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Exploring and yet failing less:

Learning from past and current exploration in R&D

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ABSTRACT

Exploration is both an important part of a firm's innovation strategy and an activity that involves a high degree of uncertainty. This paper investigates a duality in the exploratory component of R&D activity with regard to innovation failure: while exploration is likely to increase firms' exposure to failure, it might also provide learning opportunities to reduce failure. Our study contributes to the innovation management and organisational learning literatures by demonstrating the value of exploratory R&D for enabling two types of learning mechanisms. The first, *experience-based learning*, is based on the learning opportunities derived from accumulated experience in exploratory R&D: it involves improvements to procedures associated with experimentation and provides guidance for current exploration and to navigate the search space. The second, *inferential-based learning*, is based on the learning opportunities derived from current exploratory R&D efforts, which are associated with improved interpretation of ill-defined problems and timely responses to unstructured information. We draw on a longitudinal dataset of 2,226 Spanish manufacturing companies and show that, when past experience is associated with current exploration, innovation failure in the conception phase is reduced. We also find an inverted U-shaped relation between current exploratory R&D and innovation failure, in both the conception and implementation phases of innovation projects, showing that increasing levels of investment in current exploration activities attenuate the initial positive association between exploratory R&D and failure.

Keywords: *exploration; innovation failure; learning; research and development*

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1. INTRODUCTION

Exploration is an important part of the strategies of firms striving to bring to market new products and processes that promise large revenues if they are difficult to imitate by competitors. In this sense, firms' exploration activities are essential to achieve sustained competitive advantage (March, 1991). However, while firms need to explore in order to build and retain their competitive edge, they need also to learn how to manage the greater level of uncertainty and risk involved in highly explorative innovation activity (Edmondson, 2011).

This is not an easy balance to achieve. Although firms want to minimise failure related to innovation-related activities such as exploration (Desai, 2010), they may be willing to tolerate some level of failure if the exploration activity provides valuable new knowledge and learning opportunities that are aligned to their innovation strategy (Leonard-Barton, 1995; Edmondson, 2011). However, despite the increasing interest in organisational learning from failure (Haunschild & Sullivan, 2002; Madsen & Desai, 2010; Desai, 2015) and the organisational costs associated with the termination of R&D projects (Shepherd et al., 2014), very little research focuses specifically on the relationship between exploratory R&D and innovation failure.

The present study investigates the relationship between exploratory R&D and failure in innovation projects. We examine the learning potential from two sources of information and knowledge gained in firms' exploration activities that can contribute to lowering the risks of failure associated with exploratory R&D. The first is the firm's accumulated experience in exploration (i.e. *experience-based learning* from past exploration). Prior experience affects the articulation of search routines and helps to identify the relevant search space (Nelson &

Winter, 1982). Moreover, when applied to current activities, previously elaborated schemes can be refined to improve understanding about the underlying causes of problems in innovation-related activities (Argote & Miron-Spektor, 2011). The second source is the learning opportunities derived from concurrent exploration efforts, which emerge when a significant amount of (unstructured) information collected *en route* enables better interpretation of ill-defined problems and more timely response to them (*inferential-based learning* from current exploration) (Cook & Brown, 1999). Specifically, we investigate the following interrelated questions. First, we investigate whether, and to what extent, firms can benefit from accumulated experience in exploration activities and, in particular, whether there are positive complementarities with current exploration activities in terms of reducing innovation failure. Second, we investigate whether the scale of current explorative R&D contributes to reducing the likelihood of innovation failure. To address these research questions we use longitudinal data, covering the period 2007-2012, on a sample of 2,226 manufacturing firms derived from the Spanish Technological Innovation Panel (PITEC) and exploit information on firms' expenditure on the exploratory component of R&D, and the probability of failed innovation activity.

This paper contributes to the organisational learning and innovation management literatures by shedding new light on the mechanisms that allow firms to gain valuable learning from exploratory R&D. To the best of our knowledge, the relation between exploratory R&D activities and innovation failure has not been tested explicitly. We aim to fill this gap and to challenge the conventional wisdom that recognises exploration as a high risk activity but ignores the learning opportunities that it provides. These learning opportunities improve the effectiveness of the exploration activities and attenuate the risks of innovation failure.

We show that exploratory R&D can improve organisational performance by reducing the risk of abandonment of innovation activities. We use information related to two temporal dimensions of exploratory R&D: current tasks and accumulated experience (Argote & Miron-Spektor, 2011). We find evidence of a beneficial interplay between past experience of explorative research and current exploratory R&D, although the effect is significant only for reducing failure in the conception phase of the innovation process. This suggests that information based on previous experience, when applied to current exploration, can help to identify problems and possible solutions mainly in the conception phase, when innovation activities are characterised by structured experimentation and are less dependent on context-specific issues. We show also that the intensity of investment in current exploration contributes to reducing the risk of failure in both the conception and implementation phases of innovation projects. This suggests that although current exploration is likely to generate unstructured information, which could lead to attribution and inferential errors, a substantial amount of efforts devoted to current exploration can help the firm to interpret ill-defined problems and to respond to them in a timely way.

The paper is organised as follows. Section 2 reviews the relevant literature and presents our hypotheses. Section 3 describes the data and methods. Section 4 presents our findings and some robustness checks. Section 5 concludes by discussing the implications of our findings for management and future research.

2. EXPLORATION AND INNOVATION FAILURE

2.1 Exploratory R&D: buffer to myopic learning and driver of innovation failure?

Organisational learning processes can induce myopia due to over-attention to immediate performance and a tendency to ignore exploration and distant search (Levinthal & March, 1993). Adaptive learning, in which firms prioritise effectiveness and attention to innovation in the familiar territory of current experience, limits the opportunities for learning (Gupta et al., 2006; Fang et al., 2010). This is because firms tend to focus on reliable and predictable performance at the expense of the search for new ideas or new markets, which has less certain outcomes, longer time horizons and more diffuse effects (March, 1991; Arora et al., 2015). These adaptive learning processes potentially can be self-destructive and endanger the organisation's long-term survival (March, 1991, 2006).

In contrast, organisations may try deliberately to counterbalance the bias towards myopic learning by committing to exploration activities. Exploration includes activities related to search, variation, experimentation, flexibility and discovery (March, 1991). It contributes to building capabilities outside current competencies and niches (Katila & Ahuja, 2002; Nerkar, 2003; Rosenkopf & Nerkar, 2001), helps to develop new cognitive frames (Chiva et al., 2010) and enables learning from failure (Edmondson, 2011; Madsen & Desai, 2010). Thus, exploration activities can be conceived as essential for long-term firm survival and growth.

Exploration typically is embedded in the innovation strategies of firms committed to formal R&D investment. Firms' investment in R&D nurtures expertise in fields that represent new opportunities and contributes to the building of in-house competencies to develop new products and processes (Tidd et al., 1997; Cohen & Levinthal, 1990; Dodgson et al., 2008). In particular, exploration-oriented R&D is likely to contribute to a radical departure from the organisation's current knowledge-base and avoid myopic learning.

In fact, R&D is not a homogenous activity (e.g., Barge-Gil & Lopez, 2014; Czarnitzki et al., 2011). We contend that the 'R', the research component, is the main channel for exploration within R&D activity, while the 'D', the development component, is associated mainly with exploitation activities. Research (R) can be disentangled further into basic and applied elements. Basic research is experimental or theoretical work aimed at the acquisition of new knowledge on foundations and observable facts, not aimed at any particular application (OECD, 2002). This activity, which is characterised by uncertainty and a long time horizon, is clearly exploratory in nature since it refers to the search for new ideas and relations among constructs (March, 1991). Applied research shares with basic research the search for original outcomes - i.e. new pieces of knowledge or new operational methods - while it differentiates from basic research for the specific objective of addressing practical aims (OECD, 2002). In contrast to research, the outcomes of the development component of R&D are more predictable, have a shorter time horizon and are based on existing ideas and relations (March, 1991). Development makes use of existing knowledge that emerged from the research phase or from practical experience and is directed towards the introduction of new materials, products and devices or improvements to existing ones (OECD, 2002). In sum, to use March's (1991) terminology, research can be considered as closely related to the "exploration of new possibilities", while development is concerned mainly with the "exploitation of old certainties".

While the exploratory component of R&D is necessary to avoid myopic learning, it increases the chances of innovation failure due to the inherently complex nature of the activities involved in exploration and the uncertainty related to its potential outcomes. Project failure is more frequent in companies engaged in exploration activities since this type of activity is more likely to face unpredictable contingencies. Indeed, the notion of innovation failure is typically associated with deviation from the expected and desired results from an R&D project and as involving "both avoidable errors and the unavoidable negative outcomes of experiments and risk taking" (Cannon & Edmondson, 2005: 300).

We define innovation failure as the realisation of unacceptably low performance in R&D projects that results in a managerial decision to terminate the activity, which can occur at any stage of the innovation development process (Green et al., 2003; Shepherd & Cardon, 2009; Shepherd et al., 2014). We consider two major stages associated with the development of firm innovation projects: the conception phase and the implementation (or execution) phase (Tidd et al., 1997). In the conception phase, firms search for alternative innovation choices (identifying technological and market opportunities) and select ideas that are proposed and tested to establish an intended design or proof-of-concept prototype. The implementation phase corresponds to the stage in the innovation process when innovation efforts are oriented to executing the project to achieve a functional or working prototype that can be used to scale up manufacture and deliver a marketable product. Since exploratory R&D involves expanding the current set of capabilities, firms are likely to be exposed to a wide range of possible failures in both the conception and implementation phases of the innovation process. We consider project innovation failures associated with these two phases separately, since we expect this distinction to allow us to identify similarities and differences in the relationship between exploratory R&D and innovation failures.

Based on this discussion, we hypothesize that:

H1: Exploratory R&D is positively associated to the probability of innovation failure in the conception and implementation phases of the innovation process.

H1 is our baseline hypothesis and is in line with prior contributions, although, to our knowledge, no direct test of the effect of exploratory R&D on the probability of innovation failure has been proposed in the literature. In what follows, we test this hypothesis (H1) to challenge two fundamental aspects of its underlying proposition. First, we contend that the expectation of a positive association between exploratory R&D and innovation failure is not uniform; instead, this effect may depend on both the scale of current exploratory R&D and the interplay with accumulated experience of exploratory R&D. Second, we investigate whether the effects of exploratory R&D on innovation failure are different in the innovation process phases of conception and implementation.

2.2 Learning from R&D exploration activity

The above discussion refers to the increased exposure to failure associated to exploratory R&D and raises questions about whether and to what extent firms can manage this conflict. Drawing on organisational research which maintains that learning begins with experience (Fiol & Lyles, 1985; Argote & Miron-Spektor, 2011), we argue that experience in R&D exploration activity can provide learning opportunities that help organisations to attenuate the risk of innovation failure.

Search processes are not unstructured activities (Nelson & Winter, 1982). Firms engaging in exploratory search activities establish programmed procedures and standard practices to increase the returns from experimentation and to increase the efficiency of the process by reducing the chances of errors and mistakes. Consequently, firms can improve the performance of their exploration-related activities based on accumulated experience.

