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There is nothing more practical than a good theory to make strategic decisions: evidence from field experiments in developