Structural Change and Economic Dynamics 70 (2024) 481–493

Contents lists available at ScienceDirect

Structural Change and Economic Dynamics

journal homepage: www.elsevier.com/locate/strueco

Is innovation failure just a dead end?[☆,☆☆]

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ARTICLE INFO

JEL codes:
O3
L2

Keywords:
Innovation failure
CIS
Innovation
Complex technology environment

ABSTRACT

This paper explores whether failures in innovation projects at the firm level contribute to strengthening firms' innovative activities and the odds of future innovation. Building on the literature on NK fitness landscapes, our paper focuses on technological complexity as a key factor that influences the response to innovation failures, guiding whether to discontinue the current path or, alternatively, to leverage the failure as a foundation for future innovation success. We then test the hypothesis derived from our model using a panel data set constituted by ten waves of the Community Innovation Survey held in the Netherlands from 1996 to 2014. Our findings show the fundamental relevance of the different forms of learning that are available to the firm. In particular, we highlight the positive role of learning after a previous innovation project has been abandoned. Previous failure in innovating produces some forms of learning inside the firms, and this learning positively contributes to subsequent successful innovation. Moreover, by differentiating between radical and incremental innovation, and between complex and less-complex innovation landscapes, we highlight the role of incremental innovation over the whole spectrum of landscape complexity, while the role of radical innovation appears to be more limited to less turbulent technological landscapes.

1. Introduction

Learning activities are the most important way for an organisation to succeed: "Learning generates successes rather than failures. […] As learners settle into those domains in which they have competence and accumulate experience in them, they experience fewer and fewer failures" (Levinthal and March 1993, p. 104). As learning is the key element through which organisations develop novelty, organisations face the difficult task of organising knowledge through a conscious process of elaboration. In this way, pre-existing knowledge is transformed into a qualitatively different one, which is the basis for innovation. Hence, organisations explore potentially useful new knowledge (Levitt and March 1988), and the creation of new ideas leads to producing innovation (Schumpeter 1934).[1]

However, as reported by surveys among executives, also these activities are prone to failure: only slightly more than one-third of them acknowledged that corporate venturing within their organisations was successful (Kuratko et al., 2009). Indeed, as innovative activity deals with true uncertainty, even in the absence of obstacles to innovation (e.g., D'Este et al., 2014), innovative activity will frequently fail. Moreover, some elements such as complacency (as success reinforces the actual processes, and makes organisations less alert to negative signals), low level of attention (as individuals will trust old well-known routines) and homogeneity (as organisations will stick to successful personnel and task management) are likely to make success a sort of liability (Sitkin 1992).

☆ The authors thank the participants to the 15th ENEF Workshop, Sept.13–14, 2018, Brighton; 60th SIE, Oct. 24–26, 2019, Palermo; 17th SIEPI, Jan. 29-Feb.1, 2019, Rome; 16th ENEF, Sept. 12–13, 2019, WIFO, Wien; 15th EMNET Conference, Nov. 15—17, 2018, La Habana.☆☆ The empirical part of this research was carried out at Microdata – Centraal Bureau voor Statistiek (CBS), the Netherlands. The views expressed in this paper are those of the authors and do not necessarily reflect the policies of Statistics Netherlands. Elena Cefis acknowledges financial support from the University of Bergamo (grants ex 60 %, n. 60CEFI18 and n. 60CEFI19).

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[1] Attempts to start and sustain successful innovative projects are deemed so important that they have been put forward within large organisations, even throughout corporate venturing activities. Indeed, as innovative activities face rising costs in front of increasing pressures for innovative results, organisations are increasingly resorting to start-ups to better react to market pulls with new business developments (Lerner 2013).

https://doi.org/10.1016/j.strueco.2024.05.004
Received 25 September 2023; Received in revised form 29 February 2024; Accepted 1 May 2024
Available online 15 May 2024

Failure is usually seen as a problem and as such it is considered a drawback for both organisations and employees. As for the former, innovation failures frequently lead to the downsizing of the activities and of the investments that are deemed 'responsible' for the failure. Hence, firms are more prone to head towards less risky alternatives, rather than attempting to build incentives for creative activities that deserve to be developed within the organisation but that eventually go wrong (Eggers 2012). Moreover, employees that were part of a failing innovative project are affected by lower status in their transition to subsequent employers (Rider and Negro 2015).

Recent literature (e.g., Madsen and Desai 2010; Chesbrough 2010; Leoncini 2016; Maslach 2016; Tsinopoulos et al., 2019; Love et al., 2020. See Rhaiem and Amara 2021 for a review) emphasised that a fundamental element that contributes to highlighting the opportunities offered by learning patterns to innovative activity is that furnished by failure in innovative activities. The early literature pointed out that in case of failure, firms typically pursue strategies aimed at surviving. Innovation failure is thus seen as a problem for firms' survival (especially for small firms) or their economic performance. However, the more recent literature emphasises that failures can also have a positive role in organisational activity because they show where and how organisations were unable to cope with the techno/economic challenges and draw attention to improvements and innovative possibilities that were previously overlooked.

Failures do not conform to expectations and thus call for deeper attention and a closer look at previously unnoticed problems. Therefore, it becomes relatively easier to spot what *did not* work well, rather than identifying what *will* work well. It is easier to recognise faults or weaknesses rather than identify effectiveness and efficacy. It is easier to define the right criteria for something that is not working properly, rather than the right criteria for desirable outcomes.[2] The failure of an innovation project might indeed generate valuable new knowledge: if firms are thought of as learning organisations, their patterns of learning are surely more solicited when they are put under stress from negative results. From this perspective, the only case in which the organisational routines are thoroughly investigated is when they fail systematically to produce a certain level of satisfying performance, i.e., when an innovation project fails to deliver a certain performance. Therefore, failure appears to be relevant in driving innovative activity, as it operates as a supplementary element to build organizational knowledge.

In this paper, we offer an alternative view of why failed innovations may have a positive role. If technological change is not a random process but proceeds along constrained path-dependent trajectories (Dosi 1982) then the value of an innovation is not only given by the innovation itself but also by the additional novelties it can subsequently generate, i.e., by the value of the innovation path or trajectory that it opens up.

We refer here to Joseph Schumpeter who said that "…innovation combines factors in a new way, or that it consists in carrying out New Combinations." (Schumpeter, 1939, p. 84). Hence, we assume that innovation can be generated in two ways: either a new technology is developed by *branching* from another (older) one, or a new technology can be the result of *recombination* of at least two other (older) technologies (Antonelli et al., 2010; Frenken et al., 2012). Recombinant innovations are thus created as a result of a process of integration of some previously existing technologies that were considered not to "belong together" (Fleming, 2001, p. 118), but that eventually were successfully recombined following a new technological or social construction.

This closely resembles what evolutionary biologist Stuart Kauffman calls the principle of the "adjacent possible" (Kauffman 1995), which states that every novelty opens a new space of possibilities by making accessible a set of further novelties that were not accessible before. The resulting process is one of the ever-increasing opportunities in open-world dynamics. Thus, recombinant technologies are to be seen, on the one hand, as the discovery of some new possibilities that are triggered by the possibilities opened by some technical or social novelty. On the other hand, a recombinant technology may be the answer to how failure forces a firm to reorganise how elements of a technology are bound together and this may well produce an innovative path.

Thus, when either discarding or accepting a novelty, one should consider not only the value of the novelty itself but also of the additional adjacent novelties which would not become accessible without passing through that novelty. In other words, discarding a novelty may imply discarding the paths that the novelty could open up.

Suppose an innovation is attempted and delivers a negative or unsatisfactory result. Is this negative result a reliable signal that also the paths that it makes accessible are likely to be unsatisfactory? The answer – as Kauffman (1993) shows – crucially depends on the complexity of the technological space, that is, on the extent and intensity of interdependencies among the components and elements constituting the technology. If such interdependencies are scarce and limited, then paths in the technological space tend to be smooth and therefore a novelty with a negative value is a reliable signal that also the paths made accessible by that novelty will likely have a negative value. If, on the contrary, interdependencies are widespread and intense, then paths towards better technological configurations tend to be very rough, with lots of ups and downs and therefore a novelty with a negative value might well open the door to high-valued paths.

Moreover, and related, when interdependencies are scarce there are many alternative paths conducive to the same highly valued portions of the search space. Instead, when interdependencies are strong and diffused path dependency is much stronger and the opportunity cost of abandoning one path may be very high because alternative routes to the same portion of the space could be few and far away.

These properties of complex search spaces are analysed in the so-called *NK fitness landscape model*, proposed by Kauffman (1993) but widely applied to the study of organisational and technological search and adaptation processes (see Levinthal 1997 for a pioneering contribution and Bauman et al. 2019 for a survey). Failure is an important element of this process, as it allows organisations to re-evaluate how their strategies are coping with the environment.