However, although accumulated experience is important, the transfer of existing practices to specific contexts is not always either easy or feasible, particularly in contexts that involve the identification of actionable responses related to radically new lines of inquiry - which is what exploratory search is about (Cook & Brown, 1999; Majchrzak et al., 2004). This leads to an acknowledgement of the temporal dimension of the knowledge creation and learning processes associated to exploration activity (Nerkar, 2003), and the distinction between learning from accumulated experience and learning in practice (Cook & Brown, 1999). Building on this discussion, we suggest that exploration in R&D offers two sources of learning opportunities, which could contribute to balancing the conflict between more intensive exploratory search and increased rates of failure: experiential-based learning from past exploration and inferential-based learning from current exploration. We discuss these aspects below.

2.2.1 Experiential-based learning from past exploration

Firms' accumulated experience of exploratory R&D can be embedded in routines and standard procedures, which contribute to the development of intelligence, monitoring and surveillance capabilities associated with experimentation activity. This accumulated experience and sustained exploratory R&D efforts can lead to learning opportunities to reduce the likelihood of failure in innovation activities. This is described as 'experiential-based learning from past exploration'.

First, we argue that programmed exploration can be particularly effective for reducing instances of preventable failure caused by deviance from rules, inattention or lack of ability in the conduct of routine and predictable operations (Edmondson, 2011). Along similar lines, Thomke (2001) suggests that building experimentation capabilities implies avoiding two types of mistakes: those resulting from badly conducted experiments, which produce ambiguous or not valuable information, and those that involve repeating prior failures. The extant literature suggests that longitudinal information on past performance, different perspectives on what went wrong in the past, the sharing of ideas with managers able to implement change, and careful consideration of whether change is having the desired effect contribute to building the firm's capacity to anticipate, analyse and act upon failure (Tucker & Edmondson, 2003; Cannon & Edmondson, 2005).

In addition, we contend that past experience in exploration activity can be beneficial if it leads to opportunities for more effective future exploration activities. Organisations can benefit from the interaction between current and accumulated experience in exploration activity, through a moderating effect that reduces the probability of failure. Past exploration activities can help to map and navigate the relevant search space and, thereby, contribute to making current exploration activities more efficient and to developing a learning process associated to current exploration (Eisenhardt & Martin, 2000; Zollo & Winter, 2002). Majchrzak et al. (2004) report that past experience can support different stages of current radical and exploratory innovation: from the conceptualization of new ideas, through the use of analogies and extensions linked to previously developed concepts, to final product development, in which experience is shared in the course of testing, review and improvements on prototypes. Past experience can provide an appropriate lens to analyse new information collected *en route* and to improve the accuracy of inferences related to current exploration processes (Denrell et al., 2004). This can be achieved by applying information elicited from both successful and failed past exploratory activities, to current R&D exploration (Leonard-Barton, 1995; Edmondson, 2011).

Accordingly, we acknowledge knowledge retention as central to the firm's learning process and as depending on the organisational memory embedded in employees, the tools available and the tasks to be performed (Argote & Ingram, 2000). In this framework, past experience provides meta-knowledge about who knows and does what (i.e. transactive memory), which, in turn, increases ongoing performance by improving: (i) task assignment (better matching of researchers to research tasks); (ii) problem solving and coordination (researchers know whom to approach for advice) and (iii) division of intellectual labour which leads to specialised learning of different pieces of information. In sum, past experience of exploratory R&D, if properly retained and reused in current endeavours (Argote & Miron-Spektor, 2011), can improve organisational performance and reduce the risk of failure.

However, it is important to note that applying previously elaborated data and schemes to current, and possibly different, activities requires refinement of insights from prior experience. Although the relevant information may be available in the organisation through accumulated experience, it can be difficult to find solutions to complex problems in a changed use environment (Von Hippel & Tyre, 1995). In our context, this implies that past exploration experience becomes an organisational asset if applied appropriately to current exploration. Firms can make use of previously acquired information to improve identification of the causes of problems in their innovation activities and allow their correction before they can lead to failure. Such beneficial interplay between past and current exploration resonates with the prescriptions in Schilling et al. (2003: 50), according to which learning opportunities are maximised in the case of related variation, that is, when "working on different but similar types of problems over time". This type of variation, which is likely to occur in subsequent exploratory activities within the same firm, allows a deeper understanding of the performed tasks by creating associations among similar concepts in different contexts.

These arguments lead to the following hypothesis:

H2: Past experience in exploratory R&D negatively moderates the relation between current exploratory R&D and the probability of failure in the conception and implementation phases.

2.2.2 Inferential-based learning from current exploration

We next discuss the learning potential from current exploration activities, which we describe as inferential learning in the context of practice (Cook & Brown, 1999). Efforts oriented towards exploration tend, by definition, to challenge the organisation's existing knowledge base. Indeed, the context that characterises exploration activities involves features that, typically, defy current routines and existing capabilities. New exploration activities involve causal ambiguity and resolution of ill-defined problems, since firms have a partial understanding of the causal relationships among multiple stages in search processes associated with radical new product development (Lippman & Rumelt, 1982; Segal, 2004). Current R&D exploration is characterised also by delayed performance feedback and credit assignment, since there is a temporal lag between action and observed performance (Denrell et al., 2004; Fang, 2012). These activities often involve the formulation of new agendas to define novel product portfolio and business model orientations (Fiol & Lyles, 1985; He & Wong, 2004). In this context, well-established routines may not only provide limited guidance but also may hinder the development of new cognitive frames that provide adequate representations of the nature of the problem at hand.

However, we contend that learning from current exploration can occur especially if the scale of the research expands the experimentation space and increases the number of observations to draw upon. Learning from current exploration might be even more important than learning based on past experience, whose value might depreciate over time (Argote et al., 1990; Argote & Miron-Spektor, 2011; Benkard, 2000). In the course of their current exploratory R&D, firms can devise adaptive problem-solving reactions, even if the possibility for a radical revision of the prevailing rules of action and routines is limited in the short-run (Argyris & Schön, 1978; Fiol & Lyles, 1985; Sadler-Smith et al., 2001). These learning outcomes can be guided by information elicited from projects that are ongoing. Partial information, in the form of unstructured pieces of knowledge in the problem space or intermediate clues and signals within a multistage problem, may be useful to guide exploration and avoid "random walks" (Denrell et al., 2004; Fang & Levinthal, 2009).

In organizing their exploration activities, firms generally acknowledge that more radical experiments are likely to provide both learning opportunities and also greater exposure to failure in the short-term. Leonard-Barton (1995) and Edmondson (2011) point to instances of "good" or "intelligent" innovation failure that are associated with deliberate experimentation and exploration oriented to providing valuable opportunities for acquiring new knowledge in the short term, and contributing to the interpretation of ongoing problems. Intelligent failures are likely to be particularly important in the project conception phase when firms can explore different paths and reject unfeasible alternatives at comparatively low cost. This applies especially to new simulation technologies, which have continuously reduced the costs of generating critical data on virtual, as opposed to physical prototypes (Thomke, 2001). Moreover, current R&D exploration efforts can trigger new heuristics and interpretive skills at any point in the innovation process, contributing to the adoption of new frames of reference and problem-definition schemes to avoid preventable and complexity-related failures. New heuristics and interpretive skills increase inference accuracy and compensate for the small-scale experimentation and limited experiential-based sources of learning associated with new exploration (Kim et al., 2009).

Therefore, as a consequence of inferential-based learning from exploration activities, we argue that the probability of innovation failure is likely to decline with an increased scale of current exploration efforts. Accordingly, we hypothesize a curvilinear inverted U-shaped relationship between current exploratory R&D and innovation failure. The rationale for this hypothesis is that, while current R&D exploration is likely to challenge existing routines and expose firms to higher risks of innovation failure (as put forward in Hypothesis 1), current R&D exploration efforts are likely to enhance the firm's capacity to interpret unstructured information once a threshold scale of exploration is achieved, resulting in learning opportunities that contribute to reduce innovation failure in both the conception and implementation phases.

Thus, we hypothesize that:

H3: The degree of current exploratory R&D has an inverted U-shape relationship with the probability of experiencing innovation failure in the conception and implementation phases.

3. DATA AND METHODS

3.1 Data and sample frame

Our analysis uses data from PITEC which is co-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 anonymised dataset based on survey waves (for a review of innovation surveys, see Mairesse & Mohnen, 2010).[1] PITEC's core sections are similar to sections in the CIS, a harmonised questionnaire developed by Eurostat based on the OECD's Oslo Manual (OECD, 2005). Due to its reliability, open-access policy and range of innovation-related information, PITEC is being used increasingly as the data source for empirical studies of firm level innovation.[2] PITEC data are particularly appropriate for our study because they allow identification of the exploratory character of R&D, and they provide information on innovation failures in the conception and implementation phases of the innovation process.

We focus on the period 2007-2012, aggregating information from six PITEC annual survey waves. Similar to other CIS-type surveys, some of the questions (e.g., about failure in innovation projects) refer to a three-year period (e.g., for the 2012 survey wave, some questions refer to the period 2010-2012), while other questions (e.g., on R&D spending, among others) refer to a single year (2012). For consistency, we use three consecutive waves of the PITEC survey to build measures for our key variables (i.e., 2007, 2008 and 2009; and 2010, 2011 and 2012). This allows us to build a set of variables referring to two non-overlapping periods (2007-2009 and 2010-2012). The sample contains full information for the variables of interest for 2,226 manufacturing firms over two time periods (2007-2009 and 2010-2012), resulting in a quasi-balanced panel of 4,191 firm-period observations.

Our main focus is on firms that engage in innovation-related activities and therefore are susceptible to experience different rates of innovation-related failure. Table 1 shows the

[1] PITEC data for the different waves are available at : http://icono.fecyt.es/PITEC/Paginas/descarga_bbdd.aspx (last accessed April 2017).

[2] See for instance: Molero & Garcia, 2008; Vega-Jurado et al., 2009; Santamaria et al., 2012; Trigo & Vence, 2012; Audretsch et al., 2014; Barge-Gil & Lopez, 2014; Busom et al., 2014; Afcha & Garcia-Quevedo, 2016; Marzucchi & Montresor, 2017. A list of PITEC-based publications is available at: https://icono.fecyt.es/PITEC/Documents/2016/Utilizaci%C3%B3n%20del%20PITEC%20(Nov.%202016).pdf (last accessed July 2017).

proportion of firms included in PITEC that have experienced overall failure and failure in the conception and implementation phases of innovation projects, distinguishing between those engaged in innovation-related activities and those that are not.[3] Table 1 shows that, as expected, the probability of failure is higher for companies that engage in innovation activities (the difference between the two probabilities is always statistically significant at the 1% confidence level). Given the focus of our analysis, we restrict the sample to manufacturing firms that are exposed to the risk of experiencing innovation failure, that is, companies that engage in innovation activities.[4]

INSERT Table 1 ABOUT HERE

3.2 Variables and measures

3.2.1 Dependent variables

Our dependent variables, *Failure overall*, *Failure conception* and *Failure implementation,* proxy for failure in innovation activities, reflected in the decision to terminate an innovation project, and the decision to terminate it in the stages of conception and implementation (Green et al., 2003; Shepherd & Cardon, 2009; Shepherd et al., 2014). Other studies based on CIS or PITEC data (e.g., Mohnen et al., 2008; Lhuillery & Pfister, 2009; D'Este et al., 2015;

[3] Engagement in innovation-related activities is defined as investing at least once over the period 2007-2012, in one of the following activities: intra-mural R&D; extramural R&D; acquisition of machinery, equipment and software; acquisition of other external knowledge; training; market introduction of innovations; other innovation-related activities.

