Small Changes with Big Impact: Experimental Evidence of a Scientific Approach to the Decision-Making of Entrepreneurial Firms

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Abstract

Identifying the most promising business ideas is key to the introduction of novel firms, but predicting their success can be difficult. We argue that if entrepreneurs adopt a scientific approach by formulating problems clearly, developing theories about the implications of their actions, and testing these theories, they make better decisions. In particular, this approach helps entrepreneurs to make more precise predictions of the value of their idea and to spot new ideas with higher expected returns. Precision implies that the distribution of value perceived by the entrepreneurs is more concentrated around its mean. While this cuts the right tail, it does not have important implications for the left tail because entrepreneurs will close the firm before making profits smaller than their opportunity cost. Thus, other things being equal, precision reduces expected returns, making it more likely that scientific entrepreneurs close their firm. At the same time, the scientific approach helps to see new ideas with higher probabilities at the right tail. Thus, when they do not close the firm, they perform better. Using a field experiment with 250 nascent entrepreneurs attending a pre-acceleration program, we provide evidence consistent with these mechanisms. We teach the treated group to formulate the problem scientifically and to develop and test theories about their actions, while the control group follows a standard training approach. We collect 18 data points on the decision-making and performance of all entrepreneurs for 14 months. Results show that the narrower spread of the prediction of business value of treated entrepreneurs raises the probability that they close their start-ups. Scientific entrepreneurs are also more likely to see new opportunities with higher odds at the right tail which prompts them to pivot to these new ideas and perform better.

Keywords: scientific approach, entrepreneurship, field experiment.

1. Introduction

The biggest initial challenge entrepreneurs face is to identify a feasible and profitable business idea to turn into a new venture. The process of idea identification tends to be 'incoherently chaotic and focused on the future' (Eisenhardt and Brown, 1998, p.35) and happens through iterations based on the feedback entrepreneurs obtain from peers (Chatterji et al., 2019), early customers (Parker, 2006), experts in the field and sponsors (Cohen et al., 2018), or even family and friends (Bennett and Chatterji, 2017). This process of idea identification is crucial because initial choices on the direction in which the idea should develop will determine if it can become a fully-fledged start-up (Aldrich and Martinez, 2015) and in the long run can greatly constrain or enable the performance of these firms (Dimov, 2007).

History is full of cases where entrepreneurs significantly changed the business idea they initially identified, as they realized that their original intuition was unlikely to work. Twitter, for instance, was conceived as Odeo, a platform that simplified the search for and subscription to podcasts. As iTunes started to gain popularity in the podcast space, Odeo turned into Twitter, a micro-blogging platform. This iteration represented a radical change in strategy (a 'pivot'), which allowed the owners to avoid a costly mistake. Similar radical changes also marked the early days of successful tech companies such as Instagram, Lyft, PayPal, Pinterest, Slack and YouTube. All these pivots required entrepreneurs to understand what elements of their business ideas were likely to work and in which direction they should turn.

Extant studies on this topic converge on the iterative nature of the process entrepreneurs go through as they evaluate and develop their business ideas (Baron and Ensley, 2006), but do not clarify how this process of strategic change and pivoting should be conducted. Emerging streams in entrepreneurship such as effectuation (Sarasvathy, 2001) and bricolage (Baker and Nelson, 2005) propose that entrepreneurs should rely on non-predictive techniques given the high uncertainty surrounding the creation of a new venture. Proponents of these approaches argue that entrepreneurs should 'make do' with what they have at hand and improvise to win over stakeholders that will co-create new products and markets with the entrepreneur (Wiltbank et al., 2006). Effectual and bricolage approaches are attempts to acknowledge the bounded rationality of the entrepreneur and embrace the uncertainty of the environment by setting aside predictions and focusing on controlling the environment.

Other scholars suggest, instead, that structured and disciplined processes of idea evaluation and development can mitigate fallible judgement (Hogarth and Karelaia, 2012) and reduce the cognitive biases that affect entrepreneurial decision-making (Murray and Tripsas, 2004; Camuffo et al., 2020; Cohen et al., 2018; Kahneman et al., 2019).

Drawing on the latter stream of research, we propose that entrepreneurs can better understand whether their business idea is valuable when they formulate problems clearly, develop theories about the implications of their actions, and test these theories rigorously. In conducting these actions, labelled "a scientific approach to decision-making," entrepreneurs also become better equipped to gather and interpret valuable signals from customers and other stakeholders that contribute to pivots of the initial business idea (Furr, 2009; Camuffo et al., 2020).

In this study, we first develop a theory of the implications of the scientific approach to decision-making under uncertainty. We propose that scientific entrepreneurs develop and test theories that help them to frame their problems more effectively, decompose them into sub-problems, and identify the relevant sub-problems in the sense of sub-problems whose solutions have more important implications for the value of the business. Theory and tests have two main implications. First, they enable entrepreneurs to predict the value of their business with greater precision. Second, they help them to identify new problems and their solutions that enhance the value of their business. These two effects have opposite implications on the spread of the distribution. Greater precisions makes the distribution of value more concentrated around its expected value. New problems and solutions raise, instead, the spread because they are innovations that, as such, raise uncertainty with respect to the status quo.

Since entrepreneurs have an opportunity cost below which they close the firm, greater precision implies that scientific entrepreneurs are more likely to predict a lower expected value from their business, which makes them more likely to close their firm. However, the higher spread produced by their ability to see new potential determinants of value raises the expected outcomes if they do not close the firm. Our theory also posits that the ability to see new determinants implies that entrepreneurs pivot because this may transform the original idea. However, because the search space is bounded, scientific entrepreneurs, who span this space more quickly, are more likely to see new determinants when they have not pivoted yet than when they have already pivoted some time. Our theory then predicts that scientific entrepreneurs are more likely to pivot once (or few times) than making zero pivots or many pivots. Put differently, when they pivot, they know where to go, and do not need to pivot further. In contrast, if you do not know where to pivot, you wander across ideas.

We test this theory by conducting a randomized control trial (RCT) with 250 nascent entrepreneurs attending a pre-acceleration program. We randomly assign entrepreneurs to either a treatment (being taught how to use a scientific approach when developing a business idea) or a control group (being taught how to develop a business idea). We collect detailed data about their performance and decision-making over 14 months to investigate how a scientific approach impacts the development of these business ideas. We first replicate the results of a previous study (Camuffo et al., 2020) with the different sample employed in this paper. We find that treated entrepreneurs are more likely to close their business than entrepreneurs in the control group, they are more likely to pivot, and they enjoy higher revenue. However, we extend the previous study by providing evidence about the mechanisms. We measure the scientific intensity of entrepreneurs' decisions and the spread of the perceived distribution of future value. We show that scientific intensity, instrumented by the treatment, lowers the spread, which in turn raises the probability that entrepreneurs close the firm. Scientific intensity instrumented by the treatment also raises the difference in the spread between two periods that increases the probability that entrepreneurs pivot once or twice but not zero or more than two times.

We begin in Section 2 by clarifying what a scientific approach to entrepreneurial decision-making means. Section 3 presents our theory. Section 4 describes our research design, data and methods. Section 5 shows our empirical results. Section 6 highlights limitations and directions for future research.

2. A scientific approach to decision-making

A key feature of nascent entrepreneurship is that returns from business ideas are skewed and their quality is hard to assess. Acquiring knowledge about the potential outcomes of a business idea can reduce this fundamental uncertainty (Delmar and Shane, 2003; Dencker et al., 2009), because it generates information about the ultimate value of a business idea. We propose that a scientific approach to decision-making can reveal more precise information and lead to better estimates of the value of a business idea.

Extant literature suggests there are two fundamental types of decision-making in early-stage entrepreneurship. The first type is akin to trial and error (Dencker et al., 2009), and it normally involves experimenting sequentially with various methods until entrepreneurs achieve some results. This search strategy is normally 'blind' or only guided by prior assumptions and beliefs, and consequently entrepreneurs often run the risk of engaging in confirmatory search (Shepherd et al., 2012). An alternative approach, which has been called purposeful (Murray and Tripsas, 2004), or scientific (Camuffo et al, 2020), is more systematic and structured. We define this scientific approach as a discipline, a set of behavioral routines – similar to those used by scientists – that the entrepreneurs follow to develop their ideas and assess their value . This discipline can be taught and learned, and comprises four major components:

1. A clear definition and framing of the problem and the articulation of a 'strategic representation' (Csaszar, 2018) or 'theory' (Zenger, 2016) that lead to the design of a business model as grounded on a general understanding of the problem, its solutions and implications. Entrepreneurs who adopt a scientific approach treat the problems of their business as research questions (Nickerson & Zenger, 2004) and formulate theories about them that are novel, simple, falsifiable and generalizable (Felin and Zenger, 2009 and 2017). Also, the framing of the problem and the articulation of a theory is associated with the decomposition of the problem into sub-problems that represent the specific factors or determinants of the value of the business (Nickerson, Silverman & Zenger, 2007). The theory provides logical connections that explain why each one of these factors or determinants ought to affect value.
2. The explicit formulation of hypotheses that are composed from the theory and enable the entrepreneurs to bring it to reality. Hypotheses are educated guesses about the customers, their problems, and more generally about the factors that drive value creation and value capture. Hypotheses are testable and falsifiable inasmuch as they clearly define the contingencies in which they are not false (or are definitely false) and can produce good, actionable evidence and validated learning (Eisenmann et al., 2011).
3. The empirical testing of the hypotheses, based on facts and data appropriately collected and rigorously analyzed possibly, through experiments (Murray and Tripsas, 2004; Kerr, Nanda, & Rhodes-Kropf, 2014). These tests use valid and reliable metrics. They allow entrepreneurs to assess whether the

specific determinants predicted by the theory are valuable and possibly identify causal relationships (experimental or quasi-experimental designs) (Davenport, 2009).

