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Do firms really learn from failure? The dynamics of abandoned innovation

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Do firms really learn from failure? The dynamics of abandoned innovation

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Abstract
Abandoned and failed innovations can be regarded as a part of the natural process of experimentation by firms, which can lead to important lessons being learned. Although the literature suggests some benefit from failure or abandoned innovation activities, prior studies using relatively large firm-level datasets to test the nature of this link are often unable to deal explicitly with the time dimension of learning. We contribute to the literature by showing the dynamic and causal nature of the linkage between abandoned innovation and subsequent innovation outcomes at firms. We demonstrate based on balanced panel data of Spanish manufacturing firms from 2008-2016 that innovation failure not only leads to more successful innovation, but that there is an explicit time dimension to this. We demonstrate that firms which have experienced 'failure' (as evidenced by abandoned innovation activities) in the past will have stronger positive effects of recent abandoned innovation activities on innovation output. This is a strong test of the 'learning-from-failure' hypothesis. In addition, we find evidence that in addition to enabling cumulative learning processes, abandoning innovation may also act as a dynamic corrective mechanism preventing firms carrying weaker innovation portfolios through from one period to the next.

Keywords: Innovation failure; abandoning innovation activities; learning effects; innovation performance

JEL codes: D21, D23, D92

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1. Introduction

Failure is a natural part of any business. By definition all businesses must make future investment plans, not all of which will end profitably. In the case of innovation, a process the outcomes of which are inherently uncertain, failure may not merely be commonplace but ubiquitous. In a review of the literature on innovation failure, Rhaiem and Amara (2019) summarise numerous academic studies which estimate the proportion of innovative projects failing wholly or in part to be between 40% and 90%. While failure and abandonment is costly, it need not be entirely wasted. If lessons can be learned from failed and abandoned projects which may either encourage better selection of innovative projects in the future or allow more of them to be managed to fruition, then an apparently wasteful element of corporate activity can, at least in part, be turned into something beneficial for the firm concerned.

There is evidence in the literature that learning from failed or abandoned initiatives can be met with subsequent success. For example, in a study of radical ideas suggestion by employees in a multinational firm's ideas and innovation programme, Deichmann and van den Ende (2014) find that repeated radical initiative-taking at the individual level is enhanced more by previous failure rather than success, suggesting that 'failure' can have positive subsequent effects. Madsen and Desai (2010) consider the possibility of learning from success and failure in the launch of orbital craft from 1957 to 2004. They find that others' experience of failure is negatively correlated with the likelihood of a firm's own launch failure, suggesting that firms somehow learn from the failure of others in ways that reduces their own failure rates. However, this analysis is about how success and failure influences learning, and is not conducted in the specific context of innovation activity.

If firms – and the individuals working in them – are able to learn systematically from failure this ought to be reflected in relatively large samples of firms which engage in innovation activity. Some studies have attempted to capture this by considering the link between abandoned innovation and successful innovation, and find a positive association (e.g. Leoncini 2016; Tsinopoulos et al 2019). However, the other key dimension of learning is that it takes time to absorb and implement new knowledge: although they ostensibly deal with learning issues, studies such as Leoncini (2016) and Tsinopoulos et al (2019) generally do so without explicitly modelling the time this process may take, and so tend to establish a contemporaneous link between abandonment and innovation.

Our principal contention is not simply that innovation failure leads to more successful innovation, but that there is an explicit time dimension to this which indicates a learning effect. Drawing on Love et al (2014a) who demonstrate that previous experience of external collaboration for innovation makes current collaboration more effective, we hypothesise that firms which have experienced 'failure' (as evidenced by abandoned innovation activities) in the past will have a stronger positive relationship between recent abandonment and successful innovation than those with no earlier experience of abandoned innovation. This is a strong test of the 'learning-from-failure' hypothesis: it requires not simply that previous abandonment positively affects subsequent successful innovation (i.e. merely a lag), but evidence that abandonment in the past makes recent abandoned innovation more effective in aiding subsequent successful innovation. In addition, we test the hypothesis that firms' previous investment in their learning capacity moderates the learning process between prior abandoned innovation and subsequent successful innovation.

We test these hypotheses using a balanced panel of Spanish manufacturing firms over the period 2008-16. Using an appropriate matching process, we find strong evidence that firms with previous experience of abandoned innovation are more likely to have a positive relationship between recent abandonment and subsequent product, process and organisational innovation, which we regard as indicating a form of learning from abandoned innovation. However, we also find that, contrary to expectations, this learning effect is weaker for firms which have made previous investments in R&D and innovation training.

Our contribution to the literature lies in showing for the first time the dynamic and causal nature of the linkage between abandoned innovation and subsequent innovation outcomes. There are indeed learning effects but these are complex and depend on cumulative as well as current episodes of failure. The effectiveness of this cumulative learning process, and therefore the strength of its beneficial effects on innovation outcomes, proves strongly conditional on firms' past activities. A prior history of abandonment leads to performance improvement not by reducing subsequent abandonment – indeed, abandoned innovation shows persistence through time – but by altering the process which allows firms to learn from more recent abandoned innovation episodes. This suggests that learning from failure in innovation is past dependent if not necessarily path dependent (Le Bas and Scellato 2014). In addition, we find evidence that, in addition to enabling cumulative learning processes, abandoning innovation may also act as a dynamic corrective mechanism preventing firms carrying weaker innovation portfolios through from one period to the next.

2. Literature Review and Hypotheses

The idea that there can be some learning benefit from failure has a long history, going back at least as far as Cyert and March (1963). They argued that learning can come from both success and failure, but that behavioural change is actually more likely to arise as a result of experiences of failure. Crucially, learning from failure is not the same as learning from success. Baumard and Starbuck (2005) find that it is actually very difficult to learn from failure and it may not happen, often because managers tend to regard large failures as idiosyncratic and exogenous events, while ignoring the potential lessons from small failures.

However, when learning from failure does happen it can be very beneficial: indeed occasional failure may be necessary for improvements in processes to take place. Failure is more likely to result in challenges to the existing routines and lead to more and more focused search activities by the firm. Repeated success may confirm that the past routines were at a satisficing level. Thus the routines remain unchallenged and unchanged, with strong implications for search activities by the firm. Some literature even suggests that a history of successes may lead to declining capabilities to learn, as it leads to overconfidence and a decline in the motivation to learn from the past (e.g. Tushman and Nadler 1986, KC et al. 2013). In addition, there is evidence that knowledge learned from failure, while it may be difficult to acquire, depreciates more slowly than that learned from success (Madsen and Desai 2010).