[4] Note that the firms in our sample are likely to suffer innovation failures not necessarily related only to intra-mural R&D, which should mitigate any sample selection problems in the construction of our sample. Appendix Table A1 shows the non-negligible proportion of companies that experience all three types of failure (overall, conception and implementation) and engage in different types of innovation-related activities: (i) only intramural R&D; (ii) only other innovation-related activities (i.e. non-intramural R&D); and (iii) both intramural R&D and other innovation-related activities.

Leoncini, 2016) adopt a similar approach to capture innovation failures using information on abandoned activities.

Our dependent variables are built relying on firms' responses corresponding to the relevant three-year periods: 2007-2009 and 2010-2012. *Failure overall* is a dummy that takes the value 1 if the firm faces a failure event in an innovation project, i.e. if the firm reported abandonment of an innovation project in the conception or implementation phases. Following the arguments in Section 2, we consider two phases in which failures can occur: firms were asked to "locate" the event of a failure in either the conception or the implementation phases of innovation activities. *Failure conception* is a dummy that takes the value 1 if the firm faces a failure event in the conception phase of an innovation project, that is, if a project was abandoned in the conception phase. *Failure implementation* is a dummy that takes the value 1 if the firm faces a failure event in the implementation phase of an innovation project, that is, if the firm reported abandoning an innovation project in the implementation phase.

3.2.2 Explanatory variables

We draw on previous studies and distinguish between exploratory and exploitation activities in the R&D process to build our explanatory variables (Czarnitzki et al., 2009; Czarnitzki et al., 2011; Barge-Gil & Lopéz, 2014, 2015). In Section 2.1 we discussed the connection between the characterisation of exploration and exploitation proposed in March (1991), and the standard definitions of R&D (OECD, 2002). PITEC data allow us to quantify the firm's engagement in the different components of R&D investment, in a way that is consistent with established measurement of innovation activity practices (OECD, 2002, 2005). In particular, PITEC data allow us to differentiate among investment in basic research, applied research and development. Basic research relates to "experimental or theoretical work undertaken to obtain new knowledge on the foundation of phenomena or observable facts, without any particular application in view". Also, applied research "consists of original work undertaken to obtain new knowledge" and differs from basic research in being "aimed at a particular objective". Finally, development is defined as "systematic work based on existing knowledge, derived from research or practical experience, that is directed to the production of new materials, products or devices, or to installing new processes, systems and services or to improving those already existing or installed".[5]

Based on these definitions, we construct our main explanatory variables for engagement in exploratory R&D. *R&D exploration* is obtained by averaging real expenditure on basic and applied research in 2007-2009 and in 2010-2012[6] and dividing the figures obtained by the average number of employees in the corresponding periods. To reduce distribution skewness, we apply a natural logarithmic transformation (adding +1 to avoid dropping zeros). We use *R&D exploration* to test our base-line hypothesis (H1) on the positive relationship between current exploration activities and the firm's exposure to innovation failure.

Hypothesis 2 refers to the combined effect of past exploration experience and current exploratory R&D. We test this hypothesis by including the interaction *R&D exploration X R&D exploration -1*. *R&D exploration -1* captures past exploratory R&D: in 2007-2009 for the probability of failure in the period 2010-2012, and in 2004-2006 for the probability of failure in the period 2007-2009. We obtained information on investment in explorative R&D activities during 2004-2006 from three previous waves of the PITEC survey, which maintains

[5] See https://icono.fecyt.es/PITEC/Documents/2014/cuestionario12.pdf (translated from Spanish, last accessed April 2017).
[6] Real exploration expenditure is nominal exploration expenditure deflated by the consumer price index for the corresponding period.

the panel nature of our dataset.[7] Finally, Hypothesis 3 predicts an inverted U-shaped relationship between explorative R&D and the probability of experiencing innovation failure. To capture this non-linear effect we include in our econometric specification the squared term *R&D exploration sq*.

3.2.3 Control variables

We tried to minimise omitted variables bias by including a set of controls in the econometric specification. We include a variable for the amount of investment in exploitation activities, *R&D exploitation*, measured as the natural log transformed ratio of average expenditure on development activities normalised by the average number of employees in the same period. We control for factors that might affect the likelihood of failure during innovation activities. Following the literature, we consider both financial and non-financial barriers (e.g., Blanchard et al., 2013; D'Este et al., 2012, 2014). The PITEC data do not provide continuous information on the relevance of barriers: hampering factors are recorded on likert scales that reflect the relevance of these issues for the firm. To define our barriers-related variables, we follow D'Este et al. (2012, 2014) and Antonioli et al. (2016) and create three dummies that take value 1 if the firm faced at least one highly relevant obstacle related to cost, knowledge or market. Specifically, *Cost barriers* captures whether the firm faced at least one major obstacle in the form of innovation costs, and internal or external funding for innovation. *Knowledge barriers* reflects whether the firm reported knowledge barriers as highly important, including items such as problems related to the availability of skilled personnel, information on technology, information on markets and availability of appropriate innovation partners. We consider also the potential effect of markets perceived as being dominated by

[7] Due to missing information for some relevant independent variables, such as organisational innovation, we could not include this time period, 2004-2006, in the estimation of our baseline model.

incumbents (*Market barriers - dominated*) and characterised by uncertain demand (*Market barriers - uncertainty*).

We control for different forms of engagement in innovation not included in our exploration and exploitation measures, that might be particularly relevant to small and medium sized enterprises and non-R&D intensive industries (e.g., Rammer et al., 2009; Sterlacchini, 1999). *Other innovation expenditures*, defined over the reference period as the natural log transformed average sum (adding +1 to avoid dropped zeros), include expenditure per employee on external R&D, machinery, equipment and software, external knowledge, training, introduction of innovation in the market, design and other activities. To further capture the complexity of the firm's innovation profile, we control for adoption of open innovation strategies (e.g., Chesbrough, 2003). Building upon Laursen & Salter (2006), we use two variables proxying for external knowledge search breadth (*Knowledge breadth*) and depth (*Knowledge depth*) in the firm's innovation strategy. *Knowledge breadth* takes values from 0 to 10, based on the number of sources of information for innovation used by the firm in the period considered. *Knowledge depth* ranges from 0 to 10, based on the number of information sources the firm rated as highly important in the period under consideration.[8]

In order to control for cutting-edge and risky innovation activities, we include a dummy, *Radical innovation*. In the absence of information on the number of innovations introduced, this variable takes the value 1 if the firm introduced at least one innovation that was new to the market (e.g., Monjon & Waelbroeck, 2003; Duguet, 2006). Also, we control for whether the company undertook any relevant organisational innovation in the period considered. We exploit information from responses to PITEC survey questions on organisational innovation

[8] PITEC data include information on the following sources of information for innovation: 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.

to create the dummy *Organisational innovation*, which takes the value 1 if the firm introduced new or improved management systems, changes to the firm's work organisation (with reference to decision-making and distribution of responsibilities) or changes to relations with other organisations, and zero otherwise. [9] We also include firm age (natural log transformed) (*Firm age*), which may be related to the propensity to introduce disruptive and risky innovations, and the likelihood of higher obstacles to innovation (e.g., Schneider & Veugelers, 2010). We consider a set of characteristics that might influence innovation resources, incentives and, in turn, the likelihood of engagement in unsuccessful innovation activities: number of employees dedicated to R&D activities (*Number of R&D researchers*), group affiliation (*Group*) and firm size (*Number of employees*). *Number of R&D researchers* is the (log transformed+1) number of FTE researchers in the firm's R&D department and takes account of a possible R&D size effect. Group affiliation is measured as a dummy variable, while firm size is measured as the natural logarithm of the average number of employees in the reference period (+1). Finally, we include four dummies for the effect of industry characteristics, based on Pavitt's (1984) industry sectors: science-based, specialised supplier, scale-intensive and supplier-dominated. [10]

Table 2 presents descriptive statistics for the variables used in the study; Table 3 reports the correlation matrix of these variables. Apart from variables that are transformations of other variables (*e.g. R&D exploration sq*), correlation among the independent variables is generally

[9] *Organisational innovation* takes the value 1 if the firm replied "yes" to any of the following questions: (i) "Has the firm introduced new business practices in the organization of work or company procedures?"; (ii) "Has the firm introduced new methods for the organization of workplaces with the aim of distribution of responsibilities and decision-making?" and (iii) "Has the firm introduced new methods of managing external relations with other companies or public institutions?"

[10] Each firm was assigned to a unique Pavitt category according to its 2-digit industry class (NACE rev.2 classification) following the Revised Pavitt taxonomy in Bogliacino & Pianta (2016). We estimated our empirical models using the set of 2-digit industry dummies. Although the results hold, the test of joint significance of industry dummies is always far from significant. For this reason, we prefer to rely on broader (but generally jointly significant) industry controls based on Pavitt categories.

weak and mean variance inflation factors range between 1.36 and 3.73 (well below the threshold value of 5), suggesting the absence of multi-collinearity problems. [11]

INSERT Table 2 AND Table 3 ABOUT HERE

3.2.3 Methods

To estimate the factors that influence three different types of innovation failure events, we employ probit models based on panel data:

$$P(Failure\ overall_{it} = 1 \,|\, \boldsymbol{x}_{it}, \boldsymbol{z}_{it}, \mu_i\ ) = \Phi(\boldsymbol{x}_{it}{}'\,\boldsymbol{\beta} + \boldsymbol{z}_{it}{}'\,\boldsymbol{\gamma} + \mu_i\ )$$

$$P(Failure\ conception_{it} = 1 \,|\, \boldsymbol{x}_{it}, \boldsymbol{z}_{it}, \mu_i\ ) = \Phi(\boldsymbol{x}_{it}{}'\,\boldsymbol{\beta} + \boldsymbol{z}_{it}{}'\,\boldsymbol{\gamma} + \mu_i\ )$$

$$P(Failure\ implementation_{it} = 1 \,|\, \boldsymbol{x}_{it}, \boldsymbol{z}_{it}, \mu_i\ ) = \Phi(\boldsymbol{x}_{it}{}'\,\boldsymbol{\beta} + \boldsymbol{z}_{it}{}'\,\boldsymbol{\gamma} + \mu_i\ )$$

where $\Phi(.)$ is the cumulative normal distribution function; $\boldsymbol{x}_{it}{}'$ is the vector of our key explanatory variables for firm *i* at time *t*; $\boldsymbol{z}_{it}{}'$ is the vector of controls for firm *i* at time *t;* and μ_i is the time invariant unobserved heterogeneity term.