4. The open, critical and independent analysis and interpretation of the outcomes of the tests. The honest and thorough evaluation of the evidence gathered testing hypotheses requires both individual and collective judgement (Foss & Klein, 2012; Pfeffer and Sutton, 2006), as well as critical appraisal of evidence. Openness to questioning, discussion and criticism is a crucial part of entrepreneurial decision-making, as it is in science (Rousseau, 2006).

Bennett and Chatterji (2017) and Camuffo et al. (2020) provide evidence that the majority of entrepreneurs do not 'naturally' behave in a scientific manner. We expect that entrepreneurs who 'discipline' their decisions according to this approach will make better predictions of the value of their business idea, and will act accordingly, as detailed in the next section.

3. Theory

3.1. Building blocks

We focus on entrepreneurs who, at least to some extent, base their decisions on predictions. In particular, they evaluate the attractiveness and potential returns of their business idea by predicting a performance variable. It is not easy to nail down how entrepreneurs think, particularly when they consider starting a new business and have to make early decisions such as product-market fit, the business model, or more generally the identity of their firms. Some scholars or practitioners argue that they 'just do it' or follow patterns such as effectuation (Sarasvasthy, 2001), pattern recognition (Baron and Ensley, 2006), bricolage (Baker and Nelson, 2005) or other routines or heuristics. However, in general, entrepreneurs combine thinking and doing (Ott et al., 2017) that involves some form of prediction, even if coarse and unrefined. Moreover, they are more likely to make predictions when the decision is important. Even the entrepreneurs in our trial, who operate in relatively simple businesses (such as retail and e-Commerce), tend to use predictions to make important decisions – albeit possibly in fuzzy ways, and in combination with other elements.

In our framework, entrepreneurs predict the present value v of their business idea. Because they do not observe future profits, they do not observe v when they make the decision whether to develop their business idea. Thus, the way they form this prediction is important. In general, entrepreneurs try to identify what factors or variables drive how much value the idea will create for customers and what fraction of that value they can capture. They then use these variables to make the prediction. Of course, entrepreneurs vary in the extent to which they identify these factors in fuzzier or more refined ways, and in the extent to which their predictions are coarser or more precise. However, they tend to have in mind a set of factors contributing to value creation and capture, and they weigh the importance of each factor. Even though they do not form their prediction in a strictly mathematical form, it helps our understanding of the problem to represent their expectation as a linear combination $\hat{v} = \hat{v}_1 + \hat{v}_2 + ... + \hat{v}_n$ where $\hat{v}$ is the expected v, the terms $\hat{v}_1$, $\hat{v}_2$, … $\hat{v}_n$ are the expected unit contributions of each factor to total value (created and captured) multiplied by the magnitude of the factor that entrepreneurs focus upon to make their prediction. For example, if entrepreneurs envision that gender affects the size of the potential market segment and, hence, of the value of the idea, $\hat{v}_1$ is the predicted magnitude of the effect of a higher share of men or women in the market. Similarly, if they believe that the quality of the product matters, $\hat{v}_2$ is the predicted magnitude of the effect of a given level of quality that they want to test. In principle we can think of this relation as a linear regression or, more generally, as any function comprising factors and interactions among them.

We believe that, in one way or another, all entrepreneurs break down their idea in factors and weigh them to predict its future value. They can do it in many different ways, ranging from gut feelings to the more rational and scientific approach that we discuss in this paper. Thus, we do not want to think of the formation of these expectations only in terms of a strict regression framework.

We study the early phase of the entrepreneurial decision-making process. In this phase, entrepreneurs explore and perfect ideas about their products or business models before they commit resources to the products or ideas that they produce and commercialize. Typically they go through exploration cycles and it is natural to assume that because of limited resources they explore one idea at a time (Gans et al., 2019). At the end of each exploration cycle, they either close the firm because they predict that they cannot develop a profitable idea, or they keep developing the current idea, or they pivot to a new idea, starting a new exploration cycle.

When they make this decision, entrepreneurs do not observe the value of the current idea or of any potential future ideas they could develop. Specifically, since they have decomposed the problem in sub-problems, they do not observe the exact magnitudes of the impacts of the n factors that determine value, which we label v_1, v_2, … and v_n, to distinguish them from the predicted impacts. Moreover, they know that the future total value v can also depend on factors that they do not anticipate when they make the decision. However, they know that if they keep pursuing an idea and develop it, they will gain more information about v, and eventually they will observe it. In addition, all entrepreneurs have an opportunity cost x (e.g. the foregone salary as employees) such that they will close the firm if in the future they discover that $v < x$ (assuming they have to quit their job to keep pursuing their idea). Therefore, when they have to decide whether to commit to a business idea, entrepreneurs know that they will earn x if $v < x$ and v if $v \geq x$. It is easy to envision that this implies that a probability distribution of v with the same mean and fatter tails has a higher expected value than a distribution with slimmer tails. This is because high realizations of v occur with higher probabilities than the distribution with slimmer tails; conversely, the negative realizations, which make the fatter distribution less appealing, do not occur because entrepreneurs realize x instead of the low realizations of v to the left of x.

3.2 Implications of the scientific approach

The adoption of a scientific approach affects this decision-making process. We focus on three elements: precision, modification of ideas, exhaustion of idea opportunities.

We start with precision. With a clear framing of the problem and a well-articulated theory, entrepreneurs choose the determinants of v in logical and rigorous ways. This makes it more likely that they focus on relevant determinants of value. In addition, rigorous empirical tests makes them more confident about the predicted impacts – that is, entrepreneurs who adopt a scientific approach predict impacts closer to what they will find when they have more information. This is a broad representation that encompasses, for example, the case in which entrepreneurs who adopt the scientific approach predict different factors than their counterfactuals. In this case, the former entrepreneurs predict that a given factor has no impact, while the latter entrepreneurs predict that it has an impact, or vice versa. Overall, this implies that entrepreneurs who adopt a scientific approach make more precise predictions of v in the sense of predictions more likely to be closer to the value of v that they will observe in the future. As pointed out earlier, setting an opportunity cost x implies that a more concentrated distribution of v around its mean lowers its expected value. This makes it more likely that entrepreneurs close their firms. We summarize this prediction in the following proposition.

Proposition 1. *Scientific entrepreneurs perceive distributions of value more concentrated around the mean. Given their opportunity cost, they predict lower returns which makes them more likely to close their firms.*

Our next step is to understand the process that leads to the modification of ideas during the firm's exploration cycles. Well-defined frameworks and theories help the entrepreneurs who adopt the scientific approach to interpret signals. This makes them more likely to modify some of the above described factors based on the signals. Apart from new information that unfolds during the process, the tests are an important source of signals. Rejection of some hypotheses and acceptance of others may induce entrepreneurs to rethink their business models. For example, failing to accept some hypotheses implies that they have to focus on radically different target markets, change the value proposition or that they should weigh differently other dimensions, in the end realizing that the idea they should pursue is different from the one that they originally conceived. The evidence on these patterns is systematic. Camuffo et al. (2020) tell the story of a company, Inkdome, that finds systematic evidence against its original business idea – a search engine to find tattoo artists online – and pivoted to a service that evaluates the quality of tattoo artists. Kirtley and O'Mahoney (2020) provide systematic evidence that when start-ups pivot they do not discard all the accumulated knowledge or the previous features of their products or business models. They literally *pivot* in the sense that they stand on some of this past knowledge or features, and devise new elements that, in combination with the previous ones, change their overall product or business – very much like a basketball player who stands on one foot while pivoting with the other. (See also Ries, 2011; Furr & Dyer, 2014; Hampel, Tracey & Weber, 2019.)

Entrepreneurs who do not adopt the scientific approach are less likely to see these opportunities from signals. The lack of general frameworks prevents them from interpreting these signals and translating them into actions. In particular, when they find that some elements of their business do not contribute to value as much as they expected, they either do not have alternative hypotheses or are less able to generate new ones from what they observe. The hypotheses formulated by scientific entrepreneurs are, instead, part of a more general framework that has laid out the implications of different contingencies. For example, non-scientific entrepreneurs do not have a logical framework suggesting alternative, in principle equally viable, target markets. Moreover, because they do not conduct rigorous tests, they are less able to make definitive decisions. We have systematic evidence from the firms in our sample in which the entrepreneurs who do not adopt a scientific method do not conduct tests in which they can clearly accept or reject hypotheses. Often, they do not ask falsifiable questions to understand what to do. More generally, the information they collect is too generic to understand what they should conclude. For example, they conduct surveys in which they ask customers whether they like or not their products, but then they do not have frameworks to conclude whether a given percentage of positive responses represent good evidence for validating their offer.

The bottom line is that while studying a particular business idea, the entrepreneurs who adopt a scientific method receive systematically signals that help them to envision innovations and new opportunities to revamp or change their business. These new opportunities suggest new determinants or new combinations of determinants of business value. Overall, this generates a new model of the determination of v that features some of the factors of the previous model, and some new factors. However, the entrepreneurs have not yet theorized and tested the new factors with the same depth of the previous factors, and more generally they have not yet theorized and tested the new model as much as the previous one. The new model then yields more volatile predictions about v than the previous model.

An entrepreneur who does not adopt the scientific approach does not see new potential new determinants of value as the entrepreneur who adopts the scientific approach. Thus, her model tends to remain unchanged or to change more randomly based on the available evidence. The distribution of value is then likely to have a similar volatility as the current model or idea. We argued that entrepreneurs who adopt the scientific approach perceive a less volatile distribution of the current business idea than the counterfactual entrepreneurs. Here we argue that they see new opportunities to change their business ideas that raise the volatility of the perceived distribution of value more than counterfactual non-adopters.

When entrepreneurs foresee valuable changes to their idea, they are likely to pivot – that is, they adjust their idea turning it into something significantly different from the one they were working on. Entrepreneurs decide to pivot when they foresee that the changes they might make to their idea represent valuable factors. This gives rise to a higher wedge between the spread of the modified idea vis-à-vis the past distribution of value.