With respect to the innovation process, its inherently uncertain nature makes some degree of ‘failure’ inevitable. (D’Este et al 2018). Not all innovative products will make it to market, and not all new technological or organisational processes will result in improved efficiency. Although any failure may be viewed as an unwelcome event, if the reasons for it are understood then changes in behaviour and routine may be initiated at both individual and organisational level which can not only help prevent failure in the future, but lead to subsequent performance improvements, including better innovation processes (Tsinopoulos et al 2019). Abandoned and failed innovations can therefore be regarded as part of the natural process of experimentation which can lead to important lessons being learned – as long as the organisation has processes in place to permit learning to occur, rather than simply ascribing failure to the outside influences or the failings of others. (Baumard and Starbuck 2005).

The relatively limited literature on learning from failure in innovation does suggest that it can have positive effects. In a study of failed innovation attempts in pharmaceuticals, Khanna et al (2016) find that small failures are associated with a decrease in R&D output but with an increase in the quality of R&D output as measured by forward citations to patents. They conclude that these findings arise from the ability of pharmaceutical firms to engage in multilevel learning processes arising from failures in their R&D activities. Studies using large-scale innovation surveys come to similar conclusions. Leoncini (2016) and Tsinopoulos et al (2019) both use elements of the Community Innovation Survey to study the relationship between abandoned innovation and innovation performance, and both find a consistently positive association. This leads to our first, baseline, hypothesis:

> *H1. Firms which have experienced 'failure' (as evidenced by abandoned innovation activities) are more likely to demonstrate higher levels of successful innovation.*

2.1 The dynamics of learning from failure

Although the literature suggests some benefit from failure or abandonment in innovation, studies using relatively large firm-level datasets to test the nature of this link are often unable to deal explicitly with the time dimension of learning. This is important, because there is evidence from other areas that learning effects are often cumulative in nature, with examples ranging from the adoption of quality improvement management (Bourke and Roper 2017) to learning from exporting through time (Love and Mañez 2019).

Leoncini (2016) uses a single wave of the Community Innovation Survey in testing the relationship between the likelihood of abandonment and the percentage of turnover deriving from innovative products. By contrast, Tsinopoulos et al (2019) use five waves of the UK Innovation Survey in their analysis, but do not explicitly include any lags in the structure of their estimation to allow for the time process of learning[1]. However, it is likely that if there is indeed a learning process arising from abandoned innovation, this will mean that previous experience of failure will help to shape the relationship between current episodes of failure and innovation outputs. The analogy here is with the literature on external collaboration experience and innovation. The experience gained from collaboration in one field of activity can be used to develop capabilities in collaboration that can be used with other partners (Powell et al 1996). In a study of innovation in Irish manufacturing establishments, Love et al (2014a) find that establishments with substantial experience of external collaborations in previous periods derived more innovation output from such linkages in the current period – they had learned to make their existing external collaborations more effective.

A similar situation arises in the case of the link from abandonment or failure to innovation. Managing innovation is a complex task, but for many firms innovation is not a one-off event, but something that is attempted repeatedly. Zollo and Winter (2002) demonstrate that managing such complex tasks, especially where they occur repeatedly, can not only help improve managers' skills in performing such tasks more effectively through time, but may also develop into a dynamic capability in its own right. This suggests a process of organisational learning, which, as with the case of learning from external collaboration, may occur in two ways (Love et al 2014). The first arises from the development of organisational routines; as firms develop routines for dealing with failed innovation attempts, their ability to learn the lessons of failure from current abandoned innovations increases. Cannon and Edmondson (2005) illustrate how successful organisations systematically learn the lessons of repeated relatively small failures, and thus develop routines to help prevent, and learn from, larger problems. The second learning route arises from developments not in organisational learning but in managerial cognition through time (Love et al 2014a). Management attention and 'bandwith' is inevitably limited (Ocasio 1997), while Adner and Helfat (2003) identify 'managerial cognition' as an attribute underpinning dynamic managerial capability. By learning to concentrate attention on the examples of failure from which there is most to learn, managers are able to learn the lessons of more recent failures more quickly and more effectively, improving their managerial cognition through time. Thus not only do managers cope better with repeated failures (Mueller and Shepherd 2014), they are able to apply the

[1] Both make use of the built-in lag present in such innovation surveys, as each survey involves observations over a three-year period.

lessons learned from previous experience more effectively to current examples of failure and abandoned innovation, allowing a more positive link to future successful innovation.

A key element of learning from past failure can also be *unlearning* the processes and routines which led to failure in the first place. Just as learning has a time dimension, so does useful unlearning. The capacity of an organisation to unlearn and discard obsolete knowledge and routines forms an important element of organisational adaptation (Klammer and Gueldenberg 2019). Just as managers may fail to learn from repeated success, because it can lead to overconfidence and a fall in motivation to learn (KC et al 2013), so the capacity to unlearn what led to failure can prove useful. However, the possible time dimension of this unlearning process has been relatively little researched (Klammer and Gueldenberg, 2019). In a study of team learning processes in new product development, Akgün, Lynn, and Yilmaz (2006) demonstrate that unlearning is indeed a key factor in the process; without unlearning, the other necessary sociocognitive stages of learning from failure are unlikely to take place. Firms which experience innovation failure for the first time will not have had the opportunity to unlearn the processes which led to failure, whereas firms with previous experience of failure will have the time and opportunity not merely to learn new and more useful routines as described earlier, but to unlearn and discard the problematic areas of thought and activity. In addition, because recent failure events have the greatest effect on reducing subsequent failure (Haunschild et al 2015), we expect the learning effect of previous failure experience to derive from the relatively recent past.

The joint effect of these three processes – development of organisational routines, improved managerial cognition, and useful unlearning – lead to our second hypothesis:

> *H2: Firms which have experienced prior episodes of 'failure' (as evidenced by abandoned innovation activities) will have a stronger positive relationship between recent abandonment and successful innovation than other firms.*

2.2 The moderating effect of previous investment

The lessons of failure will only be learned, and hence lead to improved future performance, if the firm has formal and/or informal mechanisms in place which allow learning at the organisational and individual level. Suitable learning is also more likely where the firm has invested in enhancing its capacity to learn from incidences of failure. We argue here that prior investment in R&D and training will have a moderating effect on the innovation effects of prior abandonment, enhancing the relationship posited in Hypothesis 2 above.

Since the work of Cohen and Levinthal (1989) it has been recognised that investment in R&D has two beneficial qualities. First, it provides the knowledge necessary for innovation; second, it helps provide the absorptive capacity for the assimilation of external knowledge. While R&D, especially exploratory R&D, may increase the likelihood of failure, as more experimentation means more may go wrong, previous R&D investment may help mitigate against failure and so enhance the link from failure to successful innovation. In a study of innovation in Spanish firms spanning six years, D'Este et al (2018) find that cumulative R&D investment helps reduce the incidence of failure. This is because the accumulated experience the firm has in R&D activity provides experience-based learning, providing improvements to procedures associated with experimentation and exploration. We argue that this effect of previous R&D will not only help mitigate against failure, but will help encourage the learning from prior episodes of abandonment which will make future successful innovation more likely. This leads to our next hypothesis:

> *H3: Prior investment in R&D positively moderates the relationship between previous abandoned innovation activity and successful innovation.*

This cumulative R&D effect is an organisational issue. There is also an individual dimension to this process. Several studies suggest that individuals can learn from failure, not only their own, but also from the failure of others within the same organisation. In a longitudinal study of the performance of cardiac surgeons, KC et al (2013) find the intriguing result that individuals tend to learn little or nothing from their own failures, but do learn from the failure of others. They suggest that the reason for this is because individuals tend to blame their own failures on chance or exogenous factors, while seeing the failures of others as being the fault of the individual concerned. This can be exacerbated by a tendency for individuals not to be open about mistakes they have made, making both individual and collective learning from failure more difficult (Husted and Michailova 2002). Organisations can mitigate against this both by engendering an ethos in which failure is openly discussed, but also by specifically providing employee training on the innovation process itself. While the nature of such training will vary widely, in cases where firms have a formal training program devoted to innovation, it seems reasonable to expect that this will make it more likely that in such firms processes of accepting, admitting and learning from episodes of failure will develop and be encouraged. This leads to our final hypothesis:

H4: Prior investment in relevant training positively moderates the relationship between previous abandoned innovation activity and successful innovation.

The theoretical model and hypotheses are summarised in Figure 1.

3. Data and Methods

3.1 Data and Descriptive Statistics

Our empirical analysis is based on innovation survey data of Spanish firms from the "Panel of Technological Innovation" (PITEC). PITEC is Spain's input to the Community Innovation Survey (CIS), it follows the methodology of the OECD Oslo Manual (2005). CIS type surveys capture information on various key aspects of firms' innovation process and have become crucial sources in the economics and management literature on innovation (Smith 2005, Mairesse and Mohnen 2010). PITEC has been developed by the Spanish Statistical Office - Instituto Nacional de Estadística (INE) – and Fundación Española para la Ciencia y la Tecnología.[2] The PITEC panel data are available for the 2003-2016 period, covering more than 12,000 firms. PITEC's key advantage compared to many other CIS type of surveys is that it is a firm-level, yearly, balanced panel and enables an investigation of the evolution and effects of innovation activities within the same firms. The panel nature of the dataset is of particular importance for our paper, as we are investigating learning from innovation activities, which implicitly requires a dynamic setting (e.g. Love et al. 2014a, 2014b).

The PITEC is based on different underlying samples: a sample of large firms listed on the Spanish Central Company Directory (DIRCE), firms with R&D from the Research Business Directory (DIRID), and two samples of smaller enterprises (with less than 200 employees) that report external R&D, but no intramural R&D expenditures, and that report no innovation expenditure. We focus here on firms in PITEC that belong to the manufacturing industry and,

[2] PITEC dataset is freely available upon request: http://icono.fecyt.es/informesypublicaciones/Paginas/Panel-de-Innovacion-Tecnologica-(PITEC).aspx

to ensure the availability and comparability of key variables for all years, to yearly data from period 2008-2016. This period enables us to cover panel data on abandoned innovation activities, as well as both technological and organisational innovation and innovation performance.

Each year in PITEC includes information on the inputs and outputs of innovation over the last 3-year period (years: *t, t-1, t-2*; where *t* is the final year of the survey), and enables us to calculate yearly proxies for firm performance such as sales per employee. Further, PITEC provides also information on a number of other enterprise level characteristics, which we use as control variables.

Abandoned innovation

A central explanatory variable of interest in our econometric analysis is a binary variable (measured in each annual survey) denoting abandoned innovation by the firm in the last 3-year period. This abandoned innovation dummy is equal to 1 if the firm answers with "yes" to either one or both of the following questions about its technological innovations: "During the … - … period, were any of your innovation activities or projects abandoned during the conception stage?"; "During the … - … period, were any of your innovation activities or projects abandoned once the activity or project had begun?" A similar binary variable has been used in other analyses of CIS data to proxy abandoned innovation or innovation failure in Leoncini (2016) and Tsinopoulos et al. (2019).

Of all the manufacturing firms in the estimation sample that we use in our econometric analysis 25.2 per cent reported abandoned innovation activities (see Table 1). Further, there is significant persistence in abandoned innovation. 55.8 per cent of firms with abandoned innovation 3 years ago (in year *t-3*) have also abandoned innovation activities 3 years later (in year *t*). At the same time, only 14 per cent of firms with no prior abandoned innovation activities have abandoned innovation 3 years later. Obviously, these are simple unconditional averages, and thus may reflect not only the effect of prior experience with abandoned innovation activities or innovation failure, but also the role of a variety of other confounders such as differences in prior firm performance or other innovation inputs.

Dependent variables

The key underlying conceptual framework of our econometric analysis is the knowledge production function or innovation production function linking various innovation inputs with innovation outputs (Griliches 1979; Pakes and Griliches 1984; Crépon et al. 1998; Roper et al. 2008). Our analysis adds to the limited set of microeconometric studies using the CIS data (Leoncini 2016, Tsinopoulos et al. 2019) and the knowledge production function framework to study the effects of abandoned innovation or innovation failure on innovation performance. These prior econometric studies tended to focus on the contemporaneous relationship between the same CIS period's abandoned innovation and innovation performance.

The dependent variables in our analysis reflect the innovation performance and outputs of the innovation process and are widely used in prior literature (e.g., Love et al. 2014b, Mairesse and Mohnen 2010). Firstly, we consider dummy variables for product, process and organisational innovation (see Table 1 for statistics). The definitions of these variables follow the ones in the OECD Oslo Manual (2005). A process innovation is defined in the PITEC questionnaire as the application of new or significantly improved methods for the production or delivery/distribution of a good or service. Product innovation is the provision of the new or significantly improved goods or services. Product innovation can be either new to market or new to firm. Organisational innovation covers new or significantly changed business practices in the organisation of work, business structure and decision-making or in ways to manage external relations. In our sample, firms with prior abandoned innovation activities have substantially higher propensity to engage in innovation than firms that do not have prior abandoned innovation: this is shown in the 68.4 vs 47.4 per cent propensity to innovate in the case of product innovation, 62.6 vs 46.4 per cent in the case of process innovation, and 57.3 vs 39.4 per cent in the case of organisational innovation (see Table 1).

Secondly, we use the information about the success of firms' innovation activity (innovation performance) as represented by the proportion of current sales derived from innovative products introduced in last 3 years. On average, the Spanish manufacturing firms in our estimation sample derived 8 per cent of sales from new-to-market products or services (see Table 1). Again, having abandoned innovation activities in the past increases these numbers. Firms with prior abandoned innovation activities had 10 per cent share of new-to-market products or services in sales; firms without prior abandoned innovation activities had 7.2 per cent share.

