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The dynamics of abandoned innovation activities: Learning from failure or learning to prevent failure?

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ABSTRACT

We contribute to the literature on abandonment and innovation by showing the dynamic nature of the linkage between abandoned innovation activities and subsequent innovation outcomes at firm level. Based on a balanced panel of Spanish manufacturing firms from 2008 to 2016, we demonstrate that abandoning innovation not only leads to more successful innovation, but that there is an explicit time dimension to this. Firms which have prior experience of abandonment have stronger positive effects of more recent abandoned innovation activities on innovation output. However, these effects are largely restricted to prior experience from – and implementation in – the early (conception) phases of the innovation process. While firms systematically develop abilities to *prevent* failure, there is little evidence of learning *from* failure in terms of innovation abandonment.

1. Introduction

Abandoning projects is a natural part of any business. By definition all businesses must make future investment plans, not all of which will come to fruition. In the case of innovation, a process the outcomes of which are inherently uncertain, 'failure' through abandonment is not merely commonplace but ubiquitous. In a recent review of the literature on innovation failure, Rhaiem and Amara (2021) summarise numerous academic studies which estimate the proportion of innovative projects which are abandoned wholly or in part to be between 40 % and 90 %. While the abandonment of innovation projects is costly, related investments may not be entirely wasted. Where lessons can be learned from abandoned projects which either encourage better selection of innovative projects in the future, or allow more of them to be managed to fruition more effectively, then an apparently wasteful element of corporate activity can, at least in part, be turned into something beneficial.

There is evidence in the literature that learning from abandoned initiatives can inform subsequent success. For example, in a study of radical ideas suggested 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 by previous success, suggesting that 'failure' can have positive subsequent effects. Nevertheless, learning from projects that do not come to fruition is neither easy nor costless, requiring a combination of opportunity, motivation and ability to be achieved successfully (Dahlin et al., 2018). If firms – and the individuals working in them – are able to learn systematically from abandoned projects 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 activity and successful innovation, and find a positive association which they interpret as 'learning from failure' (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, and so we might expect abandonment in one period to have its primary influence on innovation success in subsequent periods. Leoncini (2016) and Tsinopoulos et al. (2019) focus on the contemporaneous link between abandonment and innovation without making any explicit allowance for the dynamics of the process.

Our contention is not simply that innovation abandonment leads to more successful innovation, but that there is an explicit time dimension to this which suggests a learning effect. By learning we mean using the knowledge gained from incidents of abandonment to improve future actions through enhancing the abilities, skills and routines present within the firm (Lapré and Nembhard, 2010). Drawing on organisational

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learning theory, we hypothesise that firms which have experienced abandoned innovation activities in the past will have a stronger positive relationship between recent abandonment activity and successful innovation than those with no prior experience of abandoned innovation activity. This 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 activity more significant in aiding successful innovation. In addition, we test the hypothesis that firms' prior episodes of early stage (conception) abandonment will have a stronger moderating effect on the link between their recent abandonment and successful innovation than prior episodes of later stage abandonment when some degree of commitment has been made to the innovation process This is because the process of conception-stage abandonment is quite different from that of later-stage abandonment, and involves developing and honing the ability to *avoid* resource-committed abandonment rather than learning the lessons from subsequent abandonment.

We test these hypotheses using data on a balanced panel of Spanish manufacturing firms over the period 2008–16. Using an appropriate matching process, we find evidence that firms with previous experience of abandoned innovation activity are more likely to have a positive relationship between recent abandonment and subsequent innovation, which we regard as indicating a form of learning from abandoned innovation activity. We also find that this effect is largely confined to prior experience from – and implementation in – the conception phase of innovation. In other words, the link between abandonment and innovation previously seen in large-scale studies of abandonment is unlikely to be evidence of 'learning from failure'. Our research makes two contributions to the literature. The first lies in showing the dynamic nature of the linkage between abandoned innovation activity and subsequent innovation outcomes. There are indeed systematic effects, but these are complex and depend on previous as well as more recent episodes of abandoned innovations. The effectiveness of this cumulative 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 simply by reducing subsequent abandonment, but also by altering the process which allows firms to benefit from more recent episodes of abandoned innovation.

In our second contribution, we distinguish between two separate effects arising from the abandonment process: the first is developing the ability to select appropriate projects to proceed beyond the conception stage, while the second involves learning from abandonment once some investment and commitment has been made. Conceptually, these suggest different processes, the latter of which is more difficult to accomplish because of managerial tendency towards overinvestment and escalation of commitment, and the existence of reinforcement traps (Ross and Staw, 1993; Maslach, 2016). Strong effects from prior episodes of 'conception abandonment' contrast with much weaker effects from 'later-stage abandonment', suggesting that firms are good at developing abilities to avoid failure in innovation, but much poorer at learning from failed (i.e., abandoned) innovation projects. Thus, the emphasis is on weeding out the worst ideas and nurturing the best ideas in the early stages of the innovation process, which involves improving strategic decision-making and selection of the most promising ideas. In this way, firms develop the ability to make project selection part of a dynamic correction mechanism which prevents them from taking forward weak innovation projects beyond the conception stage, before the problems associated with escalation of commitment and the existence of reinforcement traps begin to have an effect. By contrast, once committed to innovative projects, there is very little evidence that firms are able to learn lessons from later-stage abandonment. However, in the crucial area of new-to-market innovation there are also complementarities in learning from both early and later phases of abandonment.

2. Theory and hypotheses

Although not synonymous with failure, Tsinopoulos et al. (2019) point out that abandonment has important similarities to aspects of failure: "as with the experience of a failure, the experience of having abandoned an innovation activity could encourage an organization to learn by reflecting on its processes and assumptions" (2019, p. 1400). In an extensive review and critique of the organisational learning literature, Lapré and Nembhard (2010) define organisational learning as "the organization's ongoing effort to use better knowledge to improve its actions" (p. 6). This in turn suggests a process which takes time, involves conscious effort on the part of managers, and involves enhancing the abilities of the organisation in order to improve performance. This is the basis on which we understand organisational learning in terms of abandoned innovation activities.

The theoretical basis underlying learning from failure also derives from organisational learning theory (Huber, 1991), which suggests that firms have the capacity to learn from their activities and, through a process of performance feedback, to change organisational practices and routines (Argote and Miron-Spektor, 2011). In turn, if successfully implemented, these changes can result in improved firm capabilities and ultimately improved performance, including innovation (e.g. Garvin, 1993; Jiménez-Jiménez and Sanz-Valle, 2011). 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 existing routines and lead to more focused search activities by the firm. Repeated success may confirm that past routines were at a satisficing level. Thus, routines remain unchallenged and unchanged, with strong implications for search activities by the firm. Some literature even suggests that a history of success may lead to declining capabilities to learn, as it leads to over-confidence 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 gained from success (Madsen and Desai, 2010). However, simply experiencing failure is not sufficient for learning to occur. Organisational learning theory suggests that learning requires the interpretation of outcomes arising from past actions, and an attempt to alter future behaviour as a result (Levitt and March, 1988).

With respect to the innovation process, what makes for success or failure is causally ambiguous, and innovation's 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 abandoned innovation may be viewed as an unwelcome event, if the reasons for it are understood then changes in behaviour and routines 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 innovations can therefore be regarded as part of the natural process of experimentation which innovation involves and 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).

