Research Policy 53 (2024) 105022

Contents lists available at ScienceDirect

Research Policy

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

Scientific decision-making, project selection and longer-term outcomes

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ARTICLE INFO

JEL classification:
O30 (Innovation)
L26 (Entrepreneurship)
C93 (Field Experiments)

Keywords:
Decision making
Scientific approach
Field experiments
Idea value
Project selection
Innovation

ABSTRACT

Analyzing data from two randomized controlled trials (RCTs) involving 382 entrepreneurs, this study explores the implications of training a group of entrepreneurs in a scientific approach to decision-making on their project selection. It provides evidence that the documented increased likelihood of project termination by 'scientific' entrepreneurs is associated with higher accuracy in recognizing project value. Unlike the control group, they are quicker in adjusting their expectations on project value downward before making the termination decision. This study also fills an important gap in prior research by exploring the longer-term implications (up to five years after the training began) of a scientific approach. It shows that, over the longer term, the initial discrepancy in termination rates between treated and control entrepreneurs levels out, with the control group eventually exhibiting a higher rate of project termination. Scientific entrepreneurs generate a higher number of new ideas, and a higher proportion of their projects culminate in the launch of a venture. Overall, these findings support the notion that scientific entrepreneurs are not excessively critical in their project assessments; rather, by terminating lower-potential projects earlier, they can free up resources for redeployment elsewhere.

1. Introduction

Entrepreneurs encounter critical decisions during the process of transforming their entrepreneurial ideas into viable ventures (Andries and Hünermund, 2020; Brown and Eisenhardt, 1997; Feldman, 2001; Gans and Stern, 2017; Teece, 1986). An emerging stream of research has suggested that one way to deal with this type of decision is to follow the approach used by scientists in their investigations – that is, to develop a theory about the situation and choice faced and validate it with rigorous tests. Conceptual work has referred to this as to the Entrepreneurs-as-Scientists (E-a-S) approach to decisions (Zellweger and Zenger, 2022; see also: Ehrig and Schmidt, 2022; Felin et al., 2023, 2024; Felin and Zenger, 2009, 2017; Wuebker et al., 2023). The first empirical evidence for this approach is provided in a pilot study by Camuffo et al. (2020) and corroborated in a larger scale study by Camuffo et al. (2024). They observe a randomly selected sample of entrepreneurs trained to make decisions like scientists vis-à-vis a control group undergoing a standard entrepreneurial training and find that treated entrepreneurs have a higher probability of terminating their entrepreneurial projects.

Yet, the existing empirical evidence does not provide neither much guidance on how this finding should be interpreted, nor on whether it is an economically positive phenomenon in the long-term. This gap in the literature is substantial, primarily because prior research has indicated that a firm's decision to terminate can be motivated by a variety of factors, with quite opposite connotations (Wennberg and DeTienne, 2014). For example, termination might occur as a result of the fact that entrepreneurs neglect evidence regarding the lack of value of their entrepreneurial idea and rather escalate their commitment until when they are forced to terminate due to lack of funds or other resources (Artinger and Powell, 2016). Alternatively, termination may occur as the result of the early abandonment of ventures with limited outside potential (McGrath, 1999). Distinguishing between these cases is important. While termination in the former instance aligns more closely with failure, in the latter scenario termination emerges as a favorable outcome that precludes the entrepreneur from wasting resources. The latter leads to a stricter but economically positive project selection process. However, the investigation conducted by Camuffo et al. (2020, 2024) does not enable us to distinguish between these two potential scenarios. Consequently, current studies leave unsolved the inquiry into the efficacy of the stricter selection process enacted by entrepreneurs adopting a scientific approach to decision-making.

In this paper, we address this crucial issue with a question-driven

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https://doi.org/10.1016/j.respol.2024.105022
Received 5 April 2023; Received in revised form 27 April 2024; Accepted 29 April 2024

approach that examines two primary aspects. First, we investigate whether entrepreneurs who are taught to apply a scientific approach to decision-making opt to terminate their projects due to an early adjustment in two expectations – namely, a downward revision in their project value expectations and an upward revision in the probability of project termination – as opposed to holding stable expectations until the termination event occurs. Second, we evaluate the extent to which the stricter selection process by scientific entrepreneurs is economically positive by analyzing several economic outcomes in both the short- and long- term.

We do so by exploring data from two randomized control trials (RCTs) conducted in 2017 and 2018 in the Italian cities of Milan and Turin. During the RCTs observation window, we longitudinally tracked entrepreneurs' own estimations regarding both the value of their early-stage entrepreneurial projects and the probability that they will terminate them in the future. We also measured short-term economic outcomes and entrepreneurs' decisions throughout an initial data collection spanning up to 66 weeks since the beginning of the training. We then engaged in two further rounds of data collection in 2022 and 2023 (around 5 years after the end of the training programs) to gather unique information on long-term decisions, outcomes, and entrepreneurs' motivations.

The RCTs involved 382 entrepreneurs (and corresponding startup projects), which we randomly allocated to two training groups. Entrepreneurs in both groups went through a program of eight 3-h sessions on idea validation and startup development. As in Camuffo et al. (2020, 2024), treated entrepreneurs were exposed to business tools and techniques and taught to use them in line with a scientific approach to decision making. Instead, entrepreneurs in the control group were exposed to very similar content, but they were not taught about a scientific approach to decision making.

Our first set of findings reveal that termination decisions and expectations prior to the termination event do not necessarily align, but they do so for entrepreneurs trained to think and act like scientists. Indeed, treated entrepreneurs, especially those who eventually terminate their projects, tend to adjust their expectations on the value of their ideas downward (and those about the expected probability of termination upward) and do so earlier than control entrepreneurs. A downward adjustment of entrepreneurial expectations regarding the project value can be interpreted in two ways. The first interpretation is about a more *accurate collection and interpretation of signals*: the observed downward adjustment in value expectations for eventually discontinued projects may stem from treated entrepreneurs' enhanced ability to discern limitations inherent in their less-promising projects. This ability can have a particularly positive connotation if these entrepreneurs, in parallel, shift their attention towards more viable business opportunities (Felin et al., 2020). The second interpretation is about a possible *excessively critical attitude*: the scientific treatment may instill a general critical attitude among entrepreneurs. This heightened critical attitude could lead them to attribute lower values to all entrepreneurial ideas, even those with substantial merit. Should the rate of erroneously discarded projects surpass the instances where genuinely "bad" projects are correctly avoided, then the scientific approach may be deemed less valuable to pursue as it would foster an adverse project selection.

To determine which of these two possible interpretations is more likely and make the following assumption: if the second interpretation was correct, and the treatment made entrepreneurs excessively critical, we should observe that the projects that are discarded by treated entrepreneurs are of higher quality compared to those discarded by the control group. Thus, we search for relatively "objective" measures of entrepreneurial projects' value that we can compare to entrepreneurs' expectations of their projects. We identify two such measures: (1) the successful attainment of external funding, and (2) expert evaluations of entrepreneurial projects. When focusing on treated entrepreneurs who terminated their projects, we find that the share of projects obtaining external funding is not significantly different from that of the control group. We also find that experts' scores assigned to projects terminated by treated entrepreneurs are not significantly higher than those assigned to projects terminated by the control group. Thus, both pieces of evidence support the first interpretation of a more *accurate collection and interpretation of signals* by treated entrepreneurs: the scientific approach helps them to see more clearly the limitations of their "bad" projects (as reflected in the inferior expectations that they have on them) and to terminate them, but it does not reflect in an excessively critical tendency towards all projects.

To further corroborate this thesis and understand whether the selection process performed by treated entrepreneurs is economically effective, we focus on projects not terminated and study their performance not only during the RCT window (2017/18) but also in the longer term (2022/23), filling in an important gap in the literature on the longer term performance of a scientific approach to decision making. For what concerns short-term outcomes, we find a positive impact of the treatment on entrepreneurs' revenue (as in Camuffo et al., 2020, 2024). Additionally, we find that non-terminated projects of treated entrepreneurs were more likely to obtain external funding, providing evidence that, given the selection, projects chosen by treated entrepreneurs performed better than those selected by control entrepreneurs. Regarding longer-term outcomes, we find that non-terminated projects of treated entrepreneurs were more likely to still be active after 5–7 years after the treatment, with a higher likelihood that projects developed by treated entrepreneurs resulting in the launch of a new venture. Finally, we find that treated entrepreneurs generate more novel additional project ideas than control entrepreneurs. Overall, this evidence speaks *against* the presence of an *excessively critical attitude* by treated entrepreneurs when compared to control ones and in favor of a superior ability to recognize the limitations of their current projects and focus attention on alternative ideas to be found in places that are "hidden and not obvious to others" (Felin et al., 2020).

This paper contributes to multiple streams of research. First, it contributes to research on the E-a-S approach to decision making (Camuffo et al., 2020, 2024; Zellweger and Zenger, 2021; see also Ehrig and Schmidt, 2022; Felin and Zenger, 2009; Felin and Zenger, 2017; Felin et al., 2023), by providing insights regarding the reasons why treated entrepreneurs terminate their projects more frequently and earlier, and providing evidence that their project selection process is effective both in the short and longer terms. Second, it contributes to research on project selection (Brown and Eisenhardt, 1997; Klingebiel and Rammer, 2014; Loch and Kavadias, 2008), which has used project selection decisions as the basis for inferring the logic underlying the decision-making process. In this paper we go two steps beyond by (1) measuring entrepreneur's expectations and exploring their relationship with their actual decisions; (2) analyzing the long-term results of such selection process.

2. Conceptual background

Prior research has documented the benefits that decision makers can derive from the use of well-defined approaches that support decision making, such as the use of structured managerial practices (Bloom and Van Reenen, 2007; Feldman et al., 2019; Ott et al., 2017; Yang et al., 2020). Within this context, a recent stream of research has emphasized that one way to approach decisions under uncertainty, especially in the context of entrepreneurship or innovation, is to act like scientists – namely to form theories about the problem faced, develop hypotheses, and test them (Camuffo et al., 2020, 2022; Ehrig and Schmidt, 2022; Felin et al., 2024; Felin and Zenger, 2009, 2017; Zellweger and Zenger, 2021, 2022). This approach has been referred to as the Entrepreneurs-as-Scientists (E-a-S) approach. It combines two classes of approaches to handle uncertainty (Ott et al., 2017). It includes elements of action-based approaches (Bingham and Davis, 2012; Bingham and Eisenhardt, 2011; Ries, 2011; Thomke, 1998; von Hippel and Tyre, 1995) in that it incorporates the idea that adjusting actions based on the feedback can lead to valid organizational decisions. However, it combines this insight with elements of cognition-based approaches to decision-making, (Csaszar and Laureiro-Martínez, 2018; Felin and Zenger, 2009; Gary and Wood, 2011; Walsh, 1995) positing that the process of evidence and feedback collection should be based on the development of a theory of the problem and entrepreneurial solution. In doing so, it emphasizes elements of generative rationality and belief asymmetry (Felin et al., 2024).

The notion of E-a-S is consistent with innovation and entrepreneurship work that has advanced the idea that cognition and action can be successfully combined in a "decision weaving" process that can lead to acquiring knowledge about the environment and use that knowledge as a guide for action (Eisenhardt and Ott, 2017; Ott et al., 2017). For example, McDonald and Eisenhardt (2020) elaborate on the benefits of testing the cognitive assumptions underlying a business model before committing to it. They show that such approach leads to superior and faster decision making by reducing the uncertainty faced and the extent to which decisions are based on emotions and opinions. Leatherbee and Katila (2020) show how teams that engage with a lean startup methodology – grounded on hypothesis development and fast experimentation – have positive outcomes in the 18-month period following the use of the method. Along the same line, the literature on search has emphasized the benefits that are derived from the combination of cognitive and experiential search: Gavetti and Rivkin (2007) describe in detail of how executives at Lycos developed the company's strategy by combining insights obtained from feedback on their actions, together with the executives' mental representation of the Internet Portal industry.

While entrepreneurs who adopt a scientific approach combine cognition and action in their decision-making, the alternatives to the E-a-S approach can vary. A non-scientific decision-maker might be: (a) an entrepreneur who relies solely on cognitive processes without seeking evidence to verify assumptions; (b) an entrepreneur who does not develop any theoretical framework regarding the best course of action and rather bases decisions purely on the findings that emerge in the phase of evidence collection; or (c) an entrepreneur who relies entirely on gut feelings and emotions, thus avoiding both cognition and action-based approaches.[1] The rationale for a scientific approach to decision-making is grounded in the belief that synergies emerge when cognition and action are integrated. This approach enhances purely cognition-based methods by supporting the validation and refinement of decision-makers' assumptions through evidence collection. Similarly, it augments action-based methods by providing theoretical insights that help decision makers identify the most promising areas for evidence-based investigation (Felin et al., 2020).[2]

The empirical evidence on a scientific approach to decision making is growing but still limited. Prior work identifies an overall positive impact of the scientific approach on short-term economic performance both in comparison with traditional business support program (Camuffo et al., 2024), as well as in comparison with purely evidence-based approaches (Agarwal et al., 2024). This effect is however contingent on the degree of strategy definition of the firm at the time of exposure to the approach (Novelli and Spina, 2024). Analyzing entrepreneurial pivoting, these studies find that scientific entrepreneurs engage in more focused pivots (Camuffo et al., 2024) that integrate both the core and operational components of the business model (Agarwal et al., 2024). One important outcome associated with the scientific approach is project termination: research has suggested that the use of a scientific approach to entrepreneurial decision making is associated with higher project termination (Camuffo et al., 2020, 2024), however, it does not provide evidence that can shed light on the interpretation of this outcome. Termination may indeed be prompted by an entrepreneur's recognition of the project's intrinsic lack of value. Alternatively, it could be an obligatory decision driven by external factors such as resource constraints or financial limitations, even when the entrepreneur maintains unwavering optimism regarding the idea's value. In this paper we explore the extent to which the former interpretation is appropriate.

By developing theories and translating them into hypotheses, entrepreneurs who operate like scientists focus on the relevant assumptions underlying their projects. They complement this first step of theory and hypotheses development with high quality tests that provide objective signals on the validity of their theory. This helps refining the entrepreneurs' original assessment further. It is plausible that this process leads entrepreneurs to the *accurate collection and interpretation of signals*, i.e., a more accurate assessment of the value of a project because it brings clarity on the conditions required for the project to succeed and their probabilities (Ehrig and Schmidt, 2022; Felin and Zenger, 2009, 2017; Zellweger and Zenger, 2021). This is consistent with qualitative research that has shown that factual grounding makes decision-making faster, reduces emotional conflict and facilitates de-escalation of commitment (Eisenhardt, 1989; McDonald and Eisenhardt, 2020; Raffaelli et al., 2019; Sleesman et al., 2018). Not only the scientific approach might help entrepreneurs to better assess the value of their project, but it might also help them redirect their attention towards more promising alternatives. Prior conceptual work suggests that the E-a-S approach leads entrepreneurs to broaden their search space in contrast to narrowly testing existing ideas (Felin et al., 2020). Felin et al. (2020) argue that the search of entrepreneurs who use a scientific approach is similar to that of someone who is searching for a pair of keys using a flashlight as opposed to searching for them under a lamppost: because scientific entrepreneurs are guided by a theory, there are able to look for solutions to problems in places that are hidden and not obvious to others.

However, a thorough assessment of the efficacy of a scientific

[1] An example might help to clarify. Imagine an entrepreneur interested in launching an innovative childcare service with sitters skilled in creative arts. For illustrative purposes we focus on only one specific dimension of the value proposition, which is whether families are allocated the same sitter over multiple bookings. In case (a) (cognition only), the entrepreneur theorizes that parents prefer variety to prevent children boredom, and launches a service where each booking assigns a different sitter. The entrepreneur's assumption is not validated with data and can potentially be incorrect. In case (b) (evidence-only), instead of theorizing, the entrepreneur surveys parents directly to identify desired features and implements those that emerge as more popular. This approach might imply a limited understanding of the problem, leading the entrepreneur to an imperfect implementation of the listed features or to the neglection of unlisted valuable features. Case (c) (no cognition, no evidence) describes an entrepreneur who avoids both theorizing and data collection and, following their gut feelings, launches a service where a different sitter is allocated for each booking without this being connected with a specific theory or evidence. A scientific approach that merges cognition with action, instead, would see the entrepreneur theorizing that parents value sitter variety and then testing the related hypothesis through parent feedback. The entrepreneur's offer would be adjusted based on the findings, enhancing satisfaction or revising the theory based on the evidence collected.

[2] Whereas this logic is valid for the average case, we acknowledge that there can be situations where alternative approaches – cognition-only, evidence-only, and no cognition-no evidence – may be superior to a scientific approach. For instance, when a decision maker is exploring very novel "new to the world" ideas, collecting evidence might not be feasible, making a cognition-only approach more advantageous. This could also be true when an entrepreneur has strong theoretical priors about the validity of an idea; in this context, a purely theory-based approach might save significant resources, considering that evidence collection is costly (Camuffo et al., 2023). Conversely, there might be conditions under which a purely evidence-based or even a no-cognition-no-evidence-based approach is preferable. This might be particularly relevant in situations of extreme uncertainty, where theorizing about the numerous possible scenarios becomes difficult or prohibitively expensive. Understanding the precise contingencies under which each approach is most valuable is a task for future research.

approach to decision making as an approach to project selection requires excluding an alternative interpretation, i.e., that a scientific approach triggers an *excessively critical attitude*. This heightened critical attitude may, in turn, lead to a reduction in entrepreneurial expectations regarding promising projects and not only those that lack of value. If this was the case, we would expect that the quality of projects rejected by scientific entrepreneurs be higher compared to those rejected by non-scientific entrepreneurs, with potentially very different performance implication. In the rest of the paper, we explore these considerations.

3. Data

3.1. Experimental design

We leverage data from two distinct field experiments, delivered in the context of business support programs offered to entrepreneurs in the cities of Milan and Turin (Italy).[3] The two RCTs were held asynchronously in 2017 (Milan) and 2018 (Turin), but shared the same structure, type of intervention, and data collection process. The choice of running two separate RCTs was led by the desire to ensure the reproducibility of results across different locations and increase the statistical power. Differences between the two RCTs are limited to the context in which the training was conducted (i.e., city and training location): all the other elements, including most of the instructors involved in teaching the training content, were held constant to ensure that a pooled analysis would be possible.

Both programs were advertised nationally over multiple offline and online channels. The advertisement campaign lasted for several weeks to ensure a recruitment of at least 100 entrepreneurs per batch. The campaign promoted each program as a cutting-edge business support program, offered free of charge to early-stage entrepreneurs operating in any industry. The focus on early-stage entrepreneurs ensured that participants were highly involved in the decision-making process and that they focused on one project (startup) only.[4] To apply, one entrepreneur per startup project was required to fill in an online survey and complete a telephone interview and to commit to do so for the duration of the program. In total, the data from the first RCT (Milan) includes 250 entrepreneurs, and the second (Turin) 132, corresponding to the same number of business projects.[5] All the projects of admitted entrepreneurs had no revenues at the beginning of the training program. The average project had a founding team composed of two entrepreneurs, with an average age of 31 years old. Projects spanned several industries, from agriculture to software and finance: the three most represented sector being fashion (10 % of the sample), food (11.5 %) and leisure (18.8 %). On average, teams were devoting around 11 h per week to the project development, signaling the early-stage status of these ventures. In line with this, in the periods during the training program, around 85 % of the projects were still in an early phase of market validation and did not have a prototype.

Admitted entrepreneurs were assigned to either a treatment or a control group through simple randomization. Considering both RCTs, 192 entrepreneurs were randomly allocated to the control group and 190 to the treatment group.[6] We checked that the randomization was successful with a set of balance checks across groups (Tables A1 and A2 in the Appendix). Then, each group was broken down into smaller subgroups and assigned to an instructor. A total of eight instructors were recruited among the Italian entrepreneurial ecosystem, from both academia and the practitioners' landscapes. All instructors already had previous experience in teaching and coaching entrepreneurs. Seven instructors served in the Milan RCT, five in the Turin RCT. Notably, four of the five instructors in the Turin RCT also served as instructors for the Milan RCT. Each instructor was in charge of teaching the entire curriculum (8 sessions) to each specific classroom per experimental condition (i.e. one treatment and one control classroom). This choice was made to minimize an "instructor-related bias," where outcomes could be affected by instructors' unique teaching styles if each instructor was only associated with one experimental group. The choice to have each instructor teaching both treatment and control groups allowed us to introduce instructor-specific dummies in our statistical analyses and thus control for any impact associated with the instructor's style. To avoid issues of "experimenter bias," with instructors possibly favoring one of the two groups, instructors were kept blind about the researchers' expectations. In interacting with instructors, we framed such expectation as exploratory, namely to understand whether and to what extent different teaching approaches could influence a variety entrepreneurial outcomes. To maintain neutrality and ensure instructors' unbiased attitude towards the two approaches, we acknowledged that the two teaching approaches might achieve equally desirable outcomes.[7]

3.2. Intervention details

Entrepreneurs in both experimental groups attended an entrepreneurship training focused on idea validation consisting of 8 sessions over 4 months. Program sessions were held in-person at the premises of two leading Italian universities. All the sessions were highly experiential, and the division in small classes ensured that instructors provided feedback to each participant. All entrepreneurs, regardless of the training group, followed a standard entrepreneurship training curriculum. Specifically, they were exposed to (1) general entrepreneurial frameworks (such as the Business Model Canvas), and (2) to data gathering techniques (such as interview techniques, surveys, and A/B testing). Both groups were taught how to apply frameworks and techniques and were given feedback from both instructors and peers through in-class exercises. Entrepreneurs in the treatment group were taught to apply these frameworks and techniques as parts of a systematic approach to decision-making that replicates the approach followed by scientists when conducting research (i.e., the Entrepreneurs-as-Scientists approach). Specifically, treated entrepreneurs learnt to

[3] Camuffo et al. (2024) used part of the data from these two randomized control trials in a broader replication study. This paper's empirical analysis is distinctive in that it (1) includes additional portions of the data that were not used in Camuffo et al. (2024) and (2) it also includes two rounds of targeted, novel data collection about the long-term implications of the intervention across a variety of dimensions. Specifically, we have gathered exclusive long-term outcome data and alternative metrics for project quality, elements that we are the first to explore.

[4] The sample is mostly made of early-stages startups where the average (and median) founding team is of two people. Hence, perceptions provided by the survey respondent, who was also the person attending the training and usually the main decision-maker (founder) in the startup, can be directly mapped to data at the project(startup)-level.

[5] This paper's analysis was pre-registered on the American Economic Association's online registry. The two experiments, whose funding was secured separately and at different times, were pre-registered separately. A pre-analysis plan was subsequently uploaded to the AEA RCT registry. The plan referred to the joint analysis of the two RCTs data and outlined the development of a structural model to model performance outcomes based on selection (entrepreneurs' decision to terminate or continue their projects) through a set of conditional multi-recursive equations. The structural equations and parameters were successfully estimated with results aligning with our theoretical expectations. However, we decided to deviate from this pre-registered approach because we eventually concluded that reduced form and extensive descriptive analyses confirmed the pre-registration expectations in a more straightforward and interpretable manner than the more complex structural estimation.

[6] In the Milan RCT, 125 entrepreneurs were allocated to the treatment group, and 125 to the control group. In the Turin RCT, 65 entrepreneurs were allocated to the treatment group, 67 to the control group.

[7] This was possible in all but one case. We checked the robustness of our results by replicating all analyses after removing the observations related to the relevant instructor. Results are reported in Appendix D3.

develop a theory of value on their business projects (i.e., their startups), to develop hypotheses flowing logically from the theory, and to use the evidence gathering techniques to test those hypotheses and relate the results back to the theory.

As a counterfactual to the treatment group, entrepreneurs in the control group were exposed to these same frameworks and techniques, and were invited to apply them to their project as it typically happens in any entrepreneurship class or pre-acceleration course. But the key difference was that they were not taught to apply them using the structured "theory-hypothesis-test-evaluation" approach that scientists would use.

It might be useful to clarify what each element of the scientific approach means in the context of entrepreneurial decision making. Prior work has referred to theories in this context as systems of ideas or concepts intended to explain, predict, or hypothesize the existence of a phenomenon (Camuffo et al., 2023). A theory is composed of an architecture of multiple conceptual elements related to the aspects of the problem that require attention and a series of beliefs about those elements and the causal relationships between them (Camuffo et al., 2023; Felin and Zenger, 2016). Imagine an entrepreneur planning to create a digital platform to support laundry shops in the city of Milan. This entrepreneur's theory is composed of a series of key elements related to (a) the business, the client's problems, and the suggested solution (such as laundry shops' capacity, utilization, opening hours, regulations, clients' working hours, demand for the service, willingness to pay), (b) the interrelations among these elements, and (c) the entrepreneur's beliefs about them. For example, the entrepreneur's theory might be based on the following series of relationships that connect multiple key elements. First, the entrepreneur might hold a belief about a positive connection between the shops' opening hours and the customers' working hours: the entrepreneur believes that laundry shops' customers in Milan are dissatisfied because shops' opening hours are shorter than their own working hours. Second, the entrepreneur believes that this relationship is positively moderated by the number of families of professionals with dual careers in the area. Third, the entrepreneur sees a connection between an extended hour service and customers' willingness to pay, believing that customers will be willing to pay more for the extended service. Fourth, the entrepreneur sees a connection between the customer working hours and the location and timing of alternative pick up: the entrepreneur believes that customers with long working hours would enjoy a laundry service allowing for late pick-up from centralized collection centers with extended hours.

This list could continue to include the full architecture of beliefs on the relationships underlying the entrepreneurs' theory, encompassing all the areas of the business as well as the key mechanisms underlying its economic profitability. This process also enables the entrepreneur to develop a holistic view of the business and identify any inconsistencies. For each of the relationships that compose the theory, the entrepreneur then formulates distinct hypotheses – i.e., specific statements that translate each of the relationships embedded in the theory into testable predictions. For example, each of the above relationships could be translated into distinct hypotheses such as "Families of professionals with dual careers in Milan appreciate a laundry service with extended hours" or "Families of professionals with dual careers appreciate a pick-up service from centralized collection centers with extended hours" and so forth. A suitable test could involve a survey administered to a representative sample of customers in the targeted city areas, exploring their laundry habits and satisfaction with existing shops' schedules. Proper evaluation of the test results would entail first formalizing the entrepreneur's prior and then comparing the collected evidence with the prior[8] while considering potential sample biases. Finally, based on the outcomes, the theory would either be supported, rejected, or revised. It is worth noting that the modularization of the theory into discrete predictions implies that the entrepreneur can distinguish between the elements of the theory that are supported and those that aren't. For instance, the entrepreneur might discover that a large portion of target customers would appreciate an extended hour service, but that only a small portion would be ready to pick up the items from centralized location and would rather prefer late delivery at their homes.