The models are estimated by employing a random effects specification. We prefer random effects to fixed effects because a large proportion of the firms in our sample are characterised

[11] As the correlation table shows (Table 3), the correlations between our focal variables (*R&D exploration*, *R&D exploration -1* and *R&D exploration sq*) are high and, in some cases, above an acceptable threshold (0.7). We rsn some additional diagnostic tests to check for multicollinearity problems. Notably, the condition index for the three model specifications adopted in the empirical part of the paper ranges between 28 and 31: all values are close to the threshold of 30 (Hair et al., 1998: 220). Also, the Theil R^2 multicollinearity effect for the three models ranges between 0.01 and 0.08, which is well below the value indicating multicollinearity, i.e. 1 (Theil, 1971). As further corroboration, we followed Cronbach (1987) and subtracted the mean from our core explanatory variables and then re-ran our main estimates. The results confirmed the estimates obtained using the untransformed variables and reported in the results section.

by no within-variation in the relevant dependent variables,[12] which would have significantly reduced the number of companies available for a fixed effects estimation. We preferred a larger and more representative sample and, thus, implement only random effects.[13]

4. RESULTS

4.1 Main Results

Table 4 presents our baseline results, examining the relation between current engagement in exploratory R&D and the probability of innovation failure - overall and in the conception and implementation phases. The coefficient of *R&D exploration* is always positive and highly significant, which provides evidence of the risky nature of exploration. Increasing the exploration orientation of R&D activities increases the overall risk of failure in innovation activities. Most significantly for our hypotheses, an increase in exploratory R&D activities increases the probability of failing in the conception and in the implementation phases of the innovation project life cycle as shown by the results in Table 4, columns 2 and 3. This supports Hypothesis 1. The relation is relevant from an economic perspective: an increase of 1% in exploratory R&D increases the odds of failure in the conception (implementation) phase by around 12% (6%).[14]

[12] E.g., 55% of companies that experienced failure in the conception phase in period *t,* faced same types of failure in period *t+1*.

[13] We also performed Hausman and Mundlak tests (Wooldridge, 2010) to check whether a fixed effects specification was preferred to a random effects specification. Both tests in all model specifications (Table 4, Table 5 and Table 6) cannot be rejected at the standard confidence levels, confirming our choice of random effects.

[14] Interpreting the coefficients in the non-linear models is difficult, especially in relation to the squared and interaction effects. Recent studies using cross-sectional data suggest graphing the marginal effects to obtain a better understanding of the point in the distribution when they become significant (Ai & Norton, 2003; Greene, 2010; Zelner, 2009). In our case, the longitudinal nature of our empirical models adds complexity. Specifically, the presence of an unobserved heterogeneity term does not allow application of these graphing approaches without strong assumptions concerning the behaviour of the heterogeneity term. To overcome this problem, we adopt the option suggested by Buis (2010) and interpret the coefficients as odds ratios. The main advantage of

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INSERT Table 4 ABOUT HERE

Hypothesis 2 refers to the interaction between past exploration and current engagement in exploratory R&D. Table 5 shows that the value of previous R&D exploration activities is never significant *per se* (columns 1, 3 and 5). Also, the results reported in Table 5 column 2 point to the absence of a moderating effect (*R&D exploration X R&D exploration -1* negative but not statistically significant) in the case of the overall probability of failure. Interestingly, if we split the probability of failure into its constituent parts (see Table 5 columns 3 and 4 for conception and columns 5 and 6 for implementation), we find that in the case of conception failure there is a direct effect, captured by the coefficient of *R&D exploration -1*, which is positive and significant, and a moderating effect, captured by the interaction *R&D exploration X R&D exploration -1*, which is negative and significant (see Table 5 column 4). The effect of the interaction between past experience and current exploration is small, but non-negligible: the effect of current exploration on innovation failure at the conception phase is decreased by 1.1% for a 1% increase in investment in past exploration. In contrast, we find no evidence of a negative interplay between past experience and current experimentation in the case of implementation failure, which reduces support for Hypothesis 2. We reflect on these different results in the discussion section.

INSERT Table 5 ABOUT HERE

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interpreting interaction and curvilinear effects as odds-ratios is that this interpretation (unlike use of marginal effects) does not depend on the value of the independent variable being considered.

The results related to Hypothesis 3 are reported in Table 6. The sign and significance of the coefficients of *R&D exploration* (positive and significant) and *R&D exploration sq* (negative and significant) suggest the presence of an inverted U-shaped relationship, which supports Hypothesis 3. [15] Notably, the positive relationship between exploration and failure at conception (implementation) is decreased by 3.29% (2.09%) for every additional 1% increase in current exploration. We can conclude that the intensity of engagement in exploratory R&D activity attenuates the initial positive relation between current exploratory R&D and failure. This beneficial effect occurs in the same three-year period. Hence, our results seem to confirm that firms can learn how to reduce failures from the performance of current and novel tasks if they have accumulated sufficient information from ongoing activities. Overall, our evidence points to the presence of a learning effect from exploratory R&D along the entire innovation project life cycle.

INSERT Table 6 ABOUT HERE

4.2 Robustness checks

We check the robustness of our results to three problems. First, we consider an alternative measure for past experience in exploration activities: *R&D exploration stock -1*, which

[15] When comparing the unconstrained with the constrained specification for the three different specifications, we found the difference between the log-likelihoods of the constrained and unconstrained models were always statistically significant (respectively $X^2[1]=7.22$, p-value=0.0072; $X^2[1]=11.04$, p-value=0.0009 and $X^2[1]=4.72$, p-value=0.0298).Thus, we conclude that the less restrictive model (the one with the squared term included) fits the data significantly better than the more restrictive model (our baseline model with only the linear term). Furthermore, the presence of an inverted U-shaped effect is confirmed by the test suggested in Lind & Mehlum (2010): we reject the null hypothesis of a monotonic or U-shaped relationship at the 5% significance level, in all the three specifications.

reflects the cumulated stock of expenditure on exploratory R&D in the previous period, which accounts also for obsolescent information on past engagement in exploratory R&D. Appendix Table A2 shows that the results are confirmed if we use an alternative measure of past experience, cumulated stock of exploration in R&D (*R&D exploration stock -1* and *R&D exploration X R&D exploration stock -1*). [16]

Table A2 ABOUT HERE

Second, there might be problems related to the firm-level nature of our data. To investigate the determinants of innovation failure, the ideal analytical level is the project, with information on project resources (e.g., different types of R&D), obstacles, and termination or success. Although we do not have project-level information, we can check the robustness of our results to this problem by estimating our models for the sub-sample of small companies (less than 50 employees based on the European Commission definition). [17] The rationale is that smaller sized companies, due to time and resource constraints and the absence of a formal R&D department, are more likely to have fewer (ideally no more than 1) innovation projects

[16] The stock variable is computed using the perpetual inventory method based on the following formulas: $Explor\ stock_t = Explor\ stock_{t-1}(1-\delta) + Explor_t$ and $Explor\ stock_{t0} = Explor_{t0}/(g+\delta)$. A 15% depreciation rate is assumed. As a robustness check, a range of depreciation rates (from 15% to 75% in intervals of 20 points) was used drawing on insights from the relevant literature on R&D stocks (Hall, 1993) and organisational learning (Argote et al., 1990; Baum & Ingram, 1998). The results are robust to the different specifications adopted. As for the pre-sample growth rate g, we assume it to be equal to the average growth rate of exploration at the 2-digit industry level (NACE rev.2 classification) in the period 2004-2008. We further tested the robustness of H2 by controlling for persistence in organisational commitment to exploratory R&D by including a third variable, which takes the value 1 if the firm invested in exploration in all three years in the reference period and 0 otherwise. The results are robust to this further specification and are available from the authors upon request.

[17] European Commission, "Commission Recommendation of 6 May 2003 concerning the definition of micro, small and medium-sized enterprises (Text with EEA relevance) (notified under document number C(2003) 1422)", available at: http://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32003H0361 (accessed April 2017).

per period. The results reported in Appendix Table A3, Table A4 and Table A5 mostly support our main results.

Table A3, Table A4 AND Table A5 ABOUT HERE

We also consider the interdependence between conception and implementation phase failures in a bivariate setting, since the likelihood of these types of failure were found to be correlated (Pearson and tetrachoric correlation coefficients are 0.46 and 0.7 respectively). In the absence of well-established models to control for correlation among the error terms in a non-linear panel setting, we run a set of "pooled" bivariate probit models and control for clustering of the error terms for each firm. To further corroborate our results, we build upon Roodman's (2011) recent work on fully observed recursive mixed-process models and estimate a probit Seemingly Unrelated Regression (SURE). Appendix Table A6 and Table A7 provide evidence of the robustness of our main results in both bivariate and probit SURE specifications.

Table A6 AND Table A7 ABOUT HERE

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5. DISCUSSION AND CONCLUSIONS

This paper investigated the dual effects of exploration in R&D: while exploration increases firms' exposure to disruption and abandonment of innovation activities, it provides potential learning opportunities to mitigate the risk of innovation failure. Investigation and disclosure of the learning returns from exploration, and understanding the underlying working principles, are the core contributions of this study.

Our empirical analysis confirms that exploratory R&D increases the firm's exposure to innovation failure in both the conception and implementation phases of the innovation process. This supports the argument that engagement in exploratory research is associated with higher exposure to innovation failure. However, our findings also qualify this assertion in three critical aspects. First, we highlight the presence of learning opportunities from exploratory research with regard to the capacity of firms to mitigate innovation failure. Second, we uncover two mechanisms through which learning from exploration operates: (i) the interplay between past exploration experience and current exploration practice; and (ii) the enhanced inferential capacity from current exploration efforts. Third, we show that learning opportunities differ in distinct phases of the innovation process (i.e., the conception and implementation phases). These contributions have implications for both theory and practice, which we discuss below.

This work contributes to organisational learning theory by examining learning processes from firms' exploratory research. Our results provide support for the presence of a learning process from exploration, which triggers a positive change in organisational performance by reducing innovation failure. The main conceptual contributions of the study can be summarised as follows. First, this study identifies two potential sources of learning from exploration: (i) experiential-based learning from past exploratory research; and (ii) inferential-based learning from current exploratory research. The former is based on the learning opportunities derived from accumulated experience in exploration and is associated with the formation of routines and standard procedures that enhance functional performance associated with experimentation. The latter is based on learning opportunities derived from ongoing exploration efforts and is associated with improved interpretation of ill-defined problems and enhanced inference in the presence of causal ambiguity. The study provides empirical support for the claim that these sources of learning can contribute to mitigate innovation failure, and provides a new lens to understand how exploratory R&D can contribute positively to firms' innovation performance.

