovation management research highlight two critical conditions that are particularly relevant in the context of exploration in R&D: (i) the capacity of firms to balance exploration and exploitation activities (Gupta et al., 2006; Raisch et al., 2009), and (ii) the absorptive capacity of the organization as reflected by the availability of highly research-skilled human resources (Cohen & Levinthal, 1990). We discuss below the role of these two factors.

2.3.1 Balancing exploration and exploitation

Both exploration and exploitation activities are associated with learning and innovation (March, 1991; Gupta et al., 2006). Jointly carrying out exploration and exploitation activities is both crucial for the organizational survival and difficult since the two activities compete for limited physical and human resources (March, 1991), as well as for the attention of the organisation's decision makers (Ocasio, 1997). However, the trade-offs between exploration and exploitation should not be regarded as insurmountable. Recent research suggests that firms can design organizational structures that enable employees to pursue both types of activities, for instance, by reaching an adequate balance between intergroup connectivity and semi-isolated groups within the organisation (Gibson & Vermeulen, 2003; Gibson & Birkinshaw, 2004; Fang et al., 2010). Hence, exploration and exploitation can be seen as orthogonal categories, rather than ends of a continuum (Gupta et al., 2006).

Empirical evidence suggests that firm's ambidextrous capabilities that simultaneously exploit existing competencies and explore new opportunities are expected to trigger superior economic performance (Raisch et al., 2009). Similarly, exploratory (i.e. research) and exploitative (i.e. development) components of the R&D activities are found to complement each other with regards to the firm's achievement of higher productivity (Barge-Gil & Lopez, 2013). A fundamental reason underlying the rationale for the potential complementarities between exploration and exploitation rests on the potential benefits deriving from a continuous dialogue between experimentation and prototyping (Leonard-Barton, 1992; 1995). This logic highlights that organisations can potentially benefit from a two-way flow of information and knowledge between exploration and exploitation.

First, the efficiency of downstream research activities and prototyping benefit from insights gained by an ex-ante understanding of the innovation process (Nelson, 1982; David et al., 1992). In this respect, exploration can lower the risks of applied developments by flagging promising directions for downstream phases and by developing the necessary tools for more rapid and efficient (product and process) development (Pisano, 2006). And second, exploitative phases can provide critical information and feedback to experimentation units. By conducting rapid prototyping cycles, firms can identify features that do not work as expected in the lab, feeding reactions to product (or process) concept designers before major failures might ensue further downstream along the pipeline (Leonard-Barton, 1995). Moreover, by collecting information at close to market stages of product development, organizations are likely to identify when the returns from given strategies are reaching a point of exhaustion or decreasing returns, thus helping to alert about the need of a change in exploration avenues or making a leap to newer competencies or a focus on new technological paths (Ahuja & Katila, 2004; Mudambi & Swift, 2014).

Drawing on the above discussion, we would expect that organizations that conduct a critical level of development or exploitation activities, should exhibit a more effective and faster learning process in their exploration activities, experiencing lower instances of innovation failure. Moreover, these complementarities are expected to be more effective to curve down failures at the development phase than at the conception phase. Due to the 'escalation of commitment' effect, failure at later stages of product development often involves a great loss of resources. This may translate in higher incentives for the firms to maximize the returns from the two-way flow of knowledge between experimentation and exploitation in order to reduce instances of failure in the downstream phases (Edmondson, 2011). A similar outcome emerges when considering the contextual information coming from downstream experience, which is also likely to result in new designs and open-up the opportunity-space for exploration, and "cheap" failure at the conception phase (Cannon & Edmondson, 2005; Mudambi & Swift, 2014). All in all, we expect that for a given level of exploration, higher levels of exploitation generally reduce the probability of innovation failure. We also propose that this effect is likely to be stronger for downstream failures. Therefore, we put forward the following hypotheses on the moderating effect of exploitation:

H3a: The degree of exploitation in R&D negatively moderates the relationship between exploration and innovation failure at both the conception and development phases.

H3b: The negative moderation effect of exploitation in R&D is stronger for downstream failures than conception failures.

2.3.2 *Availability of highly research-skilled human resources*

A critical pre-condition particularly relevant in the context of exploration and experimentation activities, is the availability of highly skilled human resources (Cohen & Levinthal, 1990). Highly skilled employees are expected to equip the organisations' R&D teams with an adaptable, responsive and pro-active workforce (Beltramo et al., 2001; Leiponen, 2005). The essential role of highly skilled researchers and technicians in the learning process associated to exploration lies on the following three potential contributions.

First, highly research-skilled employees are particularly well suited to set in motion procedures for the systematic detection and analysis of success and failures, which contribute to effective organisational learning from exploration. Recognition and assessment of success and failure are indeed cognitively challenging for an organisation, especially because of the inertial effect of accumulated experience (Levinthal & March, 1993), wrong inferences on existing strategies due to persistent success (Gino & Pisano, 2011; Madsen & Desai, 2010), and bias of individuals in favour of current beliefs and practices (Edmondson, 2011). Highly research-skilled employees are likely to be in a position to face these cognitive challenges and barriers associated with detection and analysis of success and failures from exploration activities and display high tolerance for causal ambiguity (Cannon & Edmondson, 2005).

Second, highly research-skilled workers are likely to be positively predisposed to experimentation and feel attracted to risk-taking in exploration activities. They acknowledge that experimentation is necessary to push the boundaries of current understanding and knowledge within the organization. These individuals are highly intrinsically motivated to conduct research as they tend to set aspiration levels above current performance, engaging in both local and distant search (Levinthal & March, 1993; Garcia-Quevedo et al., 2012). Additionally, these employees also tend to engage in exploratory and experimental research as a learned mode of interaction with the extended community of researchers in the private and public sectors. Being active in exploration activities help them plugging into the enlarged epistemic community of researchers, of which they are often an integral part (Bercovitz & Feldman, 2007; Rosenberg, 1990).

Third, highly research-skilled employees also contribute to create a favourable climate for experimentation: they bring into the organization a culture of tolerance to, and acceptance of, failure that also attenuate the emotionally charged implications of unsuccessful projects. These individuals are often prepared to recognise that identification and admission of failure is praiseworthy if taken as an opportunity that provides valuable new knowledge. This is fundamental to create an organizational attitude that does not blame for failure, but on the contrary acknowledge that failure is an inherent and an unavoidable component of experimentation, exploration and, ultimately, of learning (Cannon & Edmondson, 2005; Edmondson, 2011; Shepherd et al., 2009).

Drawing on the above discussion, we would expect that organizations that have a critical mass of highly skilled R&D employees, should exhibit a more effective and faster learning in the innovation process. More specifically, we would expect that the research-skills levels of personnel employed in R&D activities will have a particularly strong impact on the learning processes at early stages of product development, contributing to speeding up the learning processes associated with well-structured activities, either by helping to avoid failures or by eliciting faster learning from instances of failure at the conception phase (Garcia-Quevedo et al., 2012). While we also expect human capital to have an impact on the relationship between exploration and failures at the development phase, we believe these effects are likely to be more indirect and slow to materialize due to the complexity and context-specific nature of downstream innovation activities (Davidsson & Honig, 2003). Therefore, we put forward the following hypothesis:

H4a: The degree of highly skilled R&D employees negatively moderates the relationship between exploration and innovation failure at both conception and development phases.

H4b: The negative moderation effect of highly skilled R&D employees is stronger for conception failures than downstream failures.

Figure 1 summarises our theoretical argumentation. In addition to the main link between exploratory R&D activities and innovation failures both at the conception and downstream phases, it also depicts –with dashed lines- the moderating effects exerted by skilled R&D workers and exploitative R&D.

[INSERT Figure 1 ABOUT HERE]

3. DATA AND METHODS

3.1 Data and sample frame

Our analysis is based on data stemming from the Spanish Technological Innovation Panel (PITEC), which is jointly managed by the Spanish National Statistics Institute (INE), the Spanish Foundation for Science and Technology (FECYT) and the Foundation for Technical

Innovation (COTEC). PITEC is a Community Innovation Survey (CIS)-type, firm-level dataset that results from subsequent waves covering a three-year period each.[1]

Table 1 presents the percentage of companies with positive spending in the exploratory (i.e. basic and applied research) and exploitative (product and process development) components of R&D activities, with respect to both the overall sample and the sample of positive investors, which are companies with positive expenditures in innovation-related activities (not confined to R&D). As Table 1 shows, both samples always contain a non-negligible number of companies that invest financial resources in either exploration or exploitation activities (more than 46%).