There are several ways in which this learning process may occur. First, abandonments can encourage learning by initiating search for their causes. As long as individual 'failures' are not sufficiently large to compromise the existence of the firm, this permits an objective search for the reasons why projects are abandoned, and encourages lessons to be learned which may reduce the incidence of abandonment in the future (Baumard and Starbuck, 2005). Second, where abandonment is reasonably frequent and its causes explored, this provides feedback which helps the firm to reallocate resources and help to shape the future direction of its R&D and project development portfolios (Khanna et al., 2016). Finally, by encouraging a culture in which abandonment is an integral element of exploratory product development, firms can engage in experimentation alongside successful product innovation. Such firms which are able to build a 'tolerance for failure' are likely to be more innovative than counterparts which lack the capacity to learn systematically from abandonment (Tsinopoulos et al., 2019).

The relatively limited empirical literature on learning from abandonment in innovation suggests that it can indeed 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 activity and innovation performance, and both find a consistently positive association. 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 time lags in the structure of their estimation to allow for the dynamic process of learning.[1] Neither is therefore able to present evidence on the dynamics of any learning effects present in this process. However, demonstrating whether there is some association between (quasi-)contemporaneous abandonment activity and innovation output is a necessary first step in the investigation of the dynamics of learning from early and later-stage innovation activity. Testing such an association also acts as a useful replication of previous findings in different contexts and timeframes.

This leads to our first, baseline, hypothesis:

H1. Firms which have experienced recent abandoned innovation activities are more likely to demonstrate higher levels of successful innovation.

2.1. The dynamics of learning from abandonment in innovation activity

Although the literature suggests some benefit from 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 temporal dimension of learning (e.g., Leoncini, 2016; Tsinopoulos et al., 2019). 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 Máñez, 2019).

Merely allowing for time lags between abandoned innovation activity and later innovation output is, however, unlikely to account for learning effects. Rather, it is likely that if there is indeed a learning process arising from abandoned innovation activity, previous experience of abandonment will help to shape the relationship between more recent episodes of abandonment 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; Hewitt-Dundas et al., 2019). 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 both to select better partners and to make their existing external collaborations more effective.

A similar situation arises in the case of the potential link between abandonment and subsequent innovation success. Managing innovation is a complex task, but for many firms innovation is not a one-off event, but something that is attempted repeatedly. Where innovation is a repeated task this creates the opportunity for repeated success, repeated abandonment, and the potential for learning from both. 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 learning capability in its own right. Lapre et al. (2000) suggest that such learning may either be conceptual or operational. Conceptual learning relates to knowing why a particular outcome occurs, perhaps through a better understanding of an underlying technology or process. Operational learning relates to knowing how to respond, i.e., learning how to develop routines and practices which may help to avoid the need for abandonment or innovation failure. Both types of learning may arise from the abandonment of an innovation. Through repetition, however, firms may also learn how to learn, and how best to capture both the conceptual and operational lessons from innovation success, failure and abandonment (Love et al., 2014a).

Standard process models suggest that through 'learning by doing', efficiency improves and quality increases or becomes more uniform as firms' experience with a specific manufacturing or logistic activity extends (McWilliams and Zilbermanfr, 1996). In innovation, where firms may be implementing new technologies or new combinations of existing technologies, firms' prior understanding of potential technological outcomes are more limited. This creates opportunities for conceptual learning, which may be more significant where innovation projects are more radical or where the technology involved is less directly relevant related to firms' existing technology portfolio (Fores and Camison, 2016). In this context, the abandonment of innovation projects, due potentially to technology failure, underperformance, or an incompatibility with firms' existing technological competence, creates an opportunity for conceptual learning. Firms' ability to capture this learning will relate to absorptive capacity (Cordero and Ferreira, 2019), and firms' prior understanding of the technologies involved (Roper and Hewitt-Dundas, 2015).

At the same time, operational learning may occur, which, as with the case of learning from external collaboration, may arise in two ways (Love et al., 2014a). The first arises from the development of organisational routines; as firms develop routines for dealing with abandoned innovation attempts, their ability to learn the lessons of failure from recent abandoned innovations increases. Cannon and Edmondson (2005) illustrate how successful organizations systematically learn the lessons of repeated relatively small failures, and thus develop routines to help prevent, and learn from, larger problems. To do so effectively requires that firms do not simply tolerate failure, but take active steps to analyse and learn the lessons of previous failures (Daneels and Vestal, 2020). The second learning route arises from developments not in organisational routines but in managerial cognition through time. 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

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

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 also able to apply the lessons learned from previous experience more effectively to more recent 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 decline in the 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 et al. (2006) demonstrate that unlearning is indeed a key factor in the process; without unlearning, the other necessary socio-cognitive stages of learning from failure are unlikely to take place. Firms which experience innovation abandonment for the first time will not have had the opportunity to unlearn the processes which led to an unsatisfactory outcome, whereas firms with previous experience of abandonment 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 abandonment 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 abandoned innovation activities will have a stronger positive relationship between recent abandonment and successful innovation than other firms.

2.2. The timing of project abandonment: differential learning effects

Learning from abandonment in innovation not only takes time, it may also depend on the stage at which previous episodes of abandonment have occurred. Firms engaging in innovation projects may decide to abandon activity at different stages of the process: and there is reason to believe that the processes and effects of learning may differ between selecting appropriate projects to kill at an early stage (conception stage abandonment) versus abandonment after a project has started and some commitment made (later stage abandonment). Both can be a source of learning effects, but they may differ: specifically, there is more likely to be learning from abandonment which occurs at an early stage, while effective learning may be especially difficult once some degree of commitment is made.

Learning from failure is intrinsically difficult and organizations often struggle to do so (Cannon and Edmondson, 2005). In part, this is because "organisation members usually have an aversion to acknowledging failure and tend to react defensively by interpreting the causes of failure in ways that are beneficial for themselves" (Semrau et al., 2020 p. 4). For example, in a longitudinal study of the performance of cardiac surgeons, KC et al. (2013) find 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 – and organizations – not to be open about mistakes they have made, making both individual and collective learning from failure more difficult (Husted and Michailova, 2002). While understandable, acting defensively in the face of failure can hamper the information processing that is required for learning (Ocasio, 1995; Cannon and Edmondson, 2005).

Daneels and Vestal (2020) find that that mere tolerance for failure has no effect on firms' product innovation. In contrast, firms that make deliberate efforts to analyse past failures (i.e., engage in purposeful attempts to convert failure experiences into knowledge) are more likely to introduce innovative new products. However, this is a particular problem for projects which have already begun and to which some (personal as well as financial) commitment has been made. This is because of the managerial tendency towards over-investment and escalation of commitment, and the existence of reinforcement traps.

Once a project gets the go ahead, the prospect of abandonment can lead to threat-induced rigidity which prevents altering course (Staw et al., 1981; Jordan and Audia, 2012; Maslach, 2016). In addition "managers then underestimate the time and effort needed to complete a project, and overestimate its potential returns, which generally leads to over-investment" (Andries and Hünermund, 2020 p. 3). In turn this can lead to 'reinforcement traps' in which firms allocate resources for too long to failed actions (Ross and Staw, 1993) or persist with failure because of inertial forces (Tripsas and Gavetti, 2000), in the belief that things will eventually improve if they invest additional time and effort. This often leads to escalation of commitment for projects that should have been abandoned but which instead continue to absorb financial and managerial resources (Staw, 1981; George, 2005; Andries and Hünermund, 2020). This problem is especially acute in the case of projects the outcomes of which are intrinsically ambiguous, such as innovation (Adner and Levinthal, 2004). Once a project is given the green light, there is a tendency to keep going even when things are bad, and reluctance to accept this personally and institutionally makes it difficult for individuals and organizations to learn from these mistakes.[2]

Since firms typically have a portfolio of innovative projects in hand at any given time, even the presence of a stage-gate process may not eliminate the problem of reinforcement traps and escalation of commitment, because stage gates are often insufficiently strong to actually cause projects to be abandoned when they should be (Cooper, 2008), and because they can censor feedback on failure before the firm encounters it, thus inhibiting corrective action (Maslach, 2016). Nor is the tendency to fall into such problems once commitment is begun in innovation a function of a lack of resources for oversight or evaluation. Indeed, in a study of German firms using staged evaluation processes for innovation, Andries and Hünermund (2020) find that resource-abundant firms demonstrate more over-optimism and managerial discretion and are more likely to fall into reinforcement traps.