Second, our analysis highlights the intricacies associated with the capacity to realise the learning opportunities from exploration, especially in relation to the role of the temporal dimensions of learning from exploratory research activities (Argote & Miron-Spektor, 2011). On the one hand, we find that accumulated experience from past exploration activities contributes to reducing the probability of innovation failure. However, our results run contrary to the standard learning-curve which predicts that performance outcomes are an automatic by-product of accumulated experience (Zangwill & Kantor, 1998). We find that past experience, *per se*, does not reduce the risk of abandonment of innovation projects. Our results show that accumulated experience in exploration activities has a beneficial effect on the link between current exploration efforts and innovation failure: it reduces the firm's exposure to innovation failure through the interplay with current R&D exploration activity. We suggest that past experience in exploration provides critical learning for current activities by helping to navigate the relevant search space for exploration and building surveillance systems to identify deviations from established standards. In addition, when applied to current exploration, previously elaborated information can be refined and increase understanding about the causes of problems and their possible solutions. This result resonates with the "generative dance" proposed by Cook & Brown (1999) between knowledge embedded in organisational routines and knowledge gained in the context of practice, as a source of organisational learning and innovation.

It should be noted also that the moderating role of past exploration experience is significant only for reducing failure in the conception phase of the innovation process, not in the implementation phase. This is likely a consequence of the distinct challenges posed by exploration activities in the two phases of the innovation process. The conception phase is generally characterised by well-structured experimentation and standards, which exploit the analytical skills and capacity to interpret causal attribution and avoid inferential errors, of R&D unit researchers. The complementarities between past and current exploration experience seem to be less effective at reducing innovation failure in the implementation stages of the innovation process. Here, context specificities associated with the scaling up of the manufacturing processes and the generation of new working prototypes seem to benefit less from the interaction between accumulated experience and current exploration efforts.

On the other hand, we find evidence of a curvilinear relationship between current exploration and innovation failure. In particular, we found support for an inverted U-shaped relationship between current investment in exploration activity and the probability of innovation failure in the conception and implementation phases of the innovation process. We found that, initially, exploration increases the chances of experiencing failure in the conception and implementation phases of the innovation process since generally it involves committing resources to search activities beyond current competencies and expertise. However, we also observed learning returns from exploratory R&D, measured by a reduced probability of failure with increasing levels of investment in current exploration activities. We argue that this source of learning from ongoing exploration efforts is associated with the firm's improved capacity to interpret ill-defined problems, based on a better understanding of the causal relation mechanisms underlying the phenomenon being explored. This non-linear, inverted-U shaped relationship between current exploration efforts and the probability of failure, reflects the complexity of the processes involved in exploration activities. These include difficulties related to interpreting unstructured information, attribution errors due to the absence of a precise understanding of the underlying causal relationships, and inferential errors based on a restricted sample of experimental results. By identifying these beneficial learning effects, we have highlighted an additional economic payoff from the exploratory component of R&D (David et al., 1992): fewer wasted resources resulting from the lower propensity to abandon innovation projects.

Our findings provide valuable insights for innovation management. Although firms tend to prefer development-based exploitation to research-based exploration (Arora et al., 2015), we find that exploration offers two sources of learning that have the potential to reduce the risk of a failed innovation project. These sources emerge after a certain level of exploration effort and when current efforts are combined with accumulated experience in exploration activities. Hence, planning periods of peak engagement in exploratory activities, which previous research shows have a positive effect on firm performance (Mudambi & Swift, 2011, 2014), might be beneficial for reducing exposure to innovation failure. However, "compartmentalised" periods of sustained exploration could hamper the interaction between ongoing and past exploration. Our results point to the need for persistent commitment to exploration over time, avoiding major discontinuities in order to capitalise on retention, integration and reuse of previously acquired knowledge in ongoing efforts. The extent to which firms are able to connect ongoing exploration and past experience is essential to conceptualise problems and to scan, evaluate and implement reusable ideas - especially in the presence of time and resource constraints (Cook & Brown, 1999; Majchrzak et al., 2004).

Moreover, our results provide finer grained results on the interplay between accumulated experience in exploratory R&D and current exploration, showing that this interaction is more beneficial in the conception than in the implementation phases. The capacity to learn from exploration and act upon unsuccessful innovation activities is greater in the conception phase, given that both transactive memory (Argote & Miron-Spektor, 2011) and related variation (Schilling et al., 2003) enable larger learning opportunities in settings that provide better conditions for controlled experimentation and structured planning, and greater flexibility in terms of experimentation alternatives due to the lower opportunity costs of failure. Hence, it is in the early stage of a project life cycle that firms can maximise the reliance on previously developed standards and information. This beneficial connection between experience and current practice is reduced in the implementation phase when context specificities are more pronounced. Additionally, sources of organisational rigidity such as entrapment situations (Balachandra et al., 1996; Jani, 2011) or escalation of commitments (Jani, 2011; Schmidt & Calantone, 1998; Staw & Ross, 1987), which are particularly likely to emerge in the implementation phase, could further weaken the connection between prior experience and current exploration activities.

The paper has some limitations that suggest avenues for future research. First, our definition of innovation failure forces us to measure it as a binary variable (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 enrich the analysis by showing the relative importance of innovation failure to firms experiencing different levels of research exploration efforts. Second, we rely on data from one country only, i.e. Spain. Future work should extend our analysis to a range of countries in order to allow the results obtained to be generalised. Third, although our longitudinal analysis tries to minimise problems of omitted variables bias and unobserved heterogeneity, the absence of a pure experimental setting (or instrumental variables approach) suggests caution in interpreting the results in a causal way. Finally, future work could investigate the exploration-failure relation using project-level data, which would allow greater scrutiny of the mechanisms related to knowledge retention, codification and integration that might be at the basis of the beneficial interplay between past experience and current exploration.

Despite these limitations, we believe that the insights from our study could serve as a guide and foundation for future work investigating the important role of firms' exploration strategies for reducing innovation failure and achieving sustained competitive advantage.

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TABLES

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Table 1: Probability of failure in R&D projects: engagement vs non engagement in innovation activities

	Engaging in innovation-related activities	*Not engaging in innovation-related activities*	*Pearson χ^2*
% Failure overall	31.91%	9.38%	563.23[1]***
% Failure conception	24.4%	5.71%	482.62[1]***
% Failure implementation	20.84%	6.03%	336.77[1]***
Observations	3136	5628	

Degrees of freedom are in brackets. The sample refers to all manufacturing companies in for the period 2007-2012. Firms engaging in innovation-related activities refer to companies which, in the period 2007-2012, invested in at least one of the following activities: intra-mural R&D; extramural R&D; acquisition of machinery, equipment and software; acquisition of other external knowledge; training; market introduction of innovations; other activities.

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Table 2 Descriptive Statistics (N=4191)

Variable	**Mean**	**SD**	**Min**	**Max**
Dependent variables				
Fail overall	0.312	0.463	0	1
Fail conception	0.237	0.425	0	1
Fail implementation	0.202	0.401	0	1
Explanatory variables				
R&D Exploration	1702.389	4196.190	0	76390.03
R&D Exploration -1	1848.7	4513.98	0	76390.03
Controls				
R&D exploitation	2490.204	6060.781	0	114585
Num of R&D researchers	0.723	0.862	0	6.06
Other innovation expenditures	5.934	2.509	0	12.34
Cost barriers	0.167	0.373	0	1
Knowledge barriers	0.012	0.109	0	1
Market barriers uncertainty	0.266	0.442	0	1
Market barriers dominated	0.191	0.393	0	1
Knowledge breadth	6.406	3.302	0	10
Knowledge depth	1.279	1.579	0	10
Radical innovation	0.414	0.493	0	1
Organisational innovation	0.547	0.498	0	1
Firm age	3.284	0.572	1.61	5.18
Group	0.450	0.498	0	1
Number of employees	4.290	1.307	0.69	9.19
Industry dummies (Pavitt Taxonomy)				
Supplier dominated	0.343	0.475	0	1
Scale intensive	0.271	0.445	0	1
Specialised suppliers	0.211	0.408	0	1
Science based	0.175	0.380	0	1

Descriptive statistics for *R&D exploration*, *R&D Exploration -1* and *R&D exploitation* refer to the variables before natural log-transformation and are measured in euros per employee. Descriptive statistics for the following variables are reported with natural log transformation: *Number of R&D researchers*, *Other innovation expenditures*, *Firm age* and *Number of employees*.

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Table 3: Correlation Matrix (N=4191)

		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]	[16]	[17]	[18]	[19]	[20]
[1]	*Failure*	1																			
[2]	*Failure Conception*	0.82*	1																		
[3]	*Failure Implementation*	0.74*	0.46*	1																	
[4]	*R&D exploration*	0.12*	0.14*	0.1*	1																
[5]	*R&D exploration -1*	0.09*	0.10*	0.08*	0.61*	1															
[6]	*Explor X Explor -1*	0.1*	0.12*	0.09*	0.83*	0.81*	1														
[7]	*R&D exploration Sq*	0.11*	0.13*	0.09*	0.96*	0.62*	0.87*	1													
[8]	*R&D exploitation*	0.07*	0.1*	0.03*	0.11*	0.08*	0.08*	0.11*	1												
[9]	*Knowledge breadth*	0.12*	0.18*	0.09*	0.22*	0.15*	0.20*	0.22*	0.23*	1											
[10]	*Knowledge depth*	0.07*	0.11*	0.06*	0.14*	0.1*	0.14*	0.15*	0.15*	0.41*	1										
[11]	*Other innovation exp*	0.04*	0.05*	0.03*	0.06*	0.05*	0.09*	0.11*	0.08*	0.17*	0.14*	1									
[12]	*Firm age*	0.05*	0.04*	0.04*	-0.05*	-0.06*	-0.06*	-0.08*	-0.05*	0.04*	0.01	-0.05*	1								
[13]	*Group*	0.04*	0.04*	0.05*	0.01	-0.01	0.01	0.01	-0.01	0.08*	0.03*	0.05*	0.11*	1							
[14]	*Cost barriers*	-0.02	-0.02	-0.02	0.01	0.02	0.01	0.01	-0.01	-0.01	0.06*	0.01	-0.06*	-0.13*	1						
[15]	*Knowledge barriers*	0.01	0.01	0.01	0.01	0.01	0.01	0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.06*	0.12*	1					
[16]	*Mkt barriers uncertainty*	0.07*	0.06*	0.07*	0.03*	0.01	0.03*	0.03*	0.03*	0.04*	0.08*	0.03*	-0.01	-0.06*	0.15*	0.09*	1				
[17]	*Mkt barriers dominated*	0.06*	0.06*	0.04*	0.06*	0.02	0.06*	0.07*	0.04*	0.05*	0.11*	0.03*	-0.03*	-0.08*	0.13*	0.12*	0.37*	1			
[18]	*Number of Employees*	0.06*	0.07*	0.06*	-0.03*	-0.08*	-0.05*	-0.07*	-0.04*	0.14*	0.06*	0.01	0.35*	0.55*	-0.15*	-0.06*	-0.11*	-0.1*	1		
[19]	*Radical Innovation*	0.1*	0.14*	0.07*	0.15*	0.11*	0.14*	0.15*	0.21*	0.17*	0.12*	0.15*	0.01	0.04*	-0.03*	-0.01	0.03*	-0.01	0.05*	1	
[20]	*Organisational Innovation*	0.13*	0.17*	0.09*	0.09*	0.07*	0.1*	0.08*	0.09*	0.23*	0.12*	0.14*	0.05*	0.10*	-0.04*	-0.01	0.04*	0.03*	0.16*	0.14*	1
[21]	*Number R&D employees*	0.13*	0.14*	0.12*	0.34*	0.27*	0.39*	0.40*	0.37*	0.29*	0.21*	0.19*	0.07*	0.28*	-0.04*	-0.03*	-0.01	0.03*	0.4*	0.21*	0.16*

