Paper to be presented at

DRUID15, Rome, June 15-17, 2015

(Coorganized with LUISS)

Forsaking Innovation: the Effect of Failure on Exploratory and Exploitative Strategies

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Abstract

The aim of this paper is to investigate the impact of innovation failure on firms' strategies to source innovation.In doing so, we regard innovation as a process where firms develop strategies along a continuum dimension stretching from explorative to exploitative oriented strategies depending on the combination of characteristics encompassing cooperation, competition, R&D as well as knowledge base composition. The combination of the above elements can be viewed as a proxy of the innovation behaviour adopted at firm level. After discussing the different types of innovation strategies emerging from our analysis, we will look at the effects that failure plays on them. Drawing on data from the UK Innovation Survey (2008-2010), we define failure by looking at those firms which are innovation active and abandoned their innovation activity. To compare changes in innovative behaviour we build a matched sample employing propensity score matching and look at the effects of failure upon different types of innovation strategy. Our preliminary results highlight that at first failure does not have an effect on all the possible innovation strategies adopted at the firm level, but only where the firm's innovation behaviour is research oriented. Second, that the effect of failure on innovation behaviour is not homogeneous but nuanced, as failure seems to impact positively on those firm profiling innovation dynamics closer to pure exploration, whilst the effect is opposite for those firms that are more competition driven or whose strategy is mostly associated to the development rather than the pure research phase.

Jelcodes:O32,L10

Forsaking Innovation: the Effect of Firm Failure on Exploratory and Exploitative Behaviours[1]

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Abstract

The aim of this paper is to investigate the impact of innovation failure on firms' strategies to source innovation. In doing so, we regard innovation as a process where firms engage in a variety of behaviours ranging from exploration to exploitation depending on the combination of characteristics including their propensity to cooperate, to compete, to engage in research and development activities as well as on the composition of their knowledge base. We use the combination of the aforementioned elements as a proxy of the innovation behaviour adopted at firm level. We analyse the different types of innovation behaviours emerging from our analysis, and look at the effects that failure plays on them. Drawing on data from the seventh wave of the UK Innovation Survey (2008-2010), we define failure by considering specifically those firms which are innovation active but abandoned their innovation activity. To understand the relationship between changes in innovative behaviour we build a matched sample employing propensity score matching methodology and analyse how failure affected firms' innovation behaviours. Our preliminary results highlight firstly that for those firms which are strongly inclined to do research, failure affects the innovation behaviours adopted at the firm level. Second, that the effect of failure on innovative behaviour is not homogeneous but nuanced, as failure seems to impact positively on firms those firm profiling innovation dynamics closer to pure exploration, whilst the effect is opposite for those firms that are more competition driven or whose strategy is mostly associated to the development rather than the pure research phase.

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[1] This work was based on data from the UK Innovation Survey, produced by the Office for National Statistics (ONS) and supplied by the Secure Data Service at the UK Data Archive. The data are Crown Copyright and reproduced with the permission of the controller of HMSO and Queen's Printer for Scotland. The use of the data in this work does not imply the endorsement of ONS or the Secure Data Service at the UK Data Archive in relation to the interpretation or analysis of the data. This work uses research datasets which may not exactly reproduce National Statistics aggregates.

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1. Introduction

Innovation is an important element of competitive advantage and growth for many firms but pursuing innovation involves uncertainty and risk in which the probability of failure is heightened. Firms can commit considerable resources to the development of new knowledge with no guarantee the outcome will be a commercially viable proposition (Freeman et al., 1972). This is endemic to the capitalist system and to its experimental nature where failure is an outcome as much as possible as is success, and where both results coexist and contribute to the process of understanding of innovation development. However, while theoretical and empirical researches have widely investigated sources of innovation success (Cohen, 2010), few attempts have been made to understand in a systematic way the dynamics of failed innovation and how such dynamics affects innovation behaviour (van der Panne et al., 2003).

This paper aims to undercover how innovation firms react to failure. Starting from the assumption that innovation behaviour is heterogeneous across firms, we first consider the external and internal factors at the firm level that affects their propensity for exploration and exploitation. We then analyse the impact that failure or negative innovation outcomes have on firms' innovation behaviours.

Much of the innovation management literature is concerned with discovering success factors but success and failure are effectively two sides of the 'same coin'. The notion that understanding innovation failures can contribute to improving understanding of innovation successes has a relatively long history in innovation studies. Project SAPPHO (Freeman et al., 1972; Rothwell et al., 1974) was among the first of several systematic attempts to analyse the differences between successful and unsuccessful innovations (Domotor et al., 2007). However these earlier studies were based on relatively small sample sizes and, they suffered from a large variety of innovation performance measures which led to major divergence in the success factors identified (Domotor et al, 2007). With the availability of innovation specific datasets (for example Community Innovation Surveys), a new generation of scholars has begun to try to systematically understand the characteristics of firms which fail to deliver innovation focusing on factors that are both internal and external to the firm (D'Este et al., 2012; Landry et al., 2008; Mohnen and Röller, 2005)

Learning from failure is a hallmark of innovative companies but as Cannon and Edmondson (2005) cautions, there are very few firms either large or small that systematically learn from failure. Other commentators as Hess (2012) are more sanguine. He suggests that failure can actually be an 'engine of innovation'. It is:

> *'..a necessary part of the innovation process because from failure comes learning, iteration, adaptation, and the building of new conceptual and physical models through an iterative learning process. Almost all innovations are the result of prior learning from failures.' (Hess 2012, Creating an Innovative Culture: Accepting Failure as Necessary, Forbes, June 20, 2012)*

From an organizational perspective (Edmondson, 2011) recognises several types of failure, those that affect routine activities and are preventable; those that that arise due to systemic complexity and to some extent are unavoidable and those failures that she classes as intelligent in as much as they provide valuable opportunities to gain new knowledge that may not only help an organization gain an edge over the competition but also ensure its sustainability (Cannon and Edmondson, 2005).

While it is entirely possible to interpret innovation failure along these lines, in an innovation context, failure refers to the abandonment, interruption and major delays of innovation projects in firms

Failure can occur at any point in the innovation process and this process is characterised in this paper through March (1991) notion of exploration-exploitation.

In line with March and others (see for example: Lavie and Rosenkopf, 2006; Rothaermel and Deeds, 2004), this study conceptualises exploration and exploitation as the opposite ends of a continuum rather than orthogonal choices. Firms, especially SMEs, are unlikely to have separate domains for exploitation and exploration as they will have to decide which to emphasise since innovation activities competes for scarce resources (Stettner et al., 2014). Firms will therefore exhibit a variety of innovation behaviours ranging from exploration to exploitation depending on the combination of characteristics including their propensity to cooperate, to compete, to engage in research and development activities as well as on the composition of their knowledge base.

In contrast to much of the received literature in this paper we aim to focus not on obstacles to innovation but to consider the relationship between differences in implicit innovation behaviours between firms who have abandoned innovation projects (failed experiments) and those who have not. We start in the next section with a brief review of the literature pertaining to exploration exploitation approach to innovation and innovation failure. This is followed by a discussion of our data and methodology. The research findings are discussed in the final and a conclusion follows.

2. Literature Review

In this section we start by briefly outlining the innovation perspective that we adopt before reviewing the literature that addresses innovation failure. It is now widely accepted that the innovation process involves the exploration and exploitation of opportunities for a new or improved product, process or service, due to advances in technical practice or to changes in demand. It is effectively a matching process (Pavitt, 2003). Another important feature of innovation is that it is inherently uncertain. Thus it is difficult to predict with any degree of accuracy the cost and performance of the innovation, or how users take to it. It therefore inevitably involves processes of learning through either experimentation (trial and error) or improved understanding (theory). Some (but not all) of this learning is firm specific (Pavitt 2003).

We use March's (1991) exploration - exploitation framework to capture the innovation process. This framework has generated phenomenal interest in a range of literatures including organisational learning, organisational design, knowledge management, technology development and innovation (He and Wong, 2004; Lavie et al., 2010). For March (1991), exploration involves experimenting with new alternatives where returns may be uncertain, distant, or negative. Exploitation on the other hand involves the refinement and extension of existing competencies, technologies, and paradigms where return are 'positive, proximate, and predictable'.

The definitions and use of the exploration-exploitation concept has excited a lot of critical debate in terms of the meaning, scope, breadth of their use as summarized in Gupta et al 2006. There is firm support in the literature that both types of activities are important for organisational learning and sustainability as well as in innovation and as Lavie et al. (2010) note, any distinction between them is one of degree rather than substance. Thus exploration–exploitation should be envisaged as a continuum of activities as opposed to a choice between options. Such a perspective is consistent with the tendency of organisations to manoeuvre between exploration and exploitation over time. Exploration involves adding to or moving away from the organization's current knowledge base and skills (Cohen and Levinthal, 1990). Such shifts can involve acquiring new technical skills, market expertise, or developing external relationships (Lavie and Rosenkopf, 2006; Smith and Tushman, 2005). But exploration evolves into exploitation. Initial experimentation with new technology is a signal that the organisation is engaged in exploration. However if experiments are repeated or if newly acquired knowledge is applied, exploitative routines develop as familiarity with that knowledge occurs (Brunner et al, 2009).