Thus, during an exploration cycle, when they have to choose whether to close the firm, keep pursuing the current idea, or pivot, entrepreneurs look at whether the distribution that yields the highest expected value is higher than their opportunity cost. If it is lower, they close the business. If it is higher, and the current idea yields the best outcome, they pursue it, otherwise they pivot. As discussed earlier, if the mean of the distribution does not change, higher volatility implies higher expected value. Other things being equal, entrepreneurs who adopt a scientific approach are then more likely to close the firm than their counterfactual entrepreneurs, as discussed in Proposition 1. If they perceive a higher increase in volatility between the future and current ideas, they are more likely to pivot.

Before writing our next Proposition, we need the third ingredient of our story: the exhaustion of idea opportunities. Entrepreneurs search in a bounded space. In particular, they explore business ideas within their domain of expertise or within a topic or category they are interested in (Durand & Paolella, 2013). This implies that the space the can explore is limited (Hill & Birkinshaw, 2010), which in turn implies that, in the absence of exogenous interventions or information, there is a finite number of factors (and of factors' combinations) they can think of and test (and, consequently, to which they might pivot.) In addition, even if the recombination of factors can give rise to increasing returns, exploration within a limited space ultimately hits diminishing returns. Other things equal, entrepreneurs who adopt a scientific approach envision more quickly promising factors -and combinations thereof- thanks to their frameworks and tests.. However, because the space they can explore is bounded, they exhaust this space earlier. They quickly envision the potentially valuable changes to their ideas they can pivot to. Conversely, entrepreneurs who do not adopt this approach envision less promising factors within their explorable space, keep navigating this space, and are therefore more likely to pivot several times.

A simple way to represent this distinction is to consider the marginal benefit of pivoting. As shown in Figure 2, since the explorable space is limited, the benefit of an additional pivot decreases as the number of pivots increases. However, the marginal benefit of pivoting of the entrepreneurs who adopt a scientific approach is high when they have not pivoted, and falls rapidly after a few pivots, while the curve of the entrepreneurs who do not adopt this approach is flatter. If the former curve cuts the latter curve, the scientific entrepreneurs are more likely to pivot few times than to not pivot at all or pivot many times; the non-scientific entrepreneurs are either not likely to pivot because the marginal benefit of pivoting is not sufficiently high or, if they start pivoting, they are more likely to pivot after a few initial pivots when the curve is higher than the curve of the scientific entrepreneurs. Intuitively, thanks to their theoretical frameworks and tests, when scientific entrepreneurs pivot they know better how to modify their ideas, and do not need to pivot several times.

****** Figure 1 About Here ******

Thus, we expect that, before they pivot, scientific entrepreneurs exhibit a greater wedge in the spread of the distributions of value between two periods of time. If entrepreneurs stay on their current idea, they compare two distributions about the current idea that differ because of new unfolding information about it. In this case, we have no prediction that the two distributions differ systematically between scientific and non-scientific entrepreneurs. However, before they exhaust their exploration space with some pivots, scientific entrepreneurs are more likely to see more innovative and therefore uncertain opportunities that exhibit a higher spread. In this case the difference in the spreads reflect differences between the distributions of the current idea and the modified idea they can pivot to. We summarize this discussion in the following proposition.

Proposition 2. *Scientific entrepreneurs perceive a higher difference in the spreads of the distributions of value between two time periods. As a result, they are more likely to make few selected pivots.*

So far, we have been agnostic about whether the scientific approach generates better performance. However, our discussion suggests that it is reasonable to assume that the perceived distribution of the entrepreneurs who adopt the scientific approach yields outcomes closer to what they expect. If so, they are more likely to abandon less promising ideas because they close the firm, and they are more likely to pursue better ideas either because they cut worse ideas by closing the firm, or because they improve their ideas as suggested above. We can then write the following proposition.

Proposition 3. *Scientific entrepreneurs perform better because they select better ideas or they make changes (pivot) that improve their ideas.*

3.3 An illustrative case: Mimoto's scooter-sharing service

Mimoto, a scooter sharing service that attended the scientific training of our RCT, provides a good illustration of our theoretical framework. The entrepreneurs first decomposed the problem and figured out that their value proposition depended on three main factors: (a) the ideal target market is university students because young people use scooters and compared to teenagers have more systematic needs for mobility and a greater ability to pay, but still cannot afford to own a car; (b) scooters have to be large and solid for safety reasons; (c) the ideal market is larger cities because the advantage of scooters is to reduce mobility time in traffic. When they tested these three hypotheses, they rejected the first two because university students were not active users and women did not use large and solid scooters. However, they figured out that young professionals were more willing to use the service because they benefit to a greater extent from faster mobility in traffic. Mimoto's founders also understood that both men and women use lighter scooters and these scooters are equally safe.

These changes were not obvious. The process required a deep rethinking of the business model and the collection and test of new data, which took about one year. However, the initial framework helped. First, after rejecting the hypotheses, the founders stuck to the same problem architecture (the same theory) – target market, scooter type, and location of the service. They did not change problems or wander across different problems. Second, they kept the hypothesis they accepted (focus on cities with traffic) and devised new solutions for the problem-solution pairs they rejected. Finally, it took some time to test the new hypotheses because there were important uncertainties to be resolved. While we now know that young professionals and lighter scooters are a good solution, they did not know it with the same precision right after they rejected the initial hypotheses. They had initial ideas, theorized about the solutions including, of course, the ones that they developed, but still had to collect data and perfect these theories, as well as assess alternative solutions. The spread of the distribution of value of the original model was clearly more precise, albeit the expected value was smaller. The new model was promising, but at the outset of the decision to make these new changes, the uncertainty was higher. A hypothetical counterfactual non-scientific entrepreneur would probably envision less promising changes to their ideas, exploring her space quasi-randomly or starting with marginal changes, close to the factors that she rejected. Such marginal changes are less likely to raise the odds of values in the right tail of the value distribution.

4. Research design

4.1. The randomized control trial

Our research embeds a field experiment into a pre-acceleration program, or a 'start-up school' that provides training to early-stage entrepreneurs for short periods of time. This type of program represents an ideal setting for our inquiry because it selects and trains entrepreneurs that only have a business idea and have yet to undertake significant steps to bring their product or service to the market. Moreover, administering our treatment through training is a suitable choice because training programs have been shown to affect outcomes for treated entrepreneurs (Anderson et al., 2018; Campos et al., 2018).

Participants in our program are early-stage entrepreneurial firms, which are defined as those run by founders in the process of starting a business (Bosma et al., 2012). We issued a call for applications using multiple online (blogs, online communities) and offline channels (magazines for entrepreneurs, events), resulting in a total of 272 applications, out of which we selected into the intervention 258 start-ups. Seven start-ups abandoned the program before its start, so our final sample consisted of 250 participants. We used a statistical software package (Stata) to randomly assign each start-up to one of the two arms of the experiment (treatment and control groups)[1]. We checked that the treatment (125 start-ups) and control groups (125 start-ups) were balanced on a number of key covariates that might affect the absorption of the intervention and its subsequent outcomes. We report

[1] We opted for pure randomization with balance checks, as this was, in our case, a better strategy than stratified randomisation. Choosing the appropriate strata among these variables to implement stratified randomisation and to allocate the participants to the treatment and control groups was not obvious from a theoretical standpoint.

the results of these randomization checks in the Online Appendix. This analysis confirms that the two arms of the experiment are balanced on key characteristics such as demographic variables (age, highest education level, work experience of the entrepreneurial team), industry, founding team size and composition, effort, startup potential (measured by an independent third party), the self-estimated expected value of the project (min, max, avg), and the projected number of months to revenues. Given the number of checks, we are confident that the randomization was successful.

Following best practices (Baird et al., 2016), we pre-registered this randomized controlled trial on September 15, 2017. The intervention took place at the end of September 2017 and finished in December 2017 with the 250 participants attending a training program designed by the research team. Our pre-acceleration program focuses on market validation, with a series of activities aimed at testing the desirability of a product or service concept against a potential target market. These activities provide suitable information to help entrepreneurs assess the potential of their business ideas and are frequently taught in pre-acceleration programs. In order to offer engaging lessons and a valuable learning experience to participants, we divided the treated and control groups into smaller groups that were randomly matched with seven experienced instructors, recruited and trained for the purpose of this study. Since each instructor was teaching one group of treated entrepreneurs and one group of control entrepreneurs, we organized several 'train-the-trainer' sessions and conducted tests and simulations with the instructors to make sure that instructors were able to deliver the training material in accordance with our experimental design. We ensured that the instructors trained the start-ups in each group using the exact same content by providing all training material ourselves, and by attending the lectures as observers.

The course comprised eight sessions (for a total of 24 hours of training), and the content and duration of each session was the same for both groups. Both the treatment and control groups learnt about tools that are widely used in entrepreneurial education (such as the Business Model Canvas, and Minimum Viable Product). However, the treatment group was taught how to use each of these tools using a scientific approach. Throughout the training program, treated start-ups were taught to elaborate a theory behind their choices, and to articulate hypotheses and test them rigorously. The control group, meanwhile, did not learn about the scientific approach, but followed the traditional approach to market validation used by entrepreneurs, which often relies on trial-and-error techniques. We took a number of measures to ensure the internal validity of our results and the soundness of our experiment. We avoided contamination by teaching treated and control start-ups in different time slots of the same day (morning and afternoon) to prevent them from meeting and discussing key elements of the treatment. For the same reasons, we kept communications about the program separate and discrete for the two groups.

4.2. Data collection procedure

We collected detailed information on all the participants with an extensive pre-intervention survey, which we used to randomly assign participants to treatment and control groups and to assess the pre-intervention levels of a number of covariates. During and after the intervention, we collected 18 data points through telephone interviews, following Bloom and Van Reenen's (2010) approach. Telephone interviews usually lasted for 30 minutes and were conceived as open-ended conversations with entrepreneurs. To guide these conversations, we created an interview protocol for interviewers. In the first part of the interview, entrepreneurs were asked to report changes in the entrepreneurial team and describe the activities they had been conducting in the last two weeks. Using an approach similar to qualitative interviews, we let key themes emerge from entrepreneurial narratives. However, we instructed research assistants to code the content of the interview for the frequency of occurrence of themes related to scientific decision-making using non-leading questions. In the second part of the telephone interview, we asked entrepreneurs to self-report their performance, as well as to provide estimates of the value of their idea. In collecting this information, we were also able to observe entrepreneurs who abandoned their business idea altogether or who decided to pivot to a different one.