[INSERT Table 1 ABOUT HERE]

As discussed in the theoretical section, our main focus is on firms that experience different types of innovation failures, i.e. failure in the conception phase and failure in the development phase. Firms with positive investment in innovation can actually experience different rates of failure with respect to non-investors. Table 2 shows the proportion of manufacturing companies (from PITEC for period 2008-2010) experiencing failure in conception and downstream phases of innovation projects, distinguishing between positive and zero-investors. For both cases, the table clearly shows a much higher probability of failure for companies that are actively engaged in innovation (the difference between the two probabilities is statistically significant at the 1% confidence level), and it suggests that the proportion of non-innovation active firms that experience innovation failures is almost negligible.

[INSERT Table 2 ABOUT HERE]

[1] For a review on innovation surveys, see Mairesse and Mohnen (2010).

Table 3 reports the proportion of firms experiencing failure at conception and downstream, broken down into degree of investment in innovation related activities. It can be seen that for low and medium levels of investment in innovation activities the share of companies experiencing any type of failure sensibly increases. . Quite interestingly, for upper percentiles (from the 50^{th} in the case of downstream failures and from the 75^{th} in the case of conception failures) in the distribution the proportion of firms experiencing both types of failure flattens out. This may suggest a curvilinear relationship between the investment in innovation-related activities and the probability to experience failure in the innovation process.

[INSERT Table 3 ABOUT HERE]

Given the focus of our analysis, we restrict the sample to manufacturing firms that are susceptible to experience innovation failures. Specifically, we keep only those companies that do actually engage in innovation. In other terms, those firms that report a positive expenditure in innovation activities since, following evidence from Table 2, it is mainly firms involved in innovation-related activities that face instances of innovation failure.

Furthermore, we concentrate our investigation on the period 2008-2010. We do this by aggregating information from three different PITEC survey's waves. Indeed, some of the relevant questions contained in the 2010 wave of PITEC survey refer to the period 2008-2010 (e.g. different types of failure in innovation projects) while other questions refer to 2010 year only (e.g. employment, R&D spending, etc.). For consistency, we use the preceding two waves of the PITEC survey (i.e. the 2009 and 2008 survey waves) and complement information for the 2010 edition of the survey. In this way, we are able to build a full set of variables referring to the period 2008-2010. Concentrating our analysis on this period allows us to provide updated evidence, still focusing on a time-span in which the likely (and largely unobservable) concurring effect of the recent economic crisis can be deemed as stable. The resulting sample contains full information for the variables of interest for 3,625 manufacturing firms.

3.2 Methods and variables

Our interest is in estimating the factors that influence the event of two different types of failure in innovation through the use of the following probit models:

$$P(FAILCONCEPTION_i = 1 \mid X_i, Z_i) = \Phi(\beta' X_i + \gamma' Z_i)$$

$$P(FAILDOWNSTREAM_i = 1 \mid X_i, Z_i) = \Phi(\beta' X_i + \gamma' Z_i)$$

where $\Phi(\cdot)$ is the cumulative normal distribution function, X_i is the vector of our key explanatory variables and Z_i is the vector of firm-level controls.

3.2.1 Dependent variables

Our main dependent variables are *FAIL CONCEPTION* and *FAIL DOWNSTREAM*. *FAIL CONCEPTION* is a dummy that takes value 1 when the firm faced the event of a failure in the conception phase of an innovation project in the period 2008-2010, i.e. whether the firm has reported the abandonment of an innovation project at the conception phase. *FAIL DOWNSTREAM* is a dummy that takes value 1 when the firm faced the event of a failure in the downstream phase of an innovation project in the period 2008-2010, i.e. whether the firm has reported the abandonment of an innovation project at the downstream phase.

3.2.2 ***Explanatory variables***

As for the key explanatory variables, we build upon previous studies distinguishing between exploratory and exploitative activities in the R&D process (Czarnitzki et al., 2009; Czarnitzki et al., 2011: Barge-Gil and Lopéz, 2013). PITEC data allows us to distinguish the amount of investment in the different components of R&D: basic research, applied research and development. Taking advantage from the information provided, we create two variables:

EXPLORATION and *EXPLOITATION*. *EXPLORATION* is obtained by averaging, over the period 2008-2010, the sum of the expenditures in basic and applied research. The average sum is divided by the average number of employees in the same period. Finally, to reduce the skewness of the distribution, we apply a logarithmic transformation (adding +1 to avoid dropping the zeros). Similarly, *EXPLOITATION* is the log transformed ratio between the 2008-2010 average expenditure in development activities and the average number of employees in the same period. To capture the firm's human capital we use a dummy (*HUMAN CAPITAL*) that equals 1 in case the firm is in top tercile (i.e. top 33%) of the distribution of the R&D personnel with a university degree (Bachelor, Master or PhD).

Hypotheses 1 and 2 in the theoretical section predict an inverted U-shaped relationship between exploration activity in the R&D process and the probability to experience innovation failure both in the conception and development phases. To capture this non-linear effect we include in our econometric specification the squared term $EXPLORATION^2$.

We test for Hypotheses 3a and 3b interacting *EXPLOITATION* with a series of dummies that reflect the range of engagement in exploratory activities. This allows us to better capture whether *EXPLOITATION* moderates the effect of *EXPLORATION* for high or low values of the latter. To do that, we define five dummy variables: *EXPLORATION LOW*, *EXPLORATION MEDIUM LOW*, *EXPLORATION MEDIUM*, *EXPLORATION MEDIUM HIGH* and *EXPLORATION HIGH*. The key idea is that by interacting the dummies *EXPLORATION LOW, EXPLORATION MEDIUM LOW, EXPLORATION MEDIUM HIGH* and *EXPLORATION HIGH* with the continuous variable *EXPLOITATION* we will be able to single out any complementary contribution of *EXPLOITATION* in moderating the effect of exploratory activities on the probability to experience innovation failure.

Finally, Hypotheses 4a and 4b are tested by using interaction terms between the *EXPLORATION* (in its linear and quadratic form) and *HUMAN CAPITAL*.

3.2.3 Control variables

We try to minimize any problem of omitted variable bias by including a set of controls in the econometric specification. First of all, with a set of dummies we control for the hampering factors that in the period 2008-2010 may have affected the firm's innovation activities and, as a consequence, the likelihood to encounter a failure of both types. Given our focus on firms engaged in innovation we consider revealed barriers to innovation: that is, obstacles that firms experience along the innovation path (D'Este et al., 2012). As in recent contributions we consider both financial and non-financial barriers (e.g. Blanchard et al., 2013; D'Este et al., 2012, 2014). *COSTBAR* captures whether the firm faced at least one important obstacle with respect to: innovation costs, internal or external funding to innovation. *KNOWBAR* reflects whether the firm experienced at least a high barrier related to knowledge. Specifically, we consider obstacles associated to: skilled personnel, information on technology, information on markets and availability of suitable innovation partners. We finally consider the potential effect on innovation failures exerted by serious obstacles due to dominated market (*MKTDOMBAR*) and uncertain demand (*MKTUNCBAR*). We control for different forms of engagement in innovation not included in our measures of *EXPLORATION* and *EXPLOITATION* that may be particularly relevant for SMEs and non-R&D intensive industries (e.g. Rammer et al., 2009; Sterlacchini, 1999). To this aim, we employ *OTHEREXP*, defined as the log transformed 2008-2010 average sum (adding +1 to avoid dropping the zeros) of the expenditures per employee in: external R&D; machinery, equipment and software; external knowledge; training; market introduction of innovations, design and other preparations. To further capture the complex nature of the firm's innovation profile, we also control for the resort to the open innovation mode (e.g. Chesbrough, 2003).

Building upon the seminal paper by Laursen and Salter (2006), we include in our econometric specification two variables proxying for the breadth (*BREADTH*) and depth (*DEPTH*) in the external search strategies of information and knowledge for innovation. *BREADTH* takes on values from 0 to 10 according to the number of sources of information for innovation that have been used by a firm in the period under consideration. *DEPTH* ranges from 0 to 10 according to the number of sources of information rated as highly important by a firm in the period under consideration.[2]

Evidently, the likelihood to fail in innovation might be also related to the extent to which the firm carry out cutting-edge and risky innovation activities. For this reason we include a dummy (*RADICALINNO*) that captures whether the firm, in the considered period, introduced a radical innovation (i.e. new to the market). Moreover, we control for whether the company carried out organisational innovations in the period under consideration. *ORGINNO* takes on value 1 whether the firm has introduced any of the following (and zero otherwise): new or improved management systems; changes in the organization of work within the enterprise; changes in the relations with other organizations. Another relevant characteristic that we include among the controls is the (log transformed) firm's age (*AGE*), which is expected to be related to the propensity to introduce disruptive and risky innovations, as well as to face higher obstacles to innovate (e.g. Schneider and Veugelers, 2008). We also consider a set of characteristics that may influence innovation resources, incentives and, in turn, the likelihood to conduct innovation activities that lead to failure: group affiliation (*GROUP*); engagement in exports (*EXPORT*); and firm size (*SIZE*). The former two are measured as dummy variables, while firm size is measured as the natural logarithm of the average number of employees in the period 2008-2010 (plus 1). Finally, we include a set of variables to control

[2] The following sources of information for innovation are available from PITEC: suppliers; customers; competitors; consultants and private R&D institutes; Universities, public research institutes; technological transfer offices; conferences , trade fairs, exhibitions; scientific journals and trade/technical publications; professional and industry associations.

for the effect of industry characteristics. These are 2-digit industry dummies based on the NACE rev.2 classification and provided by PITEC.