This suggests that effective learning may be especially difficult once some degree of commitment is made, because an unwillingness to accept failure causes both more commitment and problems in learning from failure. By contrast, for projects abandoned at an early, conception stage, there are fewer impediments to learning from the process. For example, in a study of innovation performance in German companies, Klingebiel and Adner (2015) demonstrate that a combination of low initial commitment to projects coupled with the willingness to reallocate resources where a no-go decision is made increases performance significantly. Because there is less invested, both financially and personally, at a project's early stage, individuals need not feel threatened by having to be open about mistakes they have made or about having a project abandoned, making both individual and collective learning from failure easier (Husted and Michailova, 2002). This lessens the need for

[2] Note that considering abandonment possibilities in the context of a real options framework does not remove the issue of escalation of commitment and reinforcement traps. Adner and Levinthal (2004) provide examples of 'option traps' that hinder the timely abandonment of opportunities under different conditions of uncertainty, including managers' tendency towards escalating commitments and overconfidence.

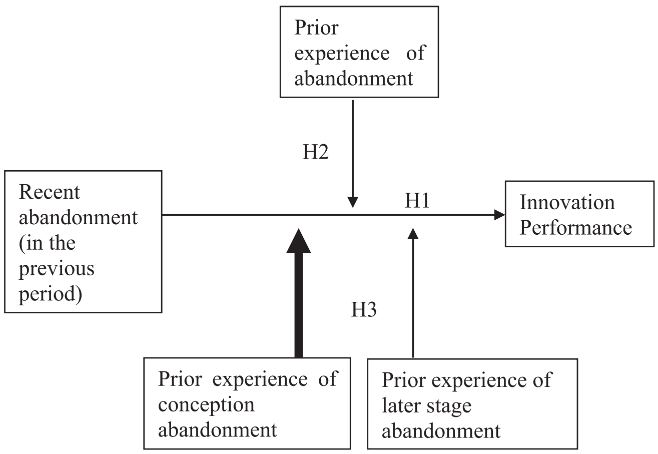

Fig. 1. Theoretical model.

defensive reactions, and the resulting problems of escalation of commitment and reinforcement traps are therefore less acute.

In addition, the lessons to be learned from early abandonment can be done with less need for the deliberate, deep-level efforts to analyse past failures identified by Daneels and Vestal (2020). This is because the process involved is quite different from learning from later-stage abandonment: rather it involves learning to *avoid* resource-committed abandonment. Here, the emphasis is on weeding out the worst ideas and nurturing the best ideas in the early stages of the innovation process, which involves improved strategic decision-making and selection of the most promising ideas. In this way, firms develop the ability to make project selection part of a dynamic correction mechanism which prevents firms from taking forward weak innovation projects beyond the conception stage, before the problems associated with escalation of commitment and the existence of reinforcement traps begin to have an effect.

This leads to our final hypothesis:

H3. Prior episodes of early stage (conception) abandonment will have a stronger moderating effect on the link between recent abandonment and successful innovation than prior episodes of later stage abandonment.

Note that H3 does not suggest that there are no lessons to be learned from prior episodes of later stage abandonment, but that it is more difficult to do so than from prior episodes of abandonment at an earlier stage, and involves considerably more time and managerial resources. Fig. 1 summarises our hypothesised relationships.

3. Data and methods

3.1. Data and descriptive statistics

Our empirical analysis is based on innovation survey data for Spanish firms from the “Panel of Technological Innovation” (PITEC). The PITEC is Spain's input to the Community Innovation Survey (CIS) and 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.[3] 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 sector and, to ensure the availability and comparability of key variables for all years, to yearly data from period 2008–2016. This period enables us to include 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.

3.2. Dependent variables: innovation outputs

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 micro-econometric 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. Prior econometric studies tended to focus on the contemporaneous relationship between abandoned innovation and innovation performance. Also, these prior studies have not distinguished between the effects of the two different types of abandonment, or whether learning from these experiences could be different.

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 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 used in the subsequent econometric analysis, 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 % propensity to innovate in the case of product innovation, 62.6 vs 46.4 % in the case of process innovation, and 57.3 vs 39.4 % in the case of organisational innovation (see Table 1).

Secondly, we use information about the success of firms' innovation activity (innovation performance) as represented by the proportion of current sales derived from innovative products introduced in the last 3 years. On average, the Spanish manufacturing firms in our estimation sample derived 8 % of sales from new-to-market products or services (see Table 1). Again, having abandoned innovation activities in the past

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

Table 1
Descriptive statistics for the estimation sample of manufacturing firms.

Variable	All firms Mean	All firms Std. Dev.	Firms with prior abandoned innovation Mean	Firms with prior abandoned innovation Std. Dev.	Firms with no prior abandoned innovation Mean	Firms with no prior abandoned innovation Std. Dev.
Dependent variables						
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
Treatment variables						
Abandoned innovation dummy	0.252	0.434	0.558	0.497	0.140	0.347
Abandoned innovation in conception phase	0.194	0.396	0.471	0.499	0.092	0.289
Abandoned innovation in later phase	0.166	0.372	0.381	0.486	0.087	0.282
Control variables						
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
Number of obs.	10,960		2955		8005	

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

increases these numbers. Firms with prior abandoned innovation activities had a 10 % share of new-to-market products or services in sales; firms without prior abandoned innovation activities had a 7.2 % share of innovative sales.

3.3. Explanatory variables: abandoned innovation

Central explanatory variables of interest in our econometric analysis are binary variables (measured in each annual survey) denoting abandoned innovation by the firm in the last 3-year period. We construct a general abandoned innovation dummy that 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). We use two further dummy variables indicating: i) innovation activities or projects abandoned in the conception development phase, and ii) innovation activities or projects abandoned in later stages, once the activity or project had begun. The important advantage of PITEC for the purposes of our paper, compared to other datasets, is that we can distinguish between these two distinct types of innovation abandonment.[4]

Among the manufacturing firms that we use in our econometric analysis, 25.2 % reported abandoned innovation activities (see Table 1). 19.4 % of firms reported innovation activities that were abandoned in their conception phase. 16.6 % of firms reported innovation activities that were abandoned after the activity or project had started. 10.8 % of firms reported having both types of abandonment. Further, there is significant persistence in abandoned innovation. 55.8 % 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 % 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 confounding factors such as differences in prior firm performance or other innovation inputs.

3.4. Other controls

We also 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, 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 (Aghion et al., 2019). To account for the quality of the internal knowledge base and availability of resources we include a dummy variable for membership of a larger group of firms and a dummy for foreign ownership. The foreign ownership dummy variable accounts for potential knowledge transfer from the rest of the multinational firm.

We observe in Table 1 that firms with prior abandoned innovation activities tend to have higher average labour productivity, higher 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.[5] Accounting for the prior realisations of these control variables is important in our 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

[4] Whereas we focus in this paper on the learning effects from abandoning innovation, D'Este et al. (2018) and García-Quevedo et al. (2018) have used PITEC data to investigate some key drivers of abandonment of innovation in conception and implementation phases. García-Quevedo et al. (2018) shows that financial constraints have the largest effect on the propensity to abandon innovation projects or activities in conception phase. D'Este et al. (2018) show that there is positive interaction between past and current exploratory R&D in effects on abandoning innovation, with significant consequent reductions of abandoning innovation in the conception phase of the innovation process.