The first telephone interview took place eight weeks after the training program had begun. We then collected data every two weeks until week 18 (the training program ended in week 12), and every four weeks until week 66. Our panel dataset includes 4500 observations for 250 firms over 18 periods. Also, for the variables defined in the next section, we have information for all 18 data points if the firm never closed or abandoned our program. For other firms we only have data up to the period before they are no longer in our dataset.

4.3. Measures

4.3.1. Dependent variables

Exit – We regularly ascertained through telephone interviews if entrepreneurs had abandoned the program and/or ceased activities related to their start-up. We coded this event into a binary variable that takes the value 0 until the firm exits (abandons the program and ceases the start-up), 1 in the time period over which the firm exits, and a missing value thereafter. To avoid attrition biases, we checked that the entrepreneurs who informed us of their decision to discontinue their initiative had truly abandoned their activity and not only the acceleration program. We found that 20 start-ups left the course but continued to develop their business ideas, while 105 abandoned their ideas as well. We kept the 20 start-ups that abandoned the course in our sample to preserve the balance checks between treatment and control, but we did not count them as start-ups that exited. When we remove these start-ups from the sample, the treatment and control groups are still balanced, and in general the results of our analyses are not qualitatively different.

Pivot – Through the telephone interviews we collected detailed information about the activities conducted by entrepreneurs and the changes they made to their business ideas during the observation period. In the first session of the course, we taught entrepreneurs to use a Business Model Canvas (BMC), a visual representation of the core aspects of their business. As entrepreneurs were taught to use this tool and keep it updated, we were able to keep track of the changes that they made in relation to nine key business elements (value proposition, customers, channels, customer relationships, key partners, key activities, key resources, costs and revenue streams). We considered a pivot as a major change in the business model – that is, if the entrepreneur moved from the original idea to another idea that changed the core value proposition of the business or its target customers. Our start-ups pivoted from zero to five times in our time frame, and we recorded the week in which the pivot took place.

Revenue – During each telephone interview, we collected the cumulative revenues generated by each start-up. To obtain the flow of revenue between two periods we subtracted one amount of revenue from another over two contiguous periods. Understandably, not all firms in our sample reached the revenue stage in the 66-week observation window. In particular, 33 of the 250 start-ups produced some revenue in this period; 16 of these firms were in the treatment group and 17 in the control group.

4.3.2. Independent variables

Intervention – The main independent variable is *Intervention*, a dummy variable taking a value of 1 for start-ups in the treatment group and 0 for those in the control group.

Scientific_intensity – This variable measures the level of adoption of the scientific approach derived from the content analysis of the telephone interviews. *Scientific_Intensity* is a time-varying score (ranging from one to five) that captures the level of adoption of the scientific approach. In order to calculate this score, a team of research assistants analyzed and coded each interview's content according to a pre-defined coding scheme. This scheme includes themes and behavioral indicators of the adoption of the four components of the scientific approach (theory, hypotheses, tests and evaluation) that quantify the extent to which entrepreneurs are scientific in their decision-making process, as detailed in the Online Appendix. Through this scheme, we obtain an overall additive score of the level of adoption. Even if we created coding guidelines and extensively trained the team of research assistants through examples that create solid reference points, *Scientific_Intensity* remains a subjective measure. To assess the reliability of the coding, we randomly selected a sample of interviews that underwent double coding with multiple research assistants who were not aware of the allocation of entrepreneurs to the treatment or control group. Additional analysis (not reported for brevity's sake) shows that there is generally agreement between multiple coders. In our regressions we use *Av_Scientific_Intensity* and *Av_Scientific_Intensity_75*. They are, respectively, the firm-specific average of scientific intensity up to each time period and the sum of the current value plus 75% of the average up to the previous period, which accounts for potential depreciation. In both cases the observation of the first time period is *Scientific_Intensity*. As we will see, our results do not change when we use one or the other variable.

Range – This variable is the difference between the maximum and the minimum value of the business predicted by the entrepreneurs at each moment in time normalized by the mid-point between the maximum and the minimum (*Mean Value*). We define value as the discounted sum of expected future profits. In order to anchor the response, we ask the entrepreneurs to indicate the minimum and maximum on a scale between 0 and 100 where we tell them that 0 corresponds to the case in which they believe that "the start-up will never make revenue" and 100 to the case in which "the start-up will be a big success." We collected this variable as soon as the firms enter our training. Therefore, we have pre-sample information about it (week 0) and not only from week 8, in which we conducted the first telephone interview. We can therefore compute *Range_lagged*, which is *Range* lagged one period. Also, *Av_Range* and *Av_Range_lagged* are the firm-specific average of *Range* and *Range_lagged* up to each week. In the result section we explain why we use this smooth measure of the prediction.

Range_diff – This variable is equal to the difference between *Range* and *Range_lagged*. We also compute *Av_Range_diff* equal to the difference between *Av_Range* and *Av_Range_lagged*. We explain the rationale for this measure in the result section.

Table 1 defines all the variables that we use in our analyses and reports descriptive statistics.

***** *Table 1 About Here* *****

5. Results

5.1. Replication

We begin by replicating the results of Camuffo et al. (2020). In this paper we employ the same research design but an entirely different sample. The sample is larger than Camuffo et al. (2020), covering 250 observations over 18 data points and 66 weeks vis-à-vis 116 observations over 16 data points and 48 weeks.

Before showing our regression results, we 'show the data' in order to display where regression results come from and mitigate the emphasis on regression estimates in the interpretation of results (Halsey et al., 2015; Bettis et al., 2016; Goldfarb and King, 2016; Starr and Goldfarb, 2018; Greve, 2018; Levine, 2018). Figure 2 summarizes whether the 250 start-ups that attended our pre-acceleration program abandoned the business (*exit*), or changed some important elements of it (*pivot*) such as the core value proposition of the business or the target customers, during the 14 months (66 weeks) in which we followed them. The figure distinguishes between the 125 start-ups in the treatment and control group. Quite a few start-ups that closed during our time frame pivoted before closing. The figure includes the pivots of the start-ups that close later on. However, the histograms remain qualitatively similar if we exclude the start-ups that close.

****** Figure 2 About Here ******

The first column of Figure 2 shows the number of start-ups that close during our time frame. As the figure shows, more start-ups in the treatment group closed their business than in the control group (59 vs 46). This result, which we also obtain in the regressions below, confirms the finding of Camuffo et al. (2020). The next columns of the figure show the number of start-ups, in the treatment and control group, that pivoted from 0 up to 5 times during the analyzed period. Fewer start-ups in the treatment group pivoted 0 times (58 vs 68 – column 2). However, they are more likely to pivot one time than controls (43 vs 29 – column 3). While the number of start-ups in the treatment and control group that pivoted two times is the same (17), fewer start-ups in the treatment group pivoted three or more times (7 vs 11). Our regressions below confirm that treated start-ups are more likely to pivot one time than zero or more than 2 times. These patterns suggest that while the scientific approach helps entrepreneurs to identify potential changes to their idea they can pivot to, once they identify potential changes to their idea, they tend to stick to it, as if they are better at envisioning changes to their idea to which they can pivot. Camuffo et al. (2020) finds that treated firms pivot more times than the control group. However, with 116 start-ups and 48 weeks the sample did not produce many observations at the right tail. In Camuffo et al. (2020) only 2 firms pivoted more than two times. In this study we also find that treated firms are more likely to make one or two pivots. However, with more firms and a longer time span we show that in the right tail treated firms becomes less likely to pivot.

Figure 3 reports on the average cumulative revenue in each week of the start-ups in the treatment group compared to the control group. This average includes start-ups that generate zero revenue. Treated start-ups systematically generate a higher average cumulative revenue, a result that confirms Camuffo et al. (2020) and we also obtain in our regressions below. This result suggests that a scientific approach leads to a more successful commercialization of the products start-ups offer. In our sample 33 start-ups make revenue during the time frame of our experiment. This number is unsurprising given that these entrepreneurs enter the pre-acceleration program with just a business idea, and we observe their performance for 14 months. Of these start-ups, 17 are in the treatment group and 16 in the control group. This is also consistent with Camuffo et al. (2020) in which 17 firms make revenue, 9 in the treatment and 8 in the control group. The treatment does not raise the odds that start-ups make revenue, but if they make revenue, they make a higher revenue. Combined with the result about exit, the treatment mostly has an effect on the tails of the sample distribution – more exit and higher average revenue conditional on making revenue.

***** *Figure 3 About Here* *****

We now turn to our regression results. In all the regressions of this section, the key independent variable is the dummy for intervention. All regressions include dummies for the instructors associated to the firm and the panel regressions include time fixed effects. Apart from controlling for time, time fixed effects control for the different length of the observation periods between some of our interviews, as discussed in Section 4.2. In all the regressions of this section we cluster errors by instructor and intervention.

We start with the regression results of exit with respect to our intervention. The first two columns of Table 2 report our cross-section results. They are, respectively, the results of a linear probability model and a probit model. The dependent variable is a binary one and equal to 0 if the start-up did not exit, and to 1 if the start-up abandoned the business during our observation window. The next two columns report the results of a panel analysis of the 250 start-ups during the 18 periods of data collection. Finally, the last column shows the results of a survival regression that predicts the time of exit. All these regressions show that the intervention makes it more likely that the start-ups close the firm. This is the same result as in Camuffo et al. (2020) where, however, the smaller sample produced a weaker statistical significance. The result is now more robust thanks to the larger sample of this paper. This finding is consistent with our framework in which we predict that the scientific approach makes the entrepreneurs more precise and thus less likely to expected higher returns because of higher opportunities in the right tail. The panel regressions and the survival also suggest that the intervention anticipates the date in which they close the firm.

