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Exploring and Yet Failing Less: The Role of Exploitation and Human Capital to Foster Learning from Exploration

Pablo D'este
Polytechnic University of Valencia
INGENIO (CSIC-UPV)
pdeste@ingenio.upv.es

Alberto Marzucchi
Catholic University of Milan
Dept. of International Economics, Institutions and Developme
alberto.marzucchi@unicatt.it

Francesco Rentocchini
University of Southampton
Southampton Management School
f.rentocchini@soton.ac.uk

Abstract

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Abstract

Exploration is both a risky activity and a key ingredient in the strategy of firms that strive for radical innovations. In this paper we analyse how firms' investment in exploration activities affects their exposure to innovation failure. Our baseline results point to an inverted U-shaped relation: while investment in exploratory activities initially increases the rate of failure in innovation, firms that overcome an experience threshold in exploration exhibit decreasing rates of innovation failure. We also show that firm's commitments to product and process development and the availability of human capital act as relevant moderators: they contribute to speed the organisational learning process enhanced by exploration and result in lowering the probability of innovation failure. We investigate these issues drawing on a sample of 2,954 Spanish manufacturing companies for the period 2008-2010.

INTRODUCTION

Exploration is a key ingredient in the strategy of firms that strive for radical innovations. As disruptive innovations in products, services or business models entail the promise of large revenue opportunities and contribute to build resources that are difficult to imitate by competitors, exploration strategies become fundamental for building a firm's sustained competitive advantage.

However, exploration also increases the exposure of firms to failure. While firms need to explore in order to build and retain a competitive edge, they also need to learn how to manage the greater uncertainty and risk involved in highly explorative innovation activities (Edmondson, 2011). This is not an easy balance. Firms want to minimise operational-based instances of failures and curve down failures to a minimum (Desai, 2010). At the same time, firms might be willing to tolerate some degree of failure so long as it provides valuable new knowledge and learning opportunities for their innovation strategies (Leonard-Barton, 1995; Edmondson, 2011).

While there is a huge and well-established literature examining the returns to basic research and development on innovation performance (Mansfield, 1980; Freeman, 1982; Rosenberg, 1990), and an increasing literature on the learning opportunities from failure (Haunschild and Sullivan, 2002; Madsen & Desai, 2010), there is much less research about the relationship between firms' exploration activities and innovation failure. This paper contributes to the literature by investigating the following two issues. First, we investigate whether, and to what extent, firms learn from exploratory research by succeeding to reduce the probability of experiencing innovation failure. And second, we investigate whether the firm's commitments to product and process development and the availability of human capital contribute to speed the organisational learning process from exploration with regards to lowering innovation failure.

CONCEPTUAL BACKGROUND AND HYPOTHESES

Exploration as a buffer to myopic learning

According to the behavioural theories of the firm, organisations learn through experience and adaptive processes. Organisational learning is an adaptive process, embedded in routines and procedures, that changes the knowledge base of the organisation in response to its interaction with the environment (Cyert and March, 1963; Nelson and Winter, 1982; Levitt and March, 1988). This adaptive learning process often entails its own limits for generating learning opportunities, as it gives pre-eminence to the effectiveness of the learning process, prioritising attention to the short run and experimentation in the near neighbourhood of current experience (Levinthal and March, 1993).

An overemphasis on the immediate performance from learning processes can interfere with learning strategies oriented to pushing the boundaries of search towards the long run or into new territories. As argued by Levinthal and March (1993), organisational learning processes are often myopic because of their tendency to ignore the long run, disregard distant search and overlook the lessons that can be gained from failure. This is largely due to the fact that the returns from exploitation, that is, the refinement and extension of existing competences and technologies, are generally positive, proximate and predictable. Thus, firms tend to give priority to the achievement of reliable performance via exploitation learning strategies, at the expense of actions oriented to the search for new ideas or markets that have less certain outcomes, involve longer time horizons and involve more diffuse effects (March, 1991).

Moreover, organisational learning processes often fail to correct for the myopic basis from experiential learning. Short-term myopia accentuates the learning pressures towards exploitation rather than exploration. It tends to favour the use and development of things already known in order to gain further efficiency and reliability – i.e. improving the returns from exploitation - as opposed to the pursuit of new knowledge and things that might come to be known – i.e. embracing an exploration strategy (Levinthal and March, 1993). This characteristic of adaptive learning processes can potentially be self-destructive as it endangers the long-term survival of the organization (March, 1991).

Nevertheless, firms may deliberately try to counterbalance the biases towards myopic learning process by committing to continuous exploration activities. Sustaining a certain level of exploration militates against the traps of myopic learning, acting as a safeguard, or a buffer, to myopia. Exploration contributes to build and compromise capabilities outside current competencies and niches, and it favours the appreciation of risk-taking and the awareness of learning opportunities from failure. While exploitation is necessary to guarantee survival in the short run, as it contributes to improve average performance, exploration is essential to secure long-term survival, as it allows for deviation from average and the potential realisation of a position of primacy and leadership among competitors (March, 1991; Levinthal and March, 1993).