In this paper, we will present a NK landscape model in which firms engage in search activities in a complex space characterised by an accessibility or proximity notion. Firms explore novel alternatives (innovations) in the vicinity of the current technology and, if the innovation has a higher performance than the current technology, then they adopt it. If instead, the innovation has a lower performance, it is classified as innovation failure and firms have the choice of either abandoning it (therefore abandoning also the additional innovation which could become accessible) or adopting it despite its negative performance hoping that this *prima facie* inferior technology could give access to successive innovations with superior performance. The simple model we present predicts that complexity (i.e., strength and extension of interdependencies among the elements that make the technology) is the crucial factor that determines whether an inferior innovation should be abandoned or not.

These theoretical results are tested using a unique panel dataset of Dutch manufacturing firms, constituted by 10 waves of Community Innovation Survey (CIS) held in the Netherlands starting with CIS 2 (1994–1996) and ending with CIS 2014 (2012–2014). We take into consideration the whole manufacturing sector and, on average, the

[2] To the point that failure has been even theorised as a way to enhance innovation through wide and free implementation of ideas that are left free to even 'intelligently' fail to understand problems at stake and to solve them before they become catastrophic failures. In this way, organisations not only learn from failure, but they even learn to fail (the so-called intelligent failure). Through this practice, firms can identify either organisational or technological barriers by experimenting in isolated, well-delimited, and 'expected' cases (sort of laboratory) that are easy to deal with and that can easily offer behavioural recommendations to improve firms' learning capacity (Cannon and Edmondson 2005; Tahirsylaj 2012; Sitkin 1992).

number of observations (i.e., of firms) in each wave is around 3500.

This paper adds to the extant literature on several topics. First, we present a simple formal model that provides a novel perspective on how innovation failures may influence firms' innovative strategies and show that the complexity of the search space is a key element that should be considered. Hence, learning-by-failing constitutes an important element in the process of climbing the "rugged landscape" of performance.

Second, we present an empirical validation of propositions derived from the model. Fitness landscape models are widely used in the managerial and economic literature, but the vast majority of studies are only theoretical and at most refer to some anecdotal evidence while empirical applications have been very uncommon so far (Fleming and Sorenson 2001 being a notable exception).

Another element we add to the literature concerns the temporal spillover in the search process. Indeed, if from a static point of view, different patterns of search constitute a trade-off that organisations need to solve, this trade–off can change its nature once it is evaluated from a dynamic perspective. Over time exploration can determine opportunities that the firms will subsequently adopt. In turn, these activities can produce knowledge to be used in future searches on the landscape.

The paper is organised as follows. Paragraph 2 deals with the literature review. Paragraph 3 will present a simulation model and the hypothesis to be empirically tested. Paragraph 4 will describe the data and methodology of the empirical analysis. Paragraph 5 will present the discussion of the results. Paragraph 6 draws some concluding remarks.

2. Theoretical background

As innovative activity is uncertain by definition, it can frequently fail. In front of failure, firms can be driven to behave myopically and reduce their efforts, which in turn generates lower levels of knowledge (Eggers 2012). This pattern seems to be quite diffused as failure has been recognised as the main factor inducing firms to scale down their effort (Denrell and March 2001).

The elements determining failure within an organisation can be either external or internal. The internal ones refer typically to either the individual level (such as emotional and/or psychological reactions, leadership, trust) or the organisational level (such as problem-solving activity, teamwork, stigmatisation, organisational complexity). The external ones refer to several behaviours related to, for instance, cost barriers, financial barriers, human capital availability, external collaborations, and industrial environment.

The relevance of failure for innovation can be appreciated from different angles. We will focus our attention mainly on two of these, that is, the organisational and the learning perspectives. From an organisational point of view, the focus is generally on the twin concepts of success and creativity. As they are usually taken to imply each other, failure results in a lack of creativity. Thus, we need to address the so-called liabilities of success. Indeed, complacency, low level of attention and homogeneity can all push a favourable environment towards failure (Sitkin 1992). It is unclear if prior failure has a negative or a positive impact on the various organisational dimensions related to these activities and ultimately on firms' performance (Deichmann and Ende 2013).

On the one hand, organisations fail to profit from previous failures because of the inability of the managers to understand the causes of a failure. This is due to their psychological disposition to attribute the causes of a failure to external elements or their inability to attribute the appropriate responsibilities due to internal biases (Baumard and Starbuck 2005), or lastly, to the negative emotional responses preventing learning patterns from failures (Shepherd 2003; Shepherd and Cardon 2009).

On the other hand, error-management culture within organisations is positively correlated to firm performance. Practices related to communication about errors, such as helping in error situations, coordinating, and effective error handling, are, among others, the elements that can help to contribute to both firms' performance and survival (Van Dyck et al., 2005). Prior failure is also shown to be positively related to firms' performance because failure can stimulate the organisation through motivational challenges that can increase (or trigger) exploratory behaviour. For instance, it has been pointed out that there might be a need within organisations for a vision that appreciates failure as it is frequently the result of a creative trial. Because of this, failure should not be stigmatised as a negative outcome but rather should be valued as an attempt to create something new that would increase the organisational experience anyway (Townsend 2010).

From a learning perspective, upon which the vast majority of the literature is based, several elements emerge (see, for instance, Huber 1991; Argote and Miron-Spektor 2011). For instance, an organisational environment characterised by mutual trust (Levin and Cross 2004) or where members do not feel a strong (and 'wrong') psychological pressure (Edmondson 1999), has been shown to be an environment where organisational learning is produced and also encouraged.

Previous failures are very important elements, although their dimension and frequency are sometimes crucial (Khanna et al., 2016). Indeed, in several cases, successful outcomes were obtained, despite minor failures that manifested during the process. Because of the positive overall result, they were largely ignored (or underplayed), with the result that in some cases these minor failures eventually piled up to become responsible for big crashes (the most famous and analysed of which is the Challenger disaster, Madsen and Desai 2010). This is what has been termed "accidents rather than incidents because of the nature of the system" (Vaughan 1990, p. 225). Hence, the severity of the failure has a very relevant role in the post–failure evaluation and, lastly, in the learning process triggered by failures. Even in the case of frequent but minor failures, the learning process is quite difficult and unsuccessful (Tucker and Edmondson 2003). Indeed, these minor failures are sometimes very unlikely to capture the managerial attention (Rerup 2009). Even organisations that should be focused on learning from failures, such as, for instance, hospitals, find it difficult to learn from the daily problems and errors that are routinely encountered by the staff (Tucker and Edmondson 2003).

Learning is usually possible only insofar as repeated action leads to success, and thus confirms that the idea of the world held by the organisation is correct. Learning is thus based on the confirmatory power of prior performance outcomes (Deichmann and Ende 2013). As learning is based on previous successes, and is the basis for future ones, cumulativeness, at both micro and industrial levels, constitutes a powerful engine for innovation. Highly innovative firms are more likely to experience higher levels of competitiveness and thus success, which in turn spurs innovative ideas. This dynamic process brings with it a certain degree of persistence of innovation (e.g., Dosi 1988).

Organisations do not build their knowledge only internally, by resorting to their inner capacities to either produce new ideas or to understand why old ideas did not work properly. Firms are open systems whose knowledge level is maintained (or increased) through exchanges with the outer environment. Starting from early contributions about the importance of R&D cooperation (Kleinknecht and Reijnen 1992), the role of external sources of knowledge has been highlighted (e.g., Nonaka 1994), especially to understand their degree of complementarity or not (Caloghirou et al., 2004).

Therefore, another element determining learning patterns in front of failure is the so-called vicarious learning from the failures of others (Kim and Miner 2007). However, in this case, learning from others is typically biased in many respects (Denrell 2003; Rerup 2009). Although learning is identified in the literature as a powerful device, some elements seem to conjure to make this particular source of learning less effective than it would seem at first sight. Therefore, learning from previous failures can be more effective when it comes to, at least, the following organisational activities. First, the capacity of the organisation to effectively understand the failures and thus the amount of internal experience that the organisation has built can help in dealing with unforecasted events, such as unexpected failure. Second, the capacity of the organisation to learn from failed innovative activity is linked to its capacity to understand what is going on in the environment and thus to its capacity to interact with the environment. The more a firm is able to establish relationships with the institutions in the outer environment (such as other firms, but also clients, suppliers, and other knowledge-producing institutions), the better it will be in dealing with unexpected failures.

In poaching from external knowledge, organisations follow different strategies as far as the degree of importance of the knowledge is concerned. Depending on the specific target, firms may target quantity rather than quality in the external knowledge they can benefit from (Laursen and Salter 2006). This can be linked to the different types of innovative activity pursued: to be on the technological frontier, high-quality knowledge might turn out to be crucial, while, being far from the frontier, drawing widely on the externally available knowledge might be a better strategy to catch up.