[5] We further report the correlations between these variables in Table A1 in Annex 1.

our analysis sector dummies at the 2-digit NACE level and year dummies.

3.5. Methods

Our analysis focuses on the following types of treatment effects. First, we study whether there are effects of recent abandoned innovation on innovation performance, to confirm whether we find similar effects to those in Leoncini (2016) or Tsinopoulos et al. (2019) (i.e., H1). Second, as a novel contribution, we investigate whether there are benefits from past abandonment of innovation: i.e., whether the effects of recent innovation abandonment are stronger if the firm also had prior abandoned innovation (at year t-3) (i.e., H2). Third, we investigate whether these beneficial effects from past experience are different depending on the stage at which prior innovation abandonment occurred (i.e. H3). Further, we study whether recent abandonment in general has a stronger effect on innovation depending on whether the firm has had prior abandonment in: i) the conception phase; ii) the later phase; iii) in both phases; or, iv) has no experience with prior abandoned innovation activities or projects. Comparison of these different types of treatment effects enables us to determine which type of experience from prior abandonment, and which type of recent abandonment, matter most for increasing innovation performance.

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 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 a higher level of abandoned innovation projects or activities.[6]

We endeavour to address to an extent the issue of non-random selection of firms into the treatment group by matching treated and untreated firms. To investigate the within-firm effects of abandoned innovation, and how the effects of the two core types of abandoned innovation differ, one needs to proxy counterfactual outcomes. The counterfactual unobserved outcome is what would have happened in terms of innovation performance of the firm in the treated group (with abandoned innovation or a particular type of abandoned innovation) if it had not had the treatment – i.e., if the firm had not had any abandoned innovation activities (Rosenbaum and Rubin, 1983; Caliendo and Kopeinig, 2008). Using all firms that have no abandoned innovation activities would not be a suitable control group here as they differ from the treated group in terms of a number of other covariates of innovation. We therefore 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 observable characteristics (such as lagged innovation outputs, firm performance and some observed key drivers of innovation) is very similar to the firms that have a certain type of abandoned innovation activities at time *t*. The identifying assumption of this approach is that we observe the central variables determining whether a firm has abandoned innovation or not, assuming 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 a suitable control group for each of the three core treatments. These treatments are then divided further depending on the firm's experience with abandonment in prior periods: whether the firm has any kind of abandoned innovation activities; whether the firm has prior abandoned innovation activities in the conception phase; and whether the firm has abandoned innovation activities in later stages of the innovation process once the activity or project has started. As a first stage in the PSM we estimate the probit model with the corresponding 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. We do this separately for all categories of treatments. The lagged firm-level controls used in the probit models 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 indicators together with a dummy for prior abandoned innovation, all lagged by 3 years.[7] Finally, we include sector dummies at 2-digit NACE level and year dummies to capture sector specific drivers and year specific effects.

The probit models of treatment aggregate the relevant information about the observed drivers of selection into one 'treatment' variable – the propensity score to engage in a certain type of 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.[8]

After this we can calculate the estimate of the effect of abandoned innovation – the average treatment effect on the treated firm (ATT), as the difference between the mean of the outcome variable in the 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 following equation:

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

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 i) abandoned innovation activities or projects at survey year *t* (i.e., for the 3-year period of *t, t-1 and t-2*); ii) innovation activities or projects abandoned at conception stage; iii) innovation activities or projects abandoned at later stage, once the activity or project had started. As outlined in the hypotheses, we would expect the effect of abandoned innovation in the conception phase to be stronger than the innovation activities abandoned in later stages of the innovation process. '*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 that the second term in brackets in the right-

[6] The question of direction of causality and the role of other confounding factors is a key limitation 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).

[7] 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*).

[8] We apply the condition of common support condition in our matching analysis. Also, note that we use matching with replacement.

hand side of Eq. (1) would be statistically insignificant. Then, the estimated *ATT* is proxied simply with the first term in brackets in the right-hand side of Eq. (1).

As an important contribution to the analysis of learning effects of innovation abandonment and in order to test Hypotheses 2 and 3 we 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 innovation activities abandoned in the conception phase or not (in *t-3*);
iii) whether the firm had prior innovation activities abandoned in the later stages of innovation process, once the activity or project had started (in *t-3*);
iv) whether the firm had both core types of prior innovation abandonment (in *t-3*).

This analysis is accomplished by dividing the firms into groups based on whether they did or did not have 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 Hypotheses 2 and 3 we would expect these prior experiences to be complementary with the recent period's engagement with abandoned innovation and correspondingly to indicate learning effects in the form of higher estimated effects from recent abandoned innovation activities.

Finally, it needs to be mentioned that in studies based on survey data with self-reported values of indicators, common method (or source) bias could be a potential concern. However, common method bias is generally not considered a major problem in official innovation survey datasets like PITEC and the Community Innovation Survey type of datasets in general (e.g., Lucena, 2016; Roper et al., 2016). This is especially the case when the analysis involves multiple time periods and time lags where the issue of the same respondent answering all questions through time is unlikely to arise. As D'Este et al. (2018: 530) point out "Due to its reliability, open-access policy and range of innovation-related information, PITEC is being used increasingly as the data source for empirical studies of firm-level innovation". As the PITEC survey and CIS surveys in general are anonymous, the respondents and the firms do not have any incentive to systematically over-report or under-report the firm's innovation indicators. Lucena (2016) has, in a study investigating drivers of innovation performance of firms using PITEC, implemented the standard tests of common method bias. This included Harman's one-factor method to test for the presence of a common-method bias. His results suggest no evidence of this problem in the case of PITEC dataset.

4. Empirical results

4.1. Is there evidence of learning from abandonment?

Our first hypothesis relates to whether having abandoned innovation activity in the earlier 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 activities (Table 2). As a first stage in the PSM process we estimate a probit model in which 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 activity 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 activity. Unlike Tranekjer (2017), however, we find no significant link between prior process innovation and the probability of having abandoned innovation.[9] Like Paunov (2012, p. 31) we also find no significant link between labour productivity and the probability of abandoning innovation, once the other key covariates are accounted for. Firms with higher levels of sales from less radical (new to the firm) innovation were less likely to abandon future innovations. Prior R&D and having abandoned innovation activity in the previous period also increase the likelihood of abandoning innovation in future periods (Table 2).

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	10,960	

Notes: Period: 2008–2016.
* Significant at 10 %.
** Significant at 5 %.
*** Significant at 1 %.

We use the probit models in Table 2 to estimate propensity scores and construct the matched control groups for each of the types of treatment. Balancing tests suggest the matching process is effective in eliminating any significant differences between the observed pre-treatment 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 A2 in Annex 2).[10]

The estimated average treatment effects (ATTs) of recent innovation abandonment on different innovation outputs are summarised in Table 3. The results provide strong support for Hypothesis 1, i.e. having abandoned innovation activity 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 activity in period *t* leads to a 9.2 % increase in the probability of product innovation in $t + 3$, an 8.1 % increase in the probability of process innovation

[9] 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.

[10] An assumption of PSM is that in the absence of the treatment the treated and matched control group would have followed similar trends in outcome variables over time. To confirm this, we have performed checks whether the key outcome variables (innovation output indicators) after matching are different in two pre-treatment periods (t-3 and t-6), between the treated and constructed control group. These additional results confirm the findings in Annex 2 also in the case of longer lags. The treated firms do not have different trends in pre-treatment period in innovation output variables such as the share of new-to-market or share of new-to-firm products in sales. However, we acknowledge that the matching procedure's results could still reflect time varying unobserved covariates and the estimates in the paper should be interpreted with caution and not necessarily as causal effects.

and an 8.4 % increase in the probability of organisational innovation (Table 3).[11] We also find a significant link between abandoned innovation activity 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 3). The positive link we identify between abandoned innovation activity 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 innovation.[12]

Now we consider the evidence concerning H2, to what extent the effect of abandonment on current innovation outcomes is conditional on abandonment in prior periods (i.e., two survey waves previously). In Table A3 in Annex 3 we report probit models for whether firms abandoned innovation in period *t*, dividing the sample between those with and without abandoned innovation activity in the previous survey wave (i.e., at *t-3*). As might have been anticipated, the pattern of significant variables is relatively similar in the two models although some coefficients differ significantly suggesting the importance of estimating propensity scores separately for each analysis (Table A3). Table A4 in Annex 3 provides the balancing tests for both PSM analyses, again suggesting that the matching process is effective in eliminating significant differences in the characteristics of the treatment and control groups.

ATTs of prior abandoned innovation activity with and without previous abandoned innovation (i.e. 2 survey waves previously) are given in Table 4. While the effect of abandonment is significant and positive in both cases, coefficients are consistently higher where firms also had abandoned innovation activity in earlier periods. These effects are statistically significantly different between the i) firms with prior abandoned innovation and ii) firms without prior abandoned innovation in the case of product, process and new-to-market innovation, indicating support for H2.[13] Tsinopoulos et al. (2019) suggest that the positive relationship between abandoned innovation activity and subsequent innovation outcomes is due to either formal or informal learning processes, arising in part from external collaborations and knowledge search: 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 subsequently 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, 2017; Clark, 2018), exporting (Love and Máñez, 2019), and knowledge management (Clark, 2018).

Next, we check whether our results in Table 4 could reflect the past building of general innovation-related capabilities and skills at the firm rather than specifically experience with prior abandonment of innovation activities and projects. To address this potential issue, we report the following robustness tests. We have further estimated with PSM the ATT effect of abandoned innovation on innovation performance for firms with and without prior R&D spending, and for firms with and without prior innovation-related training of employees. We have not reported the full tables of these results here to save space and they are available upon request.[14] This analysis reflects the potential expected moderating effect of prior R&D and prior innovation-related training in shaping the effects of recent abandoned innovation. Here, we identified a rather different pattern, with the effects of abandoned innovation being stronger where firms had no previous R&D spending compared to firms with previous R&D. Also, abandoned innovation has consistently significant effects on innovation indicators only in situations where firms had no previous training activity. Where firms were engaged in training in prior periods the effects of abandoned innovation on product innovation become insignificant.

This additional result together with the results in Table 4 suggest that our key findings on the role of past experience with abandonment (Hypothesis 2) are not likely to reflect simply the effect of 'general innovation capabilities built through past own R&D' or 'general innovation related skills' created by past training of employees. Rather, they are more likely to reflect the experience of the firm with past abandonment that is shaping the effects of recent abandonment on innovation performance. The honing of 'ability/skills' related to abandoning and better selection of innovation projects over time is important and appears to be associated with higher innovation success in later periods.

As a final robustness test we have checked that our results are not driven by the decision by some of the firms to stop innovating during the studied period, which theoretically could create a positive relationship between abandonment and innovation performance. For that, we have carried out a further robustness test. We excluded from analysis now these firms that had technological (product or process innovation) and/or organisational innovation (or both technological and organisational) in period *t-3* but had neither of these types of innovation in period *t*. Otherwise the application of PSM and estimation of ATT effects stayed exactly the same as in Table 4. We find that the conclusions about the role of prior abandoned innovation in shaping the link between recent abandonment and innovation in next periods (Hypothesis 2) stay the same as before (as in Table 4).

4.2. From what stage in the project cycle does learning originate?

Our third hypothesis is about the types of potential learning effects. Do firms develop abilities more from past abandonment in the conception stage or in later (implementation) stages of the innovation process? The distinction can help to shed further light on the question of whether learning from abandoned innovation activity, as shown in Table 4, is likely to reflect learning from the actual failure of projects in their implementation phase or rather from improved strategic decision-making and selection of the most promising ideas in the early stages of the innovation process.

Estimating the corresponding probit models and propensity scores of the different types of treatment (Table A5 in Annex 4) suggests satisfactory balancing tests of the relevant observed pre-treatment variables (Tables A6 and A7 in Annex 4). The probit models for the two types of abandonment confirm the majority of the key correlations as discussed already above in Table 2 in the case of estimation of the propensity of abandoning innovation in general. However, a key difference between the two types of abandonment is the role of persistence. Firms that have abandonment in the conception phase show significantly more persistence in innovation abandonment over time compared to those that report abandonment in later stages of the innovation process.

The PSM specifications in Table 5 focus on identifying the origin of learning. We observe in Table 5 the effects depending on whether the firm has prior (at time t-3) abandonment of innovation activity in the conception stage, in later phases of the innovation process, or in both of these stages, As previously indicated, recent abandoned innovation activity has a significant positive effect on innovation outcomes (Table 4).

[11] Similar effects are noted by Sawang and Matthews (2010) in their analysis of the Australian Business Longitudinal Survey.

[12] 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.

[13] The difference of the estimated ATT effects in two groups of firms (with and without prior abandoned innovation) is tested based on estimating an OLS regression model on the matched sample. The estimated ATT effects in the case of product innovation, process innovation and share of new to market products are statistically significantly (at 5 % level) different between the two groups in Table 4. The estimated ATT effects in Table 4 are not statistically significantly different between the two groups in the case of the share of new to firm products in sales and organisational innovation.

[14] These results are also available in the working paper version of our study (Love et al., 2020).

Table 3
The effect of abandoned innovation on innovation outputs in the next period: 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.
Statistically significant ATT effects are shown in bold. Period: 2008–2016.
* Significant at 10 %.
** Significant at 5 %.
*** Significant at 1 %.

Table 4
The effect of abandoned innovation on innovation outputs in the next period: effects of 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: Statistically significant ATT effects are shown in bold. Period: 2008–2016. The difference of the estimated ATT effects in the two studied groups of firms (with and without prior abandoned innovation) is tested using a t-test based on estimation of the OLS regression model on the matched sample. The estimated ATT effects in the case of product innovation, process innovation and share of new to market products are statistically significantly a (at 5 % level) different between the two groups in Table 4. The estimated ATT effects are not statistically significantly different (at 10 % level) between the two groups in the case of the share of new to firm products in sales and organisational innovation.
* Significant at 10 %.
** Significant at 5 %.
*** Significant at 1 %.