Innovation failure: good and bad

Since innovation failures refer to the abandonment, interruption and major delays of innovation projects conducted by organizations, it is reasonable to expect that firms aim to minimize these instances as much as they possibly can. There is however an increasing awareness in the business and management literature to further problematize the analysis of failure, by acknowledging that not all failure instances are necessarily bad for an organization.

Leonard-Barton (1995) and Edmonson (2011) have suggested the appropriateness of taking into account different types of failures. Edmonson (2011) proposes three types of failures: preventable, complexity-related and intelligent. Preventable failures are associated with deviance to rules, inattention or lack of abilities when conducting routine or predictable operations. In this sense, failures within this category are considered to be 'bad' as they should be avoided as a result of operational-based learning. Complexity-related failures refer to organisational failures due to the uncertainty associated with the systemic complexity of tasks and procedures implicated in certain forms of innovation activities. This type of failures, however undesirable, is almost unavoidable and inherent to the complexity of the tasks. Nevertheless, the organization should have the mechanisms in place to identify and act upon these failures at early stages, before they scale up into major disruptions. And finally, intelligent failures are those associated to deliberate actions towards experimentation and exploration of unknown territories. Insofar as these instances of failure provide valuable opportunities to gain new knowledge that can help an organization leap ahead of the competition and ensure its future growth and survival, they can be considered as 'good' failures.

Given that exploration involves moving into unknown and distant search spaces, it is reasonable to expect a particularly high prevalence of failure due to the inherent uncertainty of outcomes associated to experimentation. Accordingly, we would expect that firms that engage in exploration activities will exhibit a larger probability of failure experience. While these instances of failure can potentially provide an organization with a range of learning opportunities to capitalize from in their searching and experimentation processes, this learning cannot be taken for granted, and firms may succumb to an overload of exploration and to the inherent uncertainties involved.

However, exploration also involves programmed procedures and routines; experimentation is far from an unstructured activity (Nelson and Winter, 1982). In this sense, firms are expected to organise their exploration activities and set the conditions to potentially learn from instances of both success and failure. Learning from programmed exploration to curve down failures can manifest in different ways. On the one hand, sustained levels of exploration within the organisation contribute to learning from failures. Sustained efforts on exploration contribute to develop long-run intelligence, monitoring and surveillance capacities that enable firms to identify, analyse and act upon both preventable and complexity-related failures (March, 1991; Edmonson, 2011). On the other hand, the accumulation of exploration experience contributes to minimize 'preventable' failures associated with the routine tasks involved in exploration and experimentation activities themselves. Operational-based learning can lower down the risks of failure, provided that a sufficient scale of experience in exploration activities is accumulated (Desai, 2010). However, those failures that are inherently associated to experimentation ('intelligent failures') are likely to be more resilient all through the exploration activities, and be particularly prevalent at earlier stages of the exploration learning process, when firms might be willing to explore different routes of action at the conception phase.

According to the discussion above, we would expect a curvilinear relationship between exploration and the probability of experiencing failure: where failure increases with exploration up to a point beyond which operational-based learning and accumulated intelligence from exploration contributes to lower down the probability of failure.

Hypothesis 1: Exploration is expected to have a curvilinear effect, taking an inverted U-shape, on the probability to experience innovation failure.

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

In the previous section we have argued that organisations can learn from their exploration activities by lowering the occurrence of innovation failures. However, learning from exploration is unlikely to be a straightforward process. As many studies on organizational learning have pointed out, effective and faster learning demands some pre-conditions that should be satisfied by the organization (Edmonson, 2011; Gino and Pisano, 2011).

Two critical pre-conditions are particularly relevant in the context of exploration and experimentation: the capacity of firms to balance exploration and exploitation activities, and the availability of highly research-skilled human resources. We discuss below how these two contingent factors might influence the capacity of the firm to learn from exploration in order to curve down innovation failures.

Balancing exploration and exploitation

Firms often find it hard to conduct both exploration and exploitation activities, and even harder still to realize the benefits of the potential complementarities between the exploration and exploitation. In the first place, this is so because these two activities represent an important trade-off for the companies. While, firms might acknowledge that exploration and exploitation are critical to guarantee the organization survival, the two activities compete for limited physical and human resources (March, 1991), as well as for the attention of the organisation's decision makers (Ocasio, 1997). As discussed above, the different time horizons and degrees of uncertainty involved in exploration and exploitation, biases firms towards exploitation at the expense of exploration.

However, the trade-offs between exploration and exploitation should not be regarded as insurmountable. Recent research suggests that firms that develop ambidextrous capabilities, in terms of simultaneously exploiting existing competencies and exploring new opportunities, are expected to exhibit superior economic performance (Raisch et al., 2009). Also, there is evidence showing that research and development activities may complement each other with regards to the firm's achievement of higher productivity (Barge-Gil and Lopez, 2013), as well as evidence demonstrating that firms can design organizational structures that enable employees to pursue both types of activities (Gibson and Birkinshaw, 2004).

A fundamental reason underlying the rationale for the potential complementarities between exploration and exploitation rests on the potential benefits for innovation from a continuous dialogue between experimentation and prototyping (Leonard-Barton, 1992; 1995). This logic highlights that organisations can potentially benefit from a two-way flow of information and knowledge between exploration and exploitation.