3. Modelling failure in exploration

NK fitness landscape (Kauffman 1993) provides a very attractive modelling framework for our purpose. It is originally a model of biological evolution that has received increasing attention also by organisation and technology scholars (e.g., Levinthal 1997; Siggelkow 2002; Rahmandad 2019) because it provides a simple and powerful tool to study the properties of adaptation and evolution of complex entities, i.e., entities (organisms, organisations, technologies, etc.) characterised by multiple components or features interacting in non-linear and possibly non-monotonic ways. The broader and stronger such interdependencies, the more the resulting fitness landscape is rugged, with many local 'peaks' of high fitness separated by 'valleys' of low fitness.

The implications for the search processes of these characteristics of the landscape could hardly be more important. If interdependencies are absent or limited, the fitness landscape tends to be smooth and with only one or very few local optima which are located relatively close to each other. In this case, a simple adaptive search process (Simon 1955) consisting of experimenting with a small local change from the current location/configuration and adopting it if its fitness/performance is higher than the current one, will work brilliantly and quickly converge to an optimal location. If instead interdependencies are diffused and strong, such adaptive search will very quickly stop on a local (and possibly bad) local peak, while high-performance portions of the landscape could be inaccessible via local adaptation, requiring radical systemic reconfigurations. Path dependence and early lock-in tend to strongly limit the power of search in this case.

Kauffman (1993) also shows that in a system with limited interdependencies there is a high correlation between the fitness of nearby locations, whereas as interdependencies increase, such a correlation tends to fall. Thus, simple systems are characterised by highly correlated performance landscapes while complex systems tend to evolve on uncorrelated ones. This property has important implications for our research topic. Let us suppose that a searching agent introduces some innovation and observes a decrease in fitness (a 'failure'). In the case of a simple landscape, such a failure is a reliable signal that the direction taken is leading to a low-fitness portion of the landscape and should therefore be abandoned. In the case of a complex landscape instead, this inference cannot be made as one could experience a failure also when moving in the direction of optimal locations.

Evolutionary economics (Nelson and Winter 1982; Dosi et al., 1988) strongly posits that local (path-dependent) search is the usual way that organisations adopt in their R&D projects: they lean on some (or all) of the technological content that came from their prior search processes. It is fairly obvious that local has a relative, rather than an absolute meaning: local must be referred to both the organisational and the environmental dimensions. According to the literature, local search is mainly dependent on previous R&D investments and their history of success (or failure). This is easy to understand: firms search for new avenues in territories close to their technological base. Which is where their pre-existing knowledge base and their competences would lead them. Evolutionary theory, as well as organisation theory, strongly points to the existence of path dependence in innovative activity (and for the sake of empirical analysis, of previous R&D expenditure). The fitness landscape perspective adds an important qualification: this path dependence may originate from the interdependencies which characterise such complex systems as technologies and organisations. Moreover, interdependencies will not only determine whether the outcomes of search processes depend on initial and intermediate conditions (path dependence) but also whether this path will be either smooth or "bumpy".

On top of this, bounded rationality strongly addresses agents towards local search, as they are taking decisions in condition of true uncertainty, with regard to economic and technological variables. Moreover, by acting within a rugged landscape, firms can hardly compute the whole set of parameters necessary to fully evaluate the likely results of their investments in R&D. For all these reasons, together with those related to the fact that successful firms rely on the experience of their personnel and thus of their cumulated knowledge stock (i.e., their absorptive capacity, Cohen and Levinthal 1989), the management of R&D project typically involves a high degree of localness. This in turn implies that we will presumably find that successful R&D projects will gravitate where firms have accumulated their competences.

However, localness can become a liability, as soon as, for instance, a firm finds itself entrapped in a competence-destroying technological change (Tushman and Anderson 1986). In front of major technological discontinuities firms can find themselves without the knowledge base to deal with the new competitors (Henderson and Clark 1990). In these cases, firms find their competences inadequate to the new challenge posed by a different kind of radical technological change. What is more, their routines and strategies move along a path-dependent search process, thus preventing a quick and effective reaction to the new breakaway. It is, therefore, necessary to be able to revise the path-dependent strategies in case of failure, by moving in a radically different way. A way that is far from previous competences and must explore a bigger portion of the landscape. In so doing agents can move to rather new and unknown territories, where they can build new competitive advantages based on their ability to quickly adapt their knowledge base to the new situation.

3.1. A simulation model

We model a complex technological space as a *NK* fitness landscape, where *N* is the number of dimensions (components, elements, features) and *K* is the degree of interdependencies among such elements, i.e., an indicator of the complexity of the technological space. Each location $l^i = \left[l^i_1, l^i_2, \ldots, l^i_j, \ldots, l^i_N\right]$ is a vector in this space. For simplicity and in line with the standard *NK* model, we assume that each element of this vector can take only two values: 0 and 1. Therefore, l^i is a binary vector and the set of all locations in the landscape is the set of 2^N binary vectors of length *N*.

Each location is assigned a fitness value which is an indicator of the value of that specific technological 'solution'. The fitness value is a simple average of the fitness contributions of each element of the vector:

$$F\left(l^i\right) = \frac{1}{N}\sum_{j=1}^{N} f\left(l^i_j\right)$$

where $f(l_j)$ are random numbers drawn from a uniform distribution on the support $[0,1]$. Such a fitness contribution of element l^i_j is a function of the value taken by l^i_j itself and by *K* other elements with which l^i_j is linked where *K* may vary from 0 (l^i_j is independent of any other element) to $N-1$ (l^i_j is interdependent with all the other elements in the system). For simplicity, we assume that K takes the same value for all elements and therefore characterises the technological systems.

To illustrate by way of an example, suppose that $K = 0$. In this case, $f(l_1)$ can take only two values, e.g., we may have $f(l_1 = 0) = 0.23$ and $f(l_1 = 1) = 0.68$. This implies that, regardless of the values taken by all the other elements, switching l_1 from 0 to 1 always increases the overall fitness of the system. If $K = 0$ for all the elements l^i ($i = 1, 2, \ldots, N$), then each element has an optimal value that is independent of the values of all the other elements and there is a unique optimal location that can be reached by setting each element to its value with the highest fitness contribution. In other words, the optimal location can be reached by moving "uphill" in each dimension and each fitness-increasing movement is certainly a movement in the right direction towards the optimal location.

Suppose instead that $K = 1$ and the fitness contribution of l_1 depends also on the value taken by l_2. In this case, we have four different fitness contributions, for instance: $f\left(l_1 = \frac{0}{l_2} = 0\right) = 0.17$, $f\left(l_1 = \frac{0}{l_2} = 1\right) = 0.53$, $f\left(l_1 = \frac{1}{l_2} = 0\right) = 0.62$, $f\left(l_1 = \frac{1}{l_2} = 1\right) = 0.22$. In this example switching l_1 from 0 to 1 increases fitness if $l_2 = 0$ but decreases it if $l_2 = 1$. So, is it a movement in the right or wrong direction? We cannot give a general answer. Considering that also l_2 is linked with another element (e.g., l_3), the resulting landscape is rugged and the variation of fitness which is observed after a change becomes a less reliable signal that the change was "in the right" direction, i.e., approaching an optimal location.

Kauffman (1993) provides some general results on the properties of such random *NK* fitness landscape. In particular, he shows that, as K increases from 0 towards its maximum value $N - 1$, the number of local optima increases exponentially and the landscape becomes totally uncorrelated, meaning that the fitness value of a location does not convey any information on the fitness value of nearby locations. Thus, a fitness-increasing change is not a signal of a movement in the right direction and vice versa a fitness-decreasing change is not a reliable signal that we are moving in the wrong direction.

In the next subsection, we provide some numerical results on failures and their signalling value. We call 'failure' a fitness-decreasing innovation, i.e., a variation of the current vector or a movement to a novel location $l^h \neq l^i$ that produces a decrease in fitness. Then we ask: is this decrease of fitness a reliable signal that the variation is going in the wrong direction and should therefore be abandoned, or otherwise that it is a temporary decrease of fitness that may later produce a much larger improvement? In other words: is this decrease in fitness a clear sign that we have taken a downhill turn toward a bad portion of the search space or, rather, that we are only crossing a 'valley' and on the other side we will find higher peaks? Obviously, in the former case, we should immediately abandon this path, in the latter instead abandonment may imply foregoing important future gains. It turns out that the answer to this question strongly depends on the complexity of the search landscape, that is the complexity of the technological system.

3.2. Simulation results

We present numerical results for landscapes with $N = 12$ as K varies from its minimum value 0 to its maximum N-1 = 11. We have generated 1000 different random landscapes for each value of K, and the results we present are averages over these 1000 repetitions. Standard deviations are anyway very low and the numerical values we present are very robust. We have also run some simulations for larger landscapes and the results are qualitatively very similar, supporting our intuition that the properties we outline below are very general.