However, we now find that if the firm had prior (*t-3*) abandoned innovation activity exclusively in the later (implementation) stages of the innovation process, then the effect of recent abandonment on any of the innovation output variables is not significantly different from zero (specification 2 in Table 5). Thus, there seems to be, on average, a disruption effect from having had prior abandoned innovation activity only in the later stages of the innovation process: the positive effect of recent abandonment is lost.[15]

By contrast, strong positive effects of recent abandoned innovation activity on product and process innovation appear if the firm has either prior experience with abandoning in the conception phase or had prior abandonment in both the conception and later phases of innovation process. These correspond to specifications 1 and 3 in Table 5. For example, the effect of abandoned innovation activity at time *t* on the propensity to engage in product innovation in the next period (at time *t + 3*), conditional on having prior abandoned innovation in the conception stage at *t-3*, is about 10.5 % higher. The corresponding effect on process innovation is a 9.1 % higher propensity to engage in process innovation. The strongest effect on innovation performance as measured by increases in new-to-market products' share in sales occurs if firms'

[15] Note, however that this result derives from a relatively small number of observations (636).

prior experience combined both types of abandoning innovation (specification 3).[16]

Given the assumption that later-stage abandonment is more likely to reflect innovation failure compared to abandonment in the conception stage, these results point to the limitations of learning from abandoned innovation, and to stronger learning in the activities of strategic selection of the most promising innovation projects and activities in the conception phase of innovation. Firms may get better over time at weeding out the worst ideas and nurturing the best ideas in the early stages of the innovation value chain. This is not the same type of learning as that from failed innovation projects or activities (Madsen and Desai, 2010). Further confirmation of the dynamic correction mechanism underlying H3 can be found by examining what effect conception-stage abandonment has on subsequent later-stage abandonment. Additional PSM analysis indicates that as a result of abandonment at time *t* in the conception stage, there is a systematic fall in the propensity to have abandoned innovation at time $t + 3$ in the later stage of the innovation process, compared to the control group of firms that at time *t* had abandoned innovation in the later stage only.[17] This lends support for the view that the positive effects of early-stage abandonment on subsequent innovation does arise from improved strategic decision-making and selection of the most promising ideas in the early stages of the innovation process.

4.3. Extension: at what stage in the project cycle is learning implemented?

The previous results indicate that learning occurs principally *from* abandonment at the conception phase of innovation. But we can go further, and examine at which stage of the innovation process learning from abandonment is *implemented*. Does a firm's learning from past abandoned innovation activity materialise in the effects of recent abandonment in the conception phase or rather in the later phases of the innovation process?

We show the importance of different types of abandonment and their interaction with past experience in Table 6 (specifications 4–7). The difference between this and the previous analysis in Table 5 is that we now consider the effect of different types of recent abandonment (conception versus later stage) conditional on whether or not the firm had past experience with any kind of abandonment of innovation.[18] Again, there is a significant difference between firms with abandoned innovation activity in the conception stage and firms with abandoned innovation activity in later stages of innovation process. The effect of recent abandonment in the conception phase is positive, both if the firm had or had no past abandoned innovation activity (see specifications 4 and 5). The effect of recent abandonment in later phases is not significantly different from zero. This result holds whether or not the firm had prior abandoned innovation activities (specifications 6 and 7).

The positive effect of recent abandonment in the conception phase ranges between a 5 % and 14.5 % increase in the propensity to introduce product innovation in the next period ($t + 3$) depending on whether the firm had (specification 4) or had no (specification 5) past experience with abandoned innovation. Thus, the results clearly suggest learning from prior abandonment, but only if the firm has recent abandonment of innovation in the conception phase. We observe similar regularity in the case of effects on process innovation. Interestingly, the effect of innovation abandonment on organisational innovation does not differ significantly between the two specifications. This suggests that learning from prior abandonment helps firms become better at subsequently selecting suitable projects at an early stage, i.e. they learn to weed out likely failures early on: but it does not make them any better at learning from ‘failure’ in the later stages of the innovation process.

5. Discussion and conclusions

While previous cross-sectional studies have suggested that abandoned innovation activity can contribute to enhanced innovation performance, our evidence suggests for the first time the dynamic nature of the linkage between abandoned innovation activity 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. Firms which have abandoned innovation activity in one period have better innovation performance in the next. This effect is significantly stronger if firms also had abandoned innovation activity 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 periods. While this has not previously been noted in the learning from failure literature, this type of cumulative 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 learning processes also prove significant in firms' export behaviour: Love and Máñez (2019) show that cumulative 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 activity and open innovation (Tsinopoulos et al., 2019; Tranekjer, 2017).

Previous research on learning in the context of abandoned innovation focuses on the current effects of abandoning innovation and interpret these as learning effects (e.g. Leoncini, 2016; Tsinopoulos et al., 2019). The results of our analysis tell a rather different and more complex story. Contrasting our key results with those from prior research, it appears that much of the apparent ‘learning from failure’ identified in large innovation datasets is probably not about failure at all. By concentrating on the dynamics of the learning process our evidence suggests that firms do not learn *from* failure so much as develop the ability *to anticipate* failure by becoming better at selecting projects more likely to become successful innovations. They then use the experience from prior abandonment to become better at selecting projects in the future. Our main contribution thus lies in highlighting the role of abandonment of innovation as a dynamic correction mechanism – but not in the way envisaged in the learning from failure literature. The specific stage in the project cycle firms both learn from and apply learning is also of huge importance. Because we are able to identify the stage in the innovation process at which abandonment and any

[16] Specification 3 also indicates that, in addition to increasing the share of new-to-market products, prior experience combining both types of abandoning innovation significantly reduces the share of new-to-firm products in total sales. This raises the intriguing possibility that there is a shift from new-to-firm to new-to-market innovation as a result of abandoned innovation. Preliminary analysis on this topic proves indicative but indecisive. PSM analysis based on the sample of firms that had only new-to-firm innovation in t-3 suggests some evidence of a subsequent increase in the propensity to introduce new-to-market products and a fall in new-to-product percentage of sales from any form of prior abandonment, i.e. a shift towards ‘radical innovation’. However, if we run the PSM analysis based on specification 4 from Table 5 data (i.e. the effects of prior abandonment in both stages) the effects are not statistically significant. Thus there is some evidence suggesting a shift towards more ‘radical’ innovation due to abandoned innovation in general. On another hand, the combination of prior abandonment in both phases is not necessarily driving this result. (Results available on request).

[17] In this analysis the treatment group comprises firms which have abandoned innovation at time t in the conception stage only (and not in the later stage), while the control group comprises firms with abandoned innovation at time t in the later stage only (and not in conceptual stage). This is in order to eliminate the confounding effect of firms that have both types of abandoned innovation. Results are available from the authors on request.

[18] All specifications here are based on mutually exclusive groups of firms.

Table 5
At what stage does learning occur? Learning effects of abandoned innovation: ATT effects from propensity score matching.

	Effects					CONDITION (from time t-3)				
	Effect on product innovation (at t + 3)	Effect on process innovation (at t + 3),	Effect on organisational innovation (at t + 3)	Effect on share of new-to-market products in sales	Effect on share of new-to-firm products in sales	**TREATMENT: Current abandoning** (can be either in conception or later phase or in both)	If firm HAS **past** abandoning in **conception phase** (and not in later phase)	…HAS **past** abandoning in **later phase** (and not in concept phase)	…HAS **past** abandoning BOTH in **conception phase and later phase**	Number of obs.
1.	**0.105*** (0.038)**	**0.091*** (0.039)**	0.037 (0.039)	0.844 (1.682)	0.239 (2.345)	X	X			1051
2.	0.056 (0.059)	−0.031 (0.060)	0.031 (0.059)	−0.509 (2.271)	−1.224 (2.985)	X		X		636
3.	**0.085*** (0.043)**	**0.085*** (0.044)**	0.062 (0.044)	**5.159*** (1.403)**	**−6.870*** (2.900)**	X			X	1250

Notes: Each row here denotes one specification of the propensity score matching. Statistically significant ATT effects are shown in bold. Standard errors in parentheses. Period: 2008–2016. We have tested whether the estimated effects in specification 1 and 2 are statistically significantly different. The estimated ATT effects in the case of product innovation and process innovation are statistically significantly (at 1 % level) different between the subsamples of firms in Row 1 and Row 2. The difference of the estimated ATT effects in the two studied groups of firms (Row 1 vs Row 2 in Table 5) is tested using *t*-test based on estimation of the OLS regression model on the matched sample.
* Significant at 10 %.
** Significant at 5 %.
*** Significant at 1 %.