As Tushman and O'Reilly 1995 note while both exploration and exploitation are important for organisational learning and sustainability there is an uneasy tension between the concepts that needs to be carefully managed. Limited resources ensure that organisations give weight to one or other. This represents a trade-off between short term productivity goals and the longer term search for new knowledge, key to opening up innovation opportunities. The trade-off also involves a flexibility-stability dimension. Focusing on exploitation privileges stability over flexibility, encourages organisational inertia thus making change difficult when it is required. While both types of activities are important for organisational learning and prosperity they involve an inherent contradiction that need to be carefully managed (Tushman and O'Reilly, 1995).

Ambiguity and change are two of the dominating features of innovation; and the processes encompass a range of activities: exploration, experimentation, invention, and exploitation of the knowledge discovered. However the pursuit of growth and innovation is inherently messy and inefficient and failure can surface at any point along the innovation chain (Cozijnsen et al., 2000).

The relatively wide availability of innovation data over the last few years has allowed researchers to explore systematically in a range of studies the factors that constrain the innovation efforts of firms.

Many innovation projects fail. Research in the US (Carr, 1996 cited in Cozijnsen et al., 2000) shows that as much as 70-80 percent of innovation projects failed either partly or completely. Innovation activity is inherently uncertain and that uncertainty has been characterised in various ways: radical uncertainly (Knight, 1923) technical, market and political/economic uncertainty (Freeman, 1982) technological, commercial and organizational uncertainties (Freeman and Soete, 1997). Such uncertainties make it possible for there to be no innovation outcome.

Various studies pointed out that failure leads organisations to typically pursue defensive adjustment strategies, to improve cost efficiency, reduce risky investments, in effect, lightening the organisational burden (Thornhill and Amit, 2003; van der Panne et al., 2003 McKendrick and Wade, 2009. Nowhere is the threat of innovation failure more evident than in the pharmaceutical sector where despite billions of dollars of investment annually innovation output is slim. Thus, in relation to the US pharmaceutical sector (Munos, 2009) observed:

'There are more than 4,300 companies that are engaged in drug innovation, yet only 261 organizations (6%) have registered at least one NME (this parenthesis added: new molecular entity=radical innovation) since 1950. Of these, only 32 (12%) have been in existence for the entire 59-year period. The remaining 229 (88%) organizations have failed, merged, been acquired, or were created by such M&A deals, resulting in substantial turnover in the industry. Of the 261 organisations, only 105 exist today, whereas 137 have disappeared through M&A and 19 were liquidated.' (Munos, 2009, p. 960-961)

The recent literature on innovation failure appears to have taken two broad routes. The first focuses on understanding the barriers to innovation. These are many and the rationale behind this stream is that by identifying factors that lead to the breakdown of innovation projects and understanding their influence on innovation development, policy or strategy actions can be taken to avoid or minimize failure (Radas and Bozic, 2012). In an early review van der Panne et al. (2003) surveyed the literature for factors relating to success or failure in innovation. While recognising that there is a great diversity of perspectives, they identify four broad sets of factors that are likely to impact on the viability of an innovation. The first two, firm and project related factors exert influence on the innovation project's technological viability; while the latter two, factors relating to the product and market, mainly affect commercial viability. While from their meta-analysis van der Panne et al suggest that the literature was inconclusive with respect to such factors as strength of competition, R&D intensity, the degree to which a project is 'innovative' or 'technologically advanced' and top management support, there appeared to be widespread agreement on innovation success factors such as firm culture, previous innovation experience, multidisciplinary within the R&D team and explicit recognition of the collective aspect of the innovation process or the advantages of a matrix type organization.

Although rich in insights, much of the pre-2000 literature was conceptual or based on case studies not amenable to generalisation (Landry et al., 2008). More recent scholarship (in particular the empirical based studies) on innovation failure has tended to draw on specially constructed datasets or national innovation surveys.

Thus Mohnen et al. (2008) using Dutch Community Innovation Survey (CIS) data investigate firm decisions to abandon, prematurely stop, slow down or not start innovative projects in the face of hampering factors such as sources of finance, high innovation costs, lack of qualified personnel or lack of technological knowledge. While their general conclusion is that constraints/obstacles faced by innovation firms are important and have a major negative impact on innovative activity, their key result is that financial constraints have a positive effect on prematurely stopping, slowing down and not starting a project, although not necessarily on abandoning innovation projects. This finding accords with the earlier study by Galia and Legros (2004) who, using French CIS2 data, show that firms perceive the main barriers to innovation as economic risk, lack of skilled personnel, innovation costs, lack of customer responsiveness, lack of information on technologies, and organizational rigidities.

Some studies single out the role of financial factors as a constraint on innovation. Canepa and Stoneman (2004) for example using data from the second and third Community Innovation Surveys analyse the role of financial factors in the UK and Europe. They find that financial factors constrain innovative activity and the impact is particularly severe on smaller firms in market based systems and in the high-tech sectors. Using a qualitative indicator of financial constraints based on firm's own assessment (Savignac, 2008) also finds the likelihood that a firm will have innovative activities is significantly reduced by the existence of financial constraints.

Another aspect of innovation failure explored in the literature relates to cooperation. Lhuirellery & Pfister (2008) explore the relationship between firm-level characteristics and the increased risk that an innovation is stopped or delayed because of partnership difficulties, an outcome termed "cooperation failures". Their results suggest that firms engaged in partnerships with competitors and public research organizations are more likely to face "cooperation failures" and this is particularly the case when foreign partners are involved. While such results are not unexpected, this was the first time that they had been confirmed with a large and representative sample. More surprisingly however is that customers are also found to be associated with a higher probability of "cooperation failures".

The second line of failure studies focus on learning from failure. While the successful entrepreneur fuels the process of creative destruction and in so doing increases social welfare through the realignment of resources do economic benefits arise when entrepreneurs fail? It seems possible that the same creative destruction process fuelled by successful ventures may also be fuelled by unsuccessful ventures. They use the idea of excess entry to examine hypotheses of selection, competition and spillovers as mechanisms through which failure might generate economic benefits. With the selection effect excess entry produces both high failure rates and superior firms; failure is just a by-product of an excess entry process which does nothing to change the behaviour of surviving firms but determines the distribution of survivors. Under, competition however, that excess entry affects the behaviour of survivors. Excess entry increases the competitive pressure in the market leads to cost reducing investments surviving firms emerge with higher fitness than firms that have been insulated from competition. While excess entry yields 'wasted investment' (i.e. failed firms), as these investments can no longer be appropriated, their value may be captured by surviving firms through various spillover channels: advertising expenditures that expand demand for the product class, improvements in the technology supplied to the industry, and training of industry employees. While these spillovers occur even in the absence of failure, the excess entry may create a larger base of output over which the cumulative learning occurs.

It can be argued that similar mechanisms may be at work in respect to innovation failures. The fact that the same firm may fail in some innovation projects but also manages to succeed in other undertaken suggests that there may be a learning or spillover effect associated with failure (Garcia-Vega and Lopez, 2010). Failure can be seen as a crucial element to spur innovative behaviour within the organisation, to revise its operating routines and to change them in radical ways (Leoncini, 2014) although Radas and Bozic (2012) suggest that some failure is inevitable as optimal management of innovation development means that some innovation projects will be dropped long before they reach the market phase. In the context of innovation development this represents learning experience of the firm.

Leoncini (2014) moves beyond the obstacle driven analysis to explore how innovation failure can impact on organisational learning. Drawing on a large dataset of innovative firms from sixteen countries taken from the 2008 Community Innovation Survey, he develops a two-step model to first examine the patterns of abandoned (and postponed) innovation and subsequently patterns of production of innovation. He finds that failure is negatively correlated to the previous R&D

experience; in effect, that as operating experience increases firms are less likely to suffer from failures. In respect to the acquisition of external knowledge he finds a negative correlation with failure. This implies that the ability to acquire external knowledge decreases the probability of abandoning innovation projects. On the other hand, failure is positively related to the firm being part of an industrial group and producing new-to-the-market or new-to-the-firm goods. In the case of the former, the division of labour imposes coordination and strategic constraints which may be difficult to overcome while in the case of the latter, the complexity involved in developing highly innovative products may prove to be insurmountable. Moreover, his results show that the process of learning is non-linear and vicarious learning impacts negatively on firm failure for firms engaged in R&D. Firms investing in R&D start or enhance a process of learning that helps then to understand the external environment. However if firms were part of an industrial group, where linkages are built intra-group, the learning process is effectively constrained as the firm become blind to the external environment.

The present paper is in the spirit of this latter stream of work. It examines failed innovation from the perspective of an innovation process that embraces both its exploration and exploitation phases (March 1991). Exploration and exploitation have been widely studied from a variety of perspectives (Ahuja and Lampert, 2001; Jakobi 2005; Andriopoulos and Lewis, 2008). Exploration includes things 'search, variation, risk taking, experimentation, flexibility, discovery' while exploitation includes 'refinement, choice, production, efficiency, selection, implementation, and execution' (March 1991, p71). While the former involves the creation of variety, risk-taking and experimentation, the latter is variety reducing and efficiency oriented and, as March (1991) observes, not only do they involve different types of learning, there is an inherent tension between exploitation and exploration with respect to organizational learning and innovation processes. Noteboom's (2000) 'cycle of discovery' explains how these two concepts are related and mutually reinforcing. For innovation active firms, it is not strictly a question of choice between exploration and exploitation but of finding the 'right' strategic fit between exploration and exploitation (He and Wong, 2004).