It is important to further elaborate on how the intervention was delivered to facilitate the use of a scientific approach and how the two treatment conditions differed. In one of the initial sessions of the course, both the treatment and control groups were exposed to the Business Model Canvas (BMC), a widely used tool in entrepreneurship including nine elements (value proposition, customers, channels, customer relationships, key activities, key partners, key resources, revenue streams, cost structure). Entrepreneurs in the control group learnt how to complete the canvas and use it to reflect the characteristics of their project. This would support their decision-making process by helping them to reflect on their project's various components. Instead, treated entrepreneurs were taught to use the BMC for *representing the theory* underlying their business project. Entrepreneurs were invited to reflect on how each element of the BMC and the relationships between them came together to compose the theory underlying the project and identify any inconsistencies between them that would require attention. They were ultimately invited to translate the theory into individual *hypotheses* to be tested. Later in the module, entrepreneurs in both groups were exposed to various data collection and testing techniques (e.g., A/B testing). Entrepreneurs in the control group were generally encouraged to apply these techniques to the problems they were facing in their business. They were free to choose where to apply these data collection techniques and were given general feedback on how to implement different methodologies. This would support their decision making by offering them the opportunity to collect evidence on various aspects of their business. Instead, treated entrepreneurs were explicitly encouraged to use those techniques to *test the hypotheses* developed in previous sessions, to closely *evaluate* the results, and compare the results with the theory originally envisioned in order to determine whether it would need revision. The intervention was similar to that performed by Camuffo et al. (2020), with some modifications related to content update and adaptation to the context of the new RCTs. Table 1 presents a summary of the content taught in the various sessions, clarifying the distinction between the control and the treatment group.

To summarize, the key difference between the two experimental groups was that the treatment was taught to *combine* cognition-based (frameworks) and action-based (data gathering techniques) tools: this was done as part of a structured framework guiding the decision-making process, namely the scientific approach, grounded on theory development and hypothesis testing. The counterfactual to the scientific approach is that entrepreneurs were exposed to both cognition-based (frameworks) and action-based (data gathering techniques) but without being taught to combine them. It is important to note that this counterfactual corresponds to the approach used in the typical business

[8] For instance, the entrepreneur's prior might be that at least 50 % of families of professionals with dual careers in Milan appreciate a laundry service with extended hours. This prior depends on the entrepreneur's theory and could be based, for instance, on the assessment of the socioeconomic characteristics of the targeted population. Formalizing the prior before seeing the test results is crucial for entrepreneurs. This step helps maintain objectivity when setting the criteria that will validate or refute their hypotheses. Without this, there is a risk of bias influencing the results interpretation.

Table 1
Program content.

	Control	Treatment
Session 1	Business model canvas (BMC). Entrepreneurs are encouraged to reflect on their business model and articulate it into choices for each of the 9 boxes of the BMC. They then discuss about it with peers.	Business model canvas (BMC). Entrepreneurs are encouraged to reflect on the **theory** underlying their business model and articulate it into **hypotheses** for each of the 9 boxes of the BMC. They then discuss about it with peers.
Session 2	Problem validation. Entrepreneurs are exposed to the key elements of the problem validation process and encouraged to apply it to their case.	Problem validation. Entrepreneurs are exposed to the key elements of the problem validation process and encouraged to apply it to their case by developing **hypotheses.**
Session 3	Data gathering. Entrepreneurs are exposed to different types of data gathering techniques (observation, interviews, surveys…) and encouraged to use them to collect evidence on the problem they wish to solve for their customers.	Data gathering. Entrepreneurs are exposed to different types of data gathering techniques (observation, interviews, surveys…) and encouraged to use them to **test** the **hypotheses** they developed in the previous session building on their **theory**.
Session 4	In-class discussion about key findings that emerged from the data collection.	In-class discussion about key findings that emerged from the data collection, with **evaluation of whether the test supported the hypotheses** they developed in the previous session building on their **theory**.
Session 5	Problem, offer and solution validation. Activation metrics, concierge, prototyping with discussion on how to apply them.	Problem, offer and solution validation. Activation metrics, concierge, prototyping and discussion on how to use them **to test hypotheses** they developed in the previous session building on their **theory**.
Session 6	A/B testing and discussion on how to apply it.	A/B testing and discussion on how to use it to **test hypotheses** they developed in the previous session building on their **theory**.
Session 7	Data collection and data management.	Data collection and data management.
Session 8	Recap.	Recap.

support program, where entrepreneurs are often exposed to both cognition-based (frameworks) and action-based (data gathering techniques) tools and are encouraged to use both, but without being taught to use them in combination with each other. Control entrepreneurs' decision-making process would still benefit from the training, in that they would be encouraged to use tools to reflect on their choices and to use evidence gathering techniques to collect data from the environment. However, they would not learn how to combine these techniques synergistically through the application of the scientific approach.

To avoid contamination between the two groups, we scheduled sessions in different days or times of the week. Moreover, the research team ensured that acquaintances were not allocated to different groups by asking entrepreneurs if they knew other applicants to the program, ultimately allocating them to the same experimental group after randomization.[9]

It is conceivable that some entrepreneurs in the control group might naturally adopt a scientific approach to decision-making, independent of our treatment. Such a disposition could be influenced by factors such as educational background or inherent problem-solving tendencies. Specifically, some individuals may naturally employ a systematic approach to decisions, thus formulating a theoretical framework for the problem at hand, generating explicit hypotheses, conducting tests to evaluate these hypotheses, and critically analyzing the outcomes. Yet, randomization into treatment groups is meant to ensure that any natural pre-treatment level of such “scientific intensity” is balanced between groups. In this way, the RCT design enables us to interpret changes in outcomes post-intervention as consequences of the fact that the treated group was systematically taught to use a scientific approach.

3.3. Data collection process

We asked entrepreneurs to provide data on their decision-making process and business performance throughout the training program for up to 66 weeks after the beginning of the training programs to a team of research assistants (RAs) via a set of phone interviews. RAs were recruited purposefully for the two experiments among both undergraduate and graduate students. Applicants to the RA position were screened based on their academic performance, work and entrepreneurial experience, communication and analytical skills. All RAs, regardless of their background, were extensively trained by the research team on how to conduct interviews and how to code data.

RAs were responsible of conducting monthly telephone interviews with entrepreneurs. Each interview followed a predefined semi-structured script, including both closed- and open-ended questions.[10] Questions spanned several topics related to the business development of entrepreneurs' projects, including performance outcomes, decision-making choices, and entrepreneurs' perceptions and beliefs. All interviews have been recorded and stored in an encrypted cloud storage space, and RAs also took care of the encoding of qualitative answers into quantitative information. We ran random checks to ensure that RAs were respecting the guidelines and the script when conducting interviews, and to ensure the appropriate encoding of information.

Overall, for each entrepreneur during the RCT observation window we collected interviews at the baseline and up to 18 data points: if an entrepreneur decided to terminate the development of her business project, we collected information up to the data point in which the termination occurred. To reduce attrition after the first 8 sessions, entrepreneurs were offered the opportunity to attend monthly events, which did not include any additional manipulation but were scheduled at different times for the treatment and control groups.

We conducted two additional data collections rounds in February–March 2022 and June 2023[11] to gather information on the status and longer-term performance of the projects in our sample. Specifically, given the generally low survival rate of startup projects in our context, we considered survival as an alternative measure of performance.[12]

Our main independent variable is a dummy taking value 1 if the entrepreneur belongs to the treatment group (E-a-S training); 0 otherwise. Since we collected data at different points in time, we provide further details regarding the data collection process, computed variables, and econometric methodologies in the following sections, preceding the presentation of results. Table 2 describes and provides summary statistics for all the variables employed in this paper.

Since our interest is in the effect for the average individuals in the sample and the two experiments share the exact same design and intervention, in all analysis we pool the two field experiments together.

[9] After randomly allocating entrepreneurs to treatment conditions, we checked whether entrepreneurs indicating they knew other members were assigned (randomly) to the same experimental condition. If that was not the case, we randomly moved entrepreneurs that knew each other (mostly, pairs of them) into the same experimental condition.

[10] Annex 1 in the Appendix provides the interview script from the Milan RCT.

[11] Annex 2 in the Appendix provides the follow-up interview script of the data collection conducted in June 2023.

[12] *Startups, after five year only one out of two survives* (translated from Italian: “Startup, dopo cinque anni ne sopravvive solo una su due”). Il Sole 24 Ore, 12 October 2017. Link: https://www.ilsole24ore.com/art/startup-5-anni-ne-sopravvive-su-due-AEB7RAmC.

Table 2
Variables description.

Variables	Description	N	Mean	SD	Min	Max
Independent variable						
Treatment	Dummy =1 if the entrepreneur was in the scientific group	382	0.5	0.5	0	1
Dependent variables: entrepreneurs' expectations						
Expected project value	Potential value of the project estimated by entrepreneurs on a 0–100 score (panel, if active)	5182	61.29	19.29	2.5	100
Expected termination probability	Probability of project termination (in %) estimated by entrepreneurs on a 0–100 scale (panel, if active)	5182	0.18	0.23	0	1
Dependent variables: performance						
Termination	Dummy = 1 if the project was terminated during the RCT observation window	382	0.38	0.49	0	1
Week of termination	Week of termination (during the RCT; if terminated)	147	31.28	17.79	6	66
Revenue (final, €)	Cumulative revenues in the last period (if active)	235	3654.98	16,022.8	0	150,000
Revenue (final, log €)	Logged (1+) cumulative revenues in the last period (if active)	235	1.48	3.25	0	11.92
Revenue (panel, €)	Cumulative revenues in the panel (filled)	7258	865.33	6654.26	0	150,000
Revenue (panel, log €)	Logged (1+) cumulative revenues in the panel (filled)	7258	0.51	1.98	0	11.92
External funding	Dummy = 1 if the project received external fundings (e.g. investors, business angels) during the RCT observation window	382	0.09	0.29	0	1
Long-term: survival	Dummy = 1 if the project is still active (established or under development) in 2023	382	0.21	0.41	0	1
Long-term: venture launch	Dummy = 1 if the project resulted in the launch of a venture as of 2023	382	0.16	0.36	0	1
Composite experts' evaluation score	Experts' scores on the projects' potential at the baseline. Average of three distinct 0–100 items.	330	37.46	21.13	10	87
Profitability experts' evaluation score	Experts' score on the projects' commercial success potential (0–100 scale)	330	37.42	24.91	10	90
Number of novel projects	Number of novel projects generated by entrepreneurs from 2019 up to 2023.	282	0.66	1.11	0	7
Number of currently active projects	Number of novel projects generated by entrepreneurs from 2019 up to 2023 and still active in 2023.	282	0.46	0.86	0	7
Controls						
Startup experience	Team average years of experience with startups (baseline value)	382	1.27	2.75	0	30
Team size	Size of the team (baseline value)	382	2.29	1.44	1	9
Education	Highest educational level attained by team members (5 = PhD, 4 = MBA, 3 = MSc, 2 = BA, 1 = high school, 0 = otherwise; Team Average)	382	1.95	0.85	0	5
Age	Team average age (baseline value)	382	31.09	8.09	18	65.5
Hours worked	Team average hours worked weekly on startup (baseline value)	382	10.88	10.78	0	60
Share of economics degree	Team members with an economics background (%, baseline value)	382	0.30	0.39	0	1
Share of STEM degree	Team members with a STEM background (%, baseline value)	382	0.39	0.42	0	1
Self-regulation	Likert scale (average of 11 items, baseline value)	382	1.76	2.48	0	6.82

In all specifications we include an RCT dummy to account for differences between the two experiments. We report in Appendix C4 the results for the two experiments analyzed separately.

3.4. Attrition

As common in field experiments and in experimental designs with multiple post-treatment periods, experimental units drop out of the study before its natural end, leading to attrition biases (Ghanem et al., 2022). We used different mechanisms to prevent attrition. First, the program was completely free-of-charge, and offered by two of the most prestigious universities in Italy. These two institutions have a national and international reputation for being at the forefront of entrepreneurship education, and this served as an important element to encourage participation and retention. Second, whereas the main training that included the intervention lasted for 8 weeks, we organized subsequent monthly in-presence events (identical events that ran on different days for treatment and control to avoid contamination) that were both occasions of networking and further learning. A necessary condition to join these events was the participation in the data collection rounds. Thanks to these precautions we were able to keep the attrition rate at a very low level.

Nevertheless, across the two RCTs, 10 % of the entrepreneurs dropped out of the program without having terminated the development of their business projects. Importantly, this attrition rate does not include entrepreneurs who also terminated their ideas, being that an outcome of this study. If we also include entrepreneurs who terminated their projects in the computation of the attrition rate, the latter is as high as 48.4 % (44 % in the control group; 53 % in the treatment group). Data entries are thus missing either after entrepreneurs terminate projects (termination) or if they decide to opt-out of the experiment but are still active on the market (attrition). We specify below each table and figure how we dealt with missing entries. More detail about attrition is provided in the Appendix (Section B).

4. Empirical evidence

4.1. Termination

We start by replicating the results presented in Camuffo et al. (2020, 2024), in which the scientific approach treatment is associated with higher termination.

4.1.1. Data and methodology

4.1.1.1. Independent variable. Our main independent variable is a dummy taking value 1 if the entrepreneur belongs to the treatment group (E-a-S training); 0 otherwise.

4.1.1.2. Dependent variable: termination. We identify a project as terminated if the entrepreneur explicitly declared to have ceased working on her business idea. In line with Camuffo et al. (2020, 2024), we create the cross-sectional variable *Termination* as a dummy variable taking value 1 if the project was terminated at any point. To estimate survival probabilities, we record the data collection period in which the termination event occurred in the variable *Week of termination*.

4.1.1.3. Controls. As control variables we include those unbalanced at the baseline despite random allocation[13] and additional covariates potentially related to the outcomes (years of experience with startups, team size at the baseline, team average education levels, team's average age, weekly hours worked on the project at the baseline).