In our first set of simulations, we considered all 2^{12}=4096 locations in the landscape. For each such location l^i we made all 12 possible one-bit mutations, and we recorded them either as "failures" if the new (post-mutation) location had lower fitness than l^i, or as "successes" if the fitness of the new location was greater or equal than the fitness of l^i. Then, for each of these 12 new locations, recorded as either successes or failures, we tried the 11 possible one-bit mutations which generated a new location different from l^i and we recorded whether this new location had higher or lower fitness than the initial condition l^i. If the fitness of this new location was higher than the fitness of l^i, then we recorded it as "success".

Fig. 1 summarises the results, by plotting the probability of observing a success (incremental innovation by mutating one bit) after a success (dotted line), or after a failure (solid line). Results reported in this and the following figure are obtained as averages over 100 repetitions on different randomly generated landscapes. The variance among different repetitions is extremely low. On the horizontal axis, we have K, which is the measure of the complexity of the landscape we defined above. We see that while the probability of having a success conditional on a success decreases as complexity increases, the probability of a success conditional on a failure displays the opposite trend and increases with complexity.

We can thus derive the following hypothesis that we will test on empirical data:

Hypothesis 1. *The likelihood of improving innovative performance due to the introduction of a successful incremental innovation after a failure is positively correlated to the level of complexity of the technological landscape.*

In a second set of simulations, we make a similar experiment but focus on more radical rather than incremental innovations, which in a landscape correspond to the simultaneous mutations of several bits rather than only one.

More precisely, we considered all $2^{12} = 4,096$ locations in the landscape. For each such location l^i we made all possible eight-bit mutations,[3] and we recorded them either as "failures" if the new (post-mutation) location had lower fitness than l^i, or as "successes" if the fitness of the new location was greater or equal to the fitness of l^i. Then, for each of these 495 new locations, recorded as either successes or failures, we tried all possible eight-bit mutations which generated a new location different from l^i and we recorded whether this new location had higher or lower fitness than the initial condition l^i. If the fitness of this new location was higher than the fitness of l^i, then we recorded it as "success".

Fig. 2 compares the probability of observing a success after one failure following a one-bit searching strategy (for the sake of clarity this is a mere replication of the failure part of Fig. 1) with the probability of observing a success after one failure with a more radical strategy (that is, with an eight-bit[4] searching strategy).

We can thus put forward the following hypothesis:

Hypothesis 2a. *In less complex technological environments (sectors) the likelihood of improving the innovative performance due to the introduction of a successful radical innovation after a failure is higher than introducing an incremental innovation.*

Hypothesis 2b. *In complex technological environments (sectors) the likelihood of improving the innovative performance due to the introduction of a successful incremental innovation after a failure is not significantly different from introducing a radical one.*

[3] There are 12!4!8! = 495 possible eight-bit mutations for each binary string of length 12.

[4] We have experimented also with a smaller number of mutations and the results are qualitatively very similar, though of course less strong.

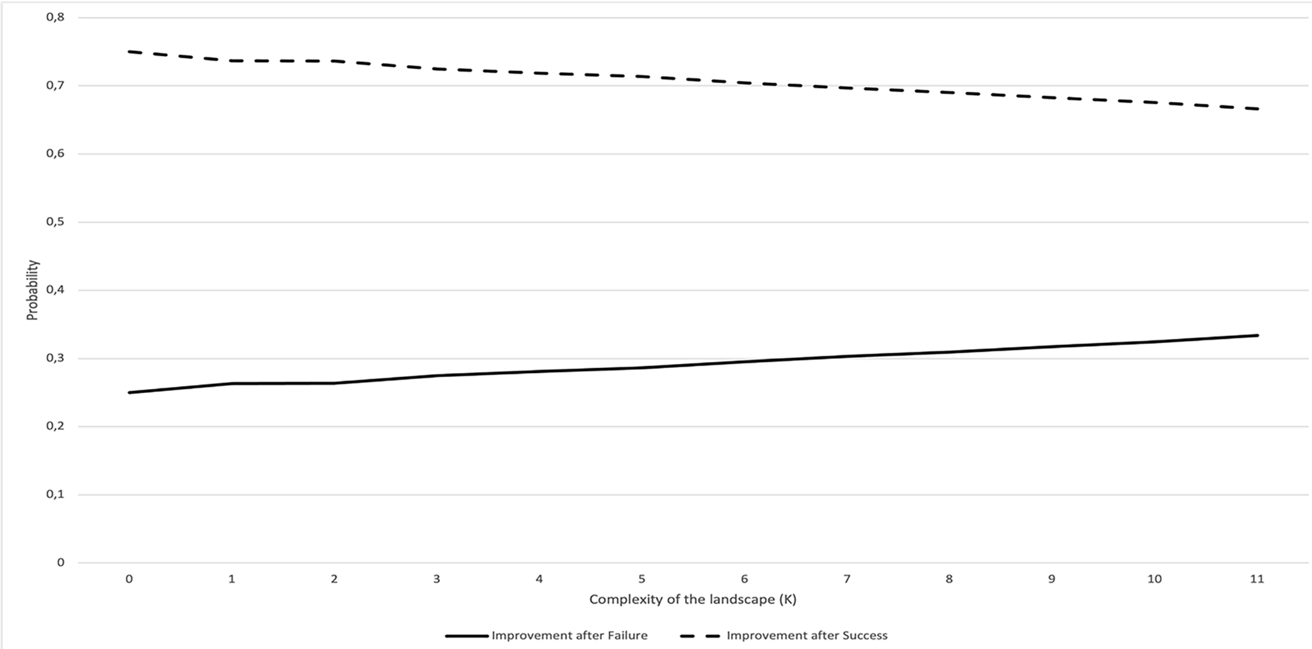

Fig. 1. Probability of success after one failure (one-bit mutation – incremental innovation).

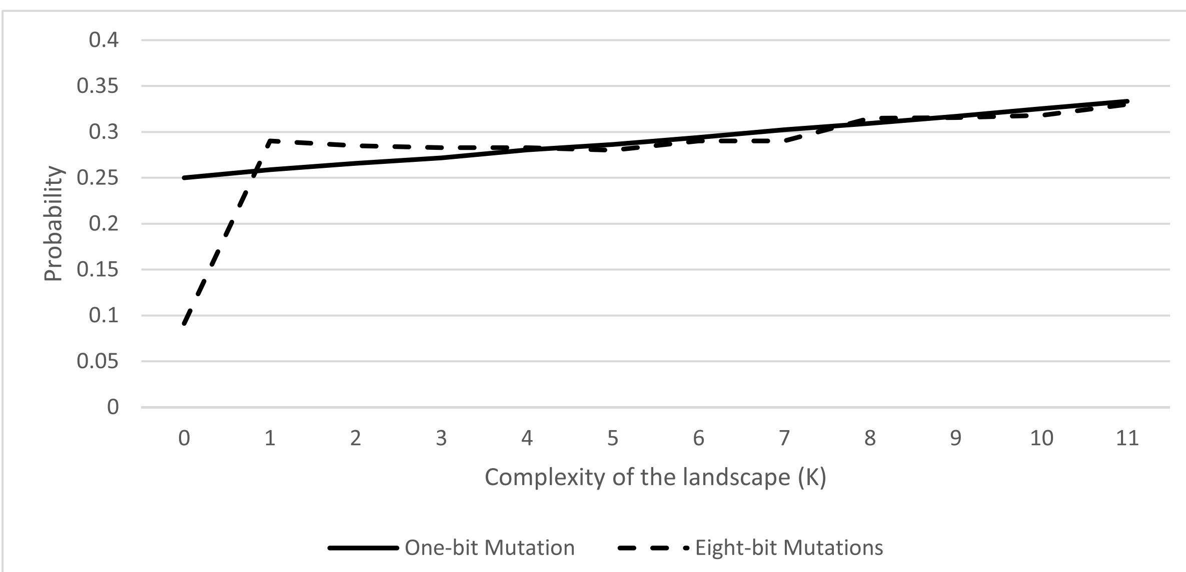

Fig. 2. Probability of success after failure with different search strategy (one-bit mutation – incremental innovation vs. eight-bit mutation – radical innovation).

4. Research design

4.1. Estimation strategy and sample

We empirically test our simulation results through the estimation of a Zero–Inflated Poisson (ZIP) model. ZIP models are designed to take into account adequately the problem related to the excess of zeros in a count model (Cameron and Trivedi, 2005). Indeed, in our dataset we have many firms reporting a zero in our dependent variables regarding their innovative performance. However, the zeros originate from two different generative processes. On the one hand, firms can report no innovative performance because they decide not to innovate. On the other hand, firms can report a zero because, in a particular year, they simply failed to produce an innovative output. Thus, we have two possible meanings for the same count variable (i.e., the zero in the innovative performance variable, that is the zero in the percentage of the total sales due to innovative products/services) that need to be distinguished. The ZIP model allows precisely to deal with this (Cameron and Trivedi, 2005).