Thus our approach is not to investigate obstacles that prevent successful innovation but to investigate differences in implicit innovation strategies and understand how these are associated with failed innovation. Can firms incorporate or adjust their behaviour or learn from their outcomes?

3. Data Description

The analysis employs data from the seventh wave of UK Innovation Survey (hereafter: UKIS). The UKIS is a nationally representative sample of businesses with 10 or more employees covering sectors B to N of the Standard Industrial Classification (SIC2007). The data is a cross section covering the two-year period between 2009 and 2010 and includes 14,342 firms corresponding to a 51% response rate (UK Office of National Statistics 2012).

From this data we select innovation active firms defined as those either engaged in technological (product or process) or non-technological innovation (implementing changing in corporate strategy, management technique or organisational structure)and from this sample, we then consider firms which declared abandoning an innovation project as firms experiencing a negative innovation outcome (possible footnote). Data cleaning reduces our sample to 9002 observations. Of this around the 8 per cent of firms (N= 723) declared they abandoned innovation.

Table 1 presents some descriptive statistics of the sample. As the table shows, the sample is skewed towards firms of small to medium size (62 per cent) operating either in the local or national (UK) market. Around the 6 per cent of these have recently been formed and less than one fifth have introduced innovation new to the market in the period considered in the analysis.

Table 1: Sample characteristics

Variables	*All*		*Treated* (*Experienced Negative Innovation Outcome*)		*Not Treated* (*Not Experienced Negative Innovation Outcome*)	
	N	*Mean*	*N*	*Mean*	*N*	*Mean*
Small	9,002	.5007	723	.4592	8,279	.5044
Medium	9,002	.1206	723	.1107	8,279	.1215
Medium-Large	9,002	.1795	723	.1853	8,279	.1790
Large	9,002	.1990	723	.2448	8,279	.1951
Log Turnover	9,000	8.451	723	8.732	8,279	8.427
Young	8,991	.0629	712	.0561	8,279	.6353
Innovation new to the market	8,995	.1538	716	.4511	8,279	.1281
Export - Local Market	9,002	.6347	723	.6376	8,279	.6344
Export -National Market	9,002	.6015	723	.7081	8,279	.5922
Export - EU Market	9,002	.3113	723	.5062	8,279	.2943
Export - Other International Market	9,002	.2303	723	.4177	8,279	.2140
Product Innovation	9,002	.3234	723	.6874	8,279	.2917
Process Innovation	9,002	.1971	723	.4481	8,279	.1752
Total Graduates	9,002	.1606	723	15.11	8,279	5.99
Graduates in Science & Engineering	9,002	.0671	723	25.89	8,279	15.20
HTM	9,002	.0125	723	.0277	8,279	.0112
MHTM	9,002	.0547	723	.0982	8,279	.0051
MLTM	9,002	.0717	723	.0871	8,279	.0704
LTM	9,002	.0738	723	.1134	8,279	.0704
KIS	9,002	.2669	723	.3485	8,279	0.2598
LKIS	9,002	.4023	723	.2517	8,279	.4155
Others	9,002	.1177	723	.0733	8,279	.1216

Table 2: Firms profiling – Innovation Intensity

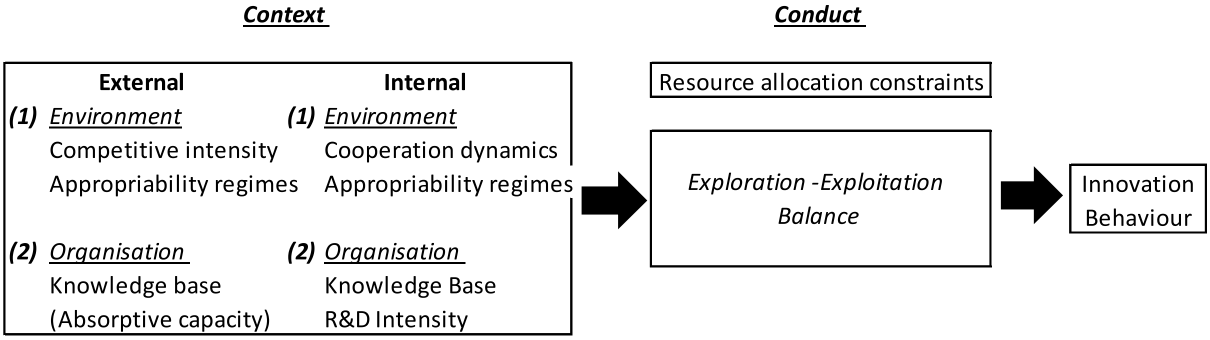
Variables	All		Treated (Experienced Negative Innovation Outcome)		Not Treated (Not Experienced Negative Innovation Outcome)	
	N	*Mean*	*N*	*Mean*	*N*	*Mean*
External R&D	8,995	.1133	716	.3212	8,279	.0954
Inward IP	8,993	.0940	714	.2408	8,279	.0814
Cooperation - Suppliers	9,002	.2168	723	.5020	8,279	.1919
Cooperation - Users	9,002	.2487	723	.6210	8,279	.2162
Cooperation - Competitors	9,002	.0932	723	.2780	8,279	.0770
Cooperation – Consultants & Private Labs	9,002	.1096	723	.3374	8,279	.0897
Cooperation - University	9,002	.0772	723	2876	8,279	.0588
Cooperation – Government & Public Labs	9,002	.0631	723	.1936	8,279	.0519
Internal R&D	8,998	.2751	719	.6453	8,279	.2430
Formal IP	9,002	.1480	723	.3983	8,279	.1262
Informal IP	9,002	.1701	723	.4757	8,279	.1434
Competition - New Goods & Services	9,002	.8649	723	.8146	8,279	.8693
Competition - New Markets	9,002	.8165	723	.7219	8,279	.8248
Competition - Increase Market share	9,002	.8806	723	.8146	8,279	.8864
Competition - Improve Quality	9,002	.9205	723	.8464	8,279	.9270
Competition - Improve Flexible Production	9,002	.8182	723	.6860	8,279	.8298
Competition - Improve Production Capacity	9,002	.7933	723	.6210	8,279	.8084
Competition - Increase Value Added	9,002	.8694	723	.7925	8,279	.8761
Acquired Skills - Graphic	8,994	.2910	715	.4587	8,279	.2766
Acquired Skills - Design	8,992	.1812	713	.3520	8,279	.1665
Acquired Skills - Multimedia	8,993	.3089	714	.4901	8,279	.2932
Acquired Skills - Software	8,994	.3133	715	.5006	8,279	.2971
Acquired Skills - Engineering	8,995	.1809	716	.3631	8,279	.1652
Acquired Skills - Mathematics	8,995	.1206	716	.2304	8,279	.1111

4. Empirical Strategy:

4.1 Outcome variables - Innovation behaviour

We consider those elements capturing innovation behaviour in line with the idea of innovation activity as a process. In particular, we follow Lavie et Al. (2012) and Levinthal and March (1993) who define such process as a balance between the pursuit of new knowledge (exploration) and the use of elements already known (exploitation) where firms' innovation behaviour is the outcome of a balancing process between environment and organisational characteristics both internal and external to the firm (Figure 1).

Figure 1: Exploration and Exploitation characteristics



Adapted from Lavie et al. (2010)

In particular, we look at those elements that represent the context for the arising of innovation behaviour both internal and external to the firm in terms of environment and organisation level factors. In terms of external characteristics we focus on competitive intensity and appropriability regimes as well as the absorptive capacity as expressed by the skill base; whilst in terms of internal factors affecting the Exploration-Exploitation balance, we look at cooperation dynamics and appropriability regimes as well as other organisational level characteristics determining the capacity of the firms to be innovative such as skill base composition and R&D intensity (Chesbrough and Crowther, 2006; van de Vrande et al., 2009)

Table 2 shows the disaggregated composition of the environmental and organisational level factors affecting internally and externally the exploratory - exploitative balance and innovation behaviour in our sample.

Exploration strategies can be proxied in terms of cooperation adopted either along the value chain (with suppliers, users or competitors), or with more research oriented partners (consultants and R&D laboratories; or universities or government and public R&D laboratories). As shown in the table, cooperation along the value chain is relatively more pronounced with respect to suppliers and users but substantially less so with research oriented institutions. Also the acquisition of external research and development and the acquisition of codified knowledge in the form of patents appear to be relatively small across the sample. Among the characteristics of exploitation reported by firms, the contextual conditions associated with competitive drivers are very prominent. About a quarter of the sample showed internal R&D activity and 17 per cent indicated using informal IP protection, compared to 15 percent making use of more formal IP strategies. Finally in terms of knowledge base composition, the innovation active firms belonging to the sample show a preference for acquiring Multimedia, Graphic and Software skills rather than the more analytical types of knowledge such as Engineering or Mathematics.

As discussed above, our aim is to first understand different patterns of innovative behaviour based upon the consideration that innovation should not be regarded as a discrete activity but as a process involving different combinations of exploratory and exploitative behaviours arising from a tension between internal and external characteristics. In this respect, and as suggested by Lavie et al. (2010), we look at innovation behaviour as a continuum and build a continuous variable accordingly.