4.1.1.4. Empirical specifications. For models with binary dependent variables, we run probit regressions and report average marginal effects to ease the interpretation of results. For survival estimates, we run Cox proportional hazards models. We report specifications both without controls and with controls and mentor dummies. We cluster standard errors at the RCT-mentor-intervention level, representing the level of administration of the intervention (24 clusters).[14] We report in the Appendix (Section D) the results of alternative specification with robust standard errors and alternative specifications for binary outcomes, including linear probability models and probit without any standard error correction.

4.1.2. Results

At the end of the observation window, 38 % of entrepreneurs terminated the development of their projects. Looking at the percentage of termination by treatment condition, it corresponds to 31,8 % for control and 45.3 % for treated entrepreneurs, in line with previous findings that in the short-term entrepreneurs trained in the scientific approach conduct a more stringent selection process. Table 3 shows the results about the decision to terminate startup projects as a function of the treatment using a probit regression (Panel A) and a Cox survival analysis (Panel B).

Table 3
Termination regressions.

Dep. variable	Panel A		Panel B	
	Termination		Week of termination	
	Model 1	Model 2	Model 1	Model 2
Treatment	0.135**	0.115**	0.445**	0.415**
	(0.049)	(0.043)	(0.154)	(0.142)
Observations	382	382	382	382
SE	Clustered	Clustered	Clustered	Clustered
Controls	No	Yes	No	Yes
RCT dummy	Yes	Yes	Yes	Yes
Mentor dummies	No	Yes	No	Yes
Model	Probit	Probit	Cox	Cox

Panel A reports average marginal effects of probit models. Panel B reports coefficient estimates of Cox survival models. Model 1 includes the treatment indicator and a dummy equal to 1 for the treatment group (0 otherwise). Model 2 also includes mentor dummies and controls. Standard errors clustered at the classroom (RCT-intervention-mentor) level in parentheses. Attritors are assumed having continued the development of the project, hence are coded as still active. In the Appendix, Section C4 we replicate results by RCT, while in Section D, we estimate linear probability models, probit with robust and non-corrected standard errors, obtaining consistent results. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; ^ $p < 0.10$.

Results from the model with the full set of controls (Model 2 in Panel A) show that entrepreneurs who received training following a scientific approach are approximately 12 percentage points more likely to terminate their projects compared to the control group. Furthermore, this higher termination rate occurs earlier (as shown in Panel B). Specifically, approximately 30 % of termination decisions by treated entrepreneurs are made within 12 weeks after the beginning of the program, whereas control group entrepreneurs take about 18 weeks to reach a comparable termination rate. Next, we explore the process underlying termination decisions.

4.2. The process towards termination: entrepreneurs' expectations

As more extensively elaborated on in Section 2, one of the key objectives of this paper is that of understanding the extent to which entrepreneurs who terminated their projects were characterized by lower expectations regarding the project value well ahead before the decision to terminate. We achieve this goal by studying the temporal evolution of entrepreneurs' own expectations on their project value and their expected probability of termination.

4.2.1. Entrepreneurs' expectations on the project value

In this subsection, we focus on entrepreneurs' expectations on the project value.

4.2.1.1. Data. We leverage information on all entrepreneurs that participated in the program and their startup projects ($N = 382$). Specifically, we pooled the panel into three periods: (i) the period before the training (*baseline*); (ii) the datapoint corresponding to 8-weeks after the beginning of the training (*early period; during training*); (iii) and the last available datapoint for each entrepreneur (*last period; at the end of the 66-weeks observation window*). For entrepreneurs who terminated their projects before the end of the 66-weeks observation window, we have information up to the data point in which they declared that they terminated the project. Note that the chronological timing of this last data point is not relevant since that analysis compares, respectively, what happens at earlier stages of the evaluation process (the *early* period) and at the latest stages available (the *last* period), with respect to the baseline.

4.2.1.1.1. Entrepreneurs' expectations. We measure the entrepreneur's *expected project value* by asking entrepreneurs to indicate the minimum and maximum value they expect the project to generate (on a scale from 0 to 100, where we clarify that 0 corresponds to "the start-up will never make revenue" and 100 corresponds to "the start-up will achieve high revenue"). Specifically, the measure was computed as the average between the minimum and the maximum.

4.2.1.2. Results. Fig. 1 shows the panel trend of entrepreneurs' expected value for four distinct groups, based on two key dimensions: whether the entrepreneurs belonged to the control or treatment group, and whether the entrepreneurs terminated their projects within the data collection window. To provide a clearer visualization of this pattern, results are presented focusing on the three specific periods (*baseline*, *early*, *last*) described above. We provide the full visualization of the panel trend in the Appendix (Fig. C.1.1).

We observe three notable patterns from Fig. 1. First, regardless of whether entrepreneurs belong to the treatment or control group, the average expected values of non-terminated projects (solid lines in Fig. 1) are higher than those of terminated projects (dashed lines in Fig. 1). This pattern is very plausible, as it indicates that the average own assessment of entrepreneurs on their terminated projects is lower than that of active projects, supporting the validity of our measure. Second, expected values exhibit a decline over time even for non-terminated projects, suggesting that all entrepreneurs tend to revise their expectations downward as they gather more information. Third, and central to our

[13] Specifically, in the Milan RCT ($N = 250$) we found significant differences between treatment and control firms in the average of the share of team members with a degree in economics or a STEM degree. In the Turin RCT ($N = 132$), we found significant differences between treatment and control firms in the in the average level of "self-regulation", defined as the team-level discipline in organization and decision-making activities measured through a 11-item Likert scale.

[14] Our decision to use standard error clustering in the main body of the paper is motivated by the intention to allow maximum comparability between this paper's results and the main studies this paper builds upon (i.e., Camuffo et al., 2020; Camuffo et al., 2024).

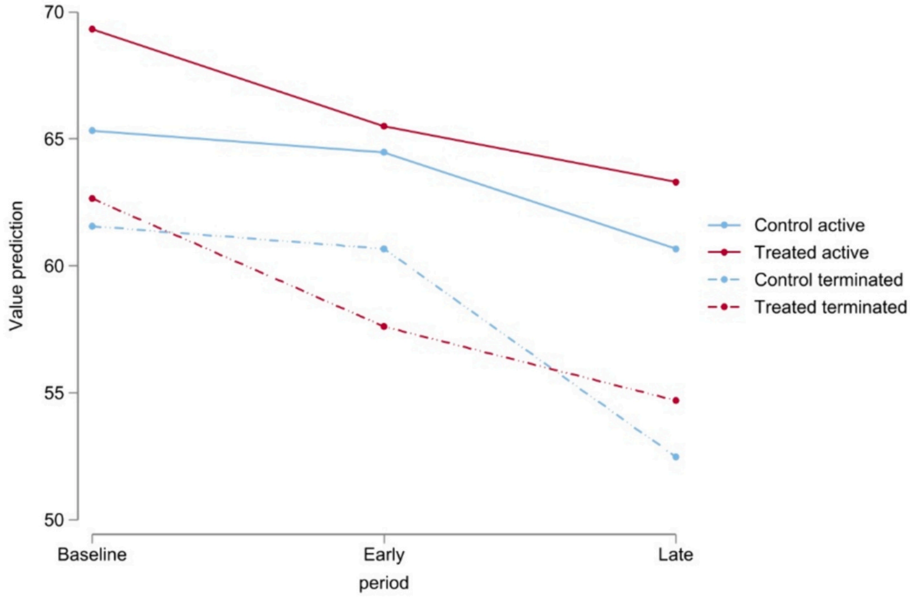

Fig. 1. Entrepreneurs' expected project value: Three periods.
This figure displays the expected project value provided by entrepreneurs before the training (*baseline*), 8-weeks after the beginning of the training (*early* – during training), and in the last available datapoint of each entrepreneur (*last*). Appendix Fig. C.1.1 reports the full panel trend.

investigation in this section, the treatment and control groups demonstrate distinct temporal patterns. Treated entrepreneurs exhibit a faster decline in their expectations compared to the control group, regardless of the eventual termination of their projects. Treated entrepreneurs begin adjusting their expectations on their project values downward earlier regardless of whether they ultimately terminate their projects. Indeed, their average expectation at the early period is lower than at the baseline (red lines), whereas those of control entrepreneurs (light blue line) tend to remain relatively stable between the *baseline* and *early* period, experiencing a significant decrease only later.

4.2.2. *Entrepreneurs' expectations on the probability of termination*

Next, we focus on entrepreneurs' expected probability of termination. Our aim is to ascertain if those who ultimately terminated their ventures were increasingly cognizant of termination as a more probable outcome. Furthermore, we seek to determine whether this heightened awareness is particularly evident among entrepreneurs who were part of the treatment group.

4.2.2.1. *Data*

4.2.2.1.1. Entrepreneurs' expectations on the probability of termination. We measure the entrepreneur's *expected termination probability* by asking entrepreneurs to provide a predicted probability from 0 to 100 of project termination at each data point.

4.2.2.2. Results. Fig. 2 (full visualization of the panel trend reported in the Appendix, Fig. C.1.2) shows that projects that were ultimately terminated are attributed higher expected probabilities of termination when compared to active projects. This is valid for both experimental groups. Interestingly, Fig. 2 shows that higher expected probabilities of project termination are observed at early stages among treated entrepreneurs who terminated their projects (red dashed line). This finding suggests that treated entrepreneurs adjusted their expectations in line with their subsequent decisions to terminate. Fig. 3 reports the size of the adjustment on the entrepreneurial expectations of the probability of termination by control and treated entrepreneurs, for active and terminated projects, between the first post-baseline observation period and the baseline (dark columns) and between the second post-baseline period and the baseline (light columns). Interestingly it highlights that treated entrepreneurs who eventually terminate their projects modify their expectations of the probability of termination already in early observation periods. On the contrary, control entrepreneurs still display a downward adjustment, even if milder when compared to projects active at the end of the observation period. This reveals that treated entrepreneurs are more aware of the potential future termination of their projects.

Overall, these results reveal a distinct pattern in the process by which treated and control entrepreneurs update their expectations of value and termination probability before their actual termination decisions. Notably, treated entrepreneurs demonstrate an early downward adjustment of their expectations on the probability of termination that is coherent with their subsequent termination decisions, while this is not the case for control entrepreneurs. Importantly, these patterns highlight that termination decisions and expectations do not always align. Nevertheless, the downward adjustment of expectations made by treated entrepreneurs is consistent with the higher termination rate observed among this group.

4.3. *Interpreting the adjustment in expectations: accurate collection and interpretation of signals or an excessively critical attitude?*

We identify two potential interpretations for the results presented so far. The first is that treated entrepreneurs are characterized by a more *accurate collection and interpretation of signals*. Treated entrepreneurs, through their use of a scientific approach, develop a theory that enables them to understand the situation that they are facing, conduct a superior data collection process and gather more precise signals regarding the value of their current ideas. This process leads to develop more accurate expectations on the value of their projects and to do so at a faster pace compared to control entrepreneurs. This first interpretation has a potentially positive connotation, because it implies that scientific entrepreneurs identify projects that are not necessarily valuable, and free up resources that can be redirected in more promising directions. The second is that adopting a scientific approach may instill *an excessively critical attitude* in entrepreneurs, causing them to assign lower expectations to the value of their ideas regardless of their true potential. This second interpretation has a potentially negative connotation regarding the efficacy of a scientific approach to decision making, because it

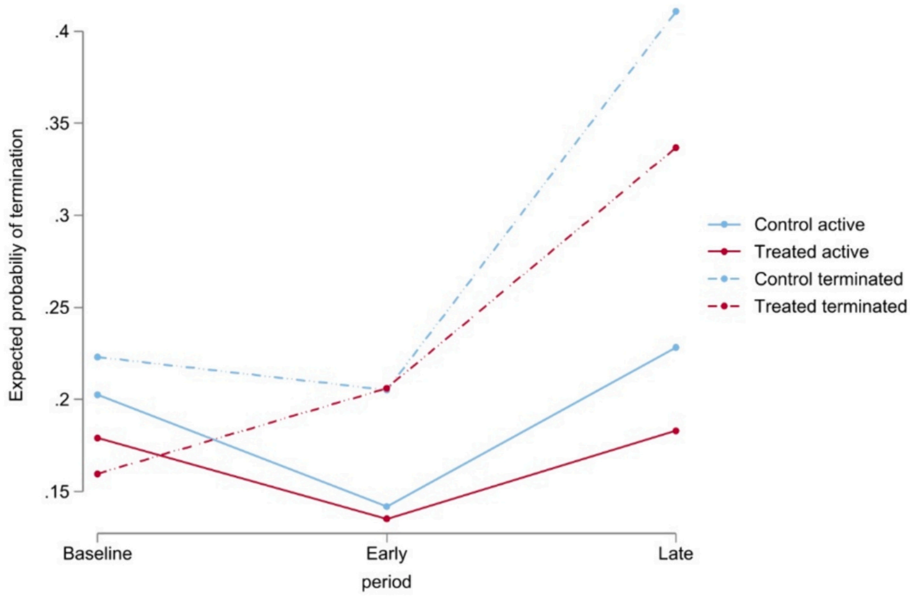

Fig. 2. Entrepreneurs' expected termination probability: Three periods.
This figure displays the expected probability of project termination provided by entrepreneurs in three specific datapoints: the period before the training (*baseline*), the datapoint corresponding to 8-weeks after the beginning of the training (*early* – during training), and the last available datapoint for each entrepreneur (*last*).