Table 6
At what stage is learning implemented? Learning effects of abandoned innovation: ATT effects from propensity score matching.

						TREATMENT (at time t)		CONDITION (from time t-3)		
	Effect on product innovation (at t + 3)	Effect on process innovation (at t + 3),	Effect on organisational innovation (at t + 3)	Effect on share of new-to-market products in sales	Effect on share of new-to-firm products in sales	Current abandoning in concept phase (and not in later phase)	Current abandoning in later phase (and not in conception phase)	HAS past abandoning	Has NO past abandoning	Number of obs.
4.	**0.145*** (0.032)**	**0.116*** (0.033)**	**0.080** (0.034)**	**4.197*** (1.382)**	−2.251 (2.038)	X		X		1829
5.	**0.050* (0.031)**	**0.052* (0.031)**	**0.074*** (0.031)**	1.598 (1.416)	0.040 (1.636)	X			X	7289
6.	−0.008 (0.045)	−0.029 (0.045)	0.021 (0.045)	−1.401 (1.432)	**−5.654*** (2.567)**		X	X		1536
7.	−0.029 (0.032)	−0.047 (0.032)	−0.021 (0.031)	−1.350 (1.186)	−0.716 (1.789)		X		X	7150

Notes: Each row here denotes one specification of the propensity score matching. Statistically significant ATT effects are shown in bold. Period: 2008–2016. The ATT effects in the case of all innovation output variables are statistically significantly (at 1 % level) different between the subsamples of firms in Row 4 and Row 6. The difference of these estimated ATT effects is tested using t-test from an OLS regression model estimated based on the matched sample.
* Significant at 10 %.
** Significant at 5 %.
*** Significant at 1 %.

associated learning effects occur, it becomes clear that not all abandonment is the same in terms of its effects. The dynamic mechanism works principally by preventing firms from taking forward weak innovation projects beyond the conception stage: learning from abandoned projects to which resources have actually been committed proves more difficult, and is rarely a source of learning effects. However, if firms do manage to learn from the later stages of abandonment (i.e. from failure) it can prove very effective, especially in developing new-to-market innovations – but only in combination with (prior) learning from abandonment at the conception stage.

Our analysis suggests the potential value of a dynamic approach to modelling the effects of abandoned innovation activity. 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 et al., 2014b). Alongside the type of organisational influences considered here Meifort (2016), for example, 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' strategic and innovation objectives and their operating context.

There are two important implications for management. The first is that it is possible to learn from previous abandonment and that there is a time dimension to this. Importantly, however, much of this learning can be acquired from becoming better at selecting which projects to advance at an early stage, rather than closely analysing the reasons for abandonment once commitment is made. The second implication is that failure to learn from the past has important consequences. Firms whose prior experience arises exclusively from the later stages of abandonment not only fail to learn from their experience, they find it highly disruptive: the strong and consistently positive effect running from recent abandonment to innovation outputs is completely absent in these firms, and only in these firms. This suggests that it is not only difficult to learn from abandonment once commitments are made (Staw, 1981; George, 2005; Andries and Hünermund, 2020), but where lessons cannot be learned from past experience the negative consequences of later-stage abandonment can last several years. However, where it can be harnessed, the learning effects of 'failure' can be considerable for the most novel forms of innovation – but only if accompanied by learning from abandonment at the conception stage. Firms which have prior experience of both types of abandonment experience very strong positive effects running from recent abandonment to current levels of new-to-market innovations, a crucial element in sustaining competitive advantage. Thus if firms wish to improve their performance in bringing more radical products to market it is worthwhile to engage in the deep-level, deliberate efforts to analyse past failures discussed by Daneels and Vestal (2020), in conjunction with improved skills at selecting which projects to proceed with at the conception stage. This also supports the findings of Maslach (2016) that persisting with apparently failed innovation trajectories can sometimes be useful in leading to important learning effects in the future. However, if the firm's strategy revolves around more routine forms of innovation, investment in costly learning from abandonment once substantial commitment is made is unlikely to be cost effective.

Despite its contributions, the study has several limitations. A potential significant limitation in observational studies endeavouring to investigate learning effects is accounting for alternative possible explanations of these effects. Even if there is a positive relationship from abandonment of innovation projects (the 'treatment') to innovation success, one can still question whether the estimated effects might be reflecting some other characteristics of firms (e.g., ability, skills, firm size, other types of experience than past experience with abandoning innovation projects, etc.) that affect both selection into abandonment of innovation projects and innovation performance. To put it differently, successful firms may be good at abandoning and selecting innovation projects and, at the same time, good at reaching higher innovation performance. Or, for example, larger firms may simultaneously have more innovation projects and thus more abandonment of projects and at the same time higher innovation performance due to other reasons.

In our econometric analysis by using PSM we account for observable common factors that could affect both selection into treatment and innovation performance, such as firm size, prior productivity, R&D, innovation-related training, and past realisations of innovation inputs and outputs, among others. We have estimated the treatment effects of abandonment of innovation based on matched treatment and control groups, that are similar, on average, in terms of their means of key pre-treatment observed confounders. Thus, the estimated effects of abandoned innovation on innovation performance are unlikely to be simply reflecting the firm size and productivity differences or general firm-level prior innovation capabilities (as, for example, proxied by prior R&D or training). However, we acknowledge that the matching approach does not account for unobserved confounders and therefore one has to be rather cautious with conclusions about causality in the case of our estimated ATT effects.

As is usual in large-scale surveys of the type employed in this study, learning effects have to be inferred from the statistical relationship between abandonment activity and innovation outcomes. Clearly such statistical associations may mask a number of heterogeneous reasons for abandoned innovation activity, and a substantial variation in the precise nature of managerial learning arising from this. For example, abandonment may occur because of strong competition effects, or because of differences in firm strategy between developing radical new-to-market innovation versus more incremental innovation, or because of some failure to meet technical rather than commercial objectives. Firms in some sectors, for example pharmaceuticals, may have their management of innovation portfolios heavily circumscribed by the relevant regulatory regime. Datasets such as PITEC are ill-equipped to shed light on such sectoral nuances, or on the precise decision-making processes managers employ, and we must therefore be circumspect in drawing general conclusions about firms' abilities to learn from abandonment activity. Insights into the precise nature of the processes that firms go through to learn from abandonment require complementary longitudinal and qualitative studies.

Nor does the evidence presented here mean that firms may not learn at all from failure. The literature using longitudinal analysis of surgeons getting better after mistakes or firms' reactions to catastrophic errors (e.g. Madsen and Desai, 2010) suggests that there is a variety of examples in different contexts when learning from failure can indeed take place. In addition, our study is restricted to manufacturing firms, and in a single country. While there is conflicting evidence on whether the nature of the innovation process differs between manufacturing and services (e.g., Love and Mansury, 2007; Tether, 2005), we cannot assume that exactly the same learning from abandonment effects will be evident in service innovation: future studies can enhance our understanding here. Finally, our findings are restricted to the timing of the available data, which relates to the 2008–16 period, and will to some extent be influenced by the macroeconomic conditions existing at that time.