We proceed to perform a Principal Component Analysis to analyse which combinations of characteristics explain the maximum variance in the original variables[3]. The first five components show an eigenvalue above one and are hence retained as expression of five different patterns of innovative behaviours of the sample.

Table 3: Principal Components Matrix - Eigenvalues

Principal components/correlation	
Number of observations	**8991**
Number of components	**24**
Trace	**24**
Rho	**1**

Component	Eigenvalue	Difference	Proportion	Cumulative
Component 1	**9.37122**	**4.6014**	**0.3905**	**0.3905**
Component 2	**4.76982**	**2.56925**	**0.1987**	**0.5892**
Component 3	**2.20057**	**1.00538**	**0.0917**	**0.6809**
Component 4	**1.19519**	**0.180641**	**0.0498**	**0.7307**
Component 5	**1.01455**	**0.222721**	**0.0423**	**0.773**
(..)	(..)	(..)	(..)	(..)
Component 24	0.0454225	.	0.0019	1

Unrotated solutions; Kaiser-Meyer-Olkin measure of sampling adequacy: 0.8743; SMC Test: Average SMC = 0.746, Upper Bound Level: 0.8923, Lower Bound Level: 0.5396

The five components express different combinations of attributes affecting firms' innovative behaviour. They comprise sets of characteristics describing exploratory or exploitative patterns of behaviour with respect to innovation. In general, the components tend to reflect more exploration oriented rather than exploitation oriented strategies which is probably due to our sample composition. Nonetheless, the internal alignment and the relative weight of the attributes in the components show a non-homogenous dynamic and a combined mixture of features characteristic of both exploration and exploitation.

[3] As the raw variables employed are all binary indicators, we run a PCA on their correlation matrix.

The first component which we label Research Intensive summarises more exploratory oriented and research intensive strategy. It is characterised by a strong use of cooperation both along the value chain and with research oriented institutions, a positive use of the knowledge base and intellectual property protection and acquisition as well as R&D activity both internal and external to the firm. Conversely, the attributes expressing competitive dynamics are not relevant within this component and instead appear to be uniformly negatively associated to a pattern as the one described above. The combination of such characteristics seems to summarize a strategy mostly exploratory in orientation and point to behaviour adopted during the discovery phase, or a stage associated to exploratory research outside the market dynamics.

The second component describes the behaviour of firms which do not acquire external R&D nor perform it internally, which do not cooperate and which do not follow soft competition dynamics associated with incremental innovation. The component seems driven by its positive link to knowledge base composition which shows the highest influence among the single attributes. Thus the component could represent an exploratory oriented strategy driven by an extensive use of the knowledge base, in combination with intellectual property protection and describe a strategy adopted by new professional service firms (von Nordenflycht, 2010).

The third component highlights innovation dynamics closer to Market driven behaviours, showing a positive relationship to all characteristics identified as exploratory and exploitative. Its internal balance however is skewed towards exploitation and in particular there is strong association with competition dynamics. As such, this component seems to describe firms which are market driven and exploitative. It is possible that this component describes the behaviour of those firms entering the market as first wave of imitators exploiting a new product or process just introduced.

The fourth component (cooperation driven) summarises the behaviour of firms again more oriented towards exploration. The loading particularly show a strong influence of cooperation dynamics all along the value chain rather than research towards. This is in line with the competitive strategies adopted which are mostly the ones of followers rather than radical innovators. The strategy describe by this components also shows a lack of R&D activity both directly undertaken or acquired from external sources, as well as a lack of analytical knowledge base. Also, little importance is attributed to means of intellectual property protection. The combination of these characteristics seems to suggest an innovative behaviour closer to exploration dynamics affected mostly by soft elements of competition which would confirm the importance of cooperation along the value chain and the lack of R&D activities.

The last retained component shows similar dynamics, in that it lacks elements of knowledge protection as well as any R&D production or acquisition, and it appears to describe the behaviour of firms applying soft competition strategies. It is too skewed towards exploratory attributes of innovation strategy. This component however seems to describe a different scenario in terms of the knowledge base composition, and in particular here, the relative importance in terms of knowledge base composition is almost opposite with the more analytical types of knowledge predominantly emerging over the other attributes. This evidence links well with the other narratives emerging from cooperating exclusively with research oriented institutions but is absent along the value chain. As such the overall component seems to describe strategies driven by analytical aspects of the knowledge base but oriented by soft competitive dynamics maybe more closely associated to incremental or applied and procedural innovators.

The five innovation behaviours identified above compose our different types and will be later tested to investigate whether or not innovation failure has an impact on the them, as well as the size and overall effect of this impact.

Table 4: Overview of significant components - Innovation behaviours

Innovation Behaviour							
Attributes			*Research intensive*	*KB intensive*	*Market driven*	*Cooperation driven*	*Analytical KB*
Cooperation	**Research**	**Consultancy & Private R&D Labs**	0.261	-0.2321	0.0941	0.0984	0.0268
		University	0.2576	-0.2379	0.1	0.0163	0.0871
		Government & Public R&D Labs	0.2369	-0.3021	0.0956	0.2171	0.1435
	Value Chain	**Suppliers**	0.264	-0.1851	0.04	0.2099	-0.0497
		Users	0.2708	-0.2176	0.0684	0.1482	-0.0525
		Competitors	0.2285	-0.2852	0.07	0.3446	-0.0087
Knowledge Base		**Graphic**	0.1824	0.4249	0.0729	0.3073	-0.1833
		Design	0.2087	0.2964	0.989	-0.0096	0.0622
		Multimedia	0.1853	0.4203	0.06	0.3214	-0.182
		Software	0.2042	0.3426	0.0688	0.1759	0.0632
		Engineering	0.1967	0.0801	0.0881	-0.2917	0.5781
		Mathematics	0.1688	0.2169	0.1041	-0.0312	0.5749
R&D		**Internal R&D**	0.2604	-0.016	0.0784	-0.3015	-0.1747
		External R&D acquisition	0.2305	-0.0192	0.1164	-0.3138	-0.2622
IP		**Inward IP**	0.2049	-0.0286	0.0972	-0.2492	-0.2803
		Formal IP	0.2163	0.096	0.1005	-0.2784	-0.1507
		Informal IP	0.236	0.0362	0.1108	-0.2789	-0.0468
Competition	**Radical**	**New Goods &Services**	-0.1205	0.008	0.3546	-0.0383	-0.0957
		New Markets	-0.1403	0.0001	0.3333	-0.1009	-0.0318
		Increase Market Share	-0.126	0.0485	0.3466	-0.0329	-0.0738
	Incremental	**Improve Quality**	-0.1049	-0.044	0.3718	0.12	0.0019
		Improve Flexible Prod	-0.162	-0.0311	0.3393	0.0608	0.0558
		Improve Productive Capacity	-0.1681	-0.0413	0.3366	0.052	0.0705
		Increase Value Added	-0.1144	-0.0217	0.3788	0.0553	0.0072

4.2 Empirical Strategy[4]: Propensity Score Model, Balancing Properties and Model Specification

In order to analyse the impact of failure on different innovation behaviours, we adopted a quasi-experimental design and created a matched sample consisting of innovative firms which experienced a negative innovation outcome (abandoned innovation) and innovative firms which did not; we then considered the relationship between those firms experiencing a negative innovation outcome on different strategies identified above.

In order to achieve this, we applied a three-fold strategy:

(i) First we create a model expressing the likelihood of selection into a treatment (Propensity score matching, or PSM hereafter);
(ii) Second, we choose a matching estimator in order to optimise the comparability between treatment and control group in the matched sample
(iii) Finally we establish the robustness of such a model by looking at its balancing properties with respect to the differences between treated and not-treated observations in the matched sample versus the unmatched sample

4.2.1 Propensity Score Matching

Propensity score matching is a quasi-experimental technique which aims at correcting the selection bias associated with observable differences in a sample and overcoming the 'naïve' approach adopted when comparing a group which is subjected to a specific treatment (or event) with a group which has not (Blundell and Costa Dias, 2000). The method, originally developed by Rosenbaum and Rubin (1984, 1983), looks at the probability of receiving a treatment conditional on the association to a set of covariates, and creates a weighting score to compare the observations (Dehejia and Wahba, 2002). This weighting score is an indicator reducing the dimensionality of the observed covariates to a unique scalar variable allowing a more straightforward comparison across the observations. The propensity score is a joint indicator which collapses a set of structural characteristics affecting the selection into treatment in a single measure expressing the joint association of each observation with the treatment conditions.

This methodology mimics natural experiments by recreating ad-hoc post-experiment conditions from observational studies which by correcting on selection bias and increasing comparability across observations can address issues of causality in observational studies. It is a non-parametric (or semi-parametric) technique where functional assumptions are relaxed in order to obtain perfectly comparable observations (or matches). The PSM score ranks observations according to their degree of comparability on the selected set of observable pre-treatment characteristics affecting the selection into treatment. This in turn allows looking at the true effect of a treatment by observing the differences in outcomes between the observations affected by the treatment versus the one which were not affected by it. The quality of the PSM model is then assessed by looking at its

[4] Propensity Score Matching estimation and the associated tests on the Balancing property of the model are performed employing the Stata user-written commands: *psmatch2* and *pstest* respectively, both developed by Leuven and Sianesi (2003).

balancing properties which reflect the robustness of the matched sample generated by the Propensity Score Model.