From exploration to exploitation, by improving the efficiency of downstream research activities and prototyping on the basis of insights gained by an ex-ante understanding of the innovation process (Nelson, 1982; David et al., 1992). In this respect, exploration can provide advances in fundamental understanding that can contribute to lowering the risks of applied developments by flagging promising directions for downstream research and by contributing to develop the necessary tools for more rapid and efficient (product and process) development (Pisano, 2006). This path can be synthesised by the idea of overcoming the downsides of a trial and error learning process from downstream activities, benefitting instead from a more ex-ante, upstream learning process gained through experimentation that contributes to reduce the risks of failure along the development pipeline.

On the other hand, gains can run in the opposite direction as well, from exploitation to exploration. As shown by Leonard-Barton (1995), prototyping can be seen as an essential practice to elicit critical information and provide feedback to the experimentation units. By conducting rapid prototyping cycles, firms can identify features that do not work as expected in the lab, feeding reactions to product (or process) concept designers before major failures might ensue further downstream along the pipeline (Leonard-Barton, 1995). Moreover, by collecting information at close to market stages of product development, organizations are likely to identify when the returns from given strategies are reaching a point of exhaustion or decreasing returns, thus helping to alert about the need of a change in exploration avenues or making a leap to newer competencies or a focus on new technological paths (Ahuja and Katila, 2004; Mudambi and Swift, 2014).

Drawing on the above discussion about the potential complementarities between exploration and exploitation, we would expect that organizations that conduct a critical level of development or exploitation activities, should exhibit a more effective and faster learning process in their exploration activities. Therefore, we put forward the following hypothesis:

Hypothesis 2: The degree of exploitation activities conducted by the firm negatively moderates the relationship between exploration and innovation failure. That is, for a given level of exploration, higher levels of exploitation reduce the probability of innovation failure.

Availability of highly research-skilled human resources

A critical pre-condition particularly relevant in the context of exploration and experimentation activities, is the availability of highly skilled human resources. Highly skilled employees are expected to equip the organisation's research teams with an adaptable, responsive and pro-active workforce. The essential role of highly skilled researchers and technicians in the organizational learning process associated to exploration lies on the following three potential contributions.

First, employees with higher education degrees and research experience are particularly well suited to set in motion procedures for the systematic detection and analysis of success and failures. Learning from exploration activities involve developing capabilities for the early detection of failures before they mushroom into disaster, and also capabilities to analyse and gain adequate interpretations from experimentation and potential breakdowns and errors. Early detection of failures is crucial not only because it contributes to save money, avoiding the deployment of additional resources into unsuccessful research projects downstream into the development pipeline; but also because it creates a favourable climate for risk-taking in experimentation, as employees gain confidence that their monitoring processes will prevent any scaling up of negative effects from inevitable failures.

Besides detection, both success and failures must also be properly analysed in order to adequately understand their root causes and contribute to effective organisational learning from exploration. However, analysis of success and failure is cognitively challenging for an organisation.

Accumulated experience can often be a poor teacher, and may involve making wrong inferences from mixed evidence, particularly in the face of complex activities such as exploration (Levinthal and March, 1993).

Moreover, learning from exploration can be also cognitively challenging because too often success experiences make organizations less reflective, as success episodes are commonly interpreted as evidence that existing strategies and practices work properly and require no change, thus limiting the opportunities for a systematic and effective learning from exploration activities (Gino and Pisano, 2011; Madsen and Desai, 2010). Similarly, when confronted with failures, individuals tend to favour evidence that supports their existing beliefs rather than alternative explanations, contributing to unintentionally masking the deep causes of failure (Edmonson, 2011).

Research trained employees are likely to possess analytical skills, command competencies to conduct systematic inquiry, and display a high tolerance for causal ambiguity. For this reasons, employees with a higher education or a postdoctoral degree, are likely to be in a position to face the cognitive challenges associated with detection and analysis of success and failures from exploration activities, in a faster and more efficient way than employees without such formal training. Therefore, organizations equipped with employees who possess formal research training should be expected to exhibit a more effective and faster learning from exploration activities.

Second, individuals with formal research training are likely to be positively predisposed to experimentation and feel attracted to risk-taking in exploration activities. Besides cognitive competencies linked to the detection and analysis of success and failures from exploration activities, these highly qualified employees are often particularly willing to engage in new exploratory avenues. They acknowledge that experimentation is necessary to push the boundaries of current understanding and knowledge within the organization. These individuals are highly intrinsically motivated to conduct research as they tend to set aspiration levels above current performance, engaging in both local and distant search (Levinthal and March, 1993; Garcia-Quevedo et al., 2012).

Additionally, employees with formal research training also tend to engage in exploratory and experimental research as a learned mode of interaction with the extended community of researchers in the private and public sectors. Being active in exploration activities help them plugging into the enlarged epistemic community of researchers, of which they are often an integral part (Rosenberg, 1990).

Third, employees with formal research training also contribute to create a favourable climate for experimentation, as they bring into the organization a culture of tolerance to, and acceptance of, failure. They contribute to creating a climate that does not blame for failure, but on the contrary acknowledge that failure is an inherent and an unavoidable component of experimentation and exploration.