Dummies for Pavitt (1984) four categories of industrial firms are not included for space reasons but correlation coefficient is never above 0.3. * p<0.05

Table 4 Innovation failures determinants: current exploration activities

	Failure overall (1)	Failure conception (2)	Failure implementation (3)
R&D exploration	0.044***	0.063***	0.033***
	[0.010]	[0.012]	[0.011]
R&D exploitation	0.026**	0.039***	0.005
	[0.011]	[0.014]	[0.012]
Knowledge breadth	0.013	0.062***	0.008
	[0.012]	[0.014]	[0.012]
Knowledge depth	0.019	0.037	0.016
	[0.023]	[0.026]	[0.024]
Other innovation expenditures	0.000	-0.002	-0.001
	[0.014]	[0.016]	[0.015]
Firm age	0.154**	0.115	0.127*
	[0.068]	[0.077]	[0.074]
Group	0.042	0.023	0.137
	[0.086]	[0.098]	[0.091]
Cost barriers	-0.081	-0.128	-0.105
	[0.093]	[0.108]	[0.099]
Knowledge barriers	0.233	0.332	0.315
	[0.308]	[0.346]	[0.316]
Market barriers - uncertainty	0.226***	0.146	0.256***
	[0.081]	[0.093]	[0.084]
Market barriers - dominated	0.099	0.176*	0.026
	[0.091]	[0.104]	[0.096]
Number of employees	0.049	0.066	0.023
	[0.040]	[0.046]	[0.043]
Radical innovation	0.135**	0.269***	0.105
	[0.068]	[0.076]	[0.072]
Org innovation	0.311***	0.516***	0.212***
	[0.068]	[0.079]	[0.073]
Number of R&D researchers	0.056	-0.003	0.107*
	[0.058]	[0.063]	[0.060]
Wald X^2	126.855[18]***	172.878[18]***	90.606[18]***
Firm-period observations	2226	2226	2226
Firm observations	4191	4191	4191

Random effects probit regressions with robust standard errors clustered by firm are in parentheses. The degrees of freedom of Wald χ^2 test for the overall significance of variables are reported in parentheses. Dummies for Pavitt (1984) four categories of industrial firms are included (but not shown) in all regressions. Year dummies are not included as the joint test of significance is never rejected at the standard confidence levels. Dependent variable is the probability to fail in any phase in column 1, the probability to fail at the conception phase in column 2 and the probability to fail at the implementation phase in column 3. Base sample in all columns is an unbalanced panel, 2009-2012, with data at 3-year intervals in levels where the start date of the panel refers to the dependent variable (i.e., if t=2007-2009, so t-1=2004-2006). * p<0.10, ** p<0.05, *** p<0.01.

Table 5 Innovation failures determinants: interaction effects

	Failure overall		Failure conception		Failure implementation	
	(1)	(2)	(3)	(4)	(5)	(6)
R&D exploration	0.039***	0.049***	0.059***	0.086***	0.028**	0.030*
	[0.011]	[0.017]	[0.013]	[0.019]	[0.012]	[0.018]
R&D exploration -1	0.013	0.023	0.009	0.037**	0.014	0.016
	[0.011]	[0.016]	[0.013]	[0.019]	[0.012]	[0.018]
R&D exploration X R&D exploration -1		-0.002		-0.006**		-0.001
		[0.003]		[0.003]		[0.003]
R&D exploitation	0.027**	0.026**	0.040***	0.037***	0.006	0.006
	[0.012]	[0.012]	[0.014]	[0.014]	[0.012]	[0.012]
Knowledge breadth	0.013	0.013	0.062***	0.061***	0.007	0.007
	[0.012]	[0.012]	[0.014]	[0.014]	[0.013]	[0.013]
Knowledge depth	0.019	0.019	0.037	0.038	0.017	0.017
	[0.023]	[0.023]	[0.026]	[0.025]	[0.024]	[0.024]
Other innovation expenditures	0.000	0.001	-0.002	-0.000	-0.001	-0.001
	[0.014]	[0.014]	[0.016]	[0.016]	[0.015]	[0.015]
Firm age	0.154**	0.154**	0.115	0.117	0.126*	0.126*
	[0.068]	[0.068]	[0.077]	[0.077]	[0.074]	[0.074]
Group	0.041	0.041	0.022	0.024	0.136	0.136
	[0.086]	[0.086]	[0.098]	[0.098]	[0.091]	[0.091]
Cost barriers	-0.083	-0.084	-0.129	-0.131	-0.107	-0.107
	[0.093]	[0.093]	[0.108]	[0.108]	[0.099]	[0.099]
Knowledge barriers	0.231	0.235	0.328	0.339	0.314	0.315
	[0.308]	[0.308]	[0.345]	[0.346]	[0.315]	[0.315]
Market barriers - uncertainty	0.227***	0.227***	0.147	0.147	0.258***	0.258***
	[0.081]	[0.081]	[0.093]	[0.093]	[0.084]	[0.084]
Market barriers - dominated	0.102	0.104	0.178*	0.182*	0.029	0.030
	[0.091]	[0.091]	[0.104]	[0.104]	[0.097]	[0.096]
Number of employees	0.055	0.053	0.070	0.063	0.029	0.028
	[0.041]	[0.041]	[0.047]	[0.047]	[0.043]	[0.043]
Radical innovation	0.135**	0.134**	0.269***	0.268***	0.105	0.104
	[0.068]	[0.068]	[0.076]	[0.076]	[0.072]	[0.072]
Org innovation	0.308***	0.308***	0.513***	0.515***	0.209***	0.209***
	[0.068]	[0.068]	[0.079]	[0.080]	[0.073]	[0.073]
Number of R&D researchers	0.046	0.054	-0.009	0.012	0.098	0.099
	[0.058]	[0.059]	[0.064]	[0.064]	[0.061]	[0.062]

Wald X^2	127.516[19]***	127.76[20]***	172.709[19]***	175.43[20]***	90.861[19]***	90.96[20]***
Firm-period observations	2226	2226	2226	2226	2226	2226
Firm observations	4191	4191	4191	4191	4191	4191

Random effects probit regressions with robust standard errors clustered by firm are in parentheses. The degrees of freedom of Wald χ^2 test for the overall significance of variables are reported in parentheses. Dummies for Pavitt (1984) four categories of industrial firms are included (but not shown) in all regressions. Year dummies are not included as the joint test of significance is never rejected at the standard confidence levels. Dependent variable is the probability to fail in any phase in columns 1-2, the probability to fail at the conception phase in columns 3-4 and the probability to fail at the implementation phase in columns 5-6. Base sample in all columns is an unbalanced panel, 2009-2012, with data at 3-year intervals in levels where the start date of the panel refers to the dependent variable (i.e., if t=2007-2009, so t-1=2004-2006). * p<0.10, ** p<0.05, *** p<0.01.

Table 6 Innovation failures determinants: curvilinear effects

	Failure overall (1)	Failure conception (2)	Failure implementation (3)
R&D exploration	0.146***	0.206***	0.121***
	[0.040]	[0.046]	[0.044]
R&D exploration sq	-0.014***	-0.019***	-0.012**
	[0.005]	[0.006]	[0.006]
R&D exploitation	0.021*	0.032**	0.001
	[0.012]	[0.014]	[0.012]
Knowledge breadth	0.014	0.063***	0.008
	[0.012]	[0.014]	[0.012]
Knowledge depth	0.019	0.037	0.017
	[0.023]	[0.025]	[0.024]
Other innovation expenditures	0.006	0.006	0.004
	[0.014]	[0.016]	[0.015]
Firm age	0.146**	0.105	0.120
	[0.068]	[0.077]	[0.073]
Group	0.054	0.039	0.146
	[0.086]	[0.097]	[0.090]
Cost barriers	-0.086	-0.136	-0.109
	[0.092]	[0.107]	[0.098]
Knowledge barriers	0.230	0.326	0.311
	[0.306]	[0.343]	[0.313]
Market barriers - uncertainty	0.218***	0.133	0.247***
	[0.081]	[0.092]	[0.084]
Market barriers - dominated	0.102	0.179*	0.028
	[0.090]	[0.103]	[0.096]
Number of employees	0.018	0.020	-0.004
	[0.042]	[0.049]	[0.045]
Radical innovation	0.135**	0.269***	0.106
	[0.067]	[0.075]	[0.072]
Org innovation	0.308***	0.512***	0.208***
	[0.068]	[0.079]	[0.072]
Number of R&D researchers	0.109*	0.073	0.153**
	[0.061]	[0.068]	[0.065]
Wald X^2	133.07[19]***	181.62[19]***	93.71[19]***
Firm-period observations	2226	2226	2226
Firm observations	4191	4191	4191

Random effects probit regressions with robust standard errors clustered by firm are in parentheses. The degrees of freedom of Wald χ^2 test for the overall significance of variables are reported in parentheses. Dummies for Pavitt (1984) four categories of industrial firms are included (but not shown) in all regressions. Year dummies are not included as the joint test of significance is never rejected at the standard confidence levels. Dependent variable is the probability to fail in any phase in column 1, the probability to fail at the conception phase in column 2 and the probability to fail at the implementation phase in column 3. Base sample in all columns is an unbalanced panel, 2009-2012, with data at 3-year intervals in levels where the start date of the panel refers to the dependent variable (i.e., if t=2007-2009, so t-1=2004-2006). * p<0.10, ** p<0.05, *** p<0.01.