PSM methodology is extensively used in the evaluation literature where various contributions have reviewed its implementation and effectiveness in different frameworks (for reviews of the method see for example: Blundell and Costa Dias, 2000; Blundell and Dias, 2002; Caliendo and Kopeinig, 2008; Lee, 2005; Ravallion, 2007; Smith and Todd, 2001; Steiner and Cook, 2013). PSM relies on two main assumptions. First is the identifying assumption of selection on observables which states that all the relevant differences between treated and non-treated should be captured by the set of covariates employed for the matching. Second, the common support assumption which implies that the subjects observed (treated and non-treated) shares the same characteristics. If these assumptions hold, than it would be possible to use the (observed) mean outcome of the non-treated to estimate the mean (counterfactual) outcome of the treated would they had not been treated.

The versatility of PSM is testified by its application across different disciplinary fields. For example, in labour economics where several contributions use PSM to study the impact of a range of labour market programmes on unemployment (Lechner, 2002; Sianesi, 2004); the effect of temporary work agency on the job market (Ichino et al., 2008); gender related wage inequality (Frölich, 2007); the influence of education on future earnings (Blundell et al., 2005), or the outcome on productivity of performance related pay schemes (Origo, 2009). The scope of PSM techniques has been reviewed in the medical literature (Austin, 2008, 2007); used to assess impact in social epidemiology (Oakes and Kaufman, 2006); and on the effectiveness of health insurances policies (Mensah et al., 2010; Trujillo et al., 2005). Also scholars from the development studies literature have started to rely on Rosenbaum and Rubin's method looking at the effect of technology on prices in agricultural markets (Aker, 2010); the impact on rural economies of genetically modified crops (Becerril and Abdulai, 2010); or the effect of migration and remittance on households (Bertoli and Marchetta, 2014; Cox-Edwards and Rodríguez-Oreggia, 2009).

In the innovation and business studies literature, PSM has been employed to investigate the impact of different technological and non-technological characteristics on firms' behaviours and performance. Several contributions focus on innovation policy implementation, in particular distinguishing by policy type; policy-levels (local, national, supra-national) or firm size. Guerzoni and Raiteri (2015) study the effect of different demand-side and supply-side technological policies and their impact on firms' innovative behaviour; Antonioli et al. (2014) focus on local innovation policy and its additionality effects on innovation; Herrera and Nieto (2008) look at the interaction between geography and innovation by comparing the effect of local economic and institutional condition over the implementation of national policies; whilst Foreman-Peck (2012) focus his attention on the impact of innovation policy devoted to Small and Medium Enterprises in UK. Instead of innovation behaviour or capacity, other authors focus their analyses on the impact on R&D generated by tax incentives (Yang et al., 2012), or by mergers and acquisitions (Szücs, 2014), or the overall performance of innovation active with respect to non-innovation active firms on employment, revenues and productivity (Kannebley et al., 2008). Other recent contributions have shifted the application of PSM from more traditional policy and R&D evaluation scenarios to new frameworks of analysis. For example, Tartari and Salter (2015) look at the gender gap in engagement activities by examining differences in university-industry collaborations between male and female scientists. On a different topic, Hanley and Monreal Pérez (2012) and Ito and Lechevalier (2010) look at the effect of exporting strategies on competitiveness and innovation resilience on a sample of Spanish and Japanese firms respectively. Again, other contributions look at differences in terms of employment and post-entry innovation outcomes between Start-ups businesses where the original idea was generated by former employees of an incumbent firm or not (Fryges et al., 2014); or at whether Spin-offs from public research institutions have greater innovation capabilities than other knowledge intensive firms (Stephan, 2014). Arza and López (2011) too focus on public research organisations, but they look at differences in drivers for innovation between firms' cooperation or not with public research organisations. In the same spirit, Harris et al. (2013) investigate whether cooperation and knowledge sourcing from Higher Education Institutions affect Total Factor Productivity on a sample of UK firms.

4.2.2 Matching Estimator

The PSM model we analyse is based on structural pre-treatment conditions which contemporarily affect the outcome (in our case innovation behaviours) and the selection into the treatment itself (abandoning an innovation project). We selected our matched sample of treated and untreated firms with a Kernel estimator. The choice of the matching algorithm extensively affects the quality of a matched sample, above all in situations where the sample size does not allow maximising the asymptotic property of the propensity score matching estimator (Smith 2000). In particular, a trade-off between bias and variance might arise, i.e. between having high accuracy in order to find a true representation of the population value (bias), and the capacity to capture the underlying changes occurring in the overall population (variance). Thus, the bias-variance relationship can be seen as a trade-off between having a model which captures with accuracy the regularities across observations and a model which can also generalise with respect of potential hidden information.

In order to mitigate the trade-off problem and by looking at our sample characteristics, we employed the Kernel specification under common support to create a matched sample of treated and untreated firms. The choice of the Kernel algorithm was driven by the properties of the estimator which allows a higher precision in the final estimates. Kernel matching is a non-parametric estimator which improve efficiency by employing for the matching the weighted averages of nearly all observations in the control group, as such a lower level of variance is achieved because of the higher amount of information used. The condition of common support is however fundamental in this framework: as more observations are used to compute the match, there is a risk of using poorly matched observations. By imposing the common support option this drawback is accounted for and the matches drawn only by a region of common support between treated and untreated (Caliendo and Kopeinig 2008).

Finally, in order to check for the robustness of our results we performed a Nearest Neighbour matching without replacement (1:1). This techniques allows each observation in the treated group to be matched with one observation in the control group, which is in turn used only once as a match for the treated individuals. This might create issues of low quality in the matched sample as the exclusive pairing of the untreated observations does not permit the maximisation of all the information available and it heavily depends on the order in which the individuals are matched. As such, the risk associated to this specification is to produce a low bias but a high variance. The size of our sample suggests that a matching without replacement could be a viable option, considering also that a comparison between the Nearest Neighbour specification without replacement and our preferred Kernel algorithm do not yield substantial changes in the results[5].

4.3.3 Balancing Properties of the Model

In order to understand changes in innovation behaviour occurring in firms which experience a negative innovation outcome (abandoned innovation) with respect of those which do not experience it, we create a matched sample in relation to a set of observable pre-treatment characteristics discussed in Table 1[6]. The table below show the balancing properties of our model and compares four methods drawn from the evaluation literature to assess whether PSM is yielding to reliable results: the t- test for equality of means in matched and unmatched group; the analysis on the reduction of standardised bias; the analyses on the Pseudo R square; and finally the joint likelihood ratio test.

Table 5: Balancing properties of the Propensity Score Model

Sample	**Pseudo R2**	**LR chi2**	**p>chi2**	**Bias (average)**
Unmatched	0.113	563.400	0.000	3.371
Matched	0.004	7.480	1.000	0.224

The t-test looks at the balancing properties of our model by looking at the results of a t-test under the hypothesis of equality of means in treatment and control groups before and after the matching: if the balancing property is satisfied we should reject the hypothesis of equality in the matched sample (Rosenbaum and Rubin 1985). Following this first assessment, and as suggested in Rosenbaum and Rubin (1985), we then analyse the reduction of average standardised bias before and after matching in our control and treatment group. A reduction to an average standardised bias below the 3% (or at least 5%) threshold level is considered a good proxy for a successful matching. Finally, following Sianesi (2004) we look at the propensity score on the matched observations and compare the Pseudo R-square of the treated and non-treated groups before and after the matching. Differences in the Pseudo R-square provide a measure of the capacity of the estimated propensity score to efficiently balance the covariates. The underlying assumption is that if the estimated propensity score is satisfactory in balancing the covariates, the Propensity score model will poorly predict the assignment into the treatment once estimated exclusively on the matched observations. This is true as the property of the Pseudo R-square is to measure the explained variance as expressed by the modelled covariates: consequently, if a (balanced) sample is created conditioned on such covariates, the pseudo R-square should be much lower than in a sample where the model conditioning has not happened. In addition to this, Sianesi (2004) suggests to perform a likelihood

[5] As well as to check the robustness of the Kernel estimator, the choice to perform a Nearest Neighbour without replacement was motivated, also in order to perform the Sensitivity analysis on our results.

[6] Full results of the Probit model are presented in the Appendix. It is worth recalling that the Probit model employed to calculate the propensity score is not a behavioural model and as such no discussion about its characteristics is offered here. Also, as the model is not intended for inference on the underlying population sampling weights have been omitted (Zanutto 2006; Caliendo and Kopeinig 2008).

ratio test to investigate the joint insignificance of all the regressors: if the propensity model is balancing effectively, then the test should be rejected before and accepted after the matching.

Table 5 shows the results of the balancing test[7]. All the results consistently suggest a good level of balancing for the model: we can observe a reduction in the overall predictive power of the matched sample (pseudo-R2), the average bias after the matching is well below the 3% threshold and the likelihood ratio test as well points to the reliability of the chosen set of covariates for the propensity model.