Highly skilled employees display a positive disposition to experimentation as they perceive it as an opportunity to enhance understanding, even in the presence of failure. That is, even though they acknowledge that further exploration and experimentation increases the chances of experiencing failures, they perceive these instances of failure as learning opportunities, as potentially providing valuable new knowledge (Edmonson, 2011).

Moreover, this type of employees contributes to form a working climate where the emotionally charged implications of identifying and admitting failure are attenuated. Analysis of the results of exploration can be emotionally challenging as failure analysis often implies the acknowledgement of responsibilities by the executing teams. Admitting failure can be emotionally unpleasant as it may harm self-esteem and/or imply some forms of penalisation from the organisations' managers. However, individuals with a formal training in research are often prepared to recognise that identification and admission of failure is praiseworthy if taken as an opportunity for learning (Edmonson, 2011).

Drawing on the above discussion, we would expect that organizations that have a critical mass of formally research trained employees in their exploration activities, should exhibit a more effective and faster learning process in their exploration activities. Therefore, we put forward the following hypothesis:

> *Hypothesis 3: The degree of highly skilled employees in research activities negatively moderates the relationship between exploration and innovation failure. Specifically, for a given level of exploration, higher levels of human capital reduce the probability of innovation failure.*

DATA AND METHODS

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

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

As discussed in the theoretical section, our main focus is on firms that experience innovation failures. Firms with positive investment in innovation can actually experience different rates of failure with respect to non-investors. Specifically, whereas the former can experience a failure along the whole innovation path (i.e. from the origin of the innovative idea to its development), the possibility that non investing firms report a failure in innovation is limited to abandonments in the early conception phases. In other terms, the failure experience is potentially more complete, and consequentially broader, for firms that actively engage in innovation. Table 1 shows the proportion of manufacturing companies (from PITEC for year 2010) reporting a failure in an innovation project distinguishing between positive and zero-investors. The table clearly shows a much higher probability of failure for companies that are actively engaged in innovation (the difference between the two probabilities is statistically significant at the 1% confidence level).

[INSERT TABLE 1 ABOUT HERE]

Given the focus of our analysis, we restrict the sample to manufacturing firms that may have potentially encountered a complete and wider range of innovation failures. Specifically, we keep only those companies that are actually engaged in innovation. In other terms, those firms that report a positive expenditure in innovation activities. Furthermore, we concentrate our investigation on the period 2008-2010. We do this by aggregating information from three different PITEC survey's waves. Indeed, some of the relevant questions contained in the 2010

* For a review on innovation surveys, see Mairesse and Mohnen (2010).

wave of PITEC survey refer to the period 2008-2010 (e.g. rate of failure in innovation projects) while other questions refer to 2010 year only (e.g. employment, R&D spending, etc.). For consistency, we use the preceding two waves of the PITEC survey (i.e. the 2009 and 2008 survey waves) and complement information for the 2010 edition of the survey. In this way, we are able to build a full set of variables referring to the period 2008-2010. Concentrating our analysis on this period allows us to provide updated evidence, still focusing on a time-span in which the likely (and largely unobservable) concurring effect of the recent economic crisis can be deemed as stable. The resulting sample contains full information for 2,954 manufacturing firms.

Our interest is in estimating the factors that influence the event of a failure in innovation through the use of the following logit model:

$$P(INNOFAIL_i = 1|X_i, Z_i) = \Lambda(\beta' \mathrm{X_i} + \gamma' \mathrm{Z_i}),$$

where $\Lambda(z) = e^z/(1+e^z)$ is a logistic function, X_i is the vector of our key explanatory variables and Z_i is the vector of firm-level controls.

Our main dependent variable is INNOFAIL: a dummy that takes value 1 when the firm faced the event of a failure in innovation in the period 2008-2010, i.e. whether the firm have reported to have abandoned an innovation project either at the conception or development phase.

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

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

Hypothesis 1 in the theoretical section predicts an inverted U-shaped relationship between exploration activity and the probability to experience innovation failure. To capture this non-linear effect we include in our econometric specification the term $EXPLORATION^2$.

We test for Hypothesis 2 interacting *EXPLOITATION* with a series of dummies that reflect the three classes of engagement in exploratory activities. This allows us to better capture whether *EXPLOITATION* moderates the effect of *EXPLORATION* for high or low values of this latter. Two alternative specifications are employed. First, we define three dummy variables: *EXPLORATION_0-4*, *EXPLORATION_4-7* and *EXPLORATION_7-max*. The first one takes on value 1 when *EXPLORATION* ranges between 0 and 4, the second equals 1 when EXPLORATION is between 4 and 7, the third captures firms with values of *EXPLORATION* higher than 7. The dummy variable referring to central values of *EXPLORATION* (*EXPLORATION_4-7*) constitutes the main reference term as this contains the values of the turning point in the inverted U-shaped relationship between exploration activity and innovation failure. The key idea is that by interacting the two dummies *EXPLORATION_0-4* and

EXPLORATION_7-max with the continuous variable *EXPLOITATION* we will be able to single out any complementary contribution of *EXPLOITATION* in moderating the effect of exploratory activities on the probability to experience an innovation failure. As robustness check, we also make use of five dummy variables instead of three (i.e. *EXPLORATION_0*, *EXPLORATION_1-4*, *EXPLORATION_4-7*, *EXPLORATION_7-8.5*, *EXPLORATION_8.5-MAX*). These capture five classes of *EXPLORATION* values: 0, from 1 to 4, from 4 to 7, from 7 to 8.5 and higher than 8.5, respectively. In line with the previous specification, we keep the same variable as reference term (i.e. *EXPLORATION_4-7*) and we interact the set of dummies with the continuous variable *EXPLOITATION*.