Other controls

We include in our propensity score matching analysis a set of control variables which prior literature has linked to innovation activity. Among these other control variables we include, in addition to the past realisations of innovation output, also past firm performance (proxied by log of sales per employee), as higher performance reflects higher ability and resources to engage successfully in innovation, and firm size (log of employment) to account for the role of scale of activities. Further, we include firms' past R&D to indicate firms that engage in R&D themselves or buy in external R&D. This variable has a dual role as an indicator of a firm's knowledge inputs for innovation (Crépon et al. 1998) and absorptive capacity (Cohen and Levinthal 1989).

We also include a dummy to indicate firms that spend on training of their employees for innovation purposes, as training and human capital in general could be expected to have both direct effects on innovation and significant complementarities with other determinants of innovation (e.g. Aghion et al. 2019). To account for the quality of the internal knowledge base and availability of resources we include a dummy for membership of a larger group of firms and a dummy for foreign ownership. Foreign ownership dummy accounts for potential knowledge transfer from abroad form the rest of the multinational firm.

We observe in Table 1 that firms with prior abandoned innovation activities tend to have on average higher labour productivity, R&D propensity, they are more likely to belong to a domestic or international group of firms, and are much more likely to spend on training of their employees compared to firms with no prior abandoned innovation activities. Accounting for the prior realisations of these control variables is important in econometric analysis, in order to not confuse the effects of these other factors with those of abandoned innovation itself.

Finally, to allow for sectoral and temporal effects we include in all of our analysis sector dummies at the 2-digit NACE level and year dummies among the controls.

3.2 Methods

An investigation of the effects of having abandoned innovation activities on firm level outcomes presents significant selection and endogeneity problems. As we observed already in Table 1, having abandoned innovation activities and projects is systematically related to firm level covariates. It is likely to depend on past innovation performance, labour productivity and a variety of innovation inputs. Therefore a simple OLS, probit or Tobit estimation of the innovation production function linking current innovation performance and current abandoned innovation activities may tell us relatively little about the causal effects of abandoned innovation. It may as well be that the higher scale or intensity of innovation activity in successful innovators reflects stronger process of trial and error and consequently higher extent of abandoned innovation projects or activities.[3]

We endeavour to address here to some extent the issues of selection and endogeneity. To investigate the within-firm effects of abandoned innovation one would need to proxy a counterfactual outcome: what would have happened in terms of innovation performance of the firm in the treated group (with abandoned innovation) if it had not had the treatment - i.e. if the firm had not had abandoned innovation activities (Rosenbaum and Rubin 1983, Caliendo and Kopeinig 2008)? All firms that do not have abandoned innovation activities would not be a suitable control group here as they differ from the treated group also in terms of a number of other covariates of innovation. We use nearest-neighbour propensity score matching (PSM) (Rosenbaum and Rubin 1983) to overcome the selection bias in such analysis and to construct a suitable proxy for the counterfactual. Using PSM enables us to construct a control group with no abandoned innovation at year *t* that in terms of the pre-treatment characteristics such as lagged innovation outputs, firm performance and some observed key drivers of innovation is similar to the firms that have abandoned innovation activities at time *t*. The identifying assumption of this approach is that we observe the central variables determining whether firm has abandoned innovation or not, that conditional on these observables the treated and non-treated firms would have had similar innovation performance.

We use lagged explanatory variables reported in Table 1 to construct the suitable control group. As a first stage in the PSM we estimate the probit model with abandoned innovation dummy (at survey year *t*, indicating that firm has abandoned innovation at years *t, t-1* or *t-2*) as the dependent variable. The lagged general firm level controls used in the probit model include the log of firm size, dummies for group membership and foreign ownership, log of sales per employee, all lagged by one year. We further include lagged innovation output and input

[3] The question of direction of causality and the role of other confounding factors is a key limitations of the recent simple Tobit model-based analysis in Tsinopoulos et al. (2019) of the effects of abandoned innovation on innovation performance (measured at the end of the same CIS period).

indicators together with a dummy for prior abandoned innovation, lagged all by 3 years.[4] Finally, we include sector dummies at 2-digit NACE level and year dummies to capture sector specific drivers and year specific effects.

The probit model aggregates the relevant information about the observed drivers of selection into 'treatment' into one variable – the propensity score to engage in abandoned innovation activities. The propensity score is calculated for all firms, both the ones that report abandoned innovation in the survey year and for those that do not. Based on these propensity scores we match each treated firm *i* with the two best matching non-treated firms.[5]

After this we can calculate the estimate of the effect of abandoned innovation – the average treatment effect on the treated (ATT), as the difference between the mean of the outcome variable in next periods (at *t+3*) and the pre-treatment period of the treated and the constructed control group (Caliendo and Kopeinig 2008), as given in the next equation:

$$ATT \quad = [\tfrac{1}{n}\sum_{i\in N}(\pi_{i,NEXT}^{treated}) - \tfrac{1}{n}\sum_{i\in N}(\pi_{i,NEXT}^{control})] - [\tfrac{1}{n}\sum_{i\in N}(\pi_{i,PRIOR}^{treated}) - \tfrac{1}{n}\sum_{i\in N}(\pi_{i,PRIOR}^{control})] \quad (1)$$

Here π denotes the outcome variable (e.g. the share of new-to-market products in sales) of firm *i* in the matched sample of treated and control units. '*treated'* denotes the set of firms that reported having abandoned innovation activities or projects at survey year *t* (i.e., for the 3-year period of *t, t-1 and t-2*). '*control'* denotes the set of control units (2 matched non-treated firms per treated firm) that are matched with each treated firm; *n* denotes the number of the treated firms; N denotes all firms in the matched sample, that also fulfil the common support property. *NEXT* denotes the *t+3* post-treatment year, *PRIOR* denotes the pre-treatment period. In the case of successful matching of the two groups, the treatment group and control group should be similar in terms of their observable pre-treatment characteristics. This would mean

[4] We use information 3 years (*t-3*) before the measured survey year of treatment (*t*) for modelling the effect of prior innovation and abandoned innovation on having current abandoned innovation. For example, using instead of *t-3* an abandoned innovation indicator from year *t-2* to predict abandoned innovation in year *t* could cause spurious results due to the overlap in the measures of abandoned innovation in *t* (covers abandoned innovation in years *t, t-1, t-2*) and *t-2* survey year (covers abandoned innovation in years *t-2, t-3* and *t-4*).