5. Results: The impact of Failure on Innovation behaviour

The table below represents the average treatment effect caused by abandoning innovation on firms' strategy to innovate (Average Treatment effect on Treated). As described above, our outcome variable represents different types of innovation behaviours: five strategies which firms adopt in order to innovate. These strategies arise from the combination of exploratory and exploitative characteristics which range in a continuum space spanning from mostly explorative to mostly exploitative attributes. Our aim is to assess whether experiencing failure has an impact on the adoption of these innovation strategies adopted by the firms in our sample. To produce a more accurate estimation of the effect of the treatment on the treated, we follow Hirano et al. (2003), and look at the significance of the effect of failure by estimating double robust regression weighted on the propensity score.

Table 6: Average Treatment Effect on the Treated (ATT)

Outcome Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Exploratory oriented -	**Unmatched**	0.815	-0.208	**1.023*** **	0.032	31.92
Research intensive	**ATT**	0.804	0.203	**0.601*** **	0.038	15.79
Exploitative oriented -	**Unmatched**	2.416	2.335	0.081	0.025	3.21
Market driven	**ATT**	2.410	2.403	0.007	0.034	0.2
Exploratory oriented -	**Unmatched**	0.217	0.215	**0.002** **	0.022	0.11
Knowledge base intensive	**ATT**	0.217	0.259	**-0.042** **	0.027	-1.56
Exploratory oriented -	**Unmatched**	0.139	0.206	-0.067	0.016	-4.05
Cooperation driven	**ATT**	0.137	0.143	-0.006	0.022	-0.28
Exploratory oriented -	**Unmatched**	-0.194	-0.101	**-0.093*** **	0.014	-6.39
Analytical KB driven	**ATT**	-0.194	-0.121	**-0.072*** **	0.018	-4.12

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[7] Due to space limitations, the results for the t-test are presented in Appendix.

Two main elements emerge from the analysis:

i. Failure is not significant across all the innovation strategies
ii. Where failure is significant, its effect is not homogenous

Failure does not seem to produce a (statistically) significant effect on those firms more involved in exploitation oriented strategies or where the innovation strategy adopted is more affected by cooperation dynamics.

The effect of failure is statistically significant only over three components, but its effect is not monotonic. The first component represents strategies which could be associated to research intensive firms. In this case, the effect of failure is positive and significant suggesting that the difference between firms which are research intensive and fail compared to the ones which are research intensive but do not fail is that failure in the presence of high investments in both soft and monetary aspects of the research and development process does little to modify the firm's approach to innovating. Moreover, the result suggests that after experiencing a failure, firms tend to intensify this own approach to innovation strategy rather than change it.

The results are different when looking at the other (significant) innovation strategies, respectively represented by the third and fifth component. In these cases the effect of experiencing failure impacts on the innovation behaviour by producing a change in the strategy. As we see by looking at the table, the effect of failure is in fact negative on the outcome, suggesting that the innovation strategy adopted decreases, i.e. the effect of being unsuccessful in an innovation project shifts the approach with which innovation is managed. This is true for those strategies where soft innovation characteristics are more prominent and where the associated costs to innovate are likely to lower as they do not involve long term elements such internal R&D or external acquisition of R&D or patents.

Our preliminary results seem to suggest that the effects of failure change depending on the degree of exploratory behaviour adopted as innovation strategy. The more failure is associated to exploration the more failure has an impact. Conversely, the more failure is associated to exploitation the less failure has an impact. Moreover, where innovation failure occurs in relation to pure exploratory strategies and is not affected by market dynamics its effect is positive, and increase the relative attributes associated to it. However, when the distance from a pure exploratory strategy increases and innovation strategy depend on softer aspects such as in the case of exploitation driven knowledge base elements, failure produces a shift in firms' innovation strategy.

Finally, as suggested in the potential outcome literature, we perform a Sensitivity analysis test[8]. The Sensitivity analysis aims at understanding if there are unobserved variables affecting contemporarily the assignment into treatment and the outcome variable. If the selection into treatment is due to hidden variables, than a bias arise and the condition of unconfoundedness does not hold with the identifying assumption of assignment on observables being violated. As it is not possible to test

[8] As our outcome variable is continuous, we performed the Sensitivity Analysis of the average treatment effect on the treated using the Stata user-written command *rbounds* (Di Prete and Gangl 2004) which requires the matching to be of the Neirest Nieghbour (1:1) type. Although *rbounds* is not the only option available to perform a Sensitivity test (we think in particular at the *sensatt* command developed by Nannicini in 2007), the command was not available to us within the ONS Secure Lab environment and as such we choose *rbounds* instead.

directly the existence of omitted variables, Rosenbaum (2002) proposes a different approach which does not test the unconfoundedness assumption itself (i.e. the presence of unobserved variables). Rosenbaum suggests instead adopting a bounding approach aimed at understanding the degree at which any significance in the results depend on this untestable assumption. The results of the sensitivity analysis on the three significant outcomes suggest that our results yield, and therefore there is no hidden bias which could contemporarily affect the likelihood of innovation strategy and failure. However, we take such result cautiously and given the complex dynamics underlying the relationship between failure and innovation strategies we believe that further investigations should be carried to check on the sensitivity of the Rosenbaum bounds analysis (Lee and Lee 2009).

6. Conclusions

In contrast to a small but growing literature which approaches innovation failure from an innovation constraint angle where the object is to remove the impediments to innovation success, we have attempted in this paper to try to consider the direct impact of failure on innovation behaviour.

In order to address this issue we looked at the casual effect failure would have on innovation behaviour by adopting a propensity score matching approach that allows us to compare differences across firms which experienced innovation failure (defined as abandoned innovation projects) and firms which were successful (did not abandon projects). As we envisaged innovation to be a process encompassing exploration and exploitation this enabled us to represent the diversity of implicit innovation strategies followed by innovation active firms. We find that the effect of failure is not significant for all strategies and that the effects of failure change depending on the type of exploratory behaviour adopted as innovation strategy.

Failure is significant in relation to more exploratory behaviour involving an intensive use of research or knowledge base but it is not (statistically) significant for exploitative oriented strategies which are market driven, and also for those exploratory strategies driven by cooperation dynamics with little involvement of R&D production or acquisition. Moreover, where innovation failure occurs in relation to research intensive exploratory strategies its effect is positive, and does increase the relative attributes associated to it. However, when the distance from a pure exploratory strategy increases and innovation strategy depend on softer aspects such as in the case of exploration driven by knowledge base elements, failure produces a shift in firms' innovation strategy.

Our results seem to hint towards a role of failure on innovation behaviour, and in particular to a potential learning effect of failure on firms' innovation strategies. We observe that the significance of failure is evident where firms' strategies lean in the direction of exploration. Depending on the attributes associated to exploration though the effect of failure is different: it could produce a shift in their strategy (where the strategy is mainly based on an highly skilled knowledge base composition), or could reinforce the same strategy (where the behaviour involves the alignment of a number of research intensive attributes).

Our hypothesis is that such difference in results between innovation strategies could rest not only on the different types of investments research intensive firms experience, but also on a different positioning on the learning curve. As firms where innovation failure has an effect are exploratory, we could interpret our results looking at firms adopting research intensive strategy as being at an higher point of their learning curve because they know that to succeed you must fail first – hence: they do not shift strategy. The others – where undoubtedly overall investments are lower (no R&D but some form of patenting), need more fine tuning of their strategy and hence failure modifies their behaviour. So, for both, there is a learning effect, just of different nature as their strategies represent different stages of their learning curve cycle.

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APPENDIX

Table 7: Principal Component Analysis - SMC and KMO Tests of Sampling adequacy

Variable	SMC
Context FlexPr	0.8636
Context MrkSha	0.7523
Context NewGS	0.7508
Context NewMrk	0.7883
Context ProdCa	0.8923
Context Qualit	0.7946
Context VA	0.7859
Cooperation Comp	0.7549
Cooperation Cons	0.7955
Cooperation Gov	0.89
Cooperation Supplier	0.7977
Cooperation Univ	0.8498
Cooperation Users	0.8837
design	0.6598
eng	0.6293
ExtRD	0.7095
graphic	0.7945
IntRD	0.7737
INW_IP	0.5551
IP_Formal	0.5601
IP_Informal	0.6592
maths	0.5396
multimedi	0.7871
software	0.6517
Average	0.746625

Variable	KMO
ExtRD	0.9066
Coop_Supp	0.9212
Coop_users	0.8638
Coop_Comp	0.9261
Coop_Cons_~b	0.9363
Coop_Univ	0.8813
Coop_Gov	0.7847
INW_IP	0.9123
IntRD	0.9158
IP_Formal	0.9426
IP_Informal	0.9233
C1_NewGS	0.8827
C2_NewMrk	0.8299
C3_MrkShare	0.839
C4_Quality	0.8608
C5_FlexProd	0.8461
C6_ProdCap~y	0.7854
C7_VA	0.8949
graphic	0.8139
design	0.8963
multimedia	0.8225
software	0.9052
eng	0.8462
maths	0.8196
Overall	0.8743