Table 4 presents descriptive statistics of the variables used in this study; Table 5 reports the correlation matrix of our variables. In general, correlation across the independent variables is low, suggesting the absence of any relevant multi-collinearity problem.

[INSERT Table 4, Table 5 ABOUT HERE]

4. RESULTS

Results emerging from our econometric analysis are reported in Tables Table 6, Table **7** and Table 8. Our baseline model considers *EXPLORATION* and *EXPLOITATION* as main regressors (Table 6, Models I and II). Both terms positively affects the probability to experience an innovation failure either at the conception or downstream phase. Investing in R&D, both in its exploratory and exploitative components, increases the chances that some innovation projects are going to reveal unsuccessful. *Per se*, skilled R&D employees seem not to affect the rate of failure of the firm, pointing to the absence of a stable direct relationship between our measure of human capital and the probability of failure. We notice the relevance of many of the controls we employed in our econometric specifications. As expected, firms tend to experience a higher probability of failure at both the stages of the innovation process when they engage in radical innovation, or when they alter the organizational structure of the firm. The same occurs for the presence of relevant knowledge barriers. Nevertheless, the two different types of failure are determined also by specific factors. In particular, an overflow of non-structured external knowledge coming from broad knowledge sourcing and uncertainty on market response increases complexity at the conception phase and thus enhances the rate of failures. On the contrary, facing relevant obstacles related to innovation costs reduces the probability of abandoning an innovation project at the early stages: financially constrained firms seem to pursue less risky projects, which guarantee a safeguard towards dispersion of resources already in the conception phase. As for downstream failures, these are reduced by firm's engagement in other types of innovation investment. This is not surprising, given that our variable *OTHEREXP* includes investment that may be particularly important to improve the effectiveness of downstream innovation phase (e.g. machinery, equipment and software; market research, among others). Finally, partially contrasting our expectations, we notice the higher probability of older firms and firms belonging to a group of companies to face innovation failure in the downstream phase.

[INSERT Table 6 ABOUT HERE]

Table 6 provides also support to our first two hypotheses (Table 6, Models III and IV). The exploration component of R&D has an inverted U-shape effect on the probability to face a failure at both conception and downstream phases of innovation projects. Despite the initial increase in the rate of innovation failure, increasing the scale of exploration in R&D engenders a learning process that reduces the abandonment of innovation projects. Capacity to analyse and act upon previously abandoned exploratory activities, acquisition of monitoring and intelligence capacities and operational-based learning (March, 1991; Desai, 2010; Edmondson, 2011) help explain the support for Hypothesis 1, while an improved capability for screening out poor alternatives at early stages and improved operational capabilities to deal with the complexity of radically new product development downstream in the process help explain the support for Hypothesis 2. Building on Models III and IV in Table 6, Figures Figure 2 and Figure 3 depict the curvilinear relationships between the value of *EXPLORATION* and the predicted probability of experiencing innovation failure at the conception and downstream phases, respectively.

[INSERT Figure 2, Figure 3 ABOUT HERE]

The second set of hypotheses put forward in the theoretical section relates to the moderating effects that contribute to speed up the learning from a sustained engagement in the exploratory component of R&D. Specifically, with our Hypotheses 3a and 3b we investigate the moderation role exerted by *EXPLOITATION* on the relation between *EXPLORATION* and the probability to fail at the conception or downstream phases.[3] To do this, we interact *EXPLOITATION* with five dummy variables for *EXPLORATION*. The first dummy takes on value 1 when *EXPLORATION* equals zero, the second equals 1 when *EXPLORATION* ranges between 0 and 4, the third captures firms with values of *EXPLORATION* between 4 and 6, the fourth from 6 to 7.6 and, the last one for values of *EXPLORATION* higher than 7.6. The dummy variable referring to central values of *EXPLORATION* (*EXPLORATION MEDIUM*) constitutes the main reference term as this contains the values of the turning point in the inverted U-shaped relationship between exploration activity and innovation failure in the conception phase (as shown by results in Table 6). Table 7 shows whether *EXPLOITATION* exerts a moderation effect for specific (ranges of) values of *EXPLORATION*.[4] From Model I we notice that when *EXPLORATION LOW* equals one, an increase in the exploitative component of R&D reduces the rate of failure at the conception phase, pointing that exploitation may compensate for the absence of exploration to reduce failures at the conception phase. This result requires cautious interpretation given the weak significance level (only 10%). On the contrary, information emerging from exploitative activities does not

[3] Our first attempt was with a specification based on interactions between the two continuous variables EXPLORATION and EXPLOITATION. None turn out to significantly affect the rate of failures, whatever is the phase of the innovation process that we consider.

[4] The boundary values of the main reference category are chosen by selecting the 95% confidence interval (CI) of the value of the maximum in the inverted U-shaped relationship between EXPLORATION and failure at conception (5.09 is the value at the maximum and 4 and 6 are the values of the 95% CI) (see Figure 2). The remaining categories are selected at sensible points of the distribution of EXPLORATION (non-investors, positive investors before the lower 95% CI boundary, from the upper boundary of the 95% CI to the 75th percentile, above 75th percentile). A similar strategy was followed with regards to the inverted U-shaped relationship found for failures at the downstream phase. Thus, in Table 7 we can interpret the interaction between EXPLOITATION and the dummies variables defined for EXPLORATION as measuring the moderating effect of exploitation activity on the relationship between EXPLORATION and rate of innovation failures (either at the conception or downstream phases) for values of EXPLORATION below and above central values (i.e. the turning point in Figure 2). Consistent results are obtained when we divide EXPLORATION in three categories instead of five (keeping the central reference category the same).

effectively combine with engagement in exploration. Although Table 7 does not entirely support our Hypothesis 3a, Model II, provides partial support to Hypothesis 3b. For high levels of *EXPLORATION* (i.e. *EXPLORATION HIGH* equals one) an increase in the investment in *EXPLOITATION* reduces the probability to face a failure at the development phase. Our results show that investment in exploitation activity does not contribute in lowering (or increasing) the rate of innovation failure for levels of exploration below the central values. On the contrary, only when the firm invests heavily in the explorative component of R&D, the complementarity with the exploitative part of R&D can be strategically oriented towards lowering the probability to experience innovation failure in the final stages of the innovation project.

[INSERT Table 7 ABOUT HERE]

Our last hypotheses (Hypotheses 4a and 4b) pertain to the analysis of the moderating effect of human capital in the relationship between exploration and innovation failure. Model I of Table 8 considers failure at the conception stage, while Model II at the downstream phase. We find support for the higher effect of highly skilled employees in moderating the curvilinear relationship between exploration in R&D activity and failures at the conception stage (Hypothesis 4b).[5] Specifically, from Model I we notice that a high level of human capital in the R&D department initially augments the relationship between investment in R&D exploration and the risk of abandonment, but it also helps fasten and anticipate the learning returns from engagement in exploratory activities, lowering the rate of failure at the conception phase. The same effect is not present in the case of failures at a downstream phase

[5] Human capital was also created as a continuous measure (proportion of R&D employees with a university degree or higher). Unfortunately Hypothesis 4b is not supported with this specification meaning that the marginal contribution of human capital does not moderate the relationship between exploration and failure at conception phase. Nevertheless Hypothesis 4b is fully supported with human capital defined at different points of the distribution (75^{th} percentile, 80^{th} percentile, 85^{th} percentile and 90^{th} percentile). This supports the robustness of this result for the right tail of the distribution meaning that high levels of human capital do play a role in moderating the relationship between investment in exploration and failure at conception phase.

of innovation activity. Again, this finds support in our theoretical argumentation. Highly-skilled employees, although more oriented towards risk-taking and challenging projects, are also endowed with skills, experience and an attitude that enhance the capacity to efficiently analyse success and failures, which results in a faster learning and reduction of failures at the conception phase. This moderation effect is represented in Figure 4. As Table 8 shows, the moderation effect of human capital is not present when we consider failures at the late stages of the innovation projects. This is possible due to the specific and idiosyncratic nature of technological problems faced in downstream stages, where the capabilities of high-skilled R&D personnel related to the analysis of success and failures do not trigger a similar learning return as found for innovation projects at the conception phase.