Finally, Hypothesis 3 is tested by using interaction terms between the *EXPLORATION* (in its linear and quadratic form) and *HUMAN CAPITAL*.

Omitted variable bias is reduced by including a set of controls in the econometric specification. First of all, with a set of dummies we control for the hampering factors that in the period 2008-2010 may have affected the firm's innovation activities and, as a consequence, the likelihood to encounter a failure. Given our focus on firms engaged in innovation we consider revealed barriers to innovation: that is, obstacles that firms experience along the innovation path (D'Este et al., 2012). As in recent contributions we consider both financial and non-financial barriers (e.g. Blanchard et al., 2013; D'Este et al., 2012, 2014). *COSTBAR* captures whether the firm faced at least a highly relevant problem with respect to: innovation costs, internal or external funding to innovation. *KNOWBAR* reflects whether the firm experienced at least a high barrier related to knowledge. Specifically, we consider obstacles associated to: skilled personnel, information on technology, information on markets and availability of suitable innovation partners. We finally consider the potential effect on innovation failures exerted by serious obstacles due to dominated market (*MKTDOMBAR*) and uncertain demand (*MKTUNCBAR*). Despite the internal R&D investment of the firm is already captured by *EXPLORATION* and *EXPLOITATION*, we control for different forms of engagement in innovation that may be particularly relevant for SMEs and non-R&D intensive industries (e.g. Rammer et al., 2009; Sterlacchini, 1999). To this aim, we employ *OTHEREXP*. This is the log transformed 2008-2010 average sum (adding +1 to avoid dropping the zeros) of the expenditures per employee in: external R&D; machinery, equipment and software; external knowledge; training; market introduction of innovations, design and other preparations. To further capture the complex nature of the firm's innovation profile, we also control for the resort to the open innovation mode (e.g. Chesbrough, 2003; Laursen and Salter, 2006). Specifically, we include in our econometric specification a dummy (*EXTKNOW*) that reflects whether the firm has acquired highly relevant information from an external source of knowledge. Obviously, the likelihood to fail in innovation might be also related to the extent to which the firm carry out cutting-edge and risky innovation activities. For this reason we include a dummy (*RADICALINNO*) that captures whether the firm, in the considered period, introduced a radical innovation. Another relevant characteristic that we include among the controls is the (log transformed) firm's age (*AGE*); this latter may be related to the propensity to introduce disruptive and risky innovations, as well as to face higher obstacles to innovate (e.g. Schneider and Veugelers, 2008). We also consider a set of characteristics that may influence innovation resources, incentives and, in turn, the likelihood to conduct innovation activities that lead to a failure. First, we consider the group affiliation and the engagement in export with two dummies (*GROUP* and *EXPORT*). Second, we include a variable related to firm size measured as the natural logarithm of the average number of employees in the period 2008-2010 (plus 1) (*SIZE*). Finally, we include a set of variables to control for the effect of industry characteristics. These are 2-digit industry dummies based on the NACE rev.2 classification.

Table 2 presents descriptive statistics of the variables used in this study; Table 3 reports the correlation matrix of our variables. In general, correlation across the independent variables is low, suggesting the absence of any relevant multi-collinearity problems.

[INSERT TABLE 2, TABLE 3 ABOUT HERE]

RESULTS

Results emerging from our econometric analysis are reported in Tables 4 and 5. Our baseline model considers *EXPLORATION* and *EXPLOITAION* as linear terms (Table 4, Model I). Both terms positively affects the probability to experience an innovation failure (i.e. to abandon an unsuccessful innovation project). Investing in R&D, both in an exploratory and exploitative way, increases the chances that some innovation projects are going to reveal unsuccessful. Similarly, a higher level of human capital increases the probability of innovation failure, denoting the risk-taking and experimentation orientation of R&D personnel with a university degree. We also notice the relevance of many of the controls we employed in our econometric specifications. As expected, firms tend to experience a higher probability of failure when they engage in radical innovation. A higher failure rate is associated also to knowledge and market barriers, while cost barriers are not significantly affecting the probability to abandon an innovation project. Adopting open innovation modes -i.e. engaging in external information sourcing- increases the probability to face a failure along the innovation path. This may be related to the exploratory and, thus, risky nature of a external knowledge sourcing. Finally, being affiliated to a group increases the chance of failure. Group affiliates, benefiting from intra-group economies of scale and the possibility to share the risk among the group members, embark in more uncertain innovation activities.

Interestingly enough, once we control for the above set of firm-level characteristics, age and size of the companies do not affect the probability of abandoning an innovation project.