Table 8: Principal Component Analysis - Loadings of all Components

Components (Eigenvectors)	Component 1	Component 2	Component 3	Component 4	Component 5	Component 6	Component 7	Component 8
ExtRD	0.2305	0.1164	-0.0192	-0.3138	-0.2622	0.3455	0.0294	0.0543
Coop_Suppliers	0.264	0.04	-0.1851	0.2099	-0.0497	0.0325	-0.3002	-0.1235
Coop_Users	0.2708	0.0684	-0.2176	0.1482	-0.0525	-0.0752	-0.2976	-0.0358
Coop_Competitors	0.2285	0.07	-0.2852	0.3446	-0.0087	-0.0543	-0.0399	-0.0038
Coop_Consultants & Priv Labs	0.261	0.0941	-0.2321	0.0984	0.0268	0.0485	0.1589	0.0054
Coop_University	0.2576	0.1	-0.2379	0.0163	0.0871	-0.1262	0.2895	0.119
Coop_Gov & Public Labs	0.2369	0.0956	-0.3021	0.2171	0.1435	-0.0673	0.3082	0.1387
Inward IP	0.2049	0.0972	-0.0286	-0.2492	-0.2803	0.5129	0.2565	0.0741
IntRD	0.2604	0.0784	-0.016	-0.3015	-0.1747	0.0372	-0.1711	-0.0056
IP_Formal	0.2163	0.1005	0.096	-0.2784	-0.1507	-0.3554	-0.045	-0.0577
IP_Informal	0.236	0.1108	0.0362	-0.2789	-0.0468	-0.3256	-0.1923	-0.08
C1_New Goods&Services	-0.1205	0.3546	0.008	-0.0383	-0.0957	-0.2195	-0.0037	0.1825
C2_Innovation New to the Market	-0.1403	0.3333	0.0001	-0.1009	-0.0318	-0.2531	0.2685	0.3883
C3_Increase Market share	-0.126	0.3466	0.0485	-0.0329	-0.0738	-0.1157	-0.1786	0.2615
C4_Increase Quality	-0.1049	0.3718	-0.044	0.12	0.0019	0.1114	-0.3391	-0.1214
C5_Improve Flexible Prod	-0.162	0.3393	-0.0311	0.0608	0.0558	0.1788	0.1657	-0.3369
C6_Imporve Prod Capacity	-0.1681	0.3366	-0.0413	0.052	0.0705	0.1624	0.1715	-0.253
C7_Increase Value Added	-0.1144	0.3788	-0.0217	0.0553	0.0072	0.0941	-0.1576	-0.119
Knowledge Base: Graphic	0.1824	0.0729	0.4249	0.3073	-0.1833	-0.0877	0.1688	0.0024
Knowledge Base: Design	0.2087	0.0989	0.2964	-0.0096	0.0622	-0.1844	0.2656	-0.521
Knowledge Base: Multimedia	0.1853	0.06	0.4203	0.3214	-0.182	-0.0047	0.0957	0.1197
Knowledge Base: Software	0.2042	0.0688	0.3426	0.1759	0.0632	0.2242	-0.2585	0.127
Knowledge Base: Engeneering	0.1967	0.0881	0.0801	-0.2917	0.5781	-0.0394	-0.0127	-0.1722
Knowledge Base: Maths	0.1688	0.1041	0.2169	-0.0312	0.5749	0.2294	-0.069	0.3759

Components (Eigenvectors)	Component 9	Component 1	Component 1	Component 1	Component 1	Component 1	Component 1	Component 16
ExtRD	-0.1376	-0.2977	-0.0508	-0.2694	-0.1183	0.02	0.1162	0.434
Coop_Suppliers	-0.0472	0.178	-0.1667	0.1208	-0.0165	0.5077	0.264	0.0102
Coop_Users	-0.1438	0.0403	0.1274	0.0696	0.0885	-0.1307	-0.2796	0.0487
Coop_Competitors	-0.1616	0.2658	0.1575	0.0048	0.1053	-0.3268	0.1703	0.4323
Coop_Consultants & Priv Labs	0.0598	0.0062	-0.3513	-0.0839	-0.1533	0.303	-0.0593	-0.3537
Coop_University	0.1358	-0.2588	-0.0734	-0.0695	-0.0221	-0.3492	-0.1397	-0.128
Coop_Gov & Public Labs	0.1217	-0.2004	0.098	-0.0285	0.0457	0.0981	0.0709	-0.0576
Inward IP	-0.0243	0.477	0.0344	0.3326	0.1242	-0.1076	-0.156	-0.1829
IntRD	-0.1961	-0.3095	0.1999	-0.2421	-0.0127	0.0597	0.1234	-0.1978
IP_Formal	0.5621	0.3048	-0.0191	-0.341	0.3463	0.0998	-0.1099	0.1396
IP_Informal	0.2308	-0.0485	0.1724	0.5205	-0.4706	-0.142	0.1731	-0.0471
C1_New Goods&Services	-0.3024	-0.0192	0.4068	0.0812	0.2129	0.3785	-0.0408	-0.0259
C2_Innovation New to the Market	-0.1346	-0.0313	-0.0938	0.2181	0.1485	0.0429	-0.0059	0.0309
C3_Increase Market share	-0.1418	0.2016	-0.5178	-0.1341	-0.1044	-0.2698	0.347	-0.0143
C4_Increase Quality	0.0223	-0.024	0.1308	-0.2614	0.0916	-0.2642	-0.158	-0.3872
C5_Improve Flexible Prod	0.1748	-0.0287	0.1719	0.0585	0.0438	-0.0071	0.0877	0.1526
C6_Imporve Prod Capacity	0.2795	-0.0784	0.0203	0.0113	-0.0165	0.0868	0.3369	0.1015
C7_Increase Value Added	0.0511	-0.0412	-0.1593	0.0687	-0.3151	0.0959	-0.5189	0.1418
Knowledge Base: Graphic	-0.0785	0.1139	-0.0294	-0.1638	-0.1836	0.1187	-0.1287	0.0383
Knowledge Base: Design	-0.3648	0.0914	-0.0005	-0.0519	0.0567	-0.1438	0.1813	-0.2476
Knowledge Base: Multimedia	0.0779	-0.1458	0.0456	0.0472	-0.1523	-0.0319	-0.1351	0.1657
Knowledge Base: Software	0.1905	-0.3341	-0.1616	0.3201	0.496	-0.0616	0.1357	-0.09
Knowledge Base: Engeneering	-0.2372	-0.0323	-0.2596	0.1036	0.1711	0.0602	-0.2447	0.2744
Knowledge Base: Maths	0.0872	0.2742	0.3283	-0.2125	-0.2452	0.0407	0.1282	-0.0633

Components (Eigenvectors)	Component 1	Component 1	Component 1	Component 2	Component 2	Component 2	Component 2	Component 24
ExtRD	-0.2146	-0.1137	-0.4096	-0.0358	-0.0964	0.0496	-0.0558	0.0248
Coop_Suppliers	-0.0295	0.3878	-0.0573	-0.0526	0.0737	0.1678	-0.3779	0.0601
Coop_Users	-0.0361	0.2676	-0.2092	0.1572	-0.0571	-0.0816	0.5625	0.3713
Coop_Competitors	-0.0187	-0.3996	0.2468	0.0734	0.1416	-0.0388	-0.1671	-0.0832
Coop_Consultants & Priv Labs	0.066	-0.5457	-0.0855	0.0059	0.2717	0.0341	0.2482	0.0845
Coop_University	-0.0877	0.1974	0.1899	-0.273	-0.0661	0.441	-0.2253	0.2908
Coop_Gov & Public Labs	0.0349	0.2107	-0.1282	0.0067	-0.3099	-0.3736	0.0683	-0.5188
Inward IP	0.1201	0.0797	0.075	-0.0586	-0.1004	-0.0646	-0.0484	-0.0389
IntRD	0.2061	0.1234	0.5501	0.2346	0.2186	-0.0927	0.0505	-0.0923
IP_Formal	-0.0718	-0.0047	0.0019	-0.0385	0.0527	-0.0667	0.0036	-0.0353
IP_Informal	0.057	-0.1682	-0.1301	0.0458	-0.1004	0.0467	-0.0273	-0.0876
C1_New Goods&Services	0.0168	-0.2229	0.0395	-0.4436	-0.1928	0.1403	0.0694	0.053
C2_Innovation New to the Market	-0.1318	0.1065	-0.1582	0.5076	0.3212	-0.0682	-0.1911	0.1222
C3_Increase Market share	0.1265	0.1476	0.0683	-0.2191	-0.1071	-0.0035	0.2621	-0.1402
C4_Increase Quality	0.2165	-0.1125	-0.353	0.105	-0.0519	-0.0264	-0.3876	-0.0619
C5_Improve Flexible Prod	0.1034	0.1668	-0.0715	0.0443	0.3457	0.4734	0.3173	-0.3012
C6_Imporve Prod Capacity	0.1474	-0.0369	0.1808	0.0965	-0.2629	-0.2992	0.008	0.5376
C7_Increase Value Added	-0.4231	0.0254	0.3304	-0.0566	0.0056	-0.1946	-0.0705	-0.1576
Knowledge Base: Graphic	0.1151	-0.0421	0.0957	0.4151	-0.4367	0.3387	0.0159	-0.0437
Knowledge Base: Design	-0.3875	0.0564	-0.0927	-0.1187	0.0831	-0.1832	-0.0076	0.0082
Knowledge Base: Multimedia	0.3756	0.1193	-0.0975	-0.3379	0.3918	-0.2774	-0.0689	0.0989
Knowledge Base: Software	-0.2457	-0.1606	0.0949	0.0257	-0.0631	0.0667	0.0775	-0.07
Knowledge Base: Engeneering	0.4181	-0.0361	-0.0074	0.0095	-0.0911	0.0067	-0.0854	-0.0328
Knowledge Base: Maths	-0.2031	0.0527	-0.0113	0.0066	0.1022	0.019	0.0531	0.0874