[INSERT Table 8 ABOUT HERE]

[INSERT Figure 4 ABOUT HERE]

We have checked for the robustness of our results to a set of potential issues that may affect our analysis. First, since failure at conception phase and failure downstream might not be independent of each other, we conducted a bivariate probit analysis to capture the possible interdependence between these two types of failure in innovation. Tables from A1 to A4 in the appendix report the results for the bivariate probit models. The Wald χ^2 tests clearly show that in all the models the null hypothesis of absence of independence between failure at conception and failure downstream cannot be rejected at standard significant levels (1%), thus pointing to bivariate probit model as better specification. Nevertheless, we include probit models in the study as they do not qualitatively differ from those reported in Tables A1-A6 and they are characterised by an easier interpretation of coefficients (Buis, 2010).

We also considered the possibility that a firm faces the joint occurrence of the two types of failure. To this aim we first estimated our models with stricter definition for failures, which captures if the firm has faced only one type of abandonment and not the other. This additional robustness check leads to consistent estimates with those presented in the paper.

A third potential issue that we consider pertains to the simultaneity between the dependent and explanatory variables that may hide a reverse causality problem. To address this point, and a related one pertaining to the lack of temporal dynamic in our baseline results, we created our key independent variables for the period 2005-2007 using information from the 2005, 2006 and 2007 PITEC waves. Results generally hold. An exception is the loss of significance for the interactions between human capital and the exploratory component of R&D, whose coefficients, however, maintain the same sign.[6]

We also control for problems of unobserved heterogeneity due to time-invariant factors, such as managerial ability, which are relevant for consistent estimation of the coefficients of the regression model. Using the information for period 2005-2007 outlined above we relied on a logit panel data random effects model.[7]

The last point concerns a crucial issue for our research. Indeed, our focus on the exploration component of R&D might be misleading, as similar insights may emerge from expenditure in the exploitative part of R&D (here captured by technological development). A first answer to the concern above comes from noticing that the two components of R&D are not strictly related, being characterized by a correlation coefficient equal to 0.142. More robust evidence

[6] We impute the lack of robustness of this result to the effect of the global economic crisis that badly affected employment in Spain starting from 2008. By measuring human capital and failure in innovation in two relatively different time periods (human capital in the before-crisis period 2005-2007 and failure in innovation in the crisis period 2008-2010) , we do not take into consideration the change in the employment structure that firms implement in response to the crisis. This should be particularly relevant for Spain given the employment shock it received at that time. We find support for this argument when we check the share of companies that exit in the following period from the top 33% of the distribution of R&D personnel with a higher education degree (25% of companies overall). We conclude that Spanish firms have sensibly reshaped their R&D personnel profile in the aftermath of the economic crisis and that this relates closely to the probability to experience different types of failure in innovation activity.

[7] We do not rely on a fixed effects specification because a large proportion of the firms in our sample are characterized by no variation in the relevant dependent variable. This induces a loss in the number of firms available for the estimation. We preferred to have a larger (and more representative) sample and implement random effects only.

comes from a further analysis we carried out. In a specular way to what we have done in the paper, we run all our models but focusing on EXPLOITATION. We notice that the two components of R&D actually lead to different effects in terms of learning and potential to reduce failures. Apart from an expected inverted-U shape relation between EXPLOITATION and the rate of failure at the downstream phase, the exploitative component of R&D does not exhibit (also considering potential moderating effects of human capital or increasing engagement in EXPLORATION) any further learning return. We believe that all the above analyses speak in favour of the robustness of our results.[8]

5. DISCUSSION AND CONCLUSIONS

This paper began by identifying a fundamental conflict that firms face when setting their strategies towards exploration in R&D activities. While firms need to explore in order to build and retain a competitive edge through the discovery and development of radical innovations, exploration increases the exposure of firms to innovation failure. Our results show that firms can balance this conflict by drawing learning returns from exploration activities. This study contributes to existing research on organizational learning and R&D management research by highlighting a dual facet of exploration in R&D: that is, while exploration increases firms' exposure to disruptions and abandonments of innovation activities, it also provides potential learning opportunities to curve down innovation failures. To disclose the presence of learning returns from exploration and understand its underlying working principles constitute the core contribution of this study.

[8] For the sake of space, we do not report these additional results. All above robustness checks are available from the authors upon request.

Our results provide evidence in support of a learning process from exploration that allows firms to reduce innovation failures, and at the same time highlight the intricacies associated to the capacity to materialize these learning returns. More specifically, our findings can be summarized as follows. First, we provide evidence of a curvilinear relationship between exploration and innovation failure. In particular, we find support for an inverted U-shaped relationship between investment in exploration R&D activity and the probability to experience innovation failure at both the conception and downstream phases of the innovation process. Thus, exploration increases the chances of experiencing failure at the conception and downstream phases of the innovation process, but only for low and intermediate levels of investment in exploration; learning returns from exploration activities, as measured by their impact on curving down the probability of failure, become apparent once a threshold in exploration is overcome.

These results run contrary to the standard learning-curve perspective that performance outcomes constitute a mechanical by-product of accumulated experience. There are good reasons to argue that the traditional learning-curve logic does not apply in the case of exploration. Principally, results from exploration are often difficult to interpret, being susceptible of multiple plausible but mistaken explanations, or obtained in controlled settings that may largely depart from real ones, opening up fundamental concerns about their actual feasibility. Causal attribution and inferential errors are thus inherently associated to learning processes from exploration. In such a context, it is reasonable to expect a non-linear relationship between engagement in exploration and learning outcomes, where firms manage to generate valuable lessons to curve down innovation failures only after a certain threshold in exploration activities is reached.

Second, our results support the existence of learning complementarities between R&D exploration and exploitation activities. That is, we find evidence that both types of learning may reinforce each other to reduce the firm's exposure to innovation failures. However, these complementarities only emerge at the downstream stage of the innovation process and for firms that are highly intensively committed to exploration. Again, this suggests that the learning returns are not linear but rather dependent on both the particular phase of the innovation process and the degree of exploration accumulated within the organisation.

We argue that our findings are explained by the contingent nature of the dialogue between R&D exploration and exploitation. The two-way flow of knowledge between the two components of R&D activities is likely to be particularly effective in drawing fruitful lessons to overcome innovation failures at downstream stages of the innovation process, where context specificities associated to scaling up processes and generation of working prototypes are most susceptible to benefit from a continuous dialogue between exploration and exploitation. This dialogue may be less effective to reduce or prevent failures at the conception phase, since it is often feedback from exploitation activities that induces further search at the design, upstream phase of the innovation process, opening up the opportunity space for exploration and its connected exposure to innovation failure.

We find support for another important moderating effect in the relationship between exploration and innovation failure. In particular, we show that firms' availability of human capital in R&D units contribute to speed the organisational learning process from exploration with regards to lowering innovation failure at the conception phase. The underlying rationale is that the firms' absorptive capacity (i.e. availability of highly research-skilled employees) enhances the capacity to obtain valuable knowledge from the learning opportunities generated by exploration activities. Highly research-skilled employees provide unique resources to overcome cognitive biases derived from the inherently complex and causal ambiguous results from exploration activities.

However, the moderating role of human capital is not without nuances. We find that higher levels of human capital in R&D departments increases the risk of abandonment at the conception phase at lower levels of exploration; it contributes to fasten the learning returns from exploration activities to lower innovation failures, only once a threshold level of exploration is achieved. We argue that firms that aim at drawing fruitful lessons from their exploration activities by escalating human capital in R&D units, should be accepting and tolerant to an early phase of turbulence and unrest regarding increasing exposure to failure, before they can actually reap the benefits of a sharper learning to overcome innovation failures. Moreover, this moderating effect is only present at the conception phase of the innovation process, rather than at the downstream phase. This is likely to be a consequence of the specific challenges of exploration activities at early stages of the innovation process, which are generally characterized by well-structured experimentation routines and replication standards, particularly suited to the analytical skills of researchers and the capacity to avoid causal attribution and inferential errors.

In sum, we contend that these findings provide valuable insights for both theory and practice on organisational learning research, revealing some critical underlying mechanisms governing the relationship between R&D exploration and innovation failure.

The paper has limitations that open up avenues for future research. First, our definition of innovation failures forces us to measure them as a binary variables only (whether the focal firm abandoned an innovation project or not in the period of reference). Providing a measure of the intensity of innovation failure at the firm level would allow us to enrich the analysis in terms of the relative importance of innovation failure for firms that experience it at different degrees. Second, a further limitation of the approach pursued in this paper is that it relies on data from one country only, i.e. Spain. Future work should extend our analysis to a wider range of countries in order to generalise the results obtained. Finally, although the analysis in this paper tries to control for some effects that might hide omitted variable bias, the absence of a pure experimental setting to allow a conclusive analysis suggests caution when interpreting the results in a causal way.