***** *Table 2 About Here* *****

In terms of effect sizes, the first column of Table 2 provides the most immediate interpretation of the results. It shows that the intervention increases the probability of exit by 10% in the cross-section. This is a sizable effect given that the entrepreneurs who adopt a scientific approach exit earlier. To appreciate what this might mean, consider the following cases. At an individual level, these results imply that one entrepreneur out of ten could avoid wasting time, money and effort developing business ideas that are not as promising as they initially thought. At an institutional level, consider an accelerator with a capacity of 100 start-ups, monthly intakes of ten start-ups and a one-year program to accelerate start-ups. The adoption of the scientific approach as an 'accelerating philosophy' could improve the time to acceleration, freeing up a considerable amount of resources (roughly more than 10% without considering faster turnover).

Table 3 reports our results for pivot. The first column of Table 3 presents the OLS results of the change in the total number of pivots produced by the intervention. As the results in the column show, the intervention does not affect the number of pivots. The next two columns of Table 3 show the linear probability models, using as dependent variables a dummy that takes the value 1 if the start-ups experience, respectively, one or one to two pivots, vis-à-vis zero and two to five, or zero and three to five pivots. In both cases, the effect of the treatment is sizable and statistically significant. Treated start-ups are more likely to pivot once or twice than zero times, or than two or three times. The last four columns of Table 3 estimate two multinomial probit models with three categories. The baseline category in both models, not shown in the table, is zero pivots. The other two categories in the first model are one and two-to-five pivots, while in the second model they are one-two and three-to-five pivots. As the table shows, the intervention raises the probability of the intermediate category vis-à-vis the other two extreme categories. These results are in line with our prediction that treated start-ups are more likely to pivot a few but not many times. As discussed earlier, they are also in line with and extend the results of Camuffo et al. (2020). We also find that treated start-ups are more likely to pivot one or two times, but we also show that they are less likely to pivot more times.

***** *Table 3 About Here* *****

The effects sizes of the regressions are more complex to interpret in the case of pivot. However, going back to the examples discussed in the case of exit, at the individual level, more selective pivoting (fewer, better pivots) allows entrepreneurs to explore ideas that would otherwise be lost (foregone options). But it also brings about the opportunity to avoid wasteful pivoting, saving significant amounts of time, money and effort. At the institutional level, acceleration programs could be more effective and efficient – redundant pivoting could be reduced by as much as 80% (one pivot instead of five).

The first two columns of Table 4 (cross-section and panel) show that entrepreneurs who adopt a scientific approach generate, on average, higher income. The statistical significance of the effect is not strong, which we expect given that only 33 firms make revenue in our study. However, this result is in line with Figure 3 and with Camuffo et al. (2020). Future work with larger samples and longer time series could provide stronger evidence in one direction or the other. The statistical significance of our results is weaker if we winsorize the dependent variable, as shown in the last two columns of Table 4. However, the point estimates are still positive and suggest that a larger sample and a longer time series might provide robust results not only for firms at the very right tail. The third column of Table 4 results of a survival regression where the dependent variable is the failure event, which is the first week in which the start-up generates revenue. The treatment has no effect – that is, scientific entrepreneurs do not seem to obtain revenue earlier than non-scientists.

***** *Insert Table 4 About Here* *****

In terms of effect sizes, the average effects obtained through the panel regressions in Table 4 (an average differential of approximately € 1,500 over 66 weeks between treated and control start-ups) are small. However, Figure 3 provides an indication of what might be the magnitude of the treatment effect after approximately one year. Entrepreneurs who adopt a scientific approach average about three times the amount of cumulative revenue of entrepreneurs who do not adopt this approach. Furthermore, the variation of scientific entrepreneurs is much higher than that of non-scientific entrepreneurs.

5.2 Evidence of the mechanisms

Figure 4 shows the trend of the average value across firms of the mid-point between the maximum and minimum value predicted by the entrepreneurs. The figure starts from week 0 which is before the beginning of the training. It shows that the mean value decreases over time, particularly between week 0 and the first data collection 8 weeks after the training. This suggests that the entrepreneurs in our sample expected higher returns at the outset, but then became gradually aware that the value of their business is probably smaller. However, for the treated firms the expected value remains slightly higher than for the control group.

***** *Figure 4 About Here* *****

Figure 5 shows the trends of *Range* and *Av_Range*. The trend of *Av_Range* is smoother and less erratic because the average of the past values eliminates the more volatile components of this measure. For treated start-ups *Av_Range* first declines and then increases. For the control group, *Av_Range* also declines initially, albeit the decline is less pronounced than for the treated group; it then remains fairly stable. The sharper decline of the treated start-ups is consistent with our framework that posits that the scientific approach makes entrepreneurs more precise. The subsequent increase in range is also consistent with our framework. Scientific entrepreneurs see more innovative and diverse potential changes to their ideas than non-scientific entrepreneurs, which raises uncertainty compared to the more local and/or random search of non-scientific entrepreneurs. Figure 5 also implies that, for the treated start-ups, *Av_Range_diff* – that is the difference in *Av_Range* between two periods – first declines more sharply and then increases more sharply. This suggests that scientific entrepreneurs first become more and more precise, but after some point they start to see the new, more uncertain ways to modify their ideas.

***** *Figure 4 About Here* *****

We provide evidence about the mechanisms by presenting the results of three sets of regressions for exit, pivot, and performance. In all these regressions we employ dummies for instructor and time fixed effects. Clustering by instructors and intervention, as we did in our previous section, produced similar but less precise estimates, most likely because we do not have enough clusters and we employ *Intervention* as the excluded instruments of all our regressions. We show all our results using robust standard errors.

The first two columns of Table 5 show that a smaller *Av_Range_lagged*, which corresponds to greater precision, increases the probability that the entrepreneurs close their firms. Statistical significance is stronger in the IV probit than in the linear probability model. In the IV probit, at the mean value of the independent variables, a one standard deviation increase in *Av_Range_lagged* (which is equal to 0.394) reduces the probability of exit by 0.204. This is a sizable impact because using the IV probit estimates, the normal density evaluated at the mean of the independent variables, which is the probability of exit in that point of the sample, is equal to 0.236. A one standard deviation increase of *Av_Range_lagged* then reduces this probability to 0.032. We employ *Av_Range_lagged* instead of

Range_lagged to focus on the more systematic components of this measure. This variable is a prediction of the distribution of the future value of the firm. At each moment in time our telephone interviews ask for an update of this prediction, which always refer to the same variable: the future value of the firm. Thus, each exact measure declared in the interview may be affected by erratic component that may depend on many factors, including the particular perception of this value at the moment of the interview or other similar contingencies of the interview or the interviewee. When we use *Range_lagged* instead of *Av_Range_lagged* we obtain similar second-stage results. In the first stage, the sign of *Intervention* does not change, but *Intervention* is a weaker instrument, which probably reflects the more volatile nature of the non-smoothed measure.

***** *Table 5 About Here* *****

The third column of Table 5 shows the first stage results. The variable *Intervention* is a strong instrument, and the correlation with *Av_Range* is negative. This is in line with Proposition 1. The intervention reduces the range, making predictions more precise. We went one step further. The fourth column of Table 5 shows the results of a 2SLS model in which *Range* is the dependent variable and the endogenous regressor is *Av_Scientific_Intensity* instrumented by *Intervention*. The fifth column is the first-stage and the last two columns of Table 5 are the same regressions using *Av_Scientific_Intensity75*. These results show that scientific intensity reduces *Range*. In the first-stage *Intervention* raises scientific intensity. This suggests that our treatment increases the scientific intensity of the decision-making process of our start-ups, and the higher scientific intensity makes them more precise. These results provide credible evidence about the greater precision provided by scientific intensity. Greater precision makes it more likely that entrepreneurs exit because they realize that opportunities at the right tail of the value distribution are less likely to occur.

Table 6 reports the results of our analysis of pivots. In the first three columns we employ IV Poisson rather than IV Probit because in the first two regressions some weeks feature no cases in which the dependent variables is different from zero. Rather than selecting the relevant weeks we show IV Poisson so that we do not have to make these choices, and we run IV Poisson for all three columns for ease of comparison. At any rate, we obtain very similar results with IV Probit regressions that aggregate week dummies when there are no cases with no pivots, or in which we replace the week dummies with a higher order polynomial of time. Our theory predicts that treated firms are more likely to pivot a few times rather than zero or many times. The first column of Table 6 shows the results of a regression in which the dependent variable takes the value 1 in the week in which the firm pivots and the firm pivots only one time in the period of the sample, and zero otherwise. Thus, the dependent variable will be equal to zero both for firms that do not pivot one time and for the firms that pivot one time in the weeks in which they do not pivot. The second column shows the results of the analog regression in which the firm pivots one or two times in the period of the sample. Finally, the third column shows the results in which the dependent variable takes the value 1 in any week in which any firm pivots, and zero otherwise.

***** *Table 6 About Here* *****

The key independent variable of these regressions is *Av_Range_diff*. We use the averages of the ranges for the same reason we used *Av_Range* in the regressions for exit: we want to focus on the systematic component of this prediction - and more specifically of its variation over time in this case. At any rate, when we use the difference between *Range* and *Av_Ranged_lagged* we obtain the same results; when we use the difference between *Range* and *Range_lagged* we obtain the same second-stage results, but *Intervention* is a weaker instrument for this difference than for *Av_Range_diff* (albeit the sign of *Intervention* in the first stage does not change.)