[5] We apply the condition of common support condition in our matching analysis. This means that we drop those treated firms whose propensity score is higher than the maximum or lower than the minimum propensity score of the full control group. Also, note that we use matching with replacement.

that the second term in brackets in the right-hand side of Equation 1 would be statistically insignificant. Then, the estimated ATT is proxied simply with the first term in brackets in the right-hand side of Equation 1.

As an important further extension of this analysis of treatment effects and in order to test the hypotheses 2-4 we next consider whether the ATT effects of having abandoned innovation activities at period *t* are different depending on:

i) whether the firm had prior abandoned innovation activities or not (i.e. in *t-3*);

ii) whether the firm had prior training activities or not (i.e. in *t-3*);

iii) whether the firm had prior intramural or extramural R&D or not (i.e. in *t-3*).

This analysis is accomplished by dividing the firms into groups based on the fact whether they had or not prior experience of type *i)*, *ii)* or *iii)* and then re-implementing the PSM and comparing the estimated ATT effects separately in each of these groups.

As outlined in our Hypotheses 2-4 we would expect each of these prior experiences to be complementary with current period's engagement with abandoned innovation and correspondingly to lead to higher estimated effects from current abandoned innovation activities.

4. Empirical Results

Our first hypothesis relates to whether having abandoned innovation in the prior survey period (i.e. three years previously) benefits current innovation. We adopt a propensity score matching approach and consider first the factors which influence the probability that manufacturing firms had abandoned innovation (Table 2). In the probit model we lag all independent variables and also include both sector and year dummies to capture any broader economic effects on the probability of abandonment (Paunov, 2012). Having abandoned innovation proves to be significantly more likely in larger firms (Tranekjer, 2017) and those which are members of a group of companies. Having prior product and organisational innovation also make it more likely that firms have abandoned innovation. Unlike Tranekjer (2017), however, we find no significant link between prior process innovation and the probability of having abandoned innovation[6]. Like Paunov (2012, p. 31) we also find no significant link between labour productivity and the probability of abandoning innovation. Firms with higher levels of sales from more radical (new to the market) innovation were less likely to abandon future innovations (Table 2). The suggestion – confirmed by the descriptives in Table 1 – is that firms with higher levels of innovation intensity are, in general, also more likely to abandon some innovation (Tranekjer, 2017). This effect is weaker, however, for the most successful innovators, i.e. those firms which have the highest levels of sales from new to the market innovations. Prior R&D and having abandoned innovation in the previous period also increase the likelihood of abandoning innovation in future periods (Table 2). This suggests the potential importance of our moderation hypotheses.

We use the probit model in Table 2 to estimate propensity scores and construct the matched control group. Balancing tests suggest the matching process is effective in eliminating any significant differences between the characteristics of the treatment and control groups, i.e. p-values of the t-tests for mean differences between groups suggest no significant differences remain (Table 3). The estimated average treatment effects (ATTs) on different innovation outputs are summarised in Table 4. The results provide strong support for Hypothesis 1, i.e. having abandoned innovation in one period (survey wave) leads to a significantly higher probability of innovation in the subsequent period (the following three years). More specifically, abandoned innovation in period t leads to a 9.2 per cent increase in the probability of product innovation in $t+3$, an 8.1 per cent increase in the probability of process innovation and an 8.4 per cent increase in the probability of organisational innovation (Table 4)[7]. We also find a significant link between abandoned innovation at time t and the share of sales of new to the market products at period $t+3$ but no similar effect on new to the firm sales (Table 4). The positive link we identify between abandoned innovation and innovation outcomes reflects the findings of (Tsinopoulos et al. 2019) although their analysis is purely cross-sectional. Our results differ from theirs, however, in that we find no link between abandonment in the previous period and sales of new to the firm innovations[8].

[6] This may, however, reflect the fact that Tranekjer (2017) does not include an indicator of organisational innovation in her models of the probability of having abandoned innovation projects (Table V, p. 928). Note also that Tranekjer (2017) is based on cross-sectional rather than panel data.
[7] Similar effects are noted by Sawang and Matthews (2010) in their analysis of the Australian Business Longitudinal Survey.
[8] See Tsinopoulos et al. (2019), Table 4, Model 7. Note again, however, that their analysis is purely cross-sectional rather than relating abandonment in the prior period to current innovation outcomes.

Now we consider the extent to which the impact of prior abandonment on current innovation outcomes is conditional on abandonment in previous periods (i.e. two survey waves previously), prior training activity and prior R&D. In each case we estimate separate probit models to generate appropriate propensity scores for each comparison. For example, in Table 5 we report probit models for whether firms abandoned innovation in period *t* dividing the sample between those with and without abandoned innovation in the previous survey wave (i.e. at *t-3*). As might have been anticipated the pattern of significant variables are relatively similar in the two models although some coefficients differ significantly suggesting the importance of estimating propensity scores separately for each analysis (Table 5). Table 6 provides the balancing tests for each PSM analysis, again suggesting that the matching process is effective in eliminating significant differences in the characteristics of the treatment and control groups.

ATTs from prior abandoned innovation with and without previous abandoned innovation (i.e. 2 survey waves previously) are given in Tables 7. While the impact of abandonment is significant and positive in both cases, coefficients are consistently higher where firms had abandoned innovation already at *t-3*. This difference is only statistically significant for the impact on the probability of product innovation, however. (Tsinopoulos et al., 2019) suggest that the positive impact of abandoned innovation on subsequent innovation outcomes is due to either formal or informal learning processes: firms may learn about routines, technologies or ideas which failed and focus on more successful innovation strategies. Our evidence suggests that this process is self-reinforcing as firms which abandon innovation in subsequent periods further refine their innovation routines and sharpen their focus on the most rewarding technologies. This reflects the benefits of cumulative learning or learning-by-doing processes in areas such as serial entrepreneurship (Lafontaine and Shaw, 2016), new technology adoption (Bourke and Roper, 2016; Bourke and Roper, 2017; Clark, 2018), exporting (Love and Máñez, 2019), and knowledge management (Clark, 2018).

Our third hypothesis reflects the potential moderating effect of previous R&D and fourth hypothesis the moderating effect of previous training (i.e. 2 survey waves previously) on the innovation effects of prior abandoned innovation. Estimating related probit models and propensity scores suggests satisfactory balancing tests and the estimated ATTs are reported in Table 8 and 9. Here, we identify a rather different pattern with the effects of abandoned innovation being stronger where firms had no previous R&D spending (Table 8, part B) compared to firms with pevious R&D (Table 8, part A). Also, abandoned innovation has consistently significant effects on product innovation and share of new-to-market products in sales only in situations where firms had no previous training activity (Table 9, part B). Where firms were engaged in training in prior periods the effects of abandoned innovation on product innovation become insignificant (Table 9, part A).

These results suggest that abandoning innovation may be an alternative learning mechanism to previous R&D as firms attempt to improve their innovation outputs. Abandoning innovation may be also substituting for or providing an alternative route to training for upgrading innovation.

5. Conclusions and discussion

Our empirical analysis suggests four key findings. First, we confirm in a dynamic (panel data) context the results of earlier studies (e.g. Tsinopoulos et al. 2019) that abandoned innovation can contribute to enhanced innovation performance. This effect is evident both for the probability that a firm will undertake product/service, process and organisational innovation but also for the share of new to the market innovation in firms' sales. Interestingly, we find no robust linkage for sales of new to the firm innovations. Previous cross-sectional studies have suggested this provides evidence of a learning process in which firms refine and reshape their developing ideas and by abandoning the weaker ideas improve innovation outcomes. Our evidence suggests for the first time the dynamic and causal nature of the linkage between abandoned innovation and subsequent innovation outcomes.

The effectiveness of this learning process, and therefore the strength of its beneficial effects on innovation outcomes, proves strongly conditional on firms' past activities. In our innovation survey dataset each wave covers firms' innovation activity over a three-year period. Our first main result suggests that firms which have abandoned innovation in one wave or three-year survey period have better innovation performance in the next wave. We also find that this effect proves stronger, however, if firms also had abandoned innovation in the previous period. In other words, firms' innovation outputs benefit from the cumulative learning from the process of abandoned innovation undertaken during the two previous survey waves. This type of long-term cumulative learning process has been noted in other contexts, particularly in the adoption of new technologies (Bourke and Roper 2016) and quality improvement management (Bourke and Roper 2017). Using similar data to that used here, both studies identified cumulative learning processes which resulted in improvements in innovation performance two waves after the introduction of new technologies or quality improvement initiative. Similar, cumulative learning processes also prove significant in firms' export behaviour. Love and Manez (2019) showing that cumulative (rather than punctuated) learning in terms of exporting can help to lengthen export spells. Essentially similar arguments have also been used to rationalise the expected positive complementarities between abandoned innovation and open innovation (TsinopoulosYan and Sousa, 2019; Tranekjer, 2017).

Our third and fourth main results relate to other dynamic conditionalities relating to R&D and training activity in the survey wave prior to the period in which innovation is abandoned. In both cases our analysis suggests that, controlling for the effects of previous abandoned innovation, the innovation benefits of abandoned innovation are stronger where firms engaged in no prior R&D or training in the previous survey wave. To illustrate, note that previous studies have strongly linked both R&D and training to innovation quality and success (Doran and O'Leary, 2016; Baumann and Kritikos, 2016; Findikli, Yozgat and Rofcanin, 2015). Firms undertaking R&D and/or training in prior period may therefore be expected to have stronger innovation portfolios in the next period. Firms with no R&D and/or training in the prior period might be expected to have weaker innovation portfolios in the next period. The benefits of abandoning a proportion of these weaker innovations in period *t-1* will then be greater in situations where firms have weaker innovation portfolios at period *t-1*, i.e. where had no R&D or training at *t-2*. This suggests that as well as enabling cumulative learning processes, abandoning innovation may also act as a dynamic corrective mechanism or mitigation process preventing firms carrying weaker innovation portfolios through from one period to the next. This type of corrective action process has been widely documented as part of quality management (Ali, 2020) and risk management systems but has previously received little or no attention in the context of firms' innovation activity.

Our analysis suggests the potential value of a dynamic approach to modelling the effects of cumulative learning and dynamic corrective mechanisms through abandoned innovation. This relates to other existing literatures on innovation portfolio management (Meifort, 2016), strategic innovation management and open innovation (Bogers *et al.*, 2019) and dynamic complementarities in innovation (Love, Roper and Vahter, 2014b). Alongside the type of organisational influences considered here, for example, Meifort (2016) also highlights the importance of strategic influences on firms' management of innovation portfolios. This suggests the potential value of linking decisions to abandon innovations to firms' innovation strategic and innovation objectives and their operating context. Both could the focus of useful future analyses.

Figure 1: Theoretical model

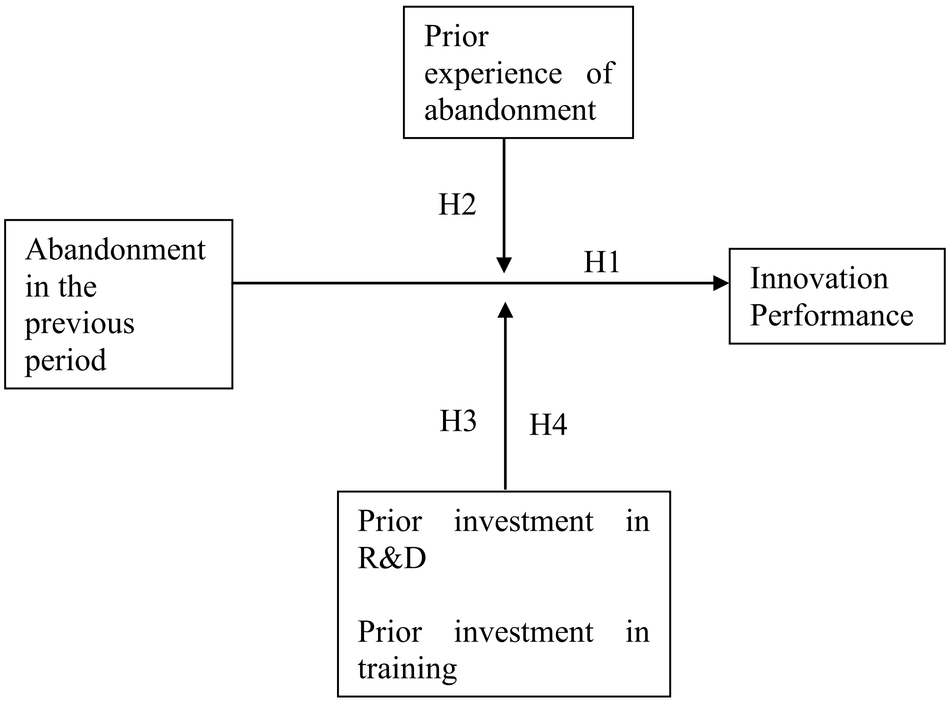

Table 1: Descriptive statistics for Manufacturing firms

	All firms		Firms with prior abandoned innovation		Firms with no prior abandoned innovation	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Abandoned innovation dummy	0.252	0.434	0.558	0.497	0.140	0.347
Log of firm size	4.239	1.339	4.442	1.339	4.164	1.331
Member of a group	0.479	0.500	0.544	0.498	0.455	0.498
Foreign ownership	0.185	0.388	0.212	0.409	0.175	0.380
Log of labour productivity	12.101	0.866	12.183	0.776	12.071	0.895
R&D dummy	0.597	0.491	0.766	0.424	0.535	0.499
Training dummy	0.133	0.340	0.197	0.398	0.109	0.312
Product innovation dummy	0.530	0.499	0.684	0.465	0.474	0.499
Process innovation dummy	0.508	0.500	0.626	0.484	0.464	0.499
Organisational innovation dummy	0.442	0.497	0.573	0.495	0.394	0.489
Share of new-to-market products in sales	8.022	20.214	10.312	20.963	7.177	19.865
Share of new-to-firm products in sales	12.814	26.391	15.186	26.231	11.938	26.397
Number of obs.	10960		2955		8005	

Notes: Sample used in propensity score matching. Period: 2008-2016.