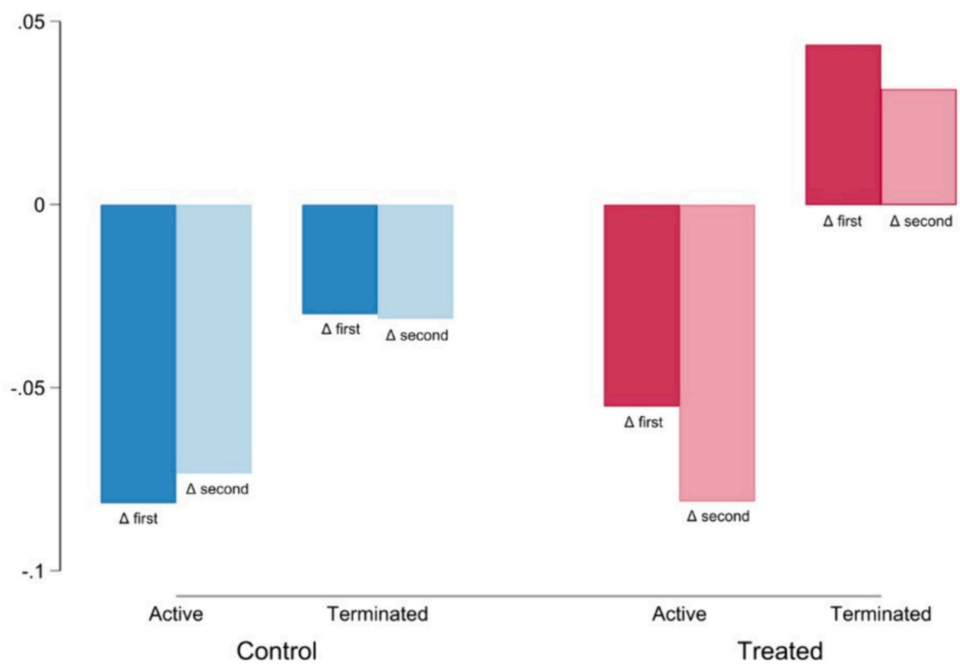

Fig. 3. Entrepreneurs' expected termination probability: Difference of first/second datapoint with baseline.
This figure displays the deltas with respect to the baseline – pre-training – value of the entrepreneurs' expected probability of project termination recorded in the first observation period (blue columns) or in the second observation period (light blue columns). Averages are shown by treatment group and project status at the end of the observation window.

implies that the scientific approach leads entrepreneurs to also discard projects that deliver value.

To rule out the second interpretation, we explore the quality of the entrepreneurial ideas that are terminated. We build on the intuition that if the treatment made entrepreneurs excessively critical, and more likely to discard also valuable ideas, we should be more likely to observe that the projects that they terminate are of higher quality compared to those terminated by the control group. To perform this analysis, we identify two external measures the quality of terminated projects: (1) whether the projects received external funding and (2) project evaluations by business experts. We report our findings in the following section. In subsequent sections we will further validate the first interpretation by looking at performance implications and at the number of projects entrepreneurs generated beyond the initial one.

4.3.1. *External funding*

We consider whether entrepreneurs received funding from external investors at any data point within the RCT observation window.

4.3.1.1. Data and methodology

4.3.1.1.1. External funding. We asked entrepreneurs whether they received external funding (for instance, from private investors, families, venture capitalists or business angels) at any data point during the RCT observation window. The variable *external funding* is a dummy taking value 1 if the entrepreneur received funding within the observation period, and 0 otherwise. We also leverage more detailed information about funding sources and amount raised for descriptive purposes.

4.3.1.1.2. Empirical specifications. We run probit regressions to estimate the probability of obtaining external funding conditional on being active on the market during the RCT observation window. We report specifications both without controls and with the same controls used in previous models, and mentor dummies. We cluster standard errors at the RCT-mentor-intervention level. We report in Appendix D results with robust standard errors and alternative specifications, as well as results by RCTs (Section C4).

4.3.1.2. Results. Among the various forms of funding observed in our sample, the three most common sources are public grant funding and non-repayable loans (30 %), bank loans (19 %), and bootstrapping or support from family and friends (18 %). Only two startup projects received pre-seed investments. Importantly, these external investors were blind to the treatment group.[15] Table 4 reports the share of firms that received external funding, categorized based on the experimental group they belonged to (treatment vs control) and on whether they terminated the project or maintained it active.

To understand whether treated entrepreneurs reconsider their expectations on the value of their ideas downward due to their accurate collection and interpretation of information versus an excessively critical attitude, we focus on treated entrepreneurs who terminated their projects. We note that the percentage of projects receiving external funding is not significantly different from that of the control group (1.2 % vs. 1.6 %). This is suggestive that treated entrepreneurs do not seem to have discarded potentially valuable projects more frequently than control entrepreneurs, supporting the intuition that that they adjust their expectation downward because they are better able to identify the flaws of projects with low potential. Coherently, this does not seem to translate into a general tendency to discard also promising projects.

Table 4 also suggests that active projects of treated entrepreneurs are more likely to receive external funding compared to control entrepreneurs (20.2.% vs 9.9 %), which we interpret as an early performance indicator. This result is statistically significant, as shown in the regressions reported in Table 5.

In terms of funding amounts, the average funding received by entrepreneurs was €40,969, with a median of €8000. This amount was higher for the treated group, with an average of €46,991 and a median of €12,000, compared to the control group, which had an average of €31,333 and a median of €8000.[16] The higher average and median funding amounts in the treated group further supports the idea that the treatment may have positively influenced the entrepreneurs' ability to secure larger funding.

Table 4
Share of projects receiving external funding.

	Terminated	Active	Difference
Control	1.6 %	9.9 %	−8.3 %
Treatment	1.2 %	20.2 %	−19.0 %
Difference	0.4 %	−10.3 %	10.7 %

Share of projects having received any type of external funding during the RCTs observational window. $N = 382$.

Table 5
Share of active projects receiving external funding: Regression results.

Dep. variable	External funding	
	Model 1	Model 2
Treatment	0.103*	0.079^
	(0.042)	(0.042)
Observations	235	235
SE	Clustered	Clustered
Controls	No	Yes
RCT dummy	Yes	Yes
Mentor dummies	No	Yes
Model	Probit	Probit

Average marginal effects reported. Model 1 includes the treatment indicator and a dummy distinguishing the two RCTs. Model 2 adds mentor dummies and controls (experience with startups at the baseline; size of the founding team at the baseline; teams' average education level; average age of the team; hours worked at the baseline; share of the team with economics or STEM degrees; self-reported measure of self-regulation). Standard errors clustered at the classroom (RCT-intervention-mentor) level in parentheses. In the Appendix, Section C4 we replicate results by RCT, while in Section D, we estimate linear probability models, probit with robust and non-corrected standard errors, obtaining consistent results. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; ^ $p < 0.10$.

4.3.2. Experts' evaluation

Further, we examine evaluations provided by experts based on the baseline pitches submitted by entrepreneurs as part of their application package, namely *prior* to receiving the treatment. The rationale for gathering and analyzing such evaluations is to obtain a reliable proxy of the pre-training project potential, which could serve as a good approximation for their "objective" value. The intuition guiding this analysis is as follows. If treated entrepreneurs are characterized by a higher tendency to discard all projects irrespective of their value, we should observe that projects terminated by treated entrepreneurs received higher experts' evaluation compared to both projects terminated by control entrepreneurs and to project that are still active at the end of the observation period. This approximation has one limitation: baseline evaluations do not incorporate changes introduced to the idea after treatment, which could have impacted the value of the project and the choice to eventually terminate it. Therefore, these experts' evaluations cannot be used to determine the impact of the training on performance because they do not incorporate any changes to the idea that the entrepreneurs might have made after the intervention. Nevertheless, we believe this is a good measure for our purposes because it serves as more objective measure of value that can be compared with the entrepreneurs' expectations.

4.3.2.1. Data

4.3.2.1.1. Experts' evaluation. We partnered with one of the biggest and most successful Italian incubators and innovation-oriented companies to obtain a professional evaluation of the value of the projects. Evaluations were made by two senior consultants dealing daily with startups and innovation projects. We decided deliberately to rely on professionals' evaluations, because we believe this to be the most reliable and precise estimate of value compared to those assigned by audiences of non-professionals. We asked the consultants to evaluate the

[15] At most, external investors could have been aware that entrepreneurs were attending a business support program. These investors were not affiliated to the program, meaning that it is extremely unlikely that they could have been aware of the experimental design behind the program.

[16] Not all entrepreneurs who received funding disclosed the amount received. The total number of observations related to funding amount is of 39, with 15 for the control group and 24 for the treated group.

company "pitches" (brief presentations of the project main activities, team, and value proposition) submitted by entrepreneurs at the *baseline*, that is, before the start of the training.[17] Our goal was to obtain an objective assessment of value of the projects that were terminated as well as retained active in both groups. At the time of the assessment, the two evaluators were blind to the treatment and to whether the project was still active or not. To make sure they were not able to retrieve other information than those included in the pitches, we anonymized all the pitch decks. Professionals were asked to make an assessment based on three elements, on a scale from 0 to 100: 1) *Profitability potential*: potential for projects' commercial success (0 = a loss is likely; 100 = a high gain is likely); 2) *Innovativeness*: innovativeness of the project (0 = not innovative at all; 100 = highly innovative) 3) *Feasibility*: project feasibility (0 = unfeasible; 100 = highly feasible). We averaged these scores to create a *composite experts' evaluation score* ranging from 0 to 100.

4.3.2.2. Results. We present the results graphically in Fig. 4, distinguishing between projects that were terminated and projects that remained active at the end of the observation window,[18] by treated and control entrepreneurs. The results indicate that the experts' scores assigned to projects terminated by treated entrepreneurs were not significantly higher than those assigned to projects terminated by the control group. In fact, projects terminated by entrepreneurs in the control group received higher scores, albeit such difference is not statistically significant. Nevertheless, these results suggest that treated entrepreneurs do not appear to have discarded valuable projects at a higher rate compared to the control group. This further supports the intuition that treated entrepreneurs, compared to control entrepreneurs, are not characterized by a higher general tendency to discard promising projects.

4.4. The consequences of selection: performance and longer-term outcomes

So far, we have found that treated entrepreneurs adjust their expectations of the value of their projects more extensively and more quickly than control entrepreneurs. This is aligned with the higher termination rate recorded for treated entrepreneurs, with further evidence suggesting that the projects discarded are not of higher quality than either those discarded by the control group or those that are active on the market at the end of the observation window. This assessment is important because it provides unique insights on the process that guides treated entrepreneurs' decisions to terminate projects.

In this section, we investigate the effects of this selection process, and of the scientific approach more generally, on performance and longer-term outcomes. Specifically, we study short- and long-term performance in terms of (a) short-term revenue; and (b) longer-term survival rates, revenue, company creation rates and idea generation. Overall, our results show a positive effect of the treatment, and of the selection process, on both sets of outcomes.

4.4.1. Short term outcome

In this subsection, we replicate results of Camuffo et al. (2020, 2024) and investigate performance outcomes within the RCT observation window. Differently from previous research, we distinguish both by experimental group and by termination decision, as to analyze patterns conditional on selection.

4.4.1.1. Data and methodology

4.4.1.1.1. Performance: revenue. We compute *revenue (panel, log €)*, the log of 1 plus the cumulative revenues in the panel. We forward-fill missing data for attritors and terminated projects with the last available observation to obtain smoother graphical trends. We use this filled measure mostly for graphical representations. For econometric analyses, we compute *Revenue (final, log €)*, the log of 1 plus the final-period figure for cumulative revenues only for entrepreneurs that are still active on the market at the end of the RCT observation window.

4.4.1.1.2. Empirical specification. We run linear models on the subset of projects active at the end of the observation period. To address the issue of missing data for attritors and terminated projects, we report non-parametric bounds of the treatment effect (e.g., Horowitz and Manski, 2000; Kling et al., 2007). We analyze both the measure in € and a logged measure, due to the skewed nature of the variable. These measures are at the project level.

4.4.1.2. Results. Our first evidence assessing projects' performance comes from the cumulative revenue trends recorded for all projects within the RCT observation window. Fig. 5 presents these trends, considering the projects' experimental group and termination decision. Panel A displays the results in euros, Panel B shows the logged values, and Panel C provides a three-period moving average of the revenue growth. To ensure smoother trends for terminated projects, we handle missing values by replacing them with the last available value.

Fig. 5 reveals that in the treatment group, the average revenue and revenue growth of active projects are significantly higher compared to active projects in the control group. Thus, we find that the treatment has a positive effect on performance.

Overall, we observe higher revenues among active projects in the treatment group compared to the control group. Such differences are economically sizeable and statistically significant, as displayed in the econometric results reported in Table 6.[19]

To summarize, these results suggest that the treatment helps entrepreneurs to identify higher-performing projects. They indicate that treated entrepreneurs are, on average, making sound decisions in their project selection, leading to better-performing active projects compared to the control group.

4.4.2. Longer term outcomes

In this subsection, we investigate the performance of the projects a few years after the program's conclusion. This exercise serves a further validation of the evidence favoring the idea of an economically positive selection process operated by treated entrepreneurs and constitutes an

[17] We used 220 pitches for the RCT conducted in Milan, and 110 pitches for the RCT conducted in Turin. The missing pitches were not available due to corrupted data in our storage space. We checked whether the firms for which pitches were not available were systematically different from the others, finding no significant differences at the baseline on the variables used in the main analyses. Our final sample included 330 pitches, of which 167 in the control group and 163 in the treatment group. Balance checks still hold for this subsample of firms, meaning that the absence of the pitch is likely a random occurrence.