The first two columns of Table 6 show clearly that a higher *Av_Range_diff* encourages the pivots of the entrepreneurs that overall pivot once or twice, and the fourth column of Table 6 shows that *Intervention* raises *Av_Range_diff*. This result is conditional on the assumption that *Intervention* does not have an additional effect on pivoting other than through *Av_Range_Diff*, and thus we have to take these results as suggestive of the mechanism we propose. With this caveat, we can fairly say that this evidence is consistent with Proposition 2. Scientific entrepreneurs see new ways to modify their ideas that widen the difference between the current and past perceived spread of value, which in turn encourages pivot. The third column of Table 6 shows that this effect disappears when we look at the pivots of firms that pivot more than once or twice. Our interpretation is that for these firms the increase in the difference of the spread between two periods is more likely to depend on shocks that raise uncertainty on the business ideas in which they are working and that do not have to do with new and more innovative ideas. As a result, in this case, the change in spread does not induce new pivots. The last two columns of Table 6 provide additional evidence about our mechanism. The two 2SLS regressions show that *Av_Scientific_Intensity* or *Av_Scientific_Intensity75*, instrumented by *Intervention*, raise *Av_Range_diff*. This makes us more confident that the scientific approach raises *Av_Range_diff*.

Table 7 shows our results on performance. The first column shows that an increase in *Av_Range_diff* increases performance. This evidence is consistent with our mechanism: a greater difference between current and past spread reflects the fact that entrepreneurs see new innovative opportunities that raise performance. As discussed in the previous paragraphs, increases in *Av_Range_diff* increase pivots. However, more generally, this wider gap between current and past spread reflects the fact that entrepreneurs discover ways to modify their idea elicited by a greater understanding of the problem, as implied by the fact that, as we have shown, *Av_Range_diff* increases with the intervention or scientific intensity. In regressions not shown here, we find that the dummies *Pivot (1 time)* or *Pivot (1 or 2 times)*, in lieu of *Av_Range_diff*, instrumented by *Intervention*, also raise revenue. However, the statistical significance is lower. This mirrors our general point that a greater *Av_Range_diff* increases performance because it is associated with the identification of new ways to change and perfect the business idea. As discussed in our theory section (Section 3.2), when these modifications are particularly important, we observe a pivot, which is also what we record empirically in our analysis. However, increases in *Av_Range_diff* may also capture innovation opportunities within the current business model or idea that increase performance.

***** *Table 7 About Here* *****

In this case as well, our result is conditional upon the fact that *Intervention* does not have a direct impact on performance. In fact, if the scientific approach rules out worse ideas because firms close their business, *Intervention* will have a direct effect. At the same time, the second and third columns of Table 7 show that scientific intensity, instrumented by *Intervention*, raises performance, and we know from Table 6 that scientific intensity also raises *Av_Range_diff*. Still, we cannot rule out that the scientific approach affects performance because of the selection of better ideas. However, the second and third column of Table 7 use as the key independent variable scientific intensity, which ought to capture both selection and improvement effects. Still, *Intervention* might directly affect performance, but in this case we can at least rule out that the direct effect of Intervention is produced by effects other than the scientific approach. We have tried to address this problem as well. In regressions not shown here we estimated the effects of the number of hours worked by the entrepreneurs, another variable that we collected in our telephone interviews. Our training might provide entrepreneurs with greater enthusiasm and energy. We find that hours worked is not correlated either with intervention or performance. Thus, overall, our evidence does not falsify Proposition 3.

The last three columns of Table 7 show that the statistical significance of our results reduces when we winsorize our measure of performance. This is natural given that, in line with what we typically observe with early stage start-ups, few firms make revenue within one year. However, the point estimates are still positive and sizable, suggesting that a limitation of this analysis may simply be the lack of statistical power for detecting phenomena that happen largely at the right tail. This is an important area for improvement in future research.

6. Discussion and Conclusion

This study offers a comprehensive framework and evidence of why and how a scientific approach improves entrepreneurial predictions and judgement. In doing so, we connect this line of reasoning to the current debate in entrepreneurship, highlighting how the scientific approach might be thought of as a ‘rational heuristic’ – a set of behavioral routines or a discipline that can mitigate decision biases (Zhang and Cueto, 2017) and improve the combination of thinking and doing that characterizes any entrepreneurial venture (Eisenhardt and Bingham, 2017; Ott et al., 2017).

We also believe the scientific approach can represent a way to reframe entrepreneurship education, at least in the early stages of entrepreneurial activity. Our intervention could represent a starting point to think about how to make some types of entrepreneurial training more effective. Finally, we believe that the adoption of the scientific approach could be beneficial for institutions that train, assist, support, mentor and accelerate entrepreneurial ventures. The scientific approach might represent a nice complement to other practices, such as peer or expert reviews, that have been proven to be successful and are conceptually consistent with a scientific approach (Cohen et al., 2018; Chatterji et al., 2019).

This study is also subject to limitations. As in most field experiments in social sciences, its design does not allow perfect identification. Given the high financial costs of running a similar field experiment, the sample size is limited, which limits the power of the experiment. However, the fact that we have repeated observation over a reasonably long period of time mitigates this problem and makes our findings more robust. Other limitations represent opportunities for extensions and directions for further research. An important point is that our theory is fundamentally a theory of precision or accuracy in the assessment of entrepreneurial ideas. However, while mitigating fallible judgement and biases is an important component of entrepreneurial decision-making, understanding decision-making dynamics and how entrepreneurs search and learn over time is also important.

In this respect, important open questions stem from the study of our mechanisms. We show how the scientific approach acts by affecting the prediction of the distribution of returns from the venture. We clearly move beyond Camuffo et al. (2020) because on the one hand we replicate their results, and on the other hand we extend their work providing evidence about the mechanisms of the scientific approach that was absent in their study. Our replication confirms the results of Camuffo et al. (2020). This is reassuring in that the sample of this paper is larger, the observation period longer, and it involves different firms. However, we work with the same types of firms (new Italian start-ups) which implies that we cannot generalize our findings to other types of firms. While this is another limitation that calls for understanding the scientific approach beyond this set of firms, we reinforce the evidence that for these types of firms the scientific approach raises exit and performance. We also confirm that the scientific firms are more likely to pivot, even though the larger sample and time line of this study highlights another interesting feature of the scientific approach: scientific firms reach their goas with a few focused pivots.

Our evidence about the mechanisms is interesting and points to promising directions. However, it is preliminary. We have a coarse measures of the perceived distribution (spread). This is largely because we were not sure about how much we could introduce sophisticated questions about distributions in our survey. We are now reassured about the tractions of these measure and future research could try both more sophisticated distributions and a clearer identification of these mechanisms.

Other limitations of our study represent opportunities for further research. Apart from extensions to other countries and industries (e.g. high-tech), we wonder what the effect might be when entrepreneurs are scientists or have a science background. Similarly, it would be interesting to observe the effect of the adoption of the scientific approach in the context of corporate entrepreneurship. Furthermore, our study uses an intervention embedded in a given learning model. It would be interesting to see under which teaching approach and learning model (e.g. more or less experiential, in presence or online, one-on-one mentorship-based versus team or class-based, etc.) the scientific approach exerts better effects. This would allow us to understand how to scale similar interventions with a view to improving entrepreneurship education, a priority for many policymakers who are looking to stimulate economic growth through entrepreneurship. Additionally, our study did not identify the micro-mechanisms that, at the individual level, drive the different perceptions and predictions of scientist entrepreneurs (Busenitz & Barney, 1997). This clearly squares with a better understanding of the mechanisms of the scientific approach, as discussed above. There is a vast body of literature about the corrections of perceptions, changes in predictive models and mitigation of biases (Astebro, Herz, Nanda & Weber, 2014). However, we did not have the data to actually go deeply into the micro-foundations of the mechanism that, given an idea, lead the scientific entrepreneurs to have different perceptions regarding the variability of its outcomes, compared to non-scientists.

Finally, it would be intriguing to evaluate the effects of the scientific approach vis-à-vis other approaches, corresponding to other entrepreneurship theories, such as effectuation. An interesting study could test if, to what extent, and under which conditions, non-predictive techniques – with entrepreneurs ‘making do’ with what they have to hand, improvising to win over stakeholders and co-creating new products and markets – are more effective than the scientific approach. Overall, our research programs point to the fact that, while the scientific method has limitations, especially if we extend it beyond science, it also has potential. We cannot claim that this potential makes it the best approach in entrepreneurial decision-making. However, we hope that this paper has made us a little more confident that it is helpful to approach business problems through mental frameworks that we test and possibly revamp.

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Table 1. Variable definitions and descriptive statistics

	Variable definition	N	MEAN	SD	MIN	MAX
	Cross-section					
Exit	Dummy=1 if firm closes, 0 otherwise	250	0.420	0.495	0	1
Week of Exit	Week of exit of the start-up	250	51.08	21.005	8	66
# Pivot	Number of pivots	250	0.816	1.060	0	5
Pivot1	Dummy=1 if firm pivots 1 time, 0 otherwise	250	0.288	0.454	0	1
Pivot2-5	Dummy=1 if firm pivots 2 to 5 times, 0 otherwise	250	0.208	0.407	0	1
Pivot1-2	Dummy=1 if firm pivots 1 or 2 times, 0 otherwise	250	0.424	0.495	0	1
Pivot3-5	Dummy=1 if firm pivots 3 to 5 times, 0 otherwise	250	0.072	0.259	0	1
Revenue	Revenue in week 66 (in euros)	250	2170.0	13191.4	0	150000
Week of Revenue	Week in which firm starts making revenue	250	61.768	12.899	8	66
Intervention	Dummy=1 for treated firms, 0 for control	250	0.500	0.501	0	1
	Panel					
Exit	Dummy=1 on the week in which the firm closes, missing after exit	3178	0.033	0.179	0	1
Pivot	Dummy=1 on the week in which firms pivot, 0 otherwise	4500	0.045	0.208	0	1
Pivot (1 time)	Dummy=1 for firms that make only 1 pivot in the week in which they make the pivot, 0 otherwise	4500	0.016	0.125	0	1
Pivot (1 or 2 times)	Dummy=1 for firms that make only 1 or 2 pivots pivot in the weeks in which they make the pivots, 0 otherwise	4500	0.031	0.174	0	1
Revenue (flow) (+)	Flow of revenue in each period (in euros)	4500	120.55	1596.2	0	65000
Mean Value (§)	Mid-point between maximum and minimum value of the business predicted by the entrepreneurs in the week of observation	4500	60.863	20.245	4	100
Range (§)	Difference between maximum and minimum value divided by Mean value in the week of observation. (*Range_lagged* = Range lagged one period)	4500	0.643	0.508	0	2
Av_Range (§)	Average of Range up to the week of observation. (*Av_Range_lagged* = *Av_Range* lagged one period)	4500	0.627	0.394	0	2
Av_Range_diff (§)	*Av_Range* in the week of observation minus *Av_Range* in the previous week	4500	-0.014	0.174	-2	2
Av_Scientific_ Intensity (§)	Average of index of scientific intensity (1-5) in each period up to the week	4500	2.364	1.173	0	5
Av_Scientific_ Intensity75 (§)	Index of scientific intensity (1-5) in each period plus 75% of firm-average up to the previous period	4500	1.111	0.812	0	5

(+) Equal to zero after firms close. (§) Equal to last available figure after firms close.