[INSERT TABLE 4 ABOUT HERE]

Table 4 provides also support to our first hypothesis (Table 4, Model II). Exploration has an inverted U-shape effect on the probability to face a failure in innovation. Despite the initial increase in the rate of innovation failure, boosting exploration engenders a learning process that reduces the risk of unsuccessful innovation projects. Capacity to analyse and act upon previously abandoned exploratory activities, acquisition of monitoring and intelligence capacities and operational-based learning (March, 1991; Desai, 2010; Edmonson, 2011) help explain this result. Building on model II in Table 4, Figure 1 depicts the curvilinear relationship between the value of EXPLORATION and the predicted probability of experiencing innovation failure.

[INSERT FIGURE 1 ABOUT HERE]

Our second hypothesis set out in the theoretical section concerns the moderating effect of exploitation activity on the relationship between exploration and innovation failure. Specifically, we test whether *EXPLOITATION* moderates *EXPLORATION* and leads to a decrease in the probability of failure. Models III and IV in Table 5 suggest that this is actually the case under specific circumstances: for particularly high levels of EXPLORATION (i.e. EXPLORATION_7-MAX or EXPLORATION_8.5-MAX equal 1) an increase in the investment in EXPLOITATION reduces the probability to face a failure. It is important to recall that the reference category for the dummies proxying for EXPLORATION is the central value of EXPLORATION (i.e. the maximum value of the inverted U-shaped relationship between exploration and innovation failure, see Figure 1). Thus, in Table 5 we can interpret the interaction between EXPLOITATION and the dummies variables defined for EXPLORATION as measuring the moderating effect of exploitation activity on the relationship between EXPLORATION and INNOFAIL for values of EXPLORATION below and above central values (i.e. the turning point in Figure 1). Our results show that investment in exploitation activity does not contribute in lowering (or increasing) the rate of innovation failure for levels of exploration below the central values. On the contrary, exploitation activity plays a complementary role for high (Model III) and very high (Model IV) levels of investment in exploration and contributes to lower the probability to experience innovation failure.

[INSERT TABLE 5 ABOUT HERE]

Our third hypothesis pertains to the analysis of the moderating effect of human capital in the relationship between exploration and innovation failure. Coefficients of the interactions between *HUMAN CAPITAL* and *EXPLORATION* (in its linear and quadratic form), are reported in Table 5, Model V. Further insights come from the graphical representation (Figure 2) of this moderation effect. Although a high level of human capital in the R&D department initially increases the risk of abandonment, it also helps fasten and anticipate the learning and reach, when combined with a high engagement in exploratory activities, a lower rate of failure. Again, this finds support in our theoretical argumentation. Trained R&D employees, although more oriented towards risk-taking and challenging projects, are also endowed with skills, experience and a positive attitude towards learning from failures that enhance the capacity to efficiently analyse success and failures in exploratory activities.

[INSERT FIGURE 2 ABOUT HERE]

CONCLUSIONS

This paper provides preliminary evidence on how firms' investment in exploration activities increases the exposure of firms to innovation failure and, for high levels of investment in exploration activities, helps them in reducing the probability to fail. This result descends from the recognition that firms need to reach a difficult balance between two contrasting effects. On the one side, firms need to explore in order to build and retain a competitive edge. This can be done by reducing operational-based instances of failures and curve down failures to a minimum. On the other side, firms also need to learn how to manage the greater uncertainty and risk involved in highly explorative innovation activities. Regarding this, companies might be willing to tolerate some degree of failure so long as it provides valuable new knowledge and learning opportunities for their innovation strategies.

Taking advantage of a comprehensive dataset containing information on the activities carried out by 2,954 Spanish companies, we find evidence of a curvilinear relationship between exploration and innovation failure. In particular, we find support of an inverted U-shaped relationship between investment in exploration activity and the probability to experience innovation failure. That is, while exploration increases the chances of experiencing failure due to the intrinsic risks associated to experimentation, there are learning economies from exploration activities that contribute to curve down the probability of failure once an experience threshold is overcome. We argue that these learning economies are likely to be associated to operational-based learning that helps to reduce both preventable and complexity-related failures.

Furthermore, we find support for at least two important moderating effects in the relationship between exploration and innovation failure. In particular, we show that firm's commitments to product and process development and the availability of human capital contribute to speed the organisational learning process from exploration with regards to lowering innovation failure.

These findings are relevant to point out that the learning economies from exploration are contingent on the attainment of an adequate balance between exploration and exploitation activities, and on the availability of highly skilled employees in the organisation's research teams.

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

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

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Table 1: Probability of failure in R&D projects: innovators vs non innovators

	Zero Investors	Positive Investors	Pearson Chi squared
% Failure	12.18%	31.20%	240.4727 [1] ***
Observations	1962	3154	

Notes: degrees of freedom are in brackets. The sample refers to all manufacturing companies contained in the 2010 edition of PITEC. All investment in innovation activities are considered.