Future work should try to address all the points mentioned above to extend our results. In spite of these limitations, we believe that the insights gained from our study will serve as a guide and foundation for future work aimed at investigating the important role of exploration strategies for lowering innovation failure and, eventually, for building a firm's sustained competitive advantage.

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Table 1: Proportion of companies with positive spending in exploitation and exploration activities: overall vs positive investors

	Overall	***Positive Investors***
% of firms with positive spending in **R&D exploitation** (per employee)	51.9	68.56
% of firms with positive spending in **R&D exploration** (per employee)	46.36	61.36
Total	5177	3890

Notes: The sample refers to all manufacturing companies for the period 2008-2010. We have missing information for twelve companies in the overall sample and for three companies in the sample of positive investors due to missing values for the number of employees and/or the spending in R&D exploitation/exploration.

Table 2: Probability of failure in R&D projects: engagement vs non engagement in innovation activities

	Zero Investors	**Positive Investors**	**Pearson χ^2**
% Failure conception	1.54%	23.76%	322.22 [1] ***
% Failure downstream	1.93%	19.68%	237.03 [1] ***
Observations	1296	3893	

Notes: degrees of freedom are in brackets. The sample refers to all manufacturing companies for the period 2008-2010. All types of investment in innovation activities are considered.

Table 3: Proportion of companies experiencing failure conception and downstream along the distribution of investment in innovation related activities per employee

	Investment in innovation related activities per employee				**Pearson χ^2**
	25th perc	*25th-50th perc*	*50th-75th perc*	*Above 75th perc*	
% Failure conception	18.09	23.54	26.31	27.13	26.93[3]***
% Failure downstream	16.34	20.25	21.27	20.86	9.49[3]**
Observations	973	973	973	973	

Notes: degrees of freedom are in brackets .We have missing information for one company due to missing value in the number of employees

Table 4 Descriptive Statistics (N=3625)

VARIABLE	MEAN	SD	MIN	MAX
FAIL CONCEPTION	0.244	0.429	0	1
FAIL DOWNSTREAM	0.202	0.401	0	1
EXPLORATION*	1940.469	4154.932	0	59282.08
EXPLOITATION*	2547.457	5798.773	0	115240.7
HUMAN CAPITAL	0.33	0.47	0	1
OTHEREXP	6.091	2.533	0	12.885
COSTBAR	0.183	0.387	0	1
KNOWBAR	0.011	0.104	0	1
MKTUNCBAR	0.283	0.45	0	1
MKTDOMBAR	0.195	0.396	0	1
BREADTH	6.204	3.401	0	10
DEPTH	1.193	1.548	0	10
RADICALINNO	0.453	0.497	0	1
ORGINNO	0.501	0.5	0	1
AGE	3.267	0.585	1.098	5.17
GROUP	0.435	0.495	0	1
EXPORT	0.87	0.335	0	1
SIZE	4.206	1.293	0.693	9.158

Notes: * denotes descriptive statistics referred to the variables before log-transformation

Table 5: Correlation Matrix

	Variable	1	2	3	4	5	6	7	8	9	10	11	12
1	FAIL CONCEPTION	1											
2	FAIL DOWNSTREAM	0.459	1										
3	EXPLORATION	0.134	0.122	1									
4	EXPLOITATION	0.132	0.068	0.142	1								
5	HUMAN CAPITAL	0.167	0.105	0.303	0.363	1							
6	OTHEREXP	0.056	-0.010	0.033	0.075	0.168	1						
7	COSTBAR	-0.036	0.000	0.011	-0.013	-0.077	-0.040	1					
8	KNOWBAR	0.020	0.059	-0.021	-0.013	-0.024	0.019	0.127	1				
9	MKTUNCBAR	0.072	0.039	0.042	0.002	0.007	0.014	0.164	0.086	1			
10	MKTDOMBAR	0.057	0.050	0.046	0.027	0.017	0.030	0.124	0.088	0.375	1		
11	BREADTH	0.158	0.074	0.227	0.244	0.322	0.178	-0.039	-0.034	0.049	0.070	1	
12	DEPTH	0.111	0.041	0.129	0.163	0.225	0.180	0.039	-0.027	0.074	0.099	0.407	1
13	RADICALINNO	0.145	0.067	0.163	0.199	0.202	0.123	-0.021	-0.001	0.000	-0.040	0.171	0.104
14	ORGINNO	0.184	0.089	0.134	0.130	0.214	0.149	-0.052	-0.037	0.041	0.060	0.262	0.171
15	AGE	0.051	0.053	0.000	-0.008	0.102	-0.053	-0.086	-0.008	-0.009	-0.005	0.076	0.018
16	GROUP	0.079	0.069	0.034	0.037	0.309	0.047	-0.152	-0.050	-0.080	-0.078	0.150	0.041
17	EXPORT	0.057	0.025	0.087	0.104	0.145	0.021	-0.067	-0.030	-0.047	-0.001	0.111	0.067

18 SIZE	0.102	0.058	-0.013	0.007	0.410	-0.005	-0.163	-0.070	-0.090	-0.087	0.204	0.080

Table 6 Innovation failures determinants: baseline and curvilinear effects

	FAIL CONCEPTION	FAIL DOWNSTREAM	FAIL CONCEPTION	FAIL DOWNSTREAM
EXPLORATION	0.0253***	0.0308***	0.1108***	0.0888***
	[0.007]	[0.007]	[0.029]	[0.030]
EXPLOITATION	0.0284***	0.0184**	0.0252***	0.0161**
	[0.008]	[0.008]	[0.008]	[0.008]
EXPLORATION^2			-0.0109***	-0.0074**
			[0.004]	[0.004]
HUMAN CAPITAL	0.0694	0.0576	0.1194*	0.0926
	[0.064]	[0.067]	[0.067]	[0.069]
OTHEREXP	-0.0024	-0.0249**	0.0026	-0.0218**
	[0.010]	[0.010]	[0.010]	[0.010]
COSTBAR	-0.1114*	0.0178	-0.1132*	0.0176
	[0.066]	[0.066]	[0.066]	[0.066]
KNOWBAR	0.3691*	0.7603***	0.3715*	0.7610***
	[0.205]	[0.212]	[0.204]	[0.211]
MKTUNCBAR	0.1936***	0.0726	0.1886***	0.0696
	[0.056]	[0.057]	[0.056]	[0.058]
MKTDOMBAR	0.0864	0.0857	0.086	0.085
	[0.063]	[0.064]	[0.063]	[0.064]
BREADTH	0.0193**	0.0031	0.0199**	0.0035
	[0.008]	[0.009]	[0.008]	[0.009]
DEPTH	0.0239	-0.0018	0.0251	-0.001
	[0.016]	[0.017]	[0.016]	[0.017]
RADICALINNO	0.2420***	0.1184**	0.2436***	0.1198**
	[0.050]	[0.051]	[0.050]	[0.051]
ORGINNO	0.3363***	0.1579***	0.3382***	0.1588***
	[0.050]	[0.051]	[0.051]	[0.051]
AGE	0.0514	0.0971**	0.0474	0.0946**
	[0.044]	[0.045]	[0.044]	[0.045]
GROUP	0.0519	0.1354**	0.0595	0.1411**
	[0.057]	[0.059]	[0.057]	[0.059]
EXPORT	0.0465	-0.0225	0.0532	-0.0197
	[0.077]	[0.077]	[0.077]	[0.078]
SIZE	0.0509*	0.0086	0.028	-0.0073
	[0.027]	[0.027]	[0.028]	[0.029]
Log-likelihood	-1854.3804	-1738.8701	-1849.9149	-1736.8934
McFadden's Pseudo R^2	0.0801	0.0479	0.0823	0.049
Wald χ^2	293.3501 [37]***	162.1341 [37]***	298.776 [38]***	165.853 [38]***
Observations	3625	3625	3625	3625

* p<0.10, ** p<0.05, *** p<0.01. Robust standard errors in parentheses. All models estimated with sector dummies and constant term included. Degrees of freedom of Wald χ^2 test are reported in parenthesis

Table 7 Innovation failures determinants: moderation effect of the exploitative component of R&D