Table 9: Sensitivity Analysis of the ATT results

Component 1 - Sensitivity Analysis						
Gamma	**sig+**	**sig-**	**t-hat+**	**t-hat-**	**CI+**	**CI-**
1	0.0000	0.0000	0.5941	0.5941	0.5104	0.6771
1.1	0.0000	0.0000	0.5480	0.6404	0.4634	0.7243
1.2	0.0000	0.0000	0.5048	0.6825	0.4199	0.7673
1.3	0.0000	0.0000	0.4655	0.7221	0.3797	0.8066
1.4	0.0000	0.0000	0.4292	0.7583	0.3437	0.8428
1.5	0.0000	0.0000	0.3951	0.7917	0.3094	0.8767
1.6	0.0000	0.0000	0.3635	0.8227	0.2762	0.9086
1.7	0.0000	0.0000	0.3350	0.8519	0.2463	0.9364
1.8	0.0000	0.0000	0.3070	0.8789	0.2168	0.9642
1.9	0.0000	0.0000	0.2798	0.9049	0.1902	0.9893
2	0.0000	0.0000	0.2547	0.9282	0.1647	1.0146
2.1	0.0000	0.0000	0.2307	0.9508	0.1405	1.0369
2.2	0.0000	0.0000	0.2086	0.9725	0.1161	1.0582
2.3	0.0001	0.0000	0.1868	0.9923	0.0938	1.0786
2.4	0.0004	0.0000	0.1668	1.0126	0.0721	1.0987
2.5	0.0016	0.0000	0.1474	1.0308	0.0531	1.1177
2.6	0.0050	0.0000	0.1280	1.0477	0.0326	1.1362
2.7	0.0137	0.0000	0.1096	1.0645	0.0126	1.1537
2.8	0.0320	0.0000	0.0920	1.0801	-0.0055	1.1702
2.9	**0.0652**	0.0000	0.0746	1.0960	-0.0230	1.1863
3	**0.1181**	0.0000	0.0593	1.1110	-0.0399	1.2019
3.1	0.1928	0.0000	0.0442	1.1257	-0.0560	1.2171
3.2	0.2874	0.0000	0.0283	1.1396	-0.0714	1.2315
3.3	0.3959	0.0000	0.0129	1.1535	-0.0873	1.2465
3.4	0.5096	0.0000	-0.0012	1.1662	-0.1023	1.2602
3.5	0.6194	0.0000	-0.0147	1.1784	-0.1161	1.2744
3.6	0.7177	0.0000	-0.0278	1.1911	-0.1307	1.2877
3.7	0.7997	0.0000	-0.0407	1.2031	-0.1454	1.2999
3.8	0.8640	0.0000	-0.0532	1.2143	-0.1583	1.3117
3.9	0.9114	0.0000	-0.0649	1.2255	-0.1708	1.3237
4	0.9446	0.0000	-0.0768	1.2367	-0.1835	1.3351

Rosenbaum bounds for PC1 delta
(N=706 matched pairs with N-N Estimator)

Component 3 - Sensitivity Analysis						
Gamma	**sig+**	**sig-**	**t-hat+**	**t-hat-**	**CI+**	**CI-**
1	0.0412	0.0412	-0.0593	-0.0593	-0.1257	0.0074
1.1	0.0023	0.2606	-0.0962	-0.0220	-0.1630	0.0445
1.2	0.0001	0.6396	-0.1302	0.0116	-0.1968	0.0780
1.3	0.0000	0.8991	-0.1613	0.0427	-0.2272	0.1087
1.4	0.0000	0.9834	-0.1896	0.0707	-0.2565	0.1375
1.5	0.0000	0.9983	-0.2158	0.0965	-0.2839	0.1640
1.6	0.0000	0.9999	-0.2409	0.1214	-0.3101	0.1888
1.7	0.0000	1.0000	-0.2637	0.1447	-0.3339	0.2122
1.8	0.0000	1.0000	-0.2858	0.1659	-0.3568	0.2335
1.9	0.0000	1.0000	-0.3070	0.1862	-0.3779	0.2540
2	0.0000	1.0000	-0.3263	0.2054	-0.3979	0.2735
2.1	0.0000	1.0000	-0.3454	0.2231	-0.4174	0.2917
2.2	0.0000	1.0000	-0.3632	0.2401	-0.4358	0.3095
2.3	0.0000	1.0000	-0.3803	0.2564	-0.4545	0.3266
2.4	0.0000	1.0000	-0.3961	0.2717	-0.4716	0.3426
2.5	0.0000	1.0000	-0.4116	0.2864	-0.4876	0.3583
2.6	0.0000	1.0000	-0.4266	0.3006	-0.5024	0.3733
2.7	0.0000	1.0000	-0.4412	0.3146	-0.5171	0.3871
2.8	0.0000	1.0000	-0.4559	0.3281	-0.5318	0.4007
2.9	0.0000	1.0000	-0.4693	0.3402	-0.5459	0.4138
3	0.0000	1.0000	-0.4824	0.3527	-0.5589	0.4261
3.1	0.0000	1.0000	-0.4940	0.3648	-0.5720	0.4379
3.2	0.0000	1.0000	-0.5056	0.3765	-0.5842	0.4495
3.3	0.0000	1.0000	-0.5170	0.3870	-0.5955	0.4604
3.4	0.0000	1.0000	-0.5286	0.3975	-0.6062	0.4709
3.5	0.0000	1.0000	-0.5394	0.4079	-0.6173	0.4810
3.6	0.0000	1.0000	-0.5500	0.4174	-0.6286	0.4909
3.7	0.0000	1.0000	-0.5596	0.4269	-0.6388	0.5005
3.8	0.0000	1.0000	-0.5697	0.4357	-0.6488	0.5103
3.9	0.0000	1.0000	-0.5791	0.4446	-0.6590	0.5195
4	0.0000	1.0000	-0.5880	0.4529	-0.6688	0.5286

Rosenbaum bounds for PC3 delta
(N=706 matched pairs with N-N Estimator)

Component 5 - Sensitivity Analysis						
Gamma	**sig+**	**sig-**	**t-hat+**	**t-hat-**	**CI+**	**CI-**
1	0.0000	0.0000	-0.0896	-0.0896	-0.1313	-0.0470
1.1	0.0000	0.0013	-0.1125	-0.0656	-0.1551	-0.0230
1.2	0.0000	0.0221	-0.1342	-0.0441	-0.1770	-0.0011
1.3	0.0000	0.1351	-0.1541	-0.0242	-0.1970	0.0192
1.4	0.0000	0.3962	-0.1721	-0.0058	-0.2156	0.0379
1.5	0.0000	0.6979	-0.1896	0.0117	-0.2335	0.0557
1.6	0.0000	0.8943	-0.2051	0.0275	-0.2495	0.0728
1.7	0.0000	0.9737	-0.2202	0.0428	-0.2653	0.0890
1.8	0.0000	0.9952	-0.2347	0.0570	-0.2801	0.1042
1.9	0.0000	0.9993	-0.2478	0.0711	-0.2940	0.1181
2	0.0000	0.9999	-0.2606	0.0841	-0.3074	0.1323
2.1	0.0000	1.0000	-0.2730	0.0966	-0.3201	0.1452
2.2	0.0000	1.0000	-0.2845	0.1085	-0.3324	0.1575
2.3	0.0000	1.0000	-0.2956	0.1200	-0.3438	0.1698
2.4	0.0000	1.0000	-0.3063	0.1312	-0.3550	0.1818
2.5	0.0000	1.0000	-0.3166	0.1416	-0.3658	0.1926
2.6	0.0000	1.0000	-0.3262	0.1513	-0.3762	0.2033
2.7	0.0000	1.0000	-0.3357	0.1611	-0.3862	0.2141
2.8	0.0000	1.0000	-0.3447	0.1709	-0.3956	0.2246
2.9	0.0000	1.0000	-0.3536	0.1802	-0.4047	0.2340
3	0.0000	1.0000	-0.3621	0.1889	-0.4136	0.2431
3.1	0.0000	1.0000	-0.3704	0.1971	-0.4225	0.2521
3.2	0.0000	1.0000	-0.3782	0.2055	-0.4312	0.2612
3.3	0.0000	1.0000	-0.3860	0.2140	-0.4390	0.2703
3.4	0.0000	1.0000	-0.3934	0.2221	-0.4467	0.2783
3.5	0.0000	1.0000	-0.4004	0.2299	-0.4543	0.2863
3.6	0.0000	1.0000	-0.4073	0.2365	-0.4619	0.2939
3.7	0.0000	1.0000	-0.4140	0.2436	-0.4694	0.3019
3.8	0.0000	1.0000	-0.4209	0.2506	-0.4761	0.3099
3.9	0.0000	1.0000	-0.4277	0.2575	-0.4830	0.3174
4	0.0000	1.0000	-0.4340	0.2643	-0.4896	0.3242

Rosenbaum bounds for PC4 delta
(N=706 matched pairs with N-N Estimator)