Table 2: Modelling the probability of having abandoned innovation: Manufacturing firms

	(1) All manufacturing firms	
Variables:	Coef.	Std. Err.
Log of firm size (t-1)	0.085***	0.014
Member of a larger group (t-1)	0.064*	0.036
Foreign ownership (t-1)	-0.005	0.041
Log of labour productivity (t-1)	-0.007	0.021
Abandoned innovation dummy (t-3)	1.060***	0.031
R&D dummy (t-3)	0.442***	0.037
Training dummy (t-3)	0.055	0.043
Product innovation dummy (t-3)	0.213***	0.042
Process innovation dummy (t-3)	0.057	0.036
Organisational innovation dummy (t-3)	0.127***	0.032
Share of new-to-market products in sales (t-3)	0.001	0.001
Share of new-to-firm products in sales (t-3)	-0.0013***	0.0006
Sector dummies (2-digit level)	Yes	
Year dummies	Yes	
Constant	-1.610***	0.367
Pseudo R-squared	0.204	
Number of observations	10960	

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Period: 2008-2016.

Table 3: Balancing property tests after PSM: All manufacturing firms

Variable	Sample	Mean Treated	Mean Control	p-value
Log of firm size (t-1)	Unmatched	4.584	4.146	0.000
	Matched	4.584	4.532	0.139
Member of a larger group (t-1)	Unmatched	0.561	0.441	0.000
	Matched	0.561	0.538	0.079
Foreign ownership (t-1)	Unmatched	0.228	0.172	0.000
	Matched	0.228	0.229	0.949
Log of labour productivity (t-1)	Unmatched	12.189	12.061	0.000
	Matched	12.189	12.169	0.334
Abandoned innovation dummy (t-3)	Unmatched	0.596	0.159	0.000
	Matched	0.596	0.604	0.501
R&D dummy (t-3)	Unmatched	0.845	0.557	0.000
	Matched	0.845	0.833	0.194
Training dummy (t-3)	Unmatched	0.189	0.099	0.000
	Matched	0.189	0.200	0.277
Product innovation dummy (t-3)	Unmatched	0.836	0.624	0.000
	Matched	0.836	0.831	0.613
Process innovation dummy (t-3)	Unmatched	0.796	0.646	0.000
	Matched	0.796	0.789	0.518
Organisational innovation dummy (t-3)	Unmatched	0.647	0.432	0.000
	Matched	0.647	0.643	0.757
Share of new-to-market products in sales (t-3)	Unmatched	12.951	9.754	0.000
	Matched	12.951	12.265	0.273

Period: 2008-2016.

Table 4: The effect of abandoned innovation on innovation outputs in next periods: Manufacturing firms

Variable	Sample	Treated	Controls	Difference (ATT)	Std. Err.	Significance
Product innovation (t+3)	Unmatched	0.673	0.445	0.228	0.011	***
ATT	Matched	0.673	0.581	**0.092**	0.016	***
Process innovation (t+3)	Unmatched	0.599	0.398	0.201	0.011	***
ATT	Matched	0.599	0.517	**0.082**	0.017	***
Organisational innovation (t+3)	Unmatched	0.547	0.355	0.192	0.011	***
ATT	Matched	0.547	0.463	**0.084**	0.017	***
Share of new to market products in sales (t+3)	Unmatched	10.306	6.089	4.217	0.427	***
ATT	Matched	10.306	7.954	**2.352**	0.698	***
Share of new to firm products in sales (t+3)	Unmatched	15.548	12.220	3.328	0.602	***
ATT	Matched	15.548	16.097	-0.549	0.963	NS

Number of observations: 10960. Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Statistically significant ATT effects are shown in bold. Period: 2008-2016.

Table 5: Modelling the probability of having abandoned innovation: Manufacturing firms with and without prior abandoned innovation

Variables:	Firms WITH prior abandoned innovation (in t-3)		Firms with NO prior abandoned innovation (in t-3)	
	Coef.	Std. Err.	Coef.	Std. Err.
Log of firm size (t-1)	0.103***	0.025	0.064***	0.017
Member of a larger group (t-1)	0.160***	0.062	0.026	0.046
Foreign ownership (t-1)	-0.078	0.069	0.029	0.052
Log of labour productivity (t-1)	0.018	0.037	-0.016	0.025
R&D dummy (t-3)	0.868***	0.071	0.264***	0.044
Training dummy (t-3)	0.034	0.065	0.052	0.058
Product innovation dummy (t-3)	0.178**	0.078	0.239***	0.050
Process innovation dummy (t-3)	0.011	0.068	0.086**	0.043
Organisational innovation dummy (t-3)	0.258***	0.056	0.062	0.039
Share of new-to-market products in sales (t-3)	0.0002	0.001	0.001	0.001
Share of new-to-firm products in sales (t-3)	-0.001	0.001	-0.001	0.001
Sector dummies (2-digit level)	Yes		Yes	
Year dummies	Yes		Yes	
Constant	-1.530*	0.773	-1.031*	0.573
Pseudo R-squared	0.119		0.050	
Number of observations	2955		8005	

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Period: 2008-2016.

Table 6: Balancing property tests after PSM: p-values of the test of difference of means between treatment and control group. Manufacturing firms with and without prior abandoned innovation activities.

Variable	Sample	Sample of firms: WITH prior abandoned innovation	Sample of firms: with NO prior abandoned innovation
Log of firm size (t-1)	Unmatched	0.000	0.000
	Matched	0.376	0.728
Member of a larger group (t-1)	Unmatched	0.000	0.000
	Matched	0.929	0.784
Foreign ownership (t-1)	Unmatched	0.000	0.001
	Matched	0.455	0.959
Log of labour productivity (t-1)	Unmatched	0.000	0.002
	Matched	0.274	0.872
Abandoned innovation dummy (t-3)	Unmatched	0.000	0.000
	Matched	0.698	0.380
R&D dummy (t-3)	Unmatched	0.000	0.000
	Matched	0.481	0.951
Training dummy (t-3)	Unmatched	0.000	0.000
	Matched	0.570	0.653
Product innovation dummy (t-3)	Unmatched	0.000	0.000
	Matched	0.725	0.830
Process innovation dummy (t-3)	Unmatched	0.000	0.000
	Matched	0.516	0.219
Organisational innovation dummy (t-3)	Unmatched	0.072	0.000
	Matched	0.868	0.413

Period: 2008-2016.