	FAIL CONCEPTION	FAIL DOWNSTREAM
EXPLORATION	0.012	0.0352***
	[0.012]	[0.013]
EXPLOITATION	0.0426***	0.0300***
	[0.011]	[0.011]
EXPLORATION LOW*EXPLOITATION	-0.0267*	-0.0091
	[0.014]	[0.015]
EXPLORATION MEDIUM LOW*EXPLOITATION	-0.0238	-0.0162
	[0.045]	[0.043]
EXPLORATION MEDIUM HIGH*EXPLOITATION	-0.007	-0.0141
	[0.011]	[0.011]
EXPLORATION HIGH*EXPLOITATION	-0.0182	-0.0345**
	[0.013]	[0.014]
HUMAN CAPITAL	0.0966	0.075
	[0.066]	[0.068]
OTHEREXP	-0.003	-0.0219**
	[0.010]	[0.010]
COSTBAR	-0.1132*	0.0146
	[0.066]	[0.066]
KNOWBAR	0.3571*	0.7621***
	[0.204]	[0.211]
MKTUNCBAR	0.1921***	0.0708
	[0.056]	[0.058]
MKTDOMBAR	0.0844	0.0833
	[0.063]	[0.064]
BREADTH	0.0202**	0.0029
	[0.008]	[0.009]
DEPTH	0.0243	-0.0009
	[0.016]	[0.017]
RADICALINNO	0.2459***	0.1211**
	[0.050]	[0.051]
ORGINNO	0.3416***	0.1595***
	[0.051]	[0.051]
AGE	0.0494	0.0924**
	[0.044]	[0.045]
GROUP	0.0556	0.1393**
	[0.057]	[0.059]
EXPORT	0.0483	-0.0215
	[0.077]	[0.078]
SIZE	0.0374	-0.0023
	[0.028]	[0.028]
Log-likelihood	-1852.0026	-1735.829
McFadden's Pseudo R^2	0.0813	0.0496
Wald χ^2	299.1467 [41]***	167.7392 [41]***
Observations	3625	3625

* p<0.10, ** p<0.05, *** p<0.01. Robust standard errors in parentheses, all models estimated with sector dummies and costant term included. Degrees of freedom of Wald χ^2 test are reported in parenthesis

Table 8 Innovation failures determinants: moderation effect of high skilled R&D employees

	FAIL CONCEPTION	FAIL DOWNSTREAM
EXPLORATION	0.0574	0.0757**
	[0.038]	[0.039]
EXPLOITATION	0.0267***	0.0168**
	[0.008]	[0.008]
EXPLORATION^2	-0.0048	-0.006
	[0.005]	[0.005]
HUMAN CAPITAL	-0.0425	0.0352
	[0.109]	[0.115]
HUMAN CAPITAL*EXPLORATION	0.1512***	0.0419
	[0.058]	[0.060]
HUMAN CAPITAL*EXPLORATION^2	-0.0161**	-0.0042
	[0.007]	[0.007]
OTHEREXP	0.0017	-0.0220**
	[0.010]	[0.010]
COSTBAR	-0.1186*	0.0167
	[0.065]	[0.066]
KNOWBAR	0.3740*	0.7605***
	[0.205]	[0.211]
MKTUNCBAR	0.1894***	0.0703
	[0.056]	[0.058]
MKTDOMBAR	0.0815	0.0835
	[0.063]	[0.064]
BREADTH	0.0200**	0.0035
	[0.008]	[0.009]
DEPTH	0.0251	-0.0012
	[0.016]	[0.017]
RADICALINNO	0.2434***	0.1195**
	[0.050]	[0.051]
ORGINNO	0.3413***	0.1599***
	[0.051]	[0.051]
AGE	0.0448	0.0936**
	[0.044]	[0.045]
GROUP	0.0587	0.1408**
	[0.058]	[0.059]
EXPORT	0.0602	-0.0179
	[0.077]	[0.078]
SIZE	0.0249	-0.0082
	[0.028]	[0.029]
Log-likelihood	-1846.4011	-1736.6085
McFadden's Pseudo R^2	0.0841	0.0491
Wald χ^2	308.7318 [40]***	167.5629 [40]***
Observations	3625	3625

* p<0.10, ** p<0.05, *** p<0.01. Robust standard errors in parentheses, all models estimated with sector dummies and costant term included. Degrees of freedom of Wald χ^2 test are reported in parenthesis

Figure 1: Graphical representation of our theoretical argumentation

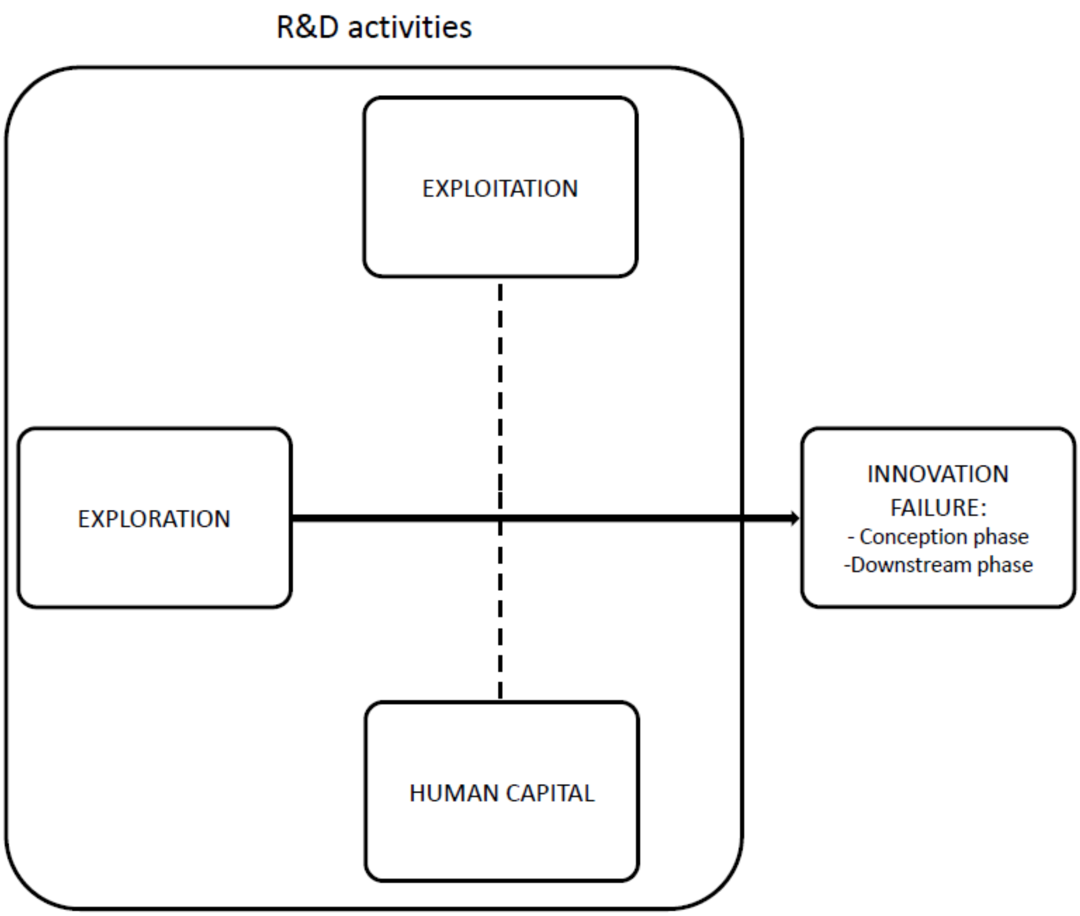


Figure 2: Curvilinear effect of exploration on the probability of facing an innovation failure in the conception phase