Table 2 Descriptive Statistics (n=2954)

Variable	Mean	S.D.	Min	Max
INNOFAIL	0.315	0.464	0	1
EXPLORATION	4.805	3.63	0	11.05
EXPLOITATION	5.427	3.5	0	11.654
HUMAN CAPITAL	0.328	0.469	0	1
COSTBAR	0.167	0.373	0	1
KNOWBAR	0.009	0.095	0	1
MKTDOMBAR	0.202	0.401	0	1
MKTUNCBAR	0.275	0.446	0	1
OTHEREXP	6.319	2.407	0	12.885
EXTKNOW	1.35	1.609	0	10
RADICALINNO	0.487	0.499	0	1
AGE	3.289	0.59	1.386	5.17
GROUP	0.465	0.498	0	1
EXPORT	0.898	0.302	0	1
SIZE	4.31	1.301	0.287	9.158

Table 3 Correlation Matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1)	INNOFAIL	1													
(2)	EXPLORATION	0.13	1												
(3)	EXPLOITATION	0.09	0.08	1											
(4)	HUMAN CAPITAL	0.15	0.26	0.3	1										
(5)	COSTBAR	-0.03	0.01	-0.002	-0.07	1									
(6)	KNOWBAR	0.03	-0.02	0.01	0.001	0.09	1								
(7)	MKTDOMBAR	0.06	0.04	0.02	-0.001	0.1	0.06	1							
(8)	MKTUNCBAR	0.06	0.03	0.01	-0.008	0.13	0.09	0.36	1						
(9)	OTHEREXP	0.03	0.04	0.09	0.15	-0.01	0.002	0.05	0.04	1					
(10)	EXTKNOW	0.09	0.1	0.12	0.16	0.06	-0.003	0.1	0.09	0.16	1				
(11)	RADICALINNO	0.11	0.15	0.18	0.16	-0.01	0.006	-0.05	-0.002	0.13	0.08	1			
(12)	AGE	0.05	-0.005	-0.03	0.08	-0.08	-0.01	-0.0006	0.006	-0.07	0.0009	0.0004	1		
(13)	GROUP	0.09	0.0182	0.0209	0.32	-0.14	-0.02	-0.08	-0.06	0.04	0.01	0.03	0.07	1	
(14)	EXPORT	0.04	0.0667	0.0788	0.12	-0.05	-0.003	0.0018	-0.02	-0.009	0.02	0.03	0.13	0.1	1
(15)	SIZE	0.09	-0.031	-0.03	0.42	-0.15	-0.04	-0.09	-0.07	-0.028	0.03	0.04	0.32	0.53	0.18

Table 4 Innovation failures determinants: baseline results

Dep.var.:INNOFAIL	**I**	**II**
EXPLORATION	0.0565***	0.2002***
	[0.0127]	[0.0509]
EXPLOITATION	0.0436***	0.0384***
	[0.0135]	[0.0137]
HUMAN CAPITAL	0.2217**	0.3110***
	[0.1117]	[0.1167]
EXPLORATION^2		-0.0180***
		[0.0062]
EXPLOITATION^2		
COSTBAR	-0.181	-0.1822
	[0.1182]	[0.1182]
KNOWBAR	0.8401**	0.8547**
	[0.4124]	[0.4134]
MKTDOMBAR	0.2567**	0.2565**
	[0.1088]	[0.1087]
MKTUNCBAR	0.2182**	0.2099**
	[0.0986]	[0.0986]
OTHEREXP	-0.0057	0.0026
	[0.0178]	[0.0182]
EXTKNOW	0.0600**	0.0622**
	[0.0254]	[0.0253]
RADICALINNO	0.3838***	0.3891***
	[0.0860]	[0.0860]
AGE	0.082	0.0757
	[0.0746]	[0.0747]
GROUP	0.1670*	0.1818*
	[0.0995]	[0.0996]
EXPORT	0.101	0.1134
	[0.1475]	[0.1481]
SIZE	0.0962**	0.0543
	[0.0459]	[0.0482]
Sector Dummies	Included	Included
Constant	-2.4399***	-2.3850***
	[0.3442]	[0.3440]
N	2954	2954
Log-likelihood	-1737.3026	-1733.0622
McFadden's Pseudo R^2	0.057	0.0593
χ^2	187.1325***(35)	195.0951***(36)

Notes: Robust standard errors are in parentheses. * p<0.10, ** p<0.05, *** p<0.01 Degrees of freedom of the Wald χ^2 test are reported in parenthesis