Along with the simulation model that distinguishes between complex and less-complex technological landscapes, the estimation strategy has considered the splitting of the sample into two sub-groups: firms belonging to sectors identified as using/producing complex technologies and firms belonging to sectors using/producing less complex (discrete) technologies. The literature widely acknowledges the distinction between discrete and complex technologies (Cohen et al., 2000; Kusonaki et al., 1998; Hall, 2005a). Discrete technologies exhibit a strong product-patent correlation, as observed in sectors such as pharmaceuticals or chemistry. Conversely, complex industries feature modular technology, where individual components can be combined with various additional components to form distinct products, with each component typically protected by one or more patents. As von Graevenitz, Wagner, and Harhoff (2013) state there are no direct measures of technological complexity or related constructs, though Kusonaki et al. (1998) and Cohen et al. (2000) categorize industries as discrete or complex based on ISIC codes.

We follow von Graevenitz, Wagner, and Harhoff (2013) to identify complex and less-complex technologies and translate their classification done on IPC patent classification through the classification of patents in industrial sectors done in Breschi, Lissoni, and Malerba (2003), obtaining a classification of 3-digit sectors into complex and less-complex technology sectors. This classification allows taking into consideration the technological environment into which firms operate, that is the technological landscape on which they move around in the simulation model. We have thus re-estimated our models on two subsets of firms depending on whether the sector in which they operate is either complex or less-complex.

Our empirical analysis is performed on a longitudinal dataset constituted by 10 waves of Community Innovation Surveys (CIS) held in the Netherlands. In this Country, the CIS waves, also before 2008, were held every two years, differently from what EUROSTAT decided for European Countries in general, where the Surveys were performed every four years. We have, thus, merged Dutch Community Innovation Surveys from the CIS2 (1994–1996) to the CIS 2014, and built a panel data considering that the same small and medium-sized firms were repeatedly present in the waves (beyond the large firms that usually are always present). In this way, we can construct a representative unbalanced panel dataset. We started considering all sectors (for around 19,000 observations). We follow the OECD classification and identify three categories of size: small firms with less than 50 employees, medium firms with more than 50 and less than 250 employees and large firms with more than 250 employees. We also use the OECD classifications for the classification in macro-sectors based on the technology intensity for manufacturing industries, and on knowledge intensity industries for services industries. We exclude five industries, namely: mining, agriculture, energy, water and waste, and construction.[5] More specifically, for the manufacturing industries we identify four macro-sectors: high-tech, medium-high-tech, medium-low-tech and low-tech sectors. For services the four macro-sectors identified are: high-tech knowledge-intensive services, knowledge-intensive market services, knowledge-intensive financial services, and other knowledge-intensive services.

We decided to restrict our analysis to Small and Medium Enterprises - SME (defined according to the OECD classification as those firms with 10 – 250 employees) because of the particular nature of our main variable of interest, the abandoned innovation projects. In fact, the CIS question asks whether a firm has abandoned an innovative project; it does not ask how many projects were carried out inside the firm. Large firms can easily drop an innovative project and keep carrying on with the others, the consequences being very limited.

However, on one hand, we reckon that if we consider only SMEs this problem could be substantially reduced for at least two reasons. On the other hand, there are at least two arguments for supporting our idea that previous abandoned research projects can influence the development of a subsequent innovation especially if they are SMEs. The first is related to the fact that firms build their knowledge stock on the entire sets of routines, procedures and competences matured during the development of an innovation. The knowledge stock so constructed does not regard only technological knowledge, but skills and capacities that concern the different phases of the innovation process, for example, when to introduce successfully an innovation into the market or how to organise the internal procedure to smooth the passage from the R&D laboratories to the industrialization department of a product or the successful marketing to sell a product innovation on the market. Therefore, when we talk about the influences of past abandoned innovations on future ones, we refer to the broad knowledge stock that is accumulated in the firm developing an innovation that concerns a large variety of skills, competencies and capabilities. The technological knowledge that can derived from a previous abandoned innovation project is just a small set of this knowledge stock.

The second is related to the fact that since firms build their knowledge stock through, formal or informal, R&D activities, even when they fail, their search must be local in order not to waste the accumulated knowledge. Thus, also the failed project helps in building the knowledge stock necessary to be successful in the next future. In this regard it is not the precise content of an innovative project (failed or not) that gives an opportunity to the firm, but it is its position in the landscape (i.e. the accumulated knowledge) that allows firms to benefit from moving on in another, presumably better, place on the rugged landscape.

Moreover, SMEs usually do not perform many innovation projects simultaneously, and the failure of one single project, being the only one innovative project, could even cause the firm's bankruptcy. Therefore, we decide to develop our analysis on a more homogeneous group of firms, the SMEs, in which the abandonment of just one innovation project can be crucial for the future and the survival of the firm. The sample of SMEs is constituted by 3496 observations during the period 1994 to 2014.

4.2. Model and variables

As explained in the previous section, in order to model what is the relationship between abandoned innovations and the firms' innovative performance, we estimate a Zero–Inflated Poisson (ZIP) model. ZIP models are designed to take into account in a proper way the problem related to different generative processes and the excess of zeros in a count model. Indeed, in our dataset we have firms reporting a zero to our categorical data regarding the performance of their innovative activity. However, the zeros can originate from two different generative processes. On the one side, firms can report zero as a measure of performance of innovative activity because they decide not to invest in, and therefore not to carry out, innovative activities. On the other side, firms can report a zero because they simply failed to produce an output out of their innovative project. Thus, we have two possible meaning for the same count variable (i.e., the zero in the innovative performance variable) that need to be distinguished (Cameron and Trivedi, 2005; pag. 681).

Formally, the ZIP model is a statistical model constituted by two components, each representing distinct zero-generating processes. The initial process is regulated by a binary distribution, that generates structural zeros (in our case a logit distribution). The subsequent process operates under a Poisson distribution, generating counts, some of which can be zero. The two-model components are described as follows:

$$Pr\left(y_j = 0\right) = \pi + (1-\pi)e^{-\lambda}$$

$$Pr\left(y_j = x_i\right) = (1-\pi)\frac{\lambda^{x_i}e^{-\lambda}}{x_i!},\ x_i \geq 1$$

where the outcome variable y_j has any non-negative integer value, λ_i is the expected Poisson count for the ith individual; and π is the probability of extra zeros. The two-model components are estimated simultaneously.

4.2.1. The binary model

We estimate the first component of the ZIP model through a Logit model. The empirical model is the following:

[5] See the OECD classification at: https://ec.europa.eu/eurostat/statisticsexplained/index.php?title=Glossary:High- tech_classification_of_manufacturing_industries for manufacturing sectors https://ec.europa.eu/eurostat/ statistics-explained/index.php?title=Glossary: Knowledge-intensive_services_(KIS) for services sectors.

$$Pr(InnovSales)_{it} = logit(\alpha + \beta Innov_{it-1} + \theta X_{it} + \gamma_s + \delta_t)$$

where i and t are firm and year subscript, whereas c stands for macro-sectors according to the OECD classification; $Innov_{it-1}$ is the main variable of interest; $X_{it}$is a vector of control variables at the level of the firm; γ_s are sectors fixed effects and $\delta_t$time fixed effects. (*t-1*) identifies the previous CIS, not the previous calendar year.

The dependent variable of the logit model (*InnovSales*) is a binary variable that is equal to 1 when, at time (t), the percentage of total sales due to innovative products/services sold is strictly positive; 0 otherwise. We differentiate among the percentage of total sales generated by producing and selling products and services new-to-the-firm and the percentage of total sales generated by producing and selling products new-to-the-market (as more extensively explained in the next subsection), and, therefore, we estimate two different models with two different dependent variables: percentage of total sales due to "New to the firms" products/services and "New to the market" ones (see Table 1).

To model such probabilities the crucial independent variable is a binary variable (*Innov* in the equation and "*Being an Innovator at (t-1)*" in the Table 1) that is equal 1 when the firm was an innovator at time *(t-1)*, that is, introduced either a product, process, organisational, or a marketing innovation at time (*t-1*) during the previous three years of the previous CIS (as defined by an entry question in the survey). In fact, several studies have shown that innovative activities carried out inside the firms are persistent due to a multiplicity of factors (investments in R&D that constitute sunk costs; the accumulation of technical and managerial knowledge, among others) and therefore past innovation is a strong predictor of future innovation (Cefis, 2003; Peters, 2009; García-Quevedo et al., 2015).

The types of markets, in terms of size and internationalisation, on which firms sell their products/services can be an important factor in predicting the probability that they will engage in innovation activities. Larger and more international markets can increase the pressure on firms to innovate and introduce new products or services. This may be due to increased competition and the need to differentiate oneself from competitors in order to succeed in the marketplace. (Belderbos et al., 2004; Cesaroni and Piccaluga, 2016). Consequently, we include four binary variables depending on the type of market firms declare they are active in: firms can be present on markets classified as local, national, European, or international markets other than the European one.