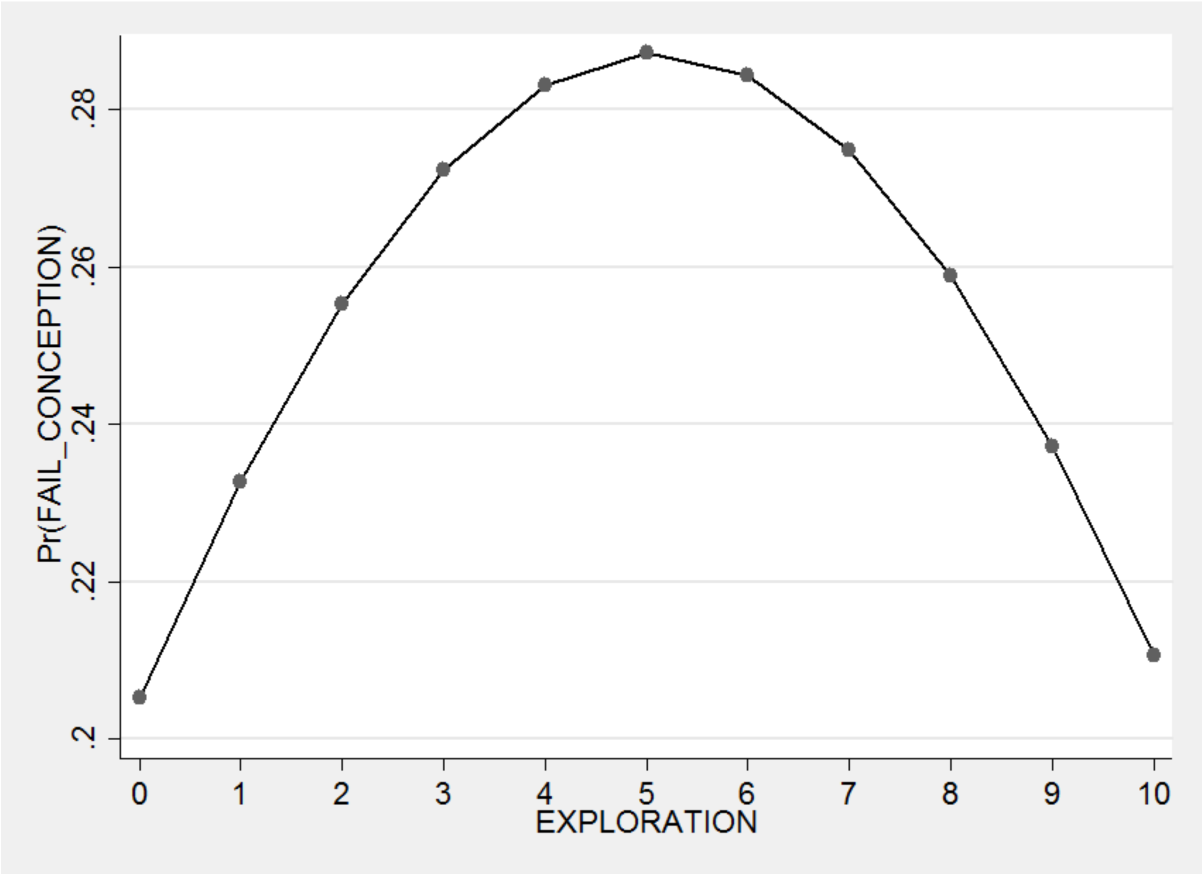


Figure 3 Curvilinear effect of exploration on the probability of facing an innovation failure in the development phase

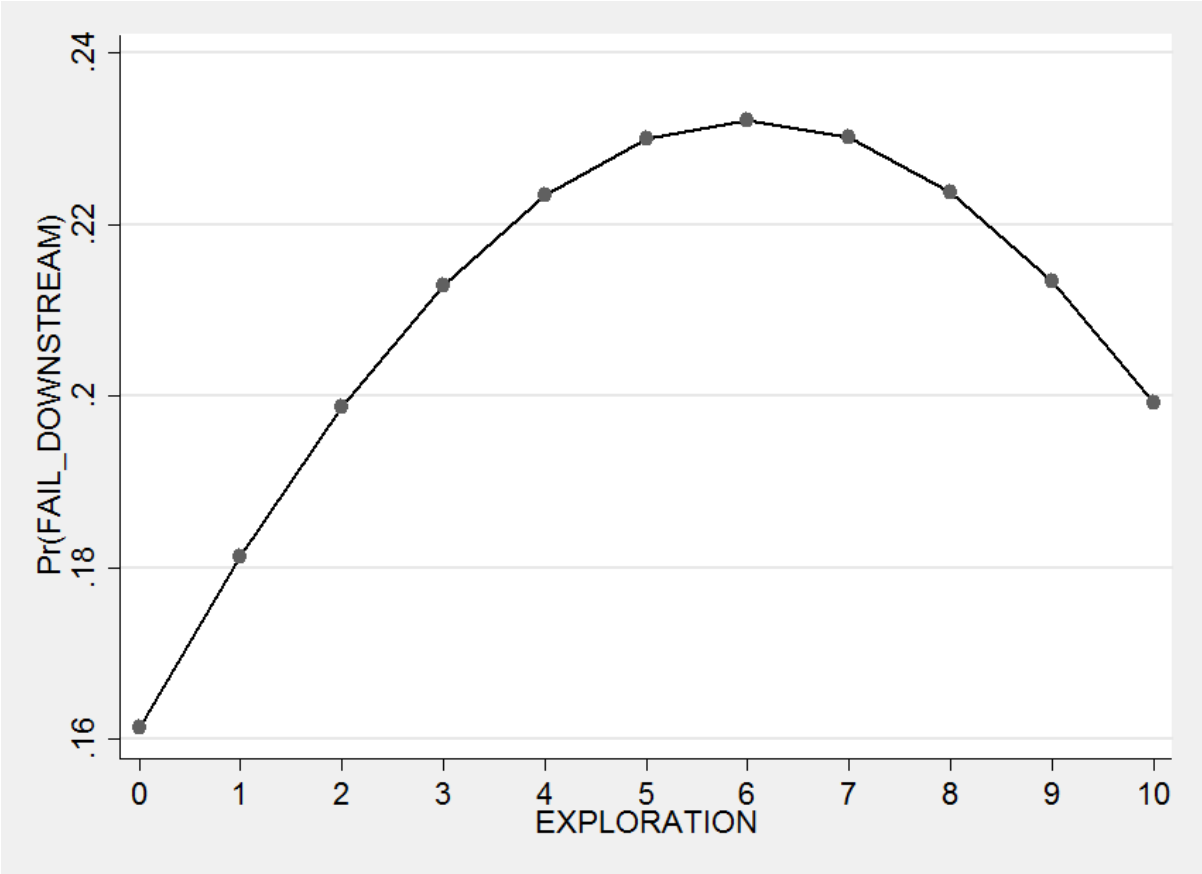
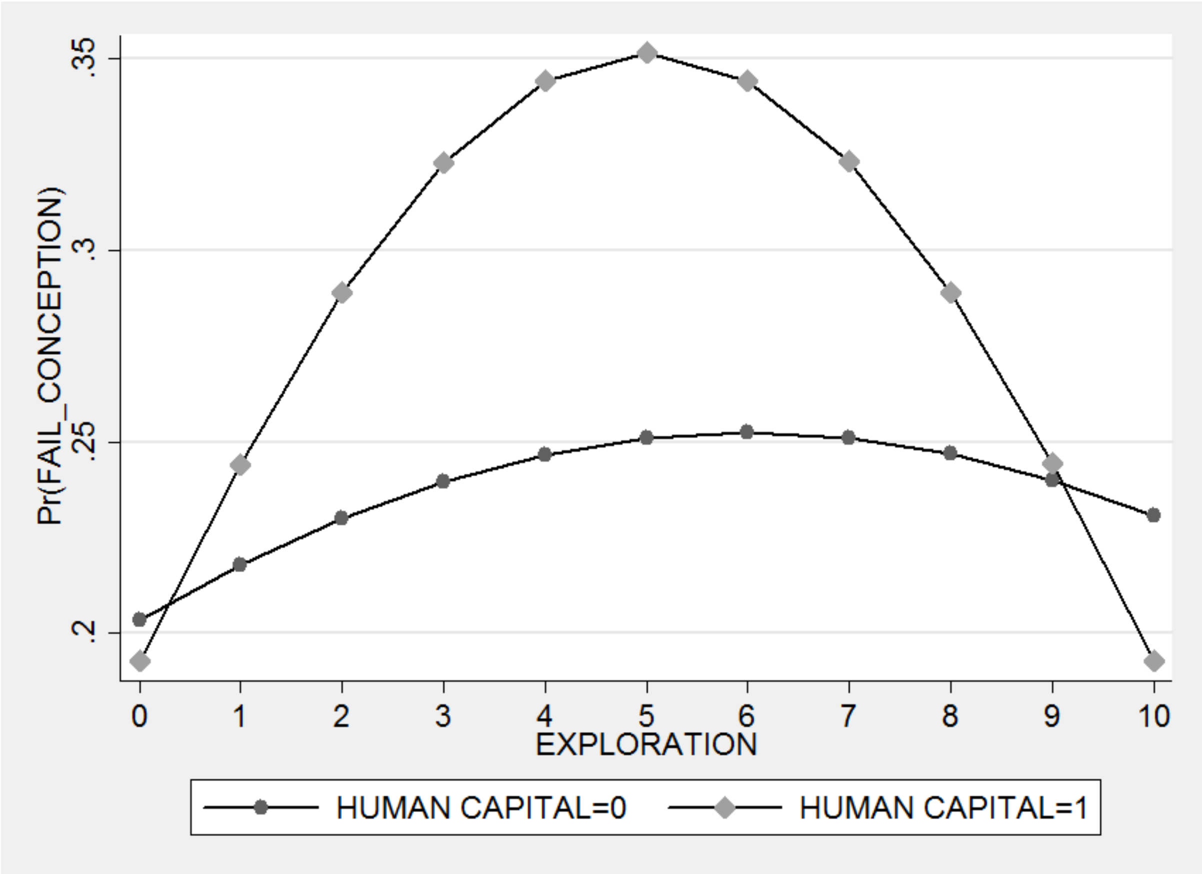