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APPENDIX

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Table A1: Proportion of companies experiencing failure (overall, conception and implementation) for different types of innovation-related activities

Types of innovation-related activities	Failure overall	Failure conception	Failure implementation	Total
Intramural R&D (only)	27.94%	20.83%	17.52%	816
Other innovation activities (only)	19.33%	10.33%	13.33%	600
Both	34.62%	27.62%	22.68%	4052

The category "other innovation activities" include the following: extramural R&D; Acquisition of machinery, equipment and software; Acquisition of other external knowledge; Training; Market introduction of innovations; Other preparations

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Table A2: Innovation failures determinants: past exploration in stock

	Failure overall		Failure conception		Failure implementation	
	(1)	(2)	(3)	(4)	(5)	(6)
R&D exploration	0.041***	0.050***	0.060***	0.088***	0.030**	0.032*
	[0.011]	[0.018]	[0.013]	[0.021]	[0.012]	[0.019]
R&D exploration stock -1	0.008	0.015	0.007	0.031*	0.007	0.009
	[0.010]	[0.014]	[0.012]	[0.017]	[0.011]	[0.015]
R&D exploration X R&D exploration stock -1		-0.002		-0.005*		-0.000
		[0.003]		[0.003]		[0.003]
R&D exploitation	0.027**	0.026**	0.040***	0.038***	0.006	0.006
	[0.012]	[0.012]	[0.014]	[0.014]	[0.012]	[0.012]
Knowledge breadth	0.013	0.013	0.062***	0.061***	0.008	0.008
	[0.012]	[0.012]	[0.014]	[0.014]	[0.013]	[0.013]
Knowledge depth	0.019	0.019	0.036	0.038	0.016	0.017
	[0.023]	[0.023]	[0.025]	[0.026]	[0.024]	[0.024]
Other innovation expenditures	0.001	0.001	-0.001	-0.001	-0.001	-0.001
	[0.014]	[0.014]	[0.016]	[0.016]	[0.015]	[0.015]
Firm age	0.151**	0.151**	0.113	0.113	0.124*	0.124*
	[0.068]	[0.068]	[0.077]	[0.077]	[0.074]	[0.074]
Group	0.040	0.041	0.021	0.022	0.136	0.136
	[0.086]	[0.086]	[0.098]	[0.098]	[0.091]	[0.091]
Cost barriers	-0.083	-0.085	-0.129	-0.134	-0.107	-0.107
	[0.093]	[0.093]	[0.108]	[0.108]	[0.099]	[0.099]
Knowledge barriers	0.234	0.235	0.331	0.336	0.317	0.317
	[0.308]	[0.308]	[0.345]	[0.345]	[0.316]	[0.316]
Market barriers - uncertainty	0.226***	0.227***	0.146	0.151	0.256***	0.257***
	[0.081]	[0.081]	[0.093]	[0.093]	[0.084]	[0.084]
Market barriers - dominated	0.101	0.101	0.177*	0.178*	0.028	0.028
	[0.091]	[0.091]	[0.104]	[0.104]	[0.097]	[0.097]
Number of employees	0.054	0.053	0.070	0.067	0.027	0.027
	[0.041]	[0.041]	[0.047]	[0.047]	[0.043]	[0.043]

Radical innovation	0.135**	0.135**	0.269***	0.268***	0.105	0.105
	[0.068]	[0.068]	[0.076]	[0.076]	[0.072]	[0.072]
Org innovation	0.310***	0.311***	0.514***	0.518***	0.211***	0.212***
	[0.068]	[0.068]	[0.079]	[0.079]	[0.073]	[0.073]
Number of R&D researchers	0.048	0.054	-0.009	0.008	0.100	0.101
	[0.059]	[0.059]	[0.064]	[0.065]	[0.061]	[0.062]
Wald X^2	127.07[19]***	127.29[20]***	172.64[19]***	174.71[20]***	90.54[19]***	90.6[20]***
Firm-period observations	2226	2226	2226	2226	2226	2226
Firm observations	4191	4191	4191	4191	4191	4191

Random effects probit regressions with robust standard errors clustered by firm are in parentheses. The degrees of freedom of Wald χ^2 test for the overall significance of variables are reported in parentheses. Dummies for Pavitt (1984) four categories of industrial firms are included (but not shown) in all regressions. Year dummies are not included as the joint test of significance is never rejected at the standard confidence levels. Dependent variable is the probability to fail in any phase in columns 1-2, the probability to fail at the conception phase in columns 3-4 and the probability to fail at the implementation phase in columns 5-6. Base sample in all columns is an unbalanced panel, 2009-2012, with data at 3-year intervals in levels where the start date of the panel refers to the dependent variable (i.e., if t=2007-2009, so t-1=2004-2006). * p<0.10, ** p<0.05, *** p<0.01.

Table A3: Innovation failures determinants: current exploration activities for SMEs (less than 50 employees)

	Failure overall (1)	Failure conception (2)	Failure implementation (3)
R&D exploration	0.037***	0.047***	0.036**
	[0.014]	[0.015]	[0.015]
R&D exploitation	0.024	0.024	0.010
	[0.015]	[0.018]	[0.017]
Knowledge breadth	-0.009	0.036*	-0.010
	[0.017]	[0.019]	[0.019]
Knowledge depth	0.013	0.007	0.027
	[0.035]	[0.039]	[0.038]
Other innovation expenditures	-0.012	-0.010	-0.009
	[0.019]	[0.022]	[0.021]
Firm age	0.165	0.236**	0.056
	[0.105]	[0.118]	[0.122]
Group	-0.027	0.004	0.006
	[0.135]	[0.153]	[0.153]
Cost barriers	-0.175	-0.188	-0.268**
	[0.120]	[0.137]	[0.134]
Knowledge barriers	0.302	0.527	0.340
	[0.334]	[0.344]	[0.367]
Market barriers - uncertainty	0.340***	0.235*	0.346***
	[0.115]	[0.129]	[0.125]
Market barriers - dominated	0.155	0.185	0.128
	[0.125]	[0.139]	[0.140]
Number of employees	-0.129	-0.166	-0.105
	[0.094]	[0.110]	[0.106]
Radical innovation	0.133	0.294***	0.025
	[0.100]	[0.109]	[0.111]
Org innovation	0.233**	0.411***	0.155
	[0.097]	[0.110]	[0.107]
Number of R&D researchers	0.008	0.143	0.053
	[0.126]	[0.135]	[0.138]
Wald X^2	52.6[18]***	70.23[18]***	33.52[18]**
Firm-period observations	1000	1000	1000
Firm observations	1805	1805	1805

Random effects probit regressions with robust standard errors clustered by firm are in parentheses. The degrees of freedom of Wald χ^2 test for the overall significance of variables are reported in parentheses. Dummies for Pavitt (1984) four categories of industrial firms are included (but not shown) in all regressions. Year dummies are not included as the joint test of significance is never rejected at the standard confidence levels. Dependent variable is the probability to fail in any phase in column 1, the probability to fail at the conception phase in column 2 and the probability to fail at the implementation phase in column 3. Base sample in all columns is an unbalanced panel, 2009-2012, with data at 3-year intervals in levels where the start date of the panel refers to the dependent variable (i.e., if t=2007-2009, so t-1=2004-2006). * p<0.10, ** p<0.05, *** p<0.01.

Table A4: Innovation failures determinants: interaction effects for SMEs (less than 50 employees)

	Failure overall		Failure conception		Failure implementation	
	(1)	(2)	(3)	(4)	(5)	(6)
R&D exploration	0.034**	0.059***	0.047***	0.079***	0.031*	0.044*
	[0.015]	[0.023]	[0.017]	[0.026]	[0.016]	[0.025]
R&D exploration -1	0.007	0.029	-0.001	0.029	0.011	0.023
	[0.015]	[0.021]	[0.017]	[0.024]	[0.017]	[0.024]
R&D exploration X R&D exploration -1		-0.005		-0.007*		-0.003
		[0.004]		[0.004]		[0.004]
R&D exploitation	0.024	0.022	0.024	0.021	0.010	0.009
	[0.018]	[0.016]	[0.018]	[0.018]	[0.017]	[0.017]
Knowledge breadth	0.036*	-0.009	0.036*	0.036*	-0.010	-0.010
	[0.019]	[0.017]	[0.019]	[0.019]	[0.019]	[0.019]
Knowledge depth	0.007	0.015	0.007	0.010	0.028	0.028
	[0.039]	[0.035]	[0.039]	[0.039]	[0.038]	[0.038]
Other innovation expenditures	-0.010	-0.012	-0.010	-0.010	-0.010	-0.010
	[0.022]	[0.019]	[0.022]	[0.022]	[0.021]	[0.021]
Firm age	0.236**	0.170	0.236**	0.240**	0.059	0.060
	[0.118]	[0.105]	[0.118]	[0.118]	[0.122]	[0.122]
Group	0.004	-0.029	0.004	0.004	0.005	0.004
	[0.153]	[0.135]	[0.153]	[0.153]	[0.153]	[0.153]
Cost barriers	-0.188	-0.174	-0.188	-0.183	-0.272**	-0.270**
	[0.137]	[0.120]	[0.137]	[0.137]	[0.135]	[0.134]
Knowledge barriers	0.527	0.310	0.528	0.542	0.337	0.343
	[0.344]	[0.335]	[0.345]	[0.345]	[0.367]	[0.367]
Market barriers - uncertainty	0.235*	0.341***	0.235*	0.237*	0.348***	0.347***
	[0.129]	[0.115]	[0.129]	[0.129]	[0.126]	[0.125]
Market barriers - dominated	0.185	0.160	0.184	0.190	0.131	0.133
	[0.139]	[0.125]	[0.139]	[0.139]	[0.140]	[0.140]
Number of employees	-0.166	-0.134	-0.166	-0.179	-0.100	-0.104
	[0.110]	[0.094]	[0.110]	[0.111]	[0.107]	[0.107]
Radical innovation	0.294***	0.134	0.294***	0.296***	0.025	0.025

	[0.109]	[0.100]	[0.110]	[0.109]	[0.112]	[0.111]
Org innovation	0.411***	0.234**	0.412***	0.414***	0.151	0.153
	[0.110]	[0.097]	[0.110]	[0.110]	[0.108]	[0.107]
Number of R&D researchers	0.143	0.026	0.144	0.174	0.043	0.056
	[0.135]	[0.127]	[0.136]	[0.137]	[0.140]	[0.140]
Wald X^2	70.23[18]***	53.89[20]***	70.46[19]***	72.71[20]***	33.31[19]**	33.69[20]***
Firm-period observations	1000	1000	1000	1000	1000	1000
Firm observations	1805	1805	1805	1805	1805	1805

Random effects probit regressions with robust standard errors clustered by firm are in parentheses. The degrees of freedom of Wald χ^2 test for the overall significance of variables are reported in parentheses. Dummies for Pavitt (1984) four categories of industrial firms are included (but not shown) in all regressions. Year dummies are not included as the joint test of significance is never rejected at the standard confidence levels. Dependent variable is the probability to fail in any phase in columns 1-2, the probability to fail at the conception phase in columns 3-4 and the probability to fail at the implementation phase in columns 5-6. Base sample in all columns is an unbalanced panel, 2009-2012, with data at 3-year intervals in levels where the start date of the panel refers to the dependent variable (i.e., if t=2007-2009, so t-1=2004-2006). * p<0.10, ** p<0.05, *** p<0.01

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Table A5: Innovation failures determinants: curvilinear effects for SMEs (less than 50 employees)

	Failure overall (1)	Failure conception (2)	Failure implementation (3)
R&D exploration	0.163***	0.201***	0.206***
	[0.060]	[0.070]	[0.068]
R&D exploration sq	-0.016**	-0.020**	-0.022***
	[0.008]	[0.009]	[0.008]
R&D exploitation	0.018	0.017	0.002
	[0.016]	[0.018]	[0.017]
Knowledge breadth	-0.006	0.038**	-0.006
	[0.017]	[0.019]	[0.019]
Knowledge depth	0.016	0.011	0.030
	[0.035]	[0.039]	[0.038]
Other innovation expenditures	-0.007	-0.004	-0.003
	[0.020]	[0.022]	[0.022]
Firm age	0.161	0.230**	0.049
	[0.104]	[0.116]	[0.120]
Group	-0.020	0.009	0.016
	[0.135]	[0.152]	[0.153]
Cost barriers	-0.177	-0.188	-0.271**
	[0.119]	[0.135]	[0.133]
Knowledge barriers	0.308	0.530	0.344
	[0.330]	[0.338]	[0.361]
Market barriers - uncertainty	0.326***	0.214*	0.325***
	[0.115]	[0.129]	[0.125]
Market barriers - dominated	0.166	0.198	0.142
	[0.125]	[0.138]	[0.139]
Number of employees	-0.178*	-0.225**	-0.174
	[0.096]	[0.113]	[0.109]
Radical innovation	0.135	0.295***	0.027
	[0.100]	[0.108]	[0.111]
Org innovation	0.229**	0.407***	0.146
	[0.097]	[0.108]	[0.107]
Number of R&D researchers	0.100	0.256*	0.179
	[0.133]	[0.144]	[0.147]
Wald X^2	58.36[19]***	75.76[19]***	40.02[19]
Firm-period observations	1000	1000	1000
Firm observations	1805	1805	1805