Then, we added control variables at the level of the firm, namely age (years) and size (number of employees). The debate on the effects of firm size and age on innovation in SMEs is similar to the broader debate on firm size and innovation, but with some nuances. On one hand, some studies suggest that larger SMEs have more resources (financial, human capital, networks, etc.) and capabilities to innovate than smaller SMEs (Love et al., 2009; Zeng et al., 2010). On the other hand, smaller SMEs may be nimbler and more flexible, able to quickly respond to changing market conditions and customer demands (Drejer, 2004; Henrekson and Johansson, 2010). Age seems to influence innovative activities inside SMEs, even if the relationship between age and innovation is a complex and multifaceted issue. While older SMEs may have certain advantages in innovation, younger SMEs may also have unique strengths that enable them to compete effectively in the marketplace (see among others Coad, 2007; Morone and Taylor, 2018; Leoncini et al., 2019).

In order to control for the industry structure, we compute the C4 index for each 3-digit sector. Based on the share of the market held by the biggest four firms in a sector the index is a measure of the concentration of the market in a particular sector which is often used as a measure of market power or competition. Starting with Schumpeter (1941) there has been quite a debate on what is the degree of competition that enhances innovation. In general, the relationship between C4 concentration and innovation is context-dependent and varies across industries and markets. While higher levels of concentration are generally associated with lower levels of innovation, there may be specific circumstances where higher concentration is associated with higher levels of innovation (Geroski, 2000; De Loecker and Eeckhout 2017).

4.2.2. The count model

We estimate the second component of the ZIP model through a Poisson model. The empirical model is the following:

$$\begin{aligned} InnovTotalSales_{it} = poisson(&\alpha + \beta AbanInnov_{it-1} + \eta Breath_{it} \\ &+ \sigma(AbanInnov_{it-1} * Breath_{it}) + \zeta lnExpInnov_{t-1} \\ &+ \varphi(\beta AbanInnov_{it-1} * lnExpInnov_{t-1}) \\ &+ \theta X_{it} + \ \gamma_s + \delta_t + \varepsilon_{it})) \end{aligned}$$

where i and t are firm and year subscript, whereas c stands for macro-sectors according to the OECD classification; $AbanInnov_{it-1}$ is the main variable of interest that takes value 1 if the firm has declared to have abandoned an innovation project in the previous 3 years; $Breath_{it}$ the breadth with which firms benefit from external sources of knowledge; $\ln ExpInnov_{t-1}$ the ln of the innovation expenses recorded in the previous CIS; $X_{it}$is a vector of control variables at the level of the firm; γ_s are sectors fixed effects and δ_t time fixed effects; ε_{it} are standard errors clustered by firm. The ZIP model estimates simultaneously the binary model and the count one.

In our count model, the dependent variable is the innovative performance of the firm, which we considered in two different specifications. Sales from innovative products/service has been widely used in the literature as a measure of the output of the innovation process (Frenz and Ietto-Gilles, 2009; Laursen and Salter, 2006; Arora et al., 2016). Our first indicator for firms' innovative performance is the percentage of total sales generated by producing and selling products and services new-to-the-market (*new to the market*). This indicator is meant to capture the high degree of novelty of the innovative products/services sold by the firm with respect to the market, to which we refer as "radical innovative products/services" Our second indicator is the percentage of total sales generated by producing and selling products and services new to (or significantly improved by) the firm (*new to the firm*), but already introduced in the market by competitors. As this indicator relates to already existing innovative products/services, it informs us on whether firms are able to carry on incremental innovations, which might be useful in the case of small and medium firms. The terms "radical" and "incremental" innovation want only to stress the fact that in order to introduce a product/service "new to the market" (radical innovation), the firm need to discover an invention and be able to transform it in a innovation, while to introduce a product/service "new to the firm" (incremental), the firm need "only" to imitate something that has already been invented. The two indicators have been extensively used in the literature, see for example: Tether, 2002; Higón, 2016; Roper and Hewitt-Dundas, 2017; Blind et al. 2022. We used the two different indicators to match, in empirical data, what in the simulation model has been referred to as one-bit mutation (incremental innovative products/service) versus eight-bit mutation (radical innovative products/services).

Since the large majority of firms' answers regarding the innovative turnover are expressed in deciles, we decide to create our two categorical variables diving the positive values (strictly greater than zero) in deciles (1–10 %; 11–20 %; …; 91–100 %), obtaining in this way our two count variables.

Firms' failure in innovation projects is our main variable of interest. We use as a proxy of such a theoretical variable a dummy variable contained in the CIS that indicates whether the firm in the previous three years has abandoned an innovative project in a new, or improved, product or service.

In the literature it has been repeatedly stated that past innovation expenses can play a significant role in shaping future firm's innovative performance by contributing to knowledge accumulation, R&D capabilities, intellectual property creation, reputation and brand, and other factors that can enhance a firm's ability to innovate and compete in the market (see among others: Nelson, 1982; Cohen and Levinthal 1989; Liao and Welsch, 2005). To capture the relation between past innovation expenses and future firm's innovative performance we added the (ln of) expenses done by the firms in all innovative activities at time (*t-1*). This indicator refers to all the expenses the firm has sustained in the last year of the CIS (*t-1*) to foster innovation: it includes R&D (intramural and extramural) expenses plus purchase of innovative machinery, computer hardware and software purchased specifically for innovation, costs for patents and licences, marketing research and training of R&D personnel.

Firm's knowledge plays a critical role in innovative performance, as it enables firms to create, share, and utilise knowledge to drive innovation and stay ahead of the competition. By investing in knowledge creation, sharing, and utilisation, firms can enhance their ability to innovate and achieve sustained competitive advantage in the marketplace. In particular, Laursen and Salter (2006) studied the role of a firm's knowledge base in shaping its innovative behaviour, specifically in terms of the breadth with which firms benefit from external sources of knowledge. The authors argue that firms with broader knowledge bases are better able to access and utilise external sources of knowledge, which in turn facilitates their ability to innovate. In order to deal with the role of firm's knowledge in innovative behaviour, we considered the breadth with which firms benefit from external sources of knowledge (*Breadth*). This variable is obtained by assigning a value of 1 if a source (out of the possible 10) is used, with no consideration for its relative importance, while it is 0 if none of the possible sources were used. A count variable is then built by summing the values for the 10 different possible sources: a high score (with a maximum of 10) indicates that the firm has used a wide array of knowledge sources, while a low score (the minimum being 0) indicates that the firms has benefited from few knowledge sources (whatever their importance) (Laursen and Salter 2006).

Finally, we also computed a dummy variable to capture whether the firm is part of an industrial group (*Group*), which could have a differentiated influence depending on the role of the firm within the group. In general, we expect that small and medium firms may be subject to the group strategy about innovative policy thus hindering their innovative activities.

As already mentioned, we also computed a dummy variable to distinguish between firms active in complex and less-complex sectors following von Graevenitz et al. (2013) classification (*Graevenitz*).

Finally, we include fixed effects in time and macro-sectors to control for unobserved heterogeneity.

5. Results

5.1. Results for the whole sample

Table 1 reports the estimates obtained through a panel dataset Zero–Inflated Poisson (ZIP) regression model. The top panel (labelled 1st component) shows the results for the first stage of the ZIP regression, that is, the binary (logit) model estimating the probability of having a zero in the dependent variable.[6] The bottom panel (labelled "The 2nd component") shows instead the count model estimating the innovative performance for those firms that present strictly positive innovation sales. For each sample (All firms; Complex Technologies; Less-Complex Technologies) the first column shows the results for firms' sales due to products new-to-the-firm, while the second column reports the results for firms' sales due to products new-to-the-market.

The logit model, testing for the probability of recording zero as the level of innovative performance, shows some interesting results. The first expected result is that being an innovator in the previous period (*t-1*) is significant and negative, that is, being an innovator at time (*t-1*) (that is, as recorded in the CIS (*t-1*)), decreases the probability that the 0 recorded as our dependent variable at time (*t*) is a true zero (firms record "true zeros" when decided not to innovate and therefore they do not have any part of total sales due to new or improved products/services). In other words, being an innovator in the previous period decreases the probability that the recorded zero is the results of the firm's decision of not to innovate at time (*t*) but rather is because the firm reports a zero due to the fact in that particular period (*t*) the firm fails to produce an innovative output. The results do not change whether we consider new-to-the-market or new-to-the-firm innovative performances. However, the coefficient is slightly larger when new-to-the-market products/services are considered. It is confirmed that innovative activities carried out inside the firms are persistent (Cefis, 2003; Cefis and Orsenigo, 2001).

The different types of markets, in terms of size and internationalisation, in which firms are active have different influences on the probability of recording a "true zero". Being active in local markets seems to be more important for not recording a "true zero" in case of new-to-the-firm innovative sales. On the other hand, being active in national markets seems to have the same importance in affecting the probability of recording a true zero either in case of new-to-the-firm or new-to-the-market innovative sales. As for these latter, foreign markets assume a more relevant role. Being active in the European market and in other international markets decreases significantly the probability of belonging to the group of firms that record zero because they decide not to innovate, especially if firms sell products/services that are new-to-the-market. These results support the previous findings that larger and more international markets increase the pressure on firms to innovate and introduce new products or services (Belderbos et al., 2004; Cesaroni and Piccaluga, 2016).

Moreover, for new-to-the-market innovative sales the industrial structure appears to be quite important: the higher is the concentration of the market, the higher is the probability that firms decide not to innovate. The coefficient of industry concentration (C4) appears only relevant for new-to-the-market innovation. The results suggest that higher levels of concentration are generally associated with lower levels of innovation (Geroski, 2000; De Loecker and Eeckhout (2017).

Finally, firm's size turns out to have a positive and relevant role, while age is never significant and does not constitute a distinctive factor in the probability to sell innovative products/services in the market.

The second stage of the regression procedure evaluates the count variables for strictly positive values of total sales due to innovative products/services. As for this, our main variable of interest, the abandonment of an innovative project in the previous three years, is significant and increases the innovative performance of the firms with regard to products/services that are either new-to-the-firm or new-to-the-market. The results support that the learning acquired from abandoned innovative projects are actually very important for being able to produce and successfully commercialise products, and it is more so for new-to-the-firm innovative sales.

The opposite holds for the variable related to the firm's knowledge base (*Knowledge breadth*) the firm. In particular, the knowledge breadth variable is only significant for new-to-the-market innovative sales, and it suggests that to produce new-to-the-market innovative sales several sources of knowledge have to be used, while they are not particularly useful for new-to-the-firm innovation. These results seem to provide support to the idea that firms with broader knowledge bases are better able to access and utilise external sources of knowledge, which in turn facilitates their ability to innovate (Laursen and Salter, 2006). Also interacting breadth with abandoned innovation, the coefficient is only significant for new-to-the-market innovative sales.

The variable that captures the firm's investment in innovation at time (t-1) is positive and significant: increasing the investment in innovative activities at time (t-1) increases the firm's innovative performance at time (t) in both new-to-the-firm and new-to-the-market

[6] It is important to note that the results of the logit model are a bit counterintuitive, as a negative sign of a parameter implies a positive probability of having a positive result, or in other words a negative probability of having a zero.

Table 1a
Zero Inflated Poisson estimates on different samples – The first component: The Binary Model.

LOGIT MODEL	SME Firms		Complex technologies		Less complex technologies	
	New to the firm Mod. 1	New to the market Mod. 2	New to the firm Mod. 3	New to the market Mod. 4	New to the firm Mod. 5	New to the market Mod. 6
Being an Innovator at (t-1)	−1.224***	−1.236***	−1.580***	−0.726**	−1.031***	−1.649***
	(0.218)	(0.236)	(0.420)	(0.366)	(0.283)	(0.318)
Local Market	−0.210**	−0.167	−0.304**	−0.0991	−0.177	−0.195
	(0.105)	(0.118)	(0.153)	(0.169)	(0.156)	(0.181)
National Market	−0.788***	−0.728***	−0.704***	−0.713***	−0.985***	−0.796***
	(0.174)	(0.192)	(0.251)	(0.267)	(0.255)	(0.291)
European Market	−0.508***	−0.564***	−0.582**	−0.624**	−0.245	−0.298
	(0.161)	(0.169)	(0.259)	(0.256)	(0.223)	(0.245)
Other Internationa Markets	−0.248**	−0.844***	−0.265	−0.764***	−0.216	−0.926***
	(0.120)	(0.130)	(0.214)	(0.210)	(0.158)	(0.185)
Concentration Index C4	0.506	2.402***	0.102	1.452*	−2.061	0.0904
	(0.625)	(0.763)	(0.765)	(0.853)	(2.737)	(2.976)
Size (ln Employees)	−0.301***	−0.285***	−0.273***	−0.276***	−0.410***	−0.342***
	(0.0610)	(0.0672)	(0.0912)	(0.0917)	(0.0904)	(0.112)
Age (ln Years)	0.00113	0.00207	0.00184	0.00347	0.00107	0.000845
	(0.00239)	(0.00273)	(0.00390)	(0.00445)	(0.00319)	(0.00383)
Constant	4.520***	3.959***	5.248***	4.008***	4.024***	3.628***
	(0.445)	(0.467)	(0.705)	(0.667)	(0.620)	(0.684)
Fixed effects:						
Sectors	Yes	yes	yes	yes	yes	yes
Years	Yes	yes	yes	yes	yes	yes

Table 1b
Zero Inflated Poisson estimates on different samples – The second component: The Count Model.

COUNT MODEL	SME Firms		Complex technologies		Less complex technologies	
	New to the firm Mod. 1	New to the market Mod. 2	New to the firm Mod. 3	New to the market Mod. 4	New to the firm Mod. 5	New to the market Mod. 6
Abandoned Innovation at (t-1)	0.640**	0.556**	1.468***	0.860***	0.979***	1.295***
	(0.254)	(0.281)	(0.474)	(0.332)	(0.321)	(0.381)
Knowledge Breadth	0.00342	0.0392*	0.0390	−0.00958	−0.00257	0.141***
	(0.0245)	(0.0233)	(0.0418)	(0.0277)	(0.0342)	(0.0395)
Abandoned x Breadth	0.00497	0.0220**	−0.1000*	0.0344**	0.0152	−0.174***
	(0.0101)	(0.0100)	(0.0579)	(0.0135)	(0.0155)	(0.0534)
Abandone Innovation x Lg Exp. Inn.	−0.102**	−0.121***	−0.130**	−0.161***	−0.152***	0.0168
	(0.0401)	(0.0455)	(0.0523)	(0.0522)	(0.0523)	(0.0336)
Log Expenditure Innovation (t-1)	0.0744***	0.0994***	0.0945**	0.157***	0.0733**	−0.0039
	(0.0248)	(0.0268)	(0.0406)	(0.0333)	(0.0309)	(0.0472
Group	0.0365	−0.330***	0.0983	−0.353***	−0.0358	−0.292**
	(0.0838)	(0.0780)	(0.118)	(0.108)	(0.113)	(0.114)
Graevenitz Dummy	0.212***	0.210***				
	(0.0816)	(0.0780)				
Constant	−0.0612	−0.276	−0.195	−0.115	−0.0789	−0.587
	(0.200)	(0.237)	(0.336)	(0.266)	(0.264)	(0.358)
Fixed effects:						
Sectors	yes	yes	yes	yes	yes	yes
Years	yes	yes	yes	yes	yes	yes
Observations	3496	3496	1496	1496	2000	2000
Chi2	22.74	46.49	34.30	46.03	12.96	22.18
p-value Chi2	0.00189	7.01e-08	0.0115	0.000294	0.0436	0.000483
log Pseudo Likelihood	−4101	−4072	−1.786	−2055	−2274	−2178

Standard errors clustered by firms in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

products and services. These results confirm what the literature has recurrently found: past innovation expenses play a significant role in future firm's innovative performance since they enhance a firm's ability to innovate and compete in the market (Nelson, 1982; Cohen and Levinthal 1989; Liao and Welsch, 2005). The investment in innovative activities to be carried out inside the firm (*Expenses in Innovation*) could also capture the source of the firm's knowledge. Investing in internal innovative activities emphasises that firms do build their knowledge base especially inside the firm and this knowledge base plays a crucial role in explaining innovative performance. Interestingly, the variable that interacts with abandoned innovation with expenses in innovation is significant and negative. The result could be interpreted as the fact that for the subsample of failed projects looking for knowledge inside the firm has a negative impact, which might imply that in front of a failure firms should rely on external knowledge more than on internal knowledge to better understand what went wrong in the abandoned innovation project.

Finally, being part of an industrial group affects radical innovation in a negative way, as within a group the level and direction of innovative activity can be well decided strategically: "local" innovativeness might be sacrificed because of its impact can be evaluated at the "global" (the group) level.

We finally used as a regressor a dummy dividing the sample into two subsets, by referring to the division of sectors into complex and discrete put forward in von Graevenitz et al. (2013), which turned out to be strongly significant. As a result of this, we decided to make a further robustness check by splitting the sample into two different sets of firms: those active in complex technologies sectors and those active in less-complex ones.

5.2. Failure and innovation with different landscapes

The results of the sample splitting into complex and less-complex landscapes are presented in Models 3 and 4 and Models 5 and 6 of Table 1 respectively. Again, also for these two sets of regressions the upper panel of Table 1 (the 1st part) refers to the first stage of the Zero Inflated Poisson regression, i.e., the logit model that calculates the probability of belonging to the group of "true zero", that is to the group of firms that decide not to innovate and therefore record zero percentage of total sales due to innovative products and services. The bottom panel of Table 1 (the 2nd part) refers to the count model that evaluates the strictly positive part of the model.