CRediT authorship contribution statement

All authors contributed equally to the various stages of the work.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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Annex 1. Correlation table

Table A1
Correlation table: key dependent and independent variables, estimation sample.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) Abandoned innovation dummy	1.0000												
(2) Log of firm size	0.1424	1.0000											
(3) Member of a group	0.1047	0.5293	1.0000										
(4) Foreign ownership	0.0631	0.3520	0.4257	1.0000									

(continued on next page)

Table A1 (*continued*)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(5) Log of labour productivity	0.0672	0.2851	0.3306	0.2148	1.0000								
(6) Training dummy	0.0959	0.0810	0.0403	0.0104	0.0425	1.0000							
(7) R&D dummy	0.2622	0.0886	0.0799	0.0346	0.0977	0.2046	1.0000						
(8) Lagged abandoned innovation dummy	0.4269	0.0915	0.0800	0.0444	0.0600	0.1023	0.2058	1.0000					
(9) Product innovation dummy	0.1972	0.0703	0.0543	0.0298	0.0811	0.1615	0.4596	0.2003	1.0000				
(10) Process innovation dummy	0.1403	0.1536	0.0885	0.0603	0.1227	0.1562	0.2649	0.1531	0.2955	1.0000			
(11) Organisational innovation dummy	0.1864	0.1841	0.1087	0.0718	0.0835	0.1928	0.3088	0.1926	0.2572	0.3311	1.0000		
(12) Share of new-to-market products in sales	0.0607	−0.0249	−0.0122	−0.0118	−0.0135	0.0366	0.1848	0.0412	0.3184	0.0714	0.0930	1.0000	
(13) Share of new-to-firm products in sales	0.0311	−0.0251	−0.0324	−0.0250	0.0024	0.0311	0.1375	0.0466	0.3871	0.1077	0.0735	−0.0366	1.0000

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

Annex 2. Balancing property test: the effects of current abandoned innovation

Table A2
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
Share of new-to-firm products in sales (t-3)	Unmatched	17.331	15.313	0.001
	Matched	17.331	17.690	0.628

Period: 2008–2016.

Annex 3. Analysis of the effects of abandoned innovation depending on prior experience (Table 3 in main text): probit models and balancing property tests

Table A3
Modelling the probability of having abandoned innovation: Manufacturing firms with and without prior abandoned innovation.

	Firms WITH prior abandoned innovation (in t-3)		Firms with NO prior abandoned innovation (in t-3)	
Variables	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

(*continued on next page*)

Table A3 (*continued*)

	Firms WITH prior abandoned innovation (in t-3)		Firms with NO prior abandoned innovation (in t-3)	
Variables	Coef.	Std. Err.	Coef.	Std. Err.
Pseudo R-squared	0.119		0.050	
Number of observations	2955		8005	

Notes: Period: 2008–2016.
* Significant at 10 %.
** Significant at 5 %.
*** Significant at 1 %.

Table A4
Balancing property tests after PSM: p-values of the test of difference of means between the 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
Share of new-to-market products in sales (t-3)	Unmatched	0.072	0.000
	Matched	0.960	0.995
Share of new-to-firm products in sales (t-3)	Unmatched	0.730	0.046
	Matched	0.935	0.521

Period: 2008–2016.

Annex 4. Analysis of the effects of innovation activities abandoned in conception stage or in later stages (Tables 5 and 6 in main text): probit models and balancing property tests

Table A5
Modelling the probability of having innovation abandoned in i) conception phase and ii) later stages.

	(1)		(2)	
Dep. Var.	Firm has current abandoning in concept phase (and not in later phase)		Firm has current abandoning in later phase (and not in conception phase)	
Explanatory variables	Coef.	Std. Err.	Coef.	Std. Err.
Log of firm size (t-1)	0.060***	0.019	0.052**	0.021
Member of a larger group (t-1)	0.066	0.049	0.005	0.053
Foreign ownership (t-1)	−0.005	0.056	−0.068	0.063
Log of labour productivity (t-1)	−0.007	0.028	−0.025	0.029
Abandoned innovation dummy (t-3)	1.008***	0.044	0.639***	0.054
R&D dummy (t-3)	0.353***	0.051	0.319***	0.053
Training dummy (t-3)	0.071	0.057	0.019	0.066
Product innovation dummy (t-3)	0.129**	0.057	0.098*	0.059
Process innovation dummy (t-3)	0.044	0.049	0.095*	0.052
Organisational innovation dummy (t-3)	0.120***	0.043	0.112**	0.046
Share of new-to-market products in sales (t-3)	0.001	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	−2.396***	0.405	−2.010***	0.415
Pseudo R-squared	0.165		0.091	
Number of observations	9138		8791	

Notes: Period: 2008–2016.
* Significant at 10 %.
** Significant at 5 %.
*** Significant at 1 %.

Table A6
Balancing property tests after PSM (for Model 1 in Table A5).

Variable	Sample	Mean Treated	Mean Control	p-value
Log of firm size (t-1)	Unmatched	4.550	4.146	0.000
	Matched	4.550	4.466	0.163
Member of a larger group (t-1)	Unmatched	0.552	0.441	0.000
	Matched	0.552	0.534	0.433
Foreign ownership (t-1)	Unmatched	0.222	0.172	0.000
	Matched	0.222	0.224	0.934
Log of labour productivity (t-1)	Unmatched	12.169	12.061	0.000
	Matched	12.169	12.114	0.114
Abandoned innovation dummy (t-3)	Unmatched	0.504	0.111	0.000
	Matched	0.504	0.524	0.382
R&D dummy (t-3)	Unmatched	0.835	0.557	0.000
	Matched	0.835	0.820	0.394
Training dummy (t-3)	Unmatched	0.178	0.099	0.000
	Matched	0.178	0.200	0.228
Product innovation dummy (t-3)	Unmatched	0.818	0.624	0.000
	Matched	0.818	0.799	0.306
Process innovation dummy (t-3)	Unmatched	0.790	0.646	0.000
	Matched	0.790	0.789	0.944
Organisational innovation dummy (t-3)	Unmatched	0.646	0.432	0.000
	Matched	0.646	0.629	0.459
Share of new-to-market products in sales (t-3)	Unmatched	13.704	9.754	0.000
	Matched	13.704	13.373	0.767
Share of new-to-firm products in sales (t-3)	Unmatched	17.416	15.313	0.031
	Matched	17.416	15.830	0.193

Period: 2008–2016.

Table A7
Balancing property tests after PSM: Model 2 in Table A5.

Variable	Sample	Mean Treated	Mean Control	p-value
Log of firm size (t-1)	Unmatched	4.413	4.141	0.000
	Matched	4.413	4.355	0.406
Member of a larger group (t-1)	Unmatched	0.502	0.440	0.003
	Matched	0.502	0.5	0.955
Foreign ownership (t-1)	Unmatched	0.186	0.172	0.369
	Matched	0.186	0.189	0.886
Log of labour productivity (t-1)	Unmatched	12.145	12.06	0.014
	Matched	12.145	12.178	0.478
Abandoned innovation dummy (t-3)	Unmatched	0.303	0.097	0.000
	Matched	0.303	0.320	0.525
R&D dummy (t-3)	Unmatched	0.778	0.556	0.000
	Matched	0.778	0.774	0.867
Training dummy (t-3)	Unmatched	0.156	0.099	0.000
	Matched	0.156	0.152	0.877
Product innovation dummy (t-3)	Unmatched	0.557	0.459	0.000
	Matched	0.557	0.579	0.412
Process innovation dummy (t-3)	Unmatched	0.522	0.451	0.000
	Matched	0.522	0.560	0.168
Organisational innovation dummy (t-3)	Unmatched	0.590	0.431	0.000
	Matched	0.590	0.579	0.691
Share of new-to-market products in sales (t-3)	Unmatched	11.591	9.371	0.046
	Matched	11.591	10.941	0.613
Share of new-to-firm products in sales (t-3)	Unmatched	16.523	15.325	0.307
	Matched	16.523	15.869	0.670

Period: 2008–2016.

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