Table 2. Exit

VARIABLES	Exit OLS (Cross-Section)	Exit Probit (Cross-Section)	Exit OLS (Panel)	Exit Probit (Panel)	Week of Exit Survival
Intervention	0.106**	0.273***	0.054***	0.130**	0.301**
	(0.019)	(0.007)	(0.002)	(0.034)	(0.023)
Observations	250	250	3,178	3,178	250
R-squared	0.030	-	-	-	-
Dummies for instructors	Yes	Yes	Yes	Yes	Yes
Time FE	-	Yes	Yes	Yes	-
Clustered Errors	Intervention Instructor	Intervention Instructor	Intervention Instructor	Intervention Instructor	Intervention Instructor
Number of id			251		

Robust p-values in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 3. Pivot (cross-section)

				Pivot = 0; 1; 2-5		Pivot = 0; 1-2; 3-5	
	# Pivot	Pivot1	Pivot1-2	Pivot1	Pivot2-5	Pivot1-2	Pivot3-5
VARIABLES	OLS	OLS	OLS	Multinomial Probit	Multinomial Probit	Multinomial Probit	Multinomial Probit
Intervention	0.028	0.108***	0.108***	0.438***	0.010	0.373***	-0.149
	(0.665)	(0.000)	(0.001)	(0.000)	(0.954)	(0.000)	(0.329)
Observations	250	250	250	250	250	250	250
R-squared	0.062	0.045	0.069	-	-	-	-
Dummies for instructors	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered Errors	Intervention Instructor	Intervention Instructor	Intervention Instructor	Intervention Instructor	Intervention Instructor	Intervention Instructor	Intervention Instructor

In multinomial probit models the omitted regression is pivot = 0. Robust p-values in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 4. Performance

VARIABLES	Revenue	Revenue (flow)	Week of Revenue Survival	Revenue (winsorized 99%)	Revenue (flow) (winsorized 99%)
	OLS (Cross-section)	OLS (Panel)		OLS (Cross-section)	OLS (Panel)
Intervention	1,573.147	87.397*	-0.157	264.656	10.544
	(0.104)	(0.077)	(0.579)	(0.359)	(0.321)
Observations	250	4,500	250	250	4,500
R-squared	0.023	-	-	0.015	-
Dummies for instructors	Yes	Yes	Yes	Yes	Yes
Time FE	-	Yes	-		
Clustered Errors	Intervention Instructor	Intervention Instructor	Intervention Instructor	Intervention Instructor	Intervention Instructor
Number of id			250		

Robust p-values in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 5. Exit (mechanism, panel)

VARIABLES	Exit	Exit	Av_Range_ lagged	Range	Av_Scientific_ Intensity	Range	Av_Scientific_ Intensity75
	2SLS	IV Probit	First stage	2SLS	First stage	2SLS	First stage
Av_Range_lagged	-0.320	-2.193***					
	(0.205)	(0.000)					
Intervention			-0.031**		0.403***		0.196***
			(0.019)		(0.000)		(0.000)
Av_Scientific_ Intensity				-0.060*			
				(0.068)			
Av_Scientific_ Intensity75						-0.123*	
						(0.068)	
Observations	3,178	3,178	3,178	3,178	3,178	3,178	3,178
Dummies for mentors	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust p-values in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 6. Pivot (mechanism, panel)

VARIABLES	Pivot (1 time) IV Poisson	Pivot (1-2 times) IV Poisson	Pivot IV Poisson	Av_Range_diff First stage	Av_Range_diff 2SLS	Av_Range_diff 2SLS
Av_Range_diff	1.824**	1.299*	0.456			
	(0.013)	(0.054)	(0.729)			
Intervention				0.017***		
				(0.001)		
Av_Scientific_ Intensity_					0.046***	
					(0.002)	
Av_Scientific_ Intensity75						0.100***
						(0.002)
Observations	4,500	4,500	4,500	4,500	4,500	4,500
Dummies for mentors	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Robust p-values in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 7. Performance (mechanism, panel, 2SLS)

VARIABLES	Revenue (flow)	Revenue (flow)	Revenue (flow)	Revenue (flow) (winsorized 99%)	Revenue (flow) (winsorized 99%)	Revenue (flow) (winsorized 99%)
Av_Range_diff	5,200.322*			622.376		
	(0.094)			(0.164)		
Av_Scientific_ Intensity_		240.999*			29.075	
		(0.053)			(0.122)	
Av_Scientific_ Intensity75			522.355*			63.018
			(0.055)			(0.123)
Observations	4,500	4,500	4,500	4,500	4,500	4,500
Dummies for mentors	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Robust p-values in parentheses *** p<0.01, ** p<0.05, * p<0.1

Figure 1. Marginal benefits of pivots

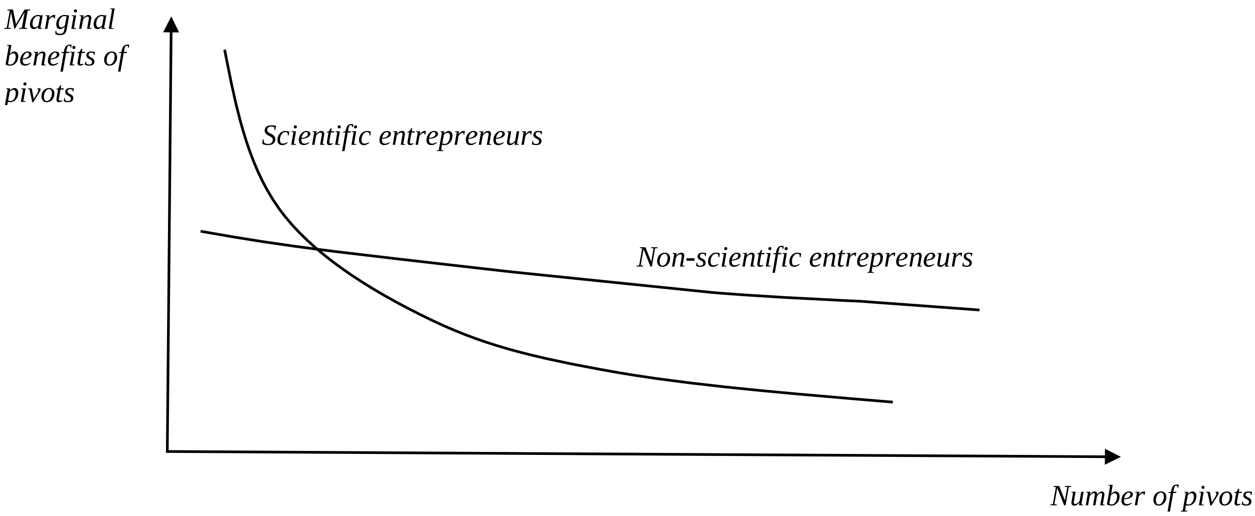


Figure 2. Number of exit and pivot

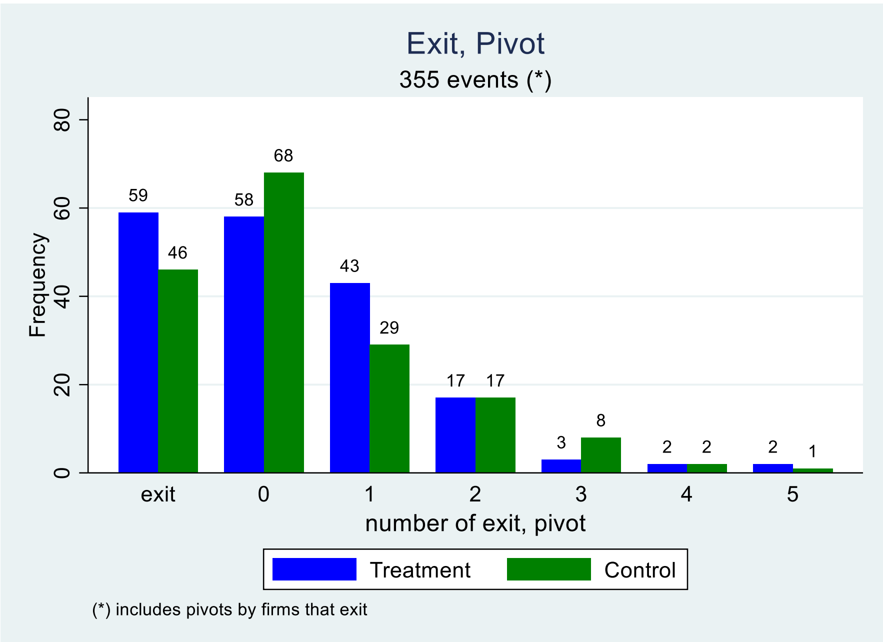


Figure 3. Average cumulative revenue (weeks 8-66)