The main results that seem to emerge from the regressions are the following.

As for the binary model, the results obtained by splitting the sample into complex and less-complex technologies substantially confirm those obtained for the whole sample but with some exceptions. In fact, there are some significant differences, confirming that considering the technological environment in which firms operate offers interesting insights on the innovative activity of the firms. First, the role of previous innovative activities is confirmed, although the coefficients are different, and they are somewhat counterintuitive, in the sense that a priori we would have expected the opposite. The largest significant coefficients are those for incremental innovative products/services (i.e., new-to-the-firm) in complex environments, and for radical innovative products/services (i.e., new-to-the-market) in less-complex ones.

The role of the market, especially the European market, emerges as more important for firms in environments with complex technologies, less so for firms in less-complex ones. Finally, also the industrial structure acts through different channels in the two different environments: through concentration for new-to-the-market innovative activities in complex landscapes (i.e., the role of concentration index), and while in less-complex landscapes, the concentration index is not significant, but the role of size is more important for both types of innovative activities. The results of the second stage highlight the role of abandoned innovation that, with respect to the whole sample, shows a higher correlation with incremental innovation in complex environments, while in less-complex ones, the higher correlation is with new-to-the-market innovative performances.

Also, the role of breadth is changed, as it is only statistically significant for new-to-the-market innovative products/services in less-complex sectors, although it is smaller whether the set of firms that abandoned innovation is considered. The opposite holds for complex landscapes, where for new-to-the-market innovation the only significant breadth co-variate is the interacted one: in this case breadth is relevant only for firms that abandoned an innovative project. The role of previous period expenditure in innovative activities is confirmed, with the only notable exception to new-to-the-market innovation in less-complex environments: the coefficient is not statistically significant, to prove that within this particular landscape, radical innovation is not the best strategy. This is confirmed by the interacted variable with abandoned innovation, which is also statistically not significant.

5.3. Discussion of the hypotheses

Overall, the estimation strategy seems to confirm our working hypotheses.

Our first testable hypothesis (Hp1: The probability of having a successful incremental innovation after a failure is positively correlated to the level of complexity of the technological landscape) is confirmed. Indeed, the coefficient of abandoned innovation in the previous 3-year period is significant and higher for new-to-the-firm innovative products/services in complex technological sectors (1.468 in Mod. 3) than that for the same type of products in less-complex technological sectors (0.979 in Mod. 5). This empirical finding confirms our simulations, as they provide empirical evidence of a positive relationship between failure in innovative projects and positive probability to improve the innovative performance. This is the most important result of our model, as it confirms the results obtained in previous works about the positive role of failure in spurring learning in innovative activity because of unexpected negative events. The positive role of search and creative trial (Townsend 2010) that was evidenced by our simulation model is thus empirically confirmed, and it is reinforced by the interaction with external knowledge sources (Kim and Miner 2007). The outside industrial environment is indeed a powerful supplier of knowledge acquisition, in both innovation collaboration (e.g., Lhuillery and Pfister, 2009) and networking (Hadjimanolis, 1999).

As for the second hypothesis, we find support for hypothesis 2a (Hp2a: In less complex technological environments (sectors) the likelihood of improving the innovative performance due to the introduction of a successful radical innovation after a failure is higher than introducing an incremental innovation). Indeed, in less-complex technological sectors, abandoned innovation has a larger impact in reference to radically (new-to-the-market) innovative products/services (1.295 in column 6) with respect to that obtained in reference to incrementally (new-to-the-firm) innovative products/services (0.979 in column 5). This is a quite significant result, as it deals with a very important issue related to the effectiveness of the different types of innovative activities (radical vs incremental) within more "predictable" (Cannon and Edmondson 2005) kind of technological environment (e.g., Chesbrough 2010; Chiou et al. 2012), and this result seems to be more counterintuitive and maybe useful for policy purposes.

We do not find, however, strong evidence on hypothesis 2b (Hp2b: In complex technological environments (sectors) the likelihood of improving the innovative performance due to the introduction of a successful incremental innovation after a failure is not significantly different from introducing a radical one). Indeed, in this case, we would have expected the two coefficients of abandoned innovation related to new-to-the-firm and to new-to-the-market in complex technologies to be very similar, while one is almost the double of the second one (1.468 vs 0.860). However, a closer look at Fig. 2 might supply some evidence in favour of our empirical results. Indeed, as the complexity of the landscape increases (i.e., as we move to the right of Fig. 2), radical innovation produces a cyclical pattern, while incremental innovation produces a steady increase in performance. This might be interpreted as a more robust performance improvement from incremental innovation with respect to the radical ones, which being cyclical would not produce a consistently better performance with respect to the incremental type of innovative activity.

6. Conclusions

The role of failure in determining how organisations learn to innovate has been nowadays established by a relevant number of both qualitative and quantitative analyses. This paper, which is positioned in the latter stream of literature, addresses the three most relevant elements characterising organisational learning: the internal one (i.e., the previous innovative experience), the external one (i.e., the knowledge acquired from outer environment), and the learning-by-failing one. Building a theoretical model, we are able to accomplish the task of establishing clear relationships among different types of learning and firm's innovative performance. Moreover, as we can also incorporate a sufficiently long observational period, we succeed in keeping endogeneity problems under control.

The main results of this paper are related to how the different dimensions of learning impact the innovative performance. Our working hypotheses, which are derived from the simulation of a formal model of learning-by-failing, confirm the main results of the budding literature on the topic, as previous failure in innovative projects is positively and statistically related on firms' innovative performance captured by the percentage of total sales due to both new-to-the-market and new-to-the-firm products and services.

Furthermore, learning-by-failing plays a crucial role in enhancing firms' innovative performance with different nuances whether we distinguish between incremental and radical innovation. In fact, the former allows firms to increase their probability of success over the whole spectrum of environment complexity, thus confirming the important role that incremental innovative activity has in many industries with different degrees of technological complexity. With respect to this, radical innovation seems to have a more localised impact, that is limited to less-complex environment characteristics.

Some managerial implications can be derived. First, learning-by-failing should be encouraged. Managers should create a culture of learning from failures within the organisation. Failure should not be stigmatised, but rather seen as a learning opportunity for the entire organisation. This can lead to improved innovative performance over time. Second, firms should invest in all types of learning to enhance their innovative performance. Investing in all types of learning can help firms enhance their innovative performance by creating a culture of continuous learning and improvement, leveraging external sources of knowledge, and fostering collaboration and knowledge-sharing across the organisation.

Also, some policy implications can be derived. Policymakers can encourage firms to experiment with new ideas and technologies by providing funding for pilot projects and experimentation. This can create a culture of learning by failing and allow firms to identify and address challenges before scaling up their innovations. Furthermore, specific incentives could be created for firms to take risks and engage in particularly risky, and therefore more probable to fail, innovative projects.

As always, it is important to contextualize the results and contributions of this study within the framework of its limitations. First, even if we have tried our best to match the simulation and the empirical analysis, of course the matching cannot be perfect as in the case of the definition of complexity. We follow Graevenitz et al. (2013) to measure Complexity, but obviously the method does not fit completely with the notion of NK-model complexity. The correspondence cannot be perfect because in mathematical models as simulations, all the conditions are set in a precise way, while in the empirical analysis we try as best as we can to control for factors, but, obviously, we do not have the precise control of what happens in realty. Second, the empirical analysis is limited and constrained by the data available. So, for example, we have empirically modelled that the investments in innovative activities should show they results in terms of sales due to innovative product/services after two years, but obviously this is an assumption that does not consider multi-year research projects or projects that successed after a time longer than two years. Despite these limitations, our study highlights how learning-by-failing constitutes an important element in the process of climbing the "rugged landscape" of performance especially because of the temporal spillovers in the search process. The trade-off in the search pattern that organisations need to solve changes its nature once it is evaluated from a dynamic perspective. Over time exploration can determine opportunities that the firms will subsequently adopt. In turn, these activities can produce knowledge to be used in future searches on the landscape.

CRediT authorship contribution statement

Elena Cefis: Conceptualization, Data curation, Formal analysis, Funding acquisition, Supervision, Validation, Visualization, Investigation, Methodology, Project administration, Resources, Software, Writing – original draft, Writing – review & editing. **Riccardo Leoncini:** Formal analysis, Funding acquisition, Investigation, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing, Methodology, Project administration, Resources, Conceptualization, Data curation. **Luigi Marengo:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing, Supervision.

Declaration of competing interest

We declare no conflict of interest whatsoever in connection to the present paper.

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Data availability

Data come from a proprietory data based which can be accessed only by subscription

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