Table 7: The effect of abandoned innovation on innovation outputs in next periods: Manufacturing firms with prior abandoned innovation

(a) Firms with prior abandoned innovation (N=2955)

Variable	Sample	Treated	Controls	Difference (ATT)	Std. Err.	Significance
Product innovation (t+3)	Unmatched	0.726	0.498	0.228	0.017	***
ATT	Matched	0.726	0.613	**0.113**	0.025	***
Process innovation (t+3)	Unmatched	0.653	0.461	0.192	0.018	***
ATT	Matched	0.653	0.545	**0.108**	0.026	***
Organisational innovation (t+3)	Unmatched	0.593	0.428	0.164	0.018	***
ATT	Matched	0.593	0.512	**0.081**	0.026	***
Share of new to market products in sales (t+3)	Unmatched	10.720	6.372	4.348	0.737	***
ATT	Matched	10.720	7.573	**3.148**	1.020	***
Share of new to firm products in sales (t+3)	Unmatched	16.293	15.018	1.275	1.054	NS
ATT	Matched	16.293	18.692	-2.399	1.576	NS

(b) Firms without prior abandoned innovation (N=8005)

Variable	Sample	Treated	Controls	Difference (ATT)	Std. Err.	Significance
Product innovation (t+3)	Unmatched	0.594	0.435	0.159	0.016	***
ATT	Matched	0.594	0.557	**0.037**	0.020	***
Process innovation (t+3)	Unmatched	0.519	0.386	0.133	0.016	***
ATT	Matched	0.519	0.456	**0.063**	0.020	***
Organisational innovation (t+3)	Unmatched	0.480	0.341	0.138	0.015	***
ATT	Matched	0.480	0.420	**0.059**	0.020	***
Share of new to market products in sales (t+3)	Unmatched	9.695	6.035	3.660	0.620	***
ATT	Matched	9.695	8.033	**1.662**	0.867	***
Share of new to firm products in sales (t+3)	Unmatched	14.450	11.689	2.761	0.868	***
ATT	Matched	14.450	14.964	-0.514	1.112	NS

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Statistically significant ATT effects are shown in bold. Period: 2008-2016.

Table 8: The effect of abandoned innovation on innovation outputs in next periods: Manufacturing firms with and without prior R&D spending

(a) Firms with prior R&D spending (N=6901)

Variable	Sample	Treated	Controls	Difference (ATT)	Std. Err.	Significance
Product innovation (t+3)	Unmatched	0.721	0.613	0.108	0.012	***
ATT	Matched	0.721	0.655	**0.066**	0.018	***
Process innovation (t+3)	Unmatched	0.631	0.501	0.131	0.013	***
ATT	Matched	0.631	0.571	**0.060**	0.019	***
Organisational innovation (t+3)	Unmatched	0.571	0.428	0.143	0.013	***
ATT	Matched	0.571	0.520	**0.050**	0.019	***
Share of new to market products in sales (t+3)	Unmatched	11.002	8.626	2.377	0.547	***
ATT	Matched	11.002	8.695	**2.308**	0.816	***
Share of new to firm products in sales (t+3)	Unmatched	16.368	16.775	-0.407	0.750	NS
ATT	Matched	16.368	18.408	-2.040	1.133	NS

(b) Firms without prior R&D spending (N=4026)

Variable	Sample	Treated	Controls	Difference (ATT)	Std. Err.	Significance
Product innovation (t+3)	Unmatched	0.411	0.233	0.179	0.022	***
ATT	Matched	0.411	0.263	**0.148**	0.030	***
Process innovation (t+3)	Unmatched	0.421	0.269	0.152	0.023	***
ATT	Matched	0.421	0.343	**0.077**	0.031	***
Organisational innovation (t+3)	Unmatched	0.418	0.262	0.156	0.023	***
ATT	Matched	0.418	0.305	**0.113**	0.031	***
Share of new to market products in sales (t+3)	Unmatched	6.498	2.789	3.709	0.732	***
ATT	Matched	6.498	2.744	**3.754**	1.099	***
Share of new to firm products in sales (t+3)	Unmatched	11.066	6.482	4.584	1.131	***
ATT	Matched	11.066	8.034	3.032	1.588	NS

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Statistically significant ATT effects are shown in bold. Period: 2008-2016.

Table 9: The effect of abandoned innovation on innovation outputs in next periods: Manufacturing firms with and without prior training

(a) Firms with prior training (N=1329)

Variable	Sample	Treated	Controls	Difference (ATT)	Std. Err.	Significance
Product innovation (t+3)	Unmatched	0.808	0.686	0.122	0.025	***
ATT	Matched	0.808	0.764	0.044	0.040	NS
Process innovation (t+3)	Unmatched	0.755	0.601	0.154	0.026	***
ATT	Matched	0.755	0.675	**0.080**	0.042	*
Organisational innovation (t+3)	Unmatched	0.688	0.542	0.146	0.027	***
ATT	Matched	0.688	0.612	**0.076**	0.044	*
Share of new to market products in sales (t+3)	Unmatched	13.018	10.056	2.962	1.246	***
ATT	Matched	13.018	10.759	2.260	1.762	NS
Share of new to firm products in sales (t+3)	Unmatched	16.739	17.582	-0.843	1.545	***
ATT	Matched	16.739	21.132	-4.393	2.619	NS

(b) Firms without prior training (N=9626)

Variable	Sample	Treated	Controls	Difference (ATT)	Std. Err.	Significance
Product innovation (t+3)	Unmatched	0.641	0.419	0.223	0.012	***
ATT	Matched	0.641	0.549	**0.092**	0.018	***
Process innovation (t+3)	Unmatched	0.563	0.376	0.186	0.012	***
ATT	Matched	0.563	0.492	**0.070**	0.018	***
Organisational innovation (t+3)	Unmatched	0.514	0.335	0.180	0.012	***
ATT	Matched	0.514	0.461	**0.054**	0.018	***
Share of new to market products in sales (t+3)	Unmatched	9.675	5.656	4.019	0.457	***
ATT	Matched	9.675	6.231	**3.444**	0.729	***
Share of new to firm products in sales (t+3)	Unmatched	15.271	11.640	3.631	0.658	***
ATT	Matched	15.271	15.617	-0.346	1.055	NS

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Statistically significant ATT effects are shown in bold. Period: 2008-2016.

Note: the balancing property tests of PSM are satisfied in the case of prior R&D=1, prior R&D=0, prior training=1 and prior training=0 sub-samples.

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