Random effects probit regressions with robust standard errors clustered by firm are in parentheses. The degrees of freedom of Wald χ^2 test for the overall significance of variables are reported in parentheses. Dummies for Pavitt (1984) four categories of industrial firms are included (but not shown) in all regressions. Year dummies are not included as the joint test of significance is never rejected at the standard confidence levels. Dependent variable is the probability to fail in any phase in column 1, the probability to fail at the conception phase in column 2 and the probability to fail at the implementation phase in column 3. Base sample in all columns is an unbalanced panel, 2009-2012, with data at 3-year intervals in levels where the start date of the panel refers to the dependent variable (i.e., if t=2007-2009, so t-1=2004-2006). * p<0.10, ** p<0.05, *** p<0.01

Table A6: Innovation failures determinants: Bivariate probit regressions

	(1)		(2)		(3)		(4)	
	Failure conception	Failure implementation	Failure conception	Failure implementation	Failure conception	Failure implementation	Failure conception	Failure implementation
R&D exploration	0.037***	0.022***	0.034***	0.019**	0.050***	0.028**	0.146***	0.103***
	[0.008]	[0.008]	[0.008]	[0.008]	[0.012]	[0.012]	[0.029]	[0.030]
R&D Exploration -1			0.006	0.005	0.023**	0.014		
			[0.008]	[0.008]	[0.012]	[0.012]		
R&D exploration X R&D Exploration -1					-0.004**	-0.002		
					[0.002]	[0.002]		
R&D exploration sq							-0.014***	-0.011***
							[0.004]	[0.004]
R&D exploitation	0.022***	-0.001	0.022***	-0.001	0.020**	-0.002	0.016*	-0.005
	[0.008]	[0.008]	[0.008]	[0.008]	[0.008]	[0.008]	[0.009]	[0.008]
Knowledge breadth	0.042***	0.012	0.041***	0.012	0.041***	0.012	0.042***	0.012
	[0.008]	[0.009]	[0.008]	[0.009]	[0.008]	[0.009]	[0.008]	[0.009]
Knowledge depth	0.012	0.001	0.012	0.001	0.013	0.001	0.012	0.001
	[0.017]	[0.017]	[0.017]	[0.017]	[0.017]	[0.017]	[0.017]	[0.017]
Other innovation expenditures	-0.007	-0.004	-0.007	-0.003	-0.006	-0.003	0.000	0.002
	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.011]
Firm age	0.079*	0.097**	0.079*	0.096**	0.079*	0.097**	0.073	0.092*
	[0.048]	[0.049]	[0.048]	[0.049]	[0.048]	[0.049]	[0.047]	[0.049]
Group	0.014	0.083	0.013	0.082	0.014	0.083	0.027	0.092
	[0.061]	[0.061]	[0.061]	[0.061]	[0.061]	[0.061]	[0.061]	[0.061]
Cost barriers	-0.072	-0.080	-0.072	-0.081	-0.074	-0.082	-0.076	-0.083
	[0.068]	[0.068]	[0.068]	[0.068]	[0.068]	[0.068]	[0.068]	[0.068]
Knowledge barriers	0.073	0.150	0.071	0.148	0.076	0.151	0.071	0.147
	[0.215]	[0.213]	[0.215]	[0.213]	[0.214]	[0.214]	[0.214]	[0.213]
Market barriers - uncertainty	0.138**	0.205***	0.139**	0.206***	0.140**	0.206***	0.130**	0.199***
	[0.058]	[0.058]	[0.058]	[0.059]	[0.058]	[0.058]	[0.058]	[0.058]
Market barriers - dominated	0.110*	0.059	0.112*	0.060	0.115*	0.062	0.114*	0.061
	[0.065]	[0.067]	[0.066]	[0.067]	[0.066]	[0.067]	[0.065]	[0.067]
Number of employees	0.040	0.014	0.042	0.016	0.038	0.013	0.005	-0.011

	[0.029]	[0.029]	[0.029]	[0.029]	[0.029]	[0.029]	[0.030]	[0.030]
Radical innovation	0.213***	0.095*	0.212***	0.094*	0.213***	0.094*	0.215***	0.096*
	[0.049]	[0.051]	[0.049]	[0.051]	[0.049]	[0.051]	[0.049]	[0.051]
Org innovation	0.335***	0.161***	0.334***	0.160***	0.334***	0.160***	0.330***	0.157***
	[0.050]	[0.051]	[0.050]	[0.051]	[0.050]	[0.051]	[0.050]	[0.051]
Number of R&D researchers	-0.009	0.073*	-0.013	0.069*	0.001	0.077*	0.049	0.116***
	[0.040]	[0.041]	[0.040]	[0.042]	[0.041]	[0.042]	[0.043]	[0.044]
Wald X^2	285.16(36)***		285.43(38)***		285.71[40]***		299.24[38]***	
Firm-period observations	2226		2226		2226		2226	
Firm observations	4191		4191		4191		4191	

Bivariate probit regressions with robust standard errors clustered by firm are in parentheses. The degrees of freedom of Wald χ^2 test for the overall significance of variables are reported in parentheses. Dummies for Pavitt (1984) four categories of industrial firms are included (but not shown) in all regressions. Year dummies are not included as the joint test of significance is never rejected at the standard confidence levels. Dependent variable is the probability to fail at the conception phase in even and the probability to fail at the implementation phase in odd columns. Base sample in all columns is a cross-section (2004-2012). * p<0.10, ** p<0.05, *** p<0.01.

Table A7: Innovation failures determinants: Probit Seemingly Unrelated Regression

	(1)		(2)		(3)		(4)	
	Failure conception	Failure implementation	Failure conception	Failure implementation	Failure conception	Failure implementation	Failure conception	Failure implementation
R&D exploration	0.037***	0.022***	0.034***	0.019**	0.050***	0.028**	0.146***	0.103***
	[0.008]	[0.008]	[0.008]	[0.008]	[0.012]	[0.012]	[0.029]	[0.030]
R&D Exploration -1			0.006	0.005	0.023**	0.014		
			[0.008]	[0.008]	[0.012]	[0.012]		
R&D exploration X R&D Exploration -1					-0.004**	-0.002		
					[0.002]	[0.002]		
R&D exploration sq							-0.014***	-0.011***
							[0.004]	[0.004]
R&D exploitation	0.022***	-0.001	0.022***	-0.001	0.020**	-0.002	0.016*	-0.005
	[0.008]	[0.008]	[0.008]	[0.008]	[0.008]	[0.008]	[0.009]	[0.008]
Knowledge breadth	0.042***	0.012	0.041***	0.012	0.041***	0.012	0.042***	0.012
	[0.008]	[0.009]	[0.008]	[0.009]	[0.008]	[0.009]	[0.008]	[0.009]
Knowledge depth	0.012	0.001	0.012	0.001	0.013	0.001	0.012	0.001
	[0.017]	[0.017]	[0.017]	[0.017]	[0.017]	[0.017]	[0.017]	[0.017]
Other innovation expenditures	-0.007	-0.004	-0.007	-0.003	-0.006	-0.003	0.000	0.002
	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.011]
Firm age	0.079*	0.097**	0.079*	0.096**	0.079*	0.097**	0.073	0.092*
	[0.048]	[0.049]	[0.048]	[0.049]	[0.048]	[0.049]	[0.047]	[0.049]
Group	0.014	0.083	0.013	0.082	0.014	0.083	0.027	0.092
	[0.061]	[0.061]	[0.061]	[0.061]	[0.061]	[0.061]	[0.061]	[0.061]
Cost barriers	-0.072	-0.080	-0.072	-0.081	-0.074	-0.082	-0.076	-0.083
	[0.068]	[0.068]	[0.068]	[0.068]	[0.068]	[0.068]	[0.068]	[0.068]
Knowledge barriers	0.073	0.150	0.071	0.148	0.076	0.151	0.071	0.147
	[0.215]	[0.213]	[0.215]	[0.213]	[0.214]	[0.214]	[0.214]	[0.213]
Market barriers - uncertainty	0.138**	0.205***	0.139**	0.206***	0.140**	0.206***	0.130**	0.199***
	[0.058]	[0.058]	[0.058]	[0.059]	[0.058]	[0.058]	[0.058]	[0.058]
Market barriers - dominated	0.110*	0.059	0.112*	0.060	0.115*	0.062	0.114*	0.061
	[0.065]	[0.067]	[0.066]	[0.067]	[0.066]	[0.067]	[0.065]	[0.067]
Number of employees	0.040	0.014	0.042	0.016	0.038	0.013	0.005	-0.011

	[0.029]	[0.029]	[0.029]	[0.029]	[0.029]	[0.029]	[0.030]	[0.030]
Radical innovation	0.213***	0.095*	0.212***	0.094*	0.213***	0.094*	0.215***	0.096*
	[0.049]	[0.051]	[0.049]	[0.051]	[0.049]	[0.051]	[0.049]	[0.051]
Org innovation	0.335***	0.161***	0.334***	0.160***	0.334***	0.160***	0.330***	0.157***
	[0.050]	[0.051]	[0.050]	[0.051]	[0.050]	[0.051]	[0.050]	[0.051]
Number of R&D researchers	-0.009	0.073*	-0.013	0.069*	0.001	0.077*	0.049	0.116***
	[0.040]	[0.041]	[0.040]	[0.042]	[0.041]	[0.042]	[0.043]	[0.044]
Wald X^2	285.16[36]***		285.43[38]***		285.71[40]***		299.24[38]***	
Firm-period observations	2226		2226		2226		2226	
Firm observations	4191		4191		4191		4191	

Probit SURE with robust standard errors clustered by firm in parentheses. The degrees of freedom of Wald X^2 test for the overall significance of variables are reported in parentheses. Dummies for Pavitt (1984) four categories of industrial firms are included (but not shown) in all regressions and Wald X^2 test is reported with the joint significance. Year dummies are not included as the joint test of significance is never rejected at the standard confidence levels. Dependent variable is the probability to fail at the conception phase in odd columns and the probability to fail at the implementation phase in even columns. Base sample in all columns is an unbalanced panel, 2009-2012, with data at 3-year intervals in levels where the start date of the panel refers to the dependent variable (i.e., if t=2007-2009, so t-1=2004-2006).
* p<0.10, ** p<0.05, *** p<0.01