Figure 4 Moderation effect of human capital on exploration for the probability of facing an innovation failure in the conception phase



Appendix

Table A1: Bivariate probit analysis – baseline model

	FAIL CONCEPTION	**FAIL DOWNSTREAM**
EXPLORATION	0.0254***	0.0305***
	[0.0072]	[0.0075]
EXPLOITATION	0.0273***	0.0181**
	[0.0077]	[0.0077]
HUMAN CAPITAL	0.0696	0.0545
	[0.0645]	[0.0673]
BREADTH	0.0157*	0.0005
	[0.0080]	[0.0087]
DEPTH	0.0234	-0.0035
	[0.0162]	[0.0172]
OTHEREXP	-0.0032	-0.0259**
	[0.0096]	[0.0101]
SIZE	0.0459*	0.0043
	[0.0267]	[0.0272]
AGE	0.0518	0.0994**
	[0.0436]	[0.0442]
GROUP	0.0572	0.1373**
	[0.0572]	[0.0586]
COSTBAR	-0.1054	0.0197
	[0.0647]	[0.0650]
KNOWBAR	0.3738*	0.7599***
	[0.2016]	[0.2136]
MKTUNCBAR	0.1929***	0.066
	[0.0561]	[0.0575]
MKTDOMBAR	0.0793	0.0919
	[0.0632]	[0.0643]
EXPORT	0.0408	-0.0118
	[0.0762]	[0.0770]
RADICALINNO	0.2423***	0.1201**
	[0.0493]	[0.0510]
ORGINNO	0.3293***	0.1580***
	[0.0505]	[0.0511]
Constant	-1.8553***	-1.4554***
	[0.1894]	[0.1928]
Log-likelihood	-3303.490	
Wald χ^2	382.54[74]***	
ρ	0.689	
Wald χ^2 test of ρ =0	487.65[1]***	
Observations	3625	

* $p<0.10$, ** $p<0.05$, *** $p<0.01$. Robust standard errors in parentheses, model estimated with sector dummies included. Degrees of freedom of Wald χ^2 test are reported in parenthesis

Table A2: Bivariate probit analysis – curvilinear exploration

	FAIL CONCEPTION	FAIL DOWNSTREAM
EXPLORATION	0.1092***	0.0866***
	[0.0292]	[0.0302]
EXPLOITATION	0.0243***	0.0160**
	[0.0078]	[0.0078]
EXPLORATION^2	-0.0107***	-0.0072*
	[0.0036]	[0.0037]
HUMAN CAPITAL	0.1185*	0.0878
	[0.0670]	[0.0695]
BREADTH	0.0163**	0.0009
	[0.0080]	[0.0087]
DEPTH	0.0246	-0.0027
	[0.0162]	[0.0172]
OTHEREXP	0.0016	-0.0228**
	[0.0097]	[0.0103]
SIZE	0.0231	-0.0109
	[0.0280]	[0.0284]
AGE	0.0487	0.0972**
	[0.0436]	[0.0442]
GROUP	0.066	0.1428**
	[0.0574]	[0.0586]
COSTBAR	-0.1067*	0.0196
	[0.0646]	[0.0650]
KNOWBAR	0.3737*	0.7598***
	[0.2009]	[0.2132]
MKTUNCBAR	0.1886***	0.0629
	[0.0561]	[0.0577]
MKTDOMBAR	0.079	0.0914
	[0.0631]	[0.0643]
EXPORT	0.0475	-0.0082
	[0.0760]	[0.0773]
RADICALINNO	0.2436***	0.1209**
	[0.0493]	[0.0509]
ORGINNO	0.3314***	0.1590***
	[0.0506]	[0.0511]
Constant	-1.8302***	-1.4357***
	[0.1889]	[0.1931]
Log-likelihood	-3298.868	
Wald χ^2	391.69[76]***	
ρ	0.688	
Wald χ2 test of ρ =0	484.99[1]***	
Observations	3625	

* $p<0.10$, ** $p<0.05$, *** $p<0.01$. Robust standard errors in parentheses, model estimated with sector dummies included. Degrees of freedom of Wald χ^2 test are reported in parenthesis

Table A3: Bivariate probit analysis – Exploitation Interaction

	FAIL CONCEPTION	FAIL DOWNSTREAM
EXPLORATION	0.0125	0.0360***
	[0.0121]	[0.0126]
EXPLOITATION	0.0445***	0.0416***
	[0.0139]	[0.0144]
EXPLORATION LOW*EXPLOITATION	-0.0295*	-0.0203
	[0.0164]	[0.0172]
EXPLORATION MEDIUM LOW*EXPLOITATION	-0.0271	-0.029
	[0.0449]	[0.0421]
EXPLORATION MEDIUM HIGH*EXPLOITATION	-0.0034	-0.0188
	[0.0140]	[0.0146]
EXPLORATION HIGH*EXPLOITATION	-0.0192	-0.0398***
	[0.0147]	[0.0153]
HUMAN CAPITAL	0.1013	0.0811
	[0.0666]	[0.0692]
BREADTH	0.0168**	0.0002
	[0.0080]	[0.0087]
DEPTH	0.0236	-0.003
	[0.0162]	[0.0172]
OTHEREXP	-0.0034	-0.0226**
	[0.0098]	[0.0103]
SIZE	0.0309	-0.0097
	[0.0278]	[0.0284]
AGE	0.0506	0.0980**
	[0.0437]	[0.0443]
GROUP	0.0616	0.1436**
	[0.0574]	[0.0586]
COSTBAR	-0.1065*	0.0163
	[0.0646]	[0.0651]
KNOWBAR	0.3639*	0.7614***
	[0.2005]	[0.2146]
MKTUNCBAR	0.1918***	0.0657
	[0.0561]	[0.0577]
MKTDOMBAR	0.0769	0.0875
	[0.0631]	[0.0644]
EXPORT	0.046	-0.0031
	[0.0761]	[0.0775]
RADICALINNO	0.2464***	0.1231**
	[0.0494]	[0.0509]
ORGINNO	0.3339***	0.1584***
	[0.0507]	[0.0511]
Log-likelihood	-3297.587	
Wald χ^2	399.93[82]***	
ρ	0.689	
Wald $\chi 2$ test of ρ =0	485.86[1]***	
Observations	3625	

* p<0.10, ** p<0.05, *** p<0.01. Robust standard errors in parentheses, model estimated with sector dummies and constant term included. Degrees of freedom of Wald χ^2 test are reported in parenthesis.

Table A4: Bivariate probit analysis – Human Capital Interaction

	FAIL CONCEPTION	FAIL DOWNSTREAM
EXPLORATION	0.0567	0.0702*
	[0.0369]	[0.0382]
EXPLOITATION	0.0257***	0.0167**
	[0.0079]	[0.0078]
EXPLORATION^2	-0.0047	-0.0054
	[0.0047]	[0.0049]
HUMAN CAPITAL	-0.0471	0.0208
	[0.1100]	[0.1152]
HUMAN CAPITAL*EXPLORATION	0.1525***	0.0528
	[0.0579]	[0.0604]
HUMAN CAPITAL*EXPLORATION^2	-0.0162**	-0.0053
	[0.0068]	[0.0070]
BREADTH	0.0164**	0.001
	[0.0080]	[0.0087]
DEPTH	0.0246	-0.0028
	[0.0162]	[0.0172]
OTHEREXP	0.0006	-0.0232**
	[0.0097]	[0.0103]
SIZE	0.0197	-0.0122
	[0.0281]	[0.0285]
AGE	0.0466	0.0960**
	[0.0437]	[0.0443]
GROUP	0.0661	0.1426**
	[0.0574]	[0.0586]
COSTBAR	-0.1125*	0.0184
	[0.0645]	[0.0651]
KNOWBAR	0.3743*	0.7601***
	[0.2015]	[0.2133]
MKTUNCBAR	0.1886***	0.0631
	[0.0560]	[0.0577]
MKTDOMBAR	0.0742	0.0902
	[0.0631]	[0.0642]
EXPORT	0.0534	-0.0061
	[0.0758]	[0.0773]
RADICALINNO	0.2431***	0.1208**
	[0.0494]	[0.0509]
ORGINNO	0.3340***	0.1601***
	[0.0506]	[0.0510]
Log-likelihood	-3295.209	
Wald χ^2	401.71[80]***	
ρ	0.688	
Wald χ2 test of ρ =0	483.51[1]***	
Observations	3625	

* p<0.10, ** p<0.05, *** p<0.01. Robust standard errors in parentheses, model estimated with sector dummies and constant term included. Degrees of freedom of Wald χ^2 test are reported in parenthesis

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