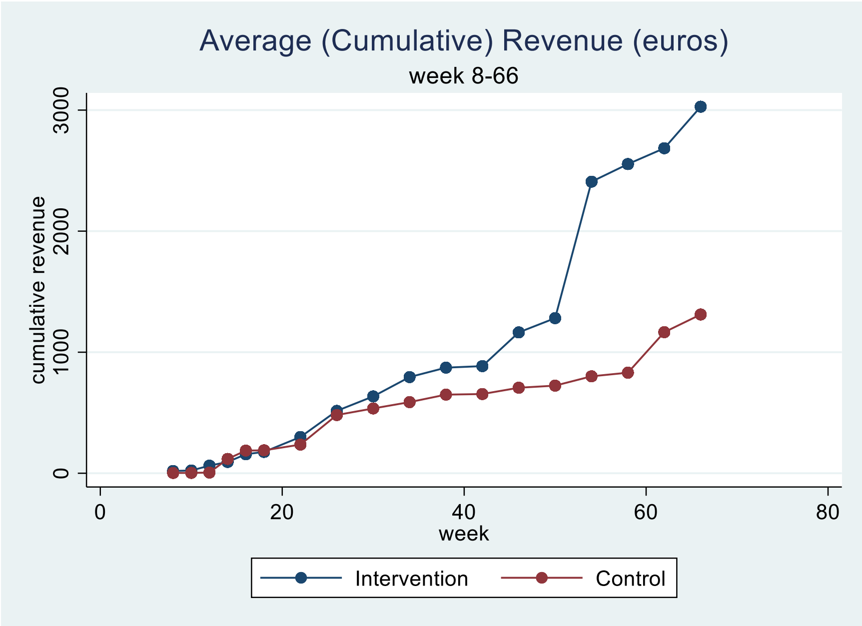


Figure 4. Mean Value

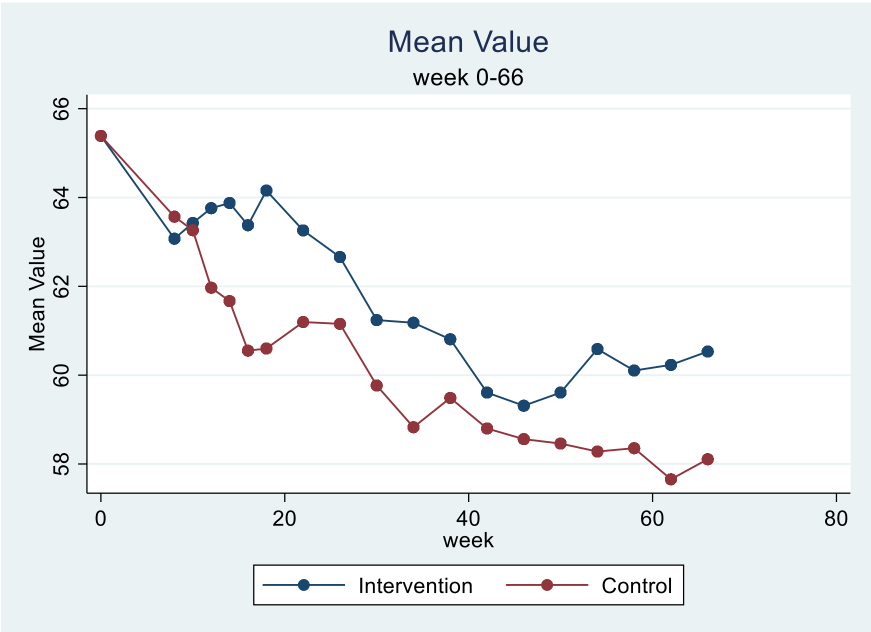
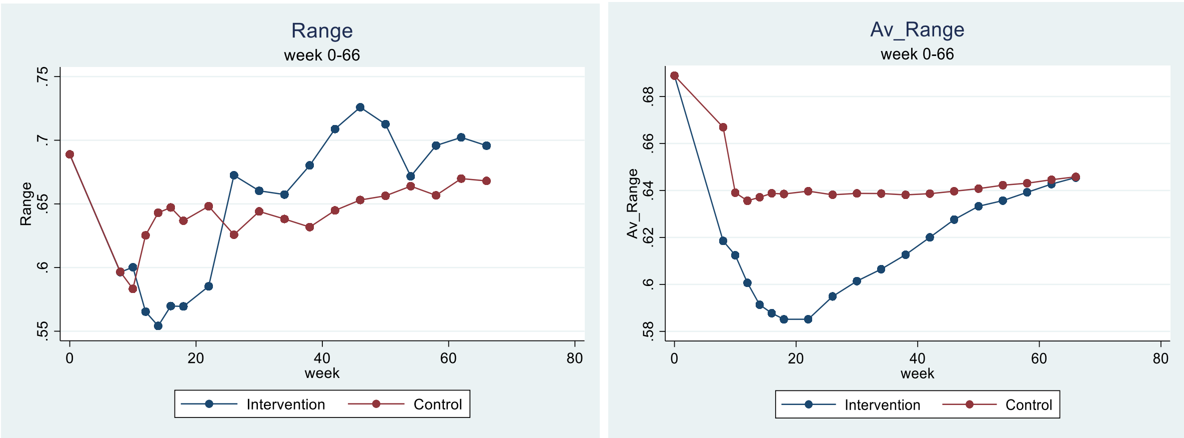


Figure 5. Range and Av_Range



Online Appendix A: Randomization checks on key covariates

Variables	Treatment		Control		Difference	
	Mean	Sd	Mean	Sd	Coefficient	P-value
Startup potential	47.22	21.22	47.31	23.25	0.09	(0.98)
Local	0.56	0.47	0.57	0.46	0.01	(0.88)
Sector experience	1.09	2.19	0.93	1.44	-0.17	(0.48)
Start-up experience	2.29	3.69	2.27	4.18	-0.02	(0.97)
Management experience	8.73	7.75	9.02	8.85	0.28	(0.79)
Work experience	10.17	9.65	10.96	11.45	0.78	(0.56)
Working hours	0.57	0.43	0.62	0.42	0.05	(0.39)
Full time	0.08	0.18	0.08	0.17	-0.00	(0.94)
Part time	0.73	0.37	0.75	0.36	0.03	(0.54)
Males	31.47	8.18	31.41	7.90	-0.06	(0.95)
Age	2.25	1.46	2.28	1.37	0.03	(0.86)
Team size	2.94	0.74	2.95	0.80	0.00	(0.97)
Probability to stay	11.52	5.80	11.51	5.85	-0.01	(0.99)
Top education	45.71	19.86	43.21	22.93	-2.50	(0.36)
Months to revenue	85.08	16.29	85.67	16.16	0.59	(0.77)
Minimum value	8.38	3.68	8.07	3.28	-0.32	(0.47)
Maximum value	4.09	1.70	3.83	1.74	-0.25	(0.24)
Observations	125		125		250	

Online Appendix B: A Description of Scientific Intensity

To understand if entrepreneurs adopt the scientific approach, and to what extent, we quantify the intensity of the adoption of key four elements (theory, hypotheses, tests, and critical evaluations) in their decision-making process.

To adequately capture different nuances of the adoption of the scientific approach, we first code for the presence of the four elements of the scientific approach (i.e. does the entrepreneur have a theory) and then assign a score to four dimensions for each element of the approach. Each dimension is assigned a score ranging from 1 to 5, where 1 indicates that the entrepreneur displays a low degree of adoption of the scientific approach and 5 indicates that the entrepreneur displays a high degree of adoption of the approach. We therefore code sixteen variables (four dimensions for each of the four elements), since theory, hypotheses, tests and evaluations are complex constructs that include several dimensions, which we detail in the table below. To calculate the variable scientific intensity, we compute the average value of the sixteen variables that measure the adoption of the scientific approach.

Element	**Dimension**	**Description**
Theory: this part of the interview aims to understand if the respondent has a theory, i.e. a cohesive story about the mechanisms underlying the problem and the building blocks that need to be in place for the business to be viable.	*Theory_Clear*	Score to quantify whether the theory is understandable
	Theory_Articulated	Score to quantify if the theory goes into details, i.e. whether the respondent can provide a high level of detail consistent with the main theory
	Theory_Alternatives	Score to quantify if the theory expressed by the respondent considers additional aspects not currently implemented by the company, but that could be implemented
	Theory_Evidence	Score to quantify if the theory is supported by data. Data could be industry reports or information gathered by the respondent itself
Hypotheses: this part of the interview aims to understand if the respondent has identified specific hypotheses based on their theory, i.e. propositions that logically flow from the	*Hypothesis_Explicit*	Score to quantify if the respondent can clearly articulate the fundamental hypotheses that make his/her business viable
	Hypothesis_Coherent	Score to quantify if the hypotheses are coherent with the theory elaborated earlier
	Hypothesis_Detailed	Score to quantify if the respondent is able to tell what he/she wants to learn in clear and concise terms

theory but that have yet to be tested.	*Hypothesis_Falsifiable*	Score to quantify if hypotheses are formulated in a way that allows the respondent to support it or refute it through tests
Testing: This part of the interview aims to understand if the respondent has tested their hypotheses based on their theory.	*Test_Coherent*	Score to quantify if the objective of the test is in line/coherent with the hypotheses expressed earlier
	Test_Valid	Score to quantify if the test measures what it is intended to measure
	Test_Representative	Score to quantify if the test uses a representative sample that accurately reflects the characteristics of the broader group targeted by the respondent
	Test_Rigorous	Score to quantify if respondents use the right type of test and with the right procedures
Evaluation: This part of the interview aims to understand if the respondent has analyzed the data collected and whether he/she is actually making use of their findings.	*Val_Data*	Score to quantify if the evaluation is based on objective data – as opposed to making an assessment based on subjective perception
	Val_Measure	Score to quantify if the key measures used in the evaluation are consistent with what respondents identified as their priorities in the earlier questions
	Val_Sistematic	Score to quantify whether the collection and analysis process are well-organized and systematic
	Val_Explanatory	Score to quantify if the respondent has clarity on the main findings of the tests and their implications for the business – e.g. what to do based on the findings