Table 5 Innovation failures determinants: moderation effects

Dep Var: INNOFAIL	III	IV	V
EXPLORATION	0.0503**	0.0539**	0.1163*
	[0.0224]	[0.0229]	[0.0641]
EXPLOITATION	0.0680***	0.0683***	0.0388***
	[0.0182]	[0.0182]	[0.0138]
HUMAN CAPITAL	0.2610**	0.2641**	0.1631
	[0.1146]	[0.1156]	[0.2000]
EXPLORATION_0-4*EXPLOITATION	-0.032		
	[0.0246]		
EXPLORATION_7-MAX*EXPLOITATION	-0.0312*		
	[0.0169]		
EXPLORATION_0*EXPLOITATION		-0.0296	
		[0.0253]	
EXPLORATION_1-4*EXPLOITATION		-0.0368	
		[0.0683]	
EXPLORATION_7-8.5*EXPLOITATION		-0.0238	
		[0.0176]	
EXPLORATION_8.5-MAX*EXPLOITATION		-0.0512**	
		[0.0226]	
$EXPLORATION^2$			-0.0076
			[0.0080]
EXPLORATION*HUMAN CAPITAL			0.2157**
			[0.1007]
$EXPLORATION^2$*HUMAN CAPITAL			-0.0250**
			[0.0115]
COSTBAR	-0.1809	-0.1846	-0.1954*
	[0.1181]	[0.1183]	[0.1183]
KNOWBAR	0.8432**	0.8406**	0.8545**
	[0.4143]	[0.4125]	[0.4102]
MKTDOMBAR	0.2527**	0.2522**	0.2510**
	[0.1086]	[0.1087]	[0.1087]
MKTUNCBAR	0.2169**	0.2138**	0.2098**
	[0.0984]	[0.0985]	[0.0988]
OTHEREXP	-0.0044	-0.0021	0.002
	[0.0181]	[0.0182]	[0.0182]
EXTKNOW	0.0602**	0.0609**	0.0622**
	[0.0254]	[0.0254]	[0.0253]
RADICALINNO	0.3876***	0.3887***	0.3870***
	[0.0863]	[0.0862]	[0.0861]
AGE	0.0808	0.0748	0.0748
	[0.0746]	[0.0746]	[0.0749]
GROUP	0.1757*	0.1749*	0.1792*
	[0.0996]	[0.0996]	[0.0998]
EXPORT	0.1111	0.107	0.1266
	[0.1480]	[0.1482]	[0.1479]
SIZE	0.0752	0.0721	0.054
	[0.0472]	[0.0480]	[0.0484]
Sector dummies	Included	Included	Included
_cons	-2.3630***	-2.3624***	-2.3447***
	[0.3624]	[0.3638]	[0.3473]
N	2954	2954	2954
Log-likelihood	-1735.2851	-1734.3319	-1730.6831
MdFadden's Pseudo R^2	0.0581	0.0587	0.0606
χ^2	192.36***(37)	193.55***(39)	202.7***(38)

Notes: Robust standard errors are in parentheses. * p<0.10, ** p<0.05, *** p<0.01. Degrees of freedom of the Wald χ^2 test are reported in parenthesis

Figure 1 Curvilinear effect of exploration on the probability of facing an innovation failure

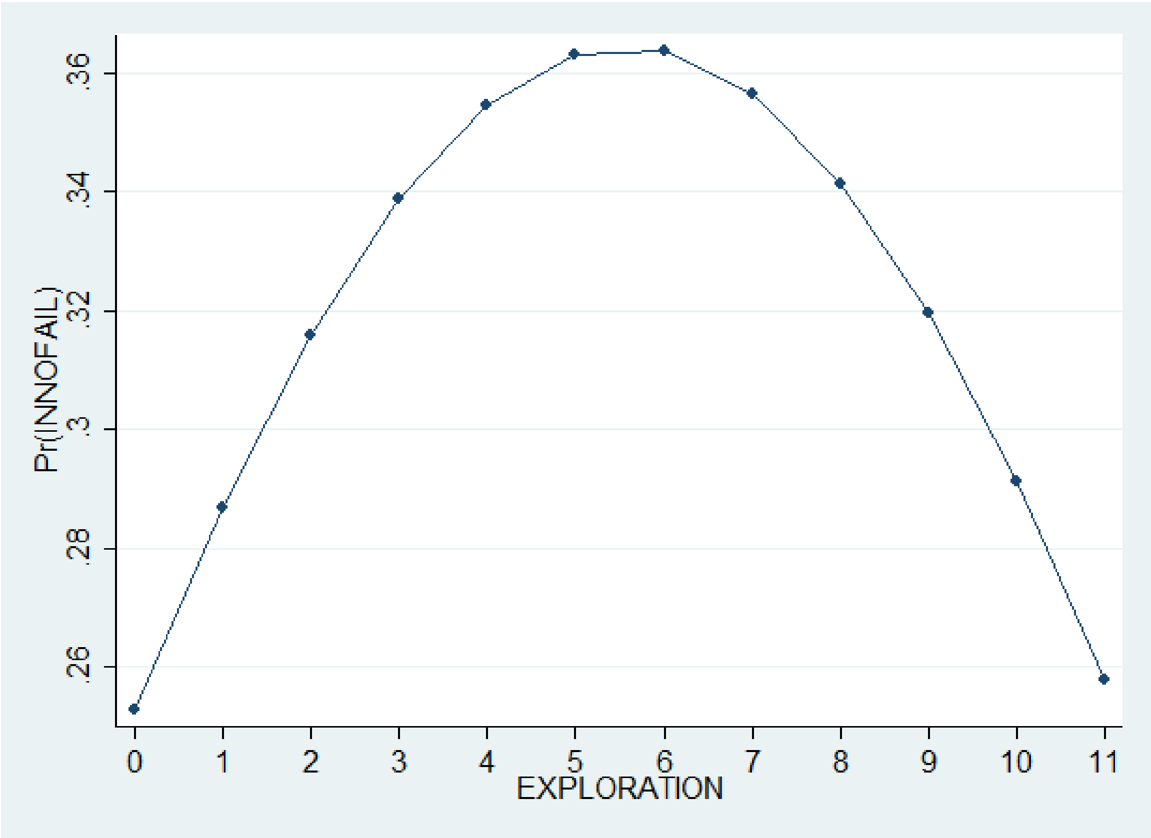

Figure 2 Moderation effect of human capital on exploration