[18] We checked the robustness of these evaluations by comparing the average score between two groups of projects: those receiving external funding during the RCTs observational window ($N = 32$) and those not receiving any external funding ($N = 298$). We find that the average (median) score of the former group is of 40.4 (38), compared to an average (median) for the latter group of 37.1 (33.3). Despite this difference not being significant at conventional levels, the qualitative evidence points towards a reliable evaluation made by the experts, who evaluated with higher scores projects that were indeed funded during the RCTs periods. Evaluators were blind to any outcome/characteristics/treatment of the evaluated projects, including their funding status.Conditioning only on treatment assignment, regardless of the termination decision, our results show no significant differences between experimental groups (Treated = 36.88; Control = 38.02; $t = 0.49$; $p = 0.62$)

[19] Table 6 reports econometric results for both the logged revenues and revenues in euros recorded at the last datapoint, conditional on being still active on the market. We also compute bounds for the treatment effect: effect bounds are skewed towards positive values, consistent with a positive impact of the treatment on performance.

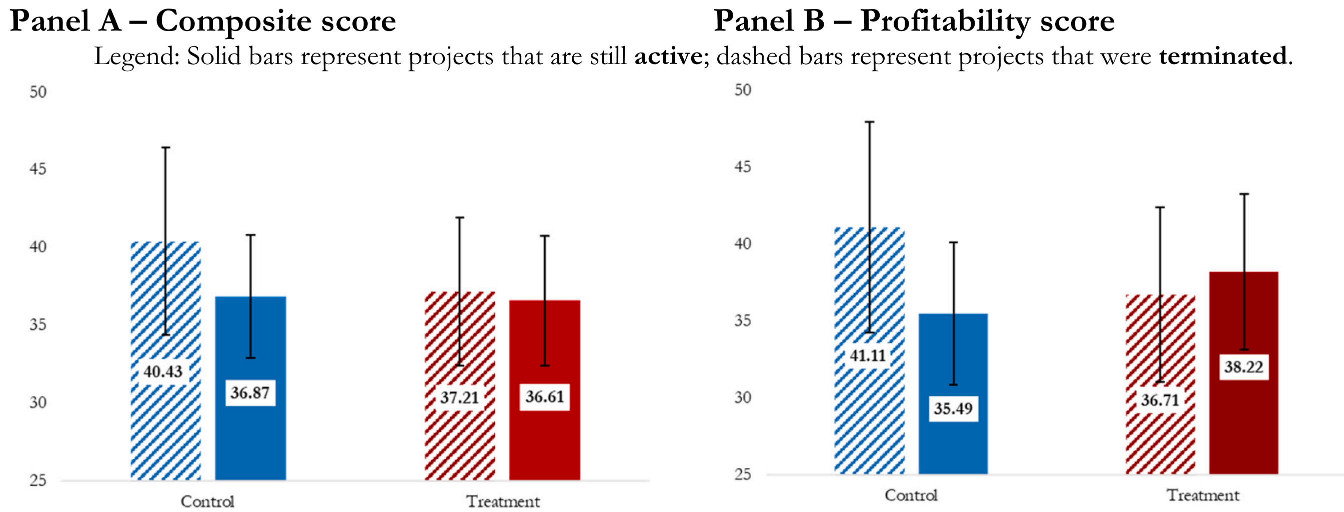

Fig. 4. Expert evaluations.
This figure reports the group averages of the expert evaluations scores. Experts were asked to evaluate each project on three dimensions, (1 to 100 scale): 1) *Profitability Potential*: potential for commercial success of the project (1 = a loss is likely; 100 = a high gain is likely); 2) *Innovativeness*: innovativeness of the project (1 = not innovative at all; 100 = highly innovative); 3) *Feasibility*: project feasibility (1 = unfeasible; 100 = highly feasible). The "Composite Score" refers to the average between the three items. The "Profitability Score" refers to the first item alone. Bars represent 95 % confidence intervals. $N = 330$; Control = 167; Treatment = 163. There are no significant differences at conventional levels between groups. Using the median produces a similar pattern.

important contribution to research in this area, which has focused exclusively on the short-term implications of a scientific approach.

4.4.2.1. Data and methodology. In the first data collection round (2022), we recruited a research assistant (RA), blind to the intervention. The RA was provided with a list of the 382 projects in our sample, including the founder's name and the name of the startup project. Their task was to conduct an online search, looking for information about the founder and the startup, to determine if the latter was still active. We considered a startup project as active if there were clear references to its activities online, such as the presence of a website, mentions of the startup in the founders' LinkedIn profiles, registration in the Chamber of Commerce registry, or recent press coverage. In 2023 we conducted a follow-up data collection round to obtain more precise data. We recruited other three RAs, also blind to the intervention. They were tasked with contacting the entrepreneurs and conducting brief phone interviews to obtain precise information on the status of their project,[20] reasons for project termination, and whether they engaged in other subsequent entrepreneurial activity. Out of the 382 entrepreneurs, we obtained responses from 282 of them, resulting in an overall response rate of 73.8 %.[21]

4.4.2.1.1. Termination, further development or venture launch. For respondents in the 2023 data collection, we identified a project as active in two instances: (1) if it was reported to be still under development; (2) whether it resulted in the launch of a venture. For non-respondents in the 2023 data collection ($N = 100$), we relied on the data collected in the 2022 data collection round. In this case, we considered projects as active if they had an online presence, as determined by the online search conducted by the RA. We created a dummy variable that took value of 1 only for projects that were launched as ventures (*Long-term: venture launch*). This variable identifies therefore a subset of the group in the survival status (*Long-term: survival*). To build this indicator, we first rely on the 2023 data collection, where entrepreneurs were directly asked if the project resulted in the launch of a venture. For the non-respondents to the 2023 data collection (N = 100), we considered a project as a venture if we found clear online evidence about it (for example, if we could identify a website for the venture, or if the entrepreneur referred to the project as to a venture, such as indicating in his or her LinkedIn profile that he or she was the founder of the venture).

4.4.2.1.2. Reason for termination. If the entrepreneur declared to have terminated the development of the project in the 2023 data collection, we directly asked for the reason behind the termination decision with an open question. We then manually coded this information into seven categories: 1) better employment opportunities; 2) lack of resources; 3) external factors (e.g., Covid-19); 4) lack of idea validation or development issues; 5) idea sold to third parties; 6) personal reasons; 7) team-related issues; 8) not defined.

4.4.2.1.3. Total revenue. We asked entrepreneurs with active projects if they could share revenue figures related to the 2022 fiscal year.

4.4.2.1.4. Generation of novel project ideas. During the phone interviews, we asked entrepreneurs whether they had attempted to develop new business ideas between the end of the training and the interview, and how many of these ideas were still under development.[22] This resulted in two variables. *Number of novel projects* first indicates the overall number of ideas generated by entrepreneurs since the end of the observation period; *number of currently active projects* indicates the subset of such ideas that were still under development.

4.4.2.1.5. Entrepreneurial career. Using information about project termination and the generation of new ideas, we classified those entrepreneurs who terminated their projects and did not have any new idea under development as having abandoned their entrepreneurial journey. Under these conditions, our RAs asked for the reason behind this choice through an open question. We manually coded this information into seven categories: 1) better employment opportunities; 2) lack of resources; 3) limitations of the entrepreneurial ecosystem; 4) Covid-19; 5) lack of motivation; 6) personal reasons; 7) lack of new ideas.

[20] Specifically, we asked entrepreneurs if the project they developed during the training course: 1) resulted in the founding of a company; 2) was still a project under development; 3) was terminated.

[21] Response rates by RCT: Milan: 187/250, 74.8 %. Turin: 95/132, 71.9 %.

[22] Specifically, we asked: From the end of the program until now, have you started or attempted to start new entrepreneurial activities or projects different from the one developed during the training? If yes, how many? And how many are still active?

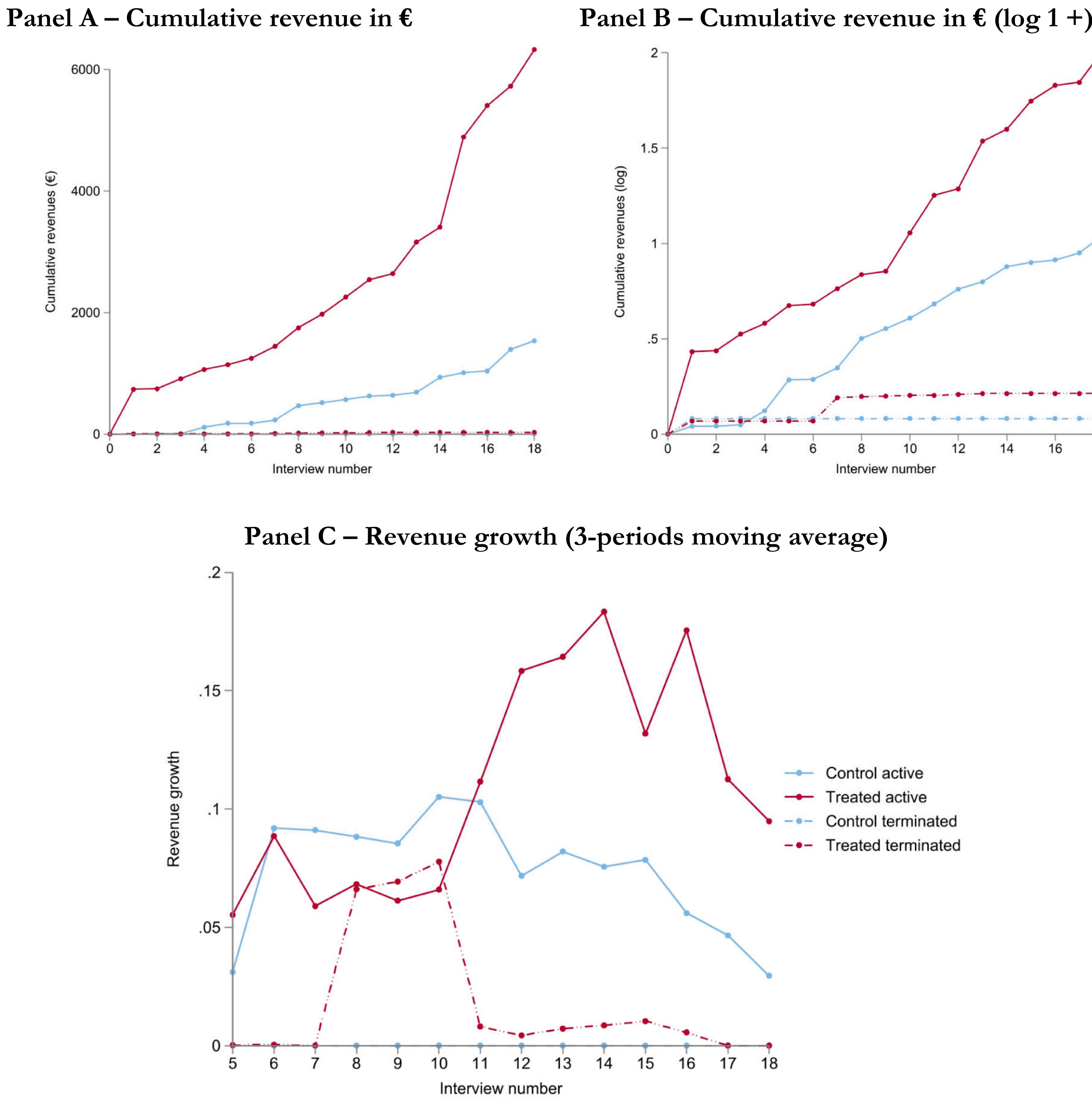

Fig. 5. Cumulative revenue during the RCT observation window.
This figure shows cumulative revenues over time. Averages per data collection period are shown by treatment group and project status at the end of the observation window. We input data for attritors and terminated projects over time with the last available datapoint to obtain smoother trends. In Appendix Fig. C.3.1 we replicate the graph with missing value for attritors or terminated projects.

4.4.2.2. Results

4.4.2.2.1. Termination, further development or venture launch. Table 7 classifies projects by their activity status given the two data collection exercises conducted in March 2022 and June 2023. Panel A describes the classification from the 2022 data collection round; Panel B the one from the data collection round conducted in 2023; Panel C combines the two data sources as described above. Projects are classified as a) terminated; b) still under development; c) resulting in the launch of a venture.

Considering the 2023 data collection exercise in Panel B, out of the 282 entrepreneurs successfully contacted, 217 terminated their projects, 21 were still in the development phase, and 44 created a firm. Next, we focus on the composite classification in Panel C and examine results by treatment condition. Results are graphically reported in Fig. 6. We observe that a higher portion of projects in the treatment group are active (24.2 % vs. 18.2 %) and are more likely to result in the launch of a venture (18.9 % vs 12.5 %). Focusing on terminated projects, we note that 75.8 % of treated entrepreneurs report having terminated their project, while this proportion rises to 81.8 % for control firms. This result is very interesting if we compare it to the termination rates observed within the first 18 month, which were 45.3 % for the treated group and 31.8 % for the control group. They suggest that, in the short term, treated entrepreneurs are more likely to terminate their projects earlier than control entrepreneurs. However, in the longer term, this difference levels out, with control entrepreneurs eventually terminating a higher number of projects. This evidence further supports the intuition that treated entrepreneurs are not excessively critical in their evaluation of projects but, rather, more accurate; it is consistent with the possibility that terminating projects earlier, they can free up resources that they can redeploy elsewhere.

Table 8 presents regression results for the probability of being active in the long term (Panel A) and for the probability of launching a venture (Panel B). We estimate the models through probit regressions, both on the whole sample and conditioning on the termination status at the end of the RCT.

Regression results show a generally positive association between the

Table 6
Revenues at the last datapoint.

Dep. variable	Panel A		Panel B	
	Revenue (final, log €)		Revenue (final, €)	
	Model 1	Model 2	Model 1	Model 2
Treatment	0.971^	0.857*	4790*	3866*
	(0.526)	(0.401)	(2066)	(1738)
Lower bound	−0.702*	−0.799**	−3117*	−3672***
Upper bound	2.728***	2.701***	13,827***	13,593***
Observations (selected)	235	235	235	235
R-squared	0.022	0.184	0.022	0.095
SE	Clustered	Clustered	Clustered	Clustered
Controls	No	Yes	No	Yes
RCT dummy	Yes	Yes	Yes	Yes
Mentor dummies	No	Yes	No	Yes
Model	OLS	OLS	OLS	OLS

Model 1 includes the treatment indicator and a dummy distinguishing the two RCTs. Model 2 adds mentor dummies and controls. Standard errors clustered at the classroom (RCT-intervention-mentor) level in parentheses. We compute lower (upper) bounds by substituting missing values for attritors or terminated projects with the within-group average minus (plus) half of the standard deviation (Horowitz and Manski, 2000; Kling et al., 2007). In the Appendix, Section D, we re-estimate Model 2 with robust standard errors, obtaining consistent results. In Appendix, Section C4, we replicate results by RCT.

*** $p < 0.001$.

** $p < 0.01$.

* $p < 0.05$.

^ $p < 0.10$.

treatment indicator and both dependent variables, across all specifications. Results reveal particularly strong patterns when conditioning the estimation on the subsample of projects that were still active at the end of the RCT observation window. Considering Column 3, they indicate that projects developed by treated entrepreneurs are 12 percentage points more likely to be active in the long-term, given the initial selection. Panel B shows that there is also a higher likelihood of having established a new venture, of about 10 percentage points (Column 7). These findings reinforce the idea that the project selection conducted by treated firms was led by a better collection and interpretation of signals and led to positive outcomes.

4.4.2.2.2. Total revenue. Focusing on projects resulting into the establishment of new ventures, the percentage of those which generated positive revenues in 2022 was similar between the control (69 %, 9 out of 13) and treated (62 %, 13 out of 21) groups, with an average (median) revenue of €415,333 (€100,000) for the control group and €720,416 (€57,000) for the treated group.

4.4.2.2.3. Generation of novel project ideas. Our earlier results show that entrepreneurs terminate projects more quickly and overall adjust their expectations for success downward. We suggested that one interpretation for this effect, in line with Felin et al. (2020), is that scientific entrepreneurs identify (early) projects that are not necessarily valuable, and free up resources that can be redirected in more promising directions. To validate this interpretation, we should see evidence that, alongside adjusting their expectations on the projects developed during the RCTs, scientific entrepreneurs are also more likely to redirect attention to other business opportunities. To explore whether this was the case we explored the generation of novel entrepreneurial projects by entrepreneurs in both conditions.

We found that 61 % of the interviewed entrepreneurs stated that they did not develop any new business ideas, while 25 % reported attempting to develop at least one more idea. As indicated in Appendix Table E1, treated entrepreneurs generated an average of 0.81 ideas, versus 0.48 for the control group. When conditioning on entrepreneurs generating at least one additional new idea, the averages are of 1.85 for treated entrepreneurs and 1.41 for control entrepreneurs. Similarly, treated entrepreneurs have a higher average of entrepreneurial projects that were still in activity at the time of the interviews. Results are graphically reported in Fig. 7.

These qualitative results are supported by the negative binomial regressions reported in Table 9. Panel A confirms that treated entrepreneurs generated a higher number of novel entrepreneurial ideas between the end of the RCT observation window and the 2023 interview date ($\beta = 0.415, p = 0.032$). The same is true for the number of ideas that were still active (or under development) as of the interview period, as shown in Panel B ($\beta = 0.418$, $p = 0.204$). Digging deeper into these results, seven entrepreneurs in the treated group reported generating more than four novel projects, while the highest number of novel projects generated by entrepreneurs in the control group was three. This provides support for the mechanism outlined by Felin et al. (2020).

4.4.2.2.4. Reason behind project termination. Focusing on terminated projects, we asked entrepreneurs about the reasons behind their decision. The top three reasons identified were team-related issues (25 %), such as disagreements or the inability to form an experienced team; failed idea-validation or development process (24 %); and lack of resources (22 %). Interestingly, the lack of idea validation or development issues was the primary reason for project termination among treated entrepreneurs (29 % of cases) compared to the control group (19 %). This is in line with the above interpretation of results that treated entrepreneurs adjust their expectations downward because they are better able to understand signals and to identify flaws in their ideas. Results are graphically reported in Fig. 8.

4.4.2.2.5. Entrepreneurial career and motivation. Finally, we collected data on whether any of the entrepreneurs in our sample decided to cease the pursuit of an entrepreneurial career. The intuition behind this investigation was that, if treatment made entrepreneur generally more cautious, this could also be reflected in their desire to be an entrepreneur in the first place. The data does not support this explanation. Overall, we found that 37 % of the overall sample decided to cease their entrepreneurial career, but we did not find significant differences between the experimental conditions in terms of overall termination rates of entrepreneurial careers (*control* = 39 %, *treated* =

Table 7
Longer term outcome: descriptives.

	Panel A 2022 data collection round			Panel B 2023 data collection round			Panel C Composite data		
	Control	Treated	Total	Control	Treated	Total	Control	Treated	Total
Terminated	165	148	313	101	116	217	157	144	301
Under development	27	42	69	11	10	21	11	10	21
Launched venture				16	28	44	24	36	60
N	192	190	382	128	154	282	192	190	382

Panel A shows data collected on the web in the 2022 data collection round, in which projects were classified as active if online presence was recorded. We did not distinguish between projects that were still under development versus those which had reached the venture status. Panel B shows the classification according to the 2023 phone interviews, in which entrepreneurs were directly asked if their projects were terminated, still under development, or resulted in the launch of a venture. Panel C shows the combined measure, where missing data from the 2023 data collection in Panel B (N = 100) were complemented with data from Panel A. To input data, we assume that online presence recorded in 2022 equals to the launch of a venture, given the higher likelihood of finding online information for a company rather than for a project still in its development stage.

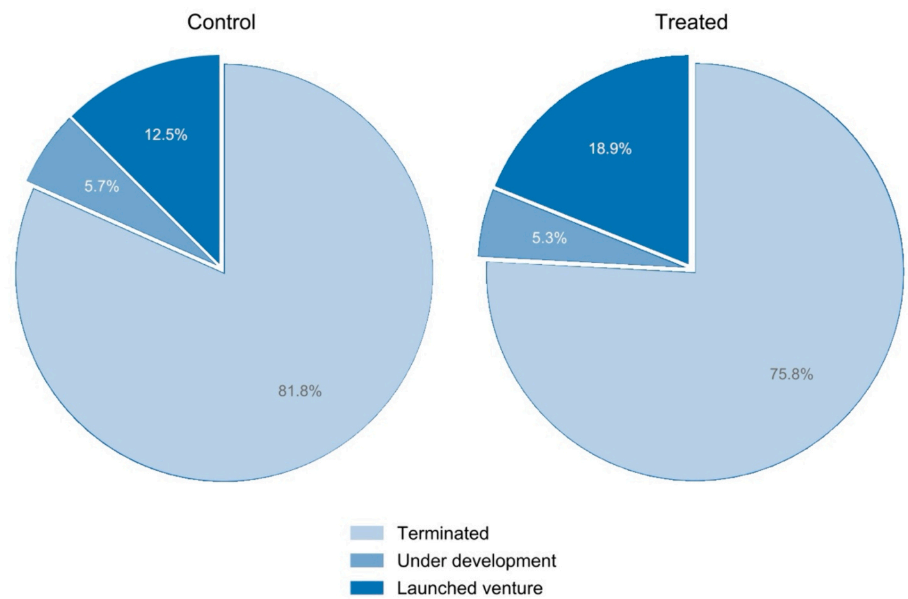

Fig. 6. Status of the ventures in 2023.

Table 8
Longer term outcome: regressions.

	Panel A				Panel B			
Dep. variable	Long-term: survival				Long-term: venture launched			
Sample	All projects		Active at the end of the RCT		All projects		Active at the end of the RCT	
	(1) Model 1	(2) Model 2	(3) Model 1	(4) Model 2	(5) Model 1	(6) Model 2	(7) Model 1	(8) Model 2
Treatment	0.059	0.059	0.124*	0.117*	0.064	0.072*	0.104^	0.114*
	(0.046)	(0.039)	(0.053)	(0.050)	(0.041)	(0.034)	(0.055)	(0.049)
Observations	382	382	235	235	382	382	235	235
SE	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered
Controls	No	Yes	No	Yes	No	Yes	No	Yes
RCT dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mentor dummies	No	No	No	No	No	No	No	No
Model	Probit	Probit	Probit	Probit	Probit	Probit	Probit	Probit

Average marginal effects reported. Model 1 includes the treatment indicator and a dummy distinguishing the two RCTs. Model 2 adds controls (experience with startups at the baseline; size of the founding team at the baseline; teams' average education level; average age of the team; hours worked at the baseline; share of the team with economics or STEM degrees; self-reported measure of self-regulation). Standard errors clustered at the classroom (RCT-intervention-mentor) level in parentheses. In the Appendix, Section D, we re-estimate Model 2 with robust standard errors, obtaining consistent results. In Appendix, Section C4, we replicate results by RCT. We estimate models using both all projects and projects classified as active at the end of the RCT ($N = 235$).
*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; ^ $p < 0.10$.

36 %). Exploring the reasons behind the decision to terminate their entrepreneurial careers, most entrepreneurs (51 % in the control condition and 53 % in the treatment condition) cited better employment opportunities as the primary reason for doing so. This suggests that employment opportunities may have been a significant factor influencing their choice to leave their entrepreneurial pursuits behind, in line with the intuition that the treatment does not lead to be excessively critical about the value of projects. Results are graphically reported in Fig. 9.

5. Discussion and conclusion

Entrepreneurial ventures are the "embodiment of innovation" (Audretsch, 1995; Feldman, 2001: 861) and decision making in this context is crucial for determining the extent to which innovators appropriate the value of their ideas (Teece, 1986). The recent stream of research suggesting that entrepreneurs can navigate the uncertainty that characterizes entrepreneurial decisions by operating like scientists (Camuffo et al., 2020, 2024; Ehrig and Schmidt, 2022; Felin and Zenger, 2009; Felin and Zenger, 2017; Felin et al., 2024; Zellweger and Zenger, 2021) has spurred a insightful conceptual debate (e.g., Sergeeva et al., 2022; Zellweger and Zenger, 2022).

In this paper we contribute to this debate, by utilizing two RCTs involving 382 entrepreneurs. We explore the extent to which entrepreneurs who employ a scientific approach to decision-making, and choose to terminate their projects, do so following an adjustment in their expectations concerning project value and expected probability of termination (as opposed to remaining firmly convinced about the values of their ideas until a later stage). We find that the decision to terminate is not always aligned to a reduction in the entrepreneurs' assessment of the expected value of the project or an increase. However, our findings show that treated entrepreneurs who terminate their projects precede such decision with an adjustment of their expectations that is consistent with their termination decision: this happens more consistently and sooner than for control entrepreneurs.

We then explore whether the tendency of treated entrepreneur to adjust their value expectations downward is driven by a more *accurate collection and interpretation of signals* versus an *excessively critical attitude*.

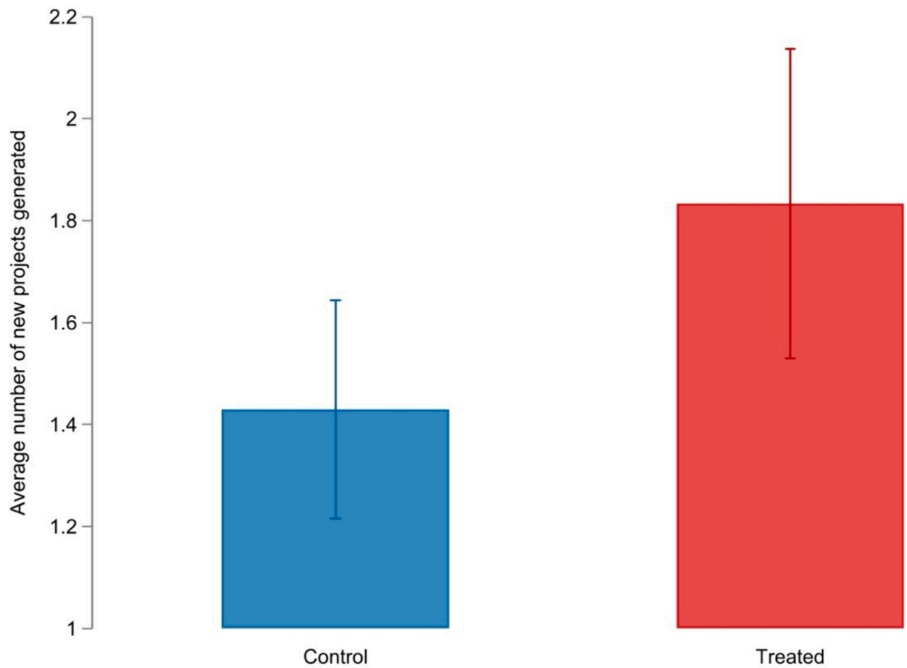

Fig. 7. Number of novel projects by treatment condition.
This figure reports the number of projects generated by entrepreneurs who have generated at least one additional project.

Table 9
Negative binomial regression, number of new projects.

	Panel A		Panel B	
	Number of new projects generated		Number of currently active projects	
	Model 1	Model 2	Model 1	Model 2
Treatment	0.503** (0.192)	0.415* (0.183)	0.451* (0.217)	0.418^ (0.204)
Observations	282	282	282	282
SE	Robust	Robust	Robust	Robust
Controls	No	Yes	No	Yes
RCT dummy	Yes	Yes	Yes	Yes
Mentor dummies	No	No	No	No
Model	Negative binomial	Negative binomial	Negative binomial	Negative binomial

Model 1 includes the treatment indicator and a dummy that distinguishes the two RCTs. Model 2 includes adds controls (experience with startups at the baseline; size of the founding team at the baseline; teams' average education level; average age of the team; hours worked at the baseline; share of the team with economics or STEM degrees; self-reported measure of self-regulation). Robust standard errors in parentheses. Results are fully robust either using non-corrected standard errors or clustered standard errors.
*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; ^ $p < 0.10$.

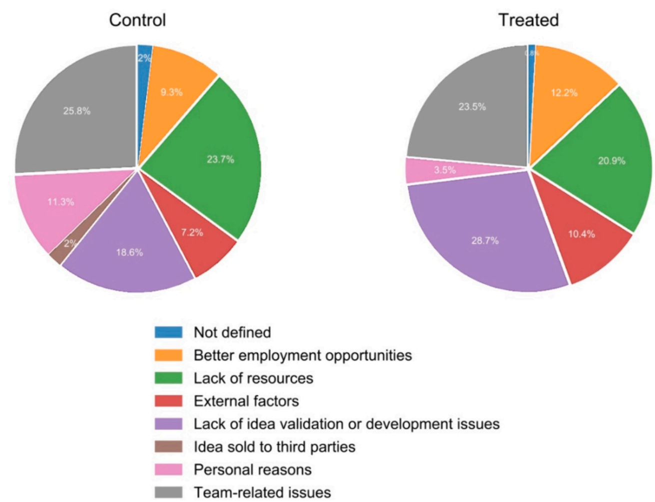

Fig. 8. Reason behind project termination.

The former would be associated with a selection process in which unpromising projects are ruled out earlier and more often, with attention potentially shifted to novel ideas. The latter, instead, would be associated with a potentially adverse selection process, in which good projects are often mistakenly discarded. Focusing initially on terminated projects, we show that the likelihood of obtaining external funding is not significantly different between experimental groups. Moreover, leveraging experts' evaluation on pre-treatment project descriptions, we do not find evidence of higher scores assigned to projects discarded by treated entrepreneurs. Using data from a novel data collection round subsequent to the RCTs, we also find that treated entrepreneurs tend to generate a higher number of novel entrepreneurial projects over time. Taken together, these results support the idea that entrepreneurs trained to follow a scientific approach tend to interpret signals more accurately, ultimately discarding less promising projects earlier and redirecting their attention to the generation of new ideas.

Lastly, we contribute to existing research in this area by analyzing long-term performance, and comparing it with short term performance. In the short term (18 months after the beginning of the training) treated entrepreneurs terminate their projects more frequently and earlier than control entrepreneurs (45.3 % for treated vs. 31.8 % for control). However, in the longer term, over five years after the program's start, this initial discrepancy between the treated and control groups levels out, with the control group entrepreneurs eventually exhibiting a higher rate of project termination (81.8 % for control vs. 75.8 % for treated). This evidence further supports the intuition that treated entrepreneurs are not excessively critical in their evaluation of projects but, rather, more accurate and quicker in assessing projects' value. By terminating projects earlier, they can liberate resources for redeployment elsewhere.

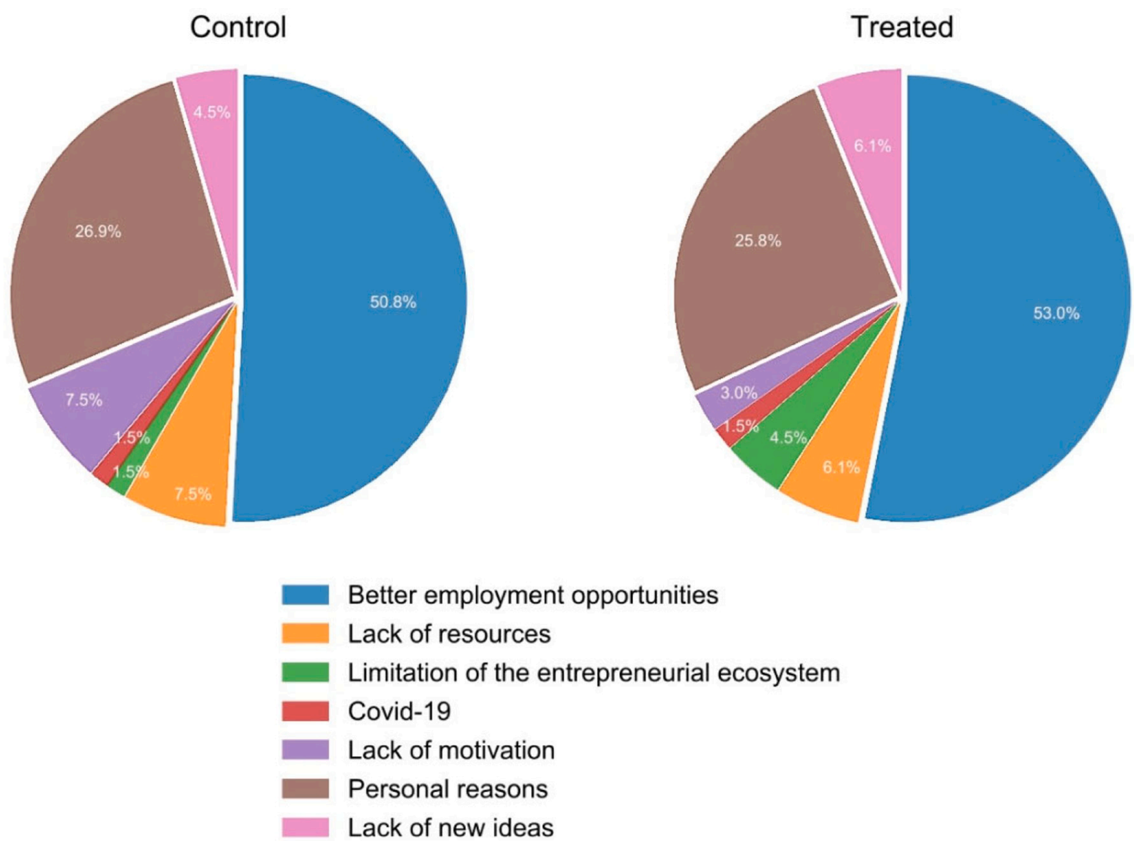

Fig. 9. Reason behind termination of entrepreneurial career.

Aligning with this perspective, our results indicate that, in the long run, a higher proportion of projects among treated entrepreneurs culminate in the launch of an actual venture (18.9 % for treated versus 12.5 % for control entrepreneurs). Moreover, treated entrepreneurs initiate a greater number of new projects in comparison to their counterparts in the control group, with an average of 0.805 new projects per treated entrepreneur versus 0.484 for those in the control group. Table 10 provides an overview of the evidence we collect on long-term performance.

Overall, these results provide several important research and policy implications. First, they contribute to research on the E-a-S approach to decision making. On the one hand, the existing conceptual research in this area has extensively elaborated on the way in such a theory-based approach could help decision makers develop a more accurate collection and interpretation of signals (Ehrig and Schmidt, 2022; Felin et al., 2020, 2023; Zellweger and Zenger, 2021). On the other hand, existing empirical research in this area has provided evidence that a scientific approach leads to faster and more frequent project termination (Camuffo et al., 2020, 2024), but never provided evidence neither about the underlying process that leads to termination nor on about how such pattern should be interpreted. In this paper, we fill this gap by exploring the effect of our intervention on entrepreneurial expectations and how they are associated with the actual decision to terminate. Our results provide important insights regarding the specific way in which the treatment affects the entrepreneurial decision-making process, specifically by showing evidence of a superior alignment between expectations and decisions for treated entrepreneurs.

Second, our study is the first to investigate the longer-term effect of an E-a-S approach, on a variety of dimensions. Among other dimensions, we look at the extent to which the approach is effective in fostering the generation of new ideas. The conceptual works by Felin et al. (2020) and Felin et al. (2023) make an important point: when entrepreneurs operate like scientists their actions are guided by a theory. In addition to supporting entrepreneurs' local search, a theory also supports entrepreneurs in identifying the most promising area to be searched within the landscape. In other words, theory endows scientific entrepreneurs with the equivalent of a "flashlight" (Felin et al., 2020: 5) that enables them to move across the landscape in a targeted way. Our findings that treated entrepreneurs terminate more projects but subsequently generate more novel ideas provides the first evidence of this theoretical intuition.

Our results also provide important policy implications. One of our core results in this area concerns the superior alignment between expectations and decisions that is associated with the treatment. Entrepreneurs who operate like scientists are essentially more aware about the direction that their venture is going. We also show that treated entrepreneurs generate more ideas and that the selected ideas have higher performance and survival rates in the long-term. Together these results suggest that policies that encourage an E-a-S approach can be effective in nudging entrepreneurs to make more informed decisions, identify lower quality projects earlier, and redirect resources in more promising directions, leading to a more efficient allocation of resources and a reduction of waste.

Our study, like any research endeavor, is not without limitations, which also presents opportunities for future research. First, while our study expands the empirical understanding of the E-a-S approach, further systematic and large-scale research is needed on this topic. For example, it is crucial to ascertain the role that each of the components of a scientific approach to decision making (theory, hypotheses, test and evaluation) has in determining the outcome we observe. Second, the evidence we present shows treated entrepreneurs who eventually terminate their projects adjust their expectations on the value of those projects downward and their expectations on the probability of termination upward, a pattern we do not observe for control entrepreneurs. This is in line with the idea that the adjustment in expectations

Table 10
Long term results overview.

	Control		Treated		*t*-Test	
	Average	SD	Average	SD	Diff	*p*-Value
Proportion of projects terminated as of 2017–2018 (18 months after beginning of the training)	0.318	0.467	0.453	0.499	−0.135	0.007
Proportion of terminated as of 2023 (over 5 years after the beginning of the training)	0.818	0.387	0.758	0.429	0.06	0.154
Proportion of resulted in the establishment of a venture as of 2023	0.125	0.332	0.189	0.393	−0.064	0.084
Proportion of still under development as of 2023	0.057	0.233	0.053	0.224	0.005	0.842
# new projects generated on average by each entrepreneur (beyond original one) as of 2023 ($N = 282$)	0.484	0.773	0.805	1.309	−0.321	0.011
N	192		190			

Note. *p*-Values from two-tailed t-test on equality of means between the two experimental conditions.

eventually leads to termination, but we cannot test the mediation directly, because our experiment did not intervene on expectations directly. More in general, following an inquiry-driven methodology (Graebner et al., 2023), we conducted a series of analyses to investigate an important phenomenon. We identified a compelling explanation and gathered supporting evidence to substantiate these explanations. We encourage readers to formulate their own interpretations of this significant phenomenon. In doing so, we believe that our study lays the foundation for future research. Scholars in the field can utilize our work as a starting point to advance theories and conduct hypothesis testing, contributing to the accumulation of knowledge in this area.

Finally, from a theoretical perspective, it would also be important for future research to gain a better understanding of the limitations associated with the scientific approach. Thinking like scientists requires cognitive effort, akin to Kahneman's System II thinking rather than relying on intuitive System I thinking (Kahneman, 2013). As a result, it may be more practical to rely on heuristics and focus on shaping the future rather than attempting to predict it (e.g., Sarasvathy, 2001; Sergeeva et al., 2021; Ehrig and Foss, 2022). This viewpoint is supported by Robert Noyce, the inventor of the integrated circuit, who, upon leaving Bell Labs to establish his own semiconductor company in California, argued that he no longer needed to understand why things worked, but rather gather "minimum information" and let things progress if they functioned (Moore and Davis, 2004). It is crucial to determine the contexts in which a scientific approach is more effective compared to alternative approaches such as effectuation (Sarasvathy, 2001), simple rules (Bingham and Eisenhardt, 2011) or the widely adopted lean startup approach (Contigiani and Levinthal, 2019; Ries, 2011). Further research is necessary to address these questions, which hold significant importance from both an academic and practical standpoint.

CRediT authorship contribution statement

Andrea Coali: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Alfonso Gambardella:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Elena Novelli:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Alfonso Gambardella reports financial support was provided by Innovation Growth Lab. Alfonso Gambardella reports financial support was provided by European Research Council. Alfonso Gambardella reports financial support was provided by Government of Italy Ministry of Education University and Research - PRIN. Elena Novelli reports a relationship with UK Government Department of Business, Energy and Industrial Strategy that includes: funding grants.

Data availability

Data will be made available on request.

Acknowledgement

We acknowledge funding support from the Innovation Growth Lab, the Government of Italy Ministry of Education University and Research (project: "Entrepreneurs As Scientists: When and How Start-ups Benefit from A Scientific Approach to Decision Making," call PRIN 2017, Prot. 2017PM7R52, CUP J44I20000220001), the European Research Council (ERC) and the UK Department of Business Energy and Industrial Strategy - Innovate UK, project: 104754, "A Scientific Approach to SMEs Productivity". This research was approved by Bocconi Research Ethics Committee with protocol references 2016-III/13.696, 77133-2. The two studies presented in this manuscript are included in the AEA RCT Registry (AEARCTR-0002205, AEARCTR-0006579). We are grateful for comments and advice to Arnaldo Camuffo.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.respol.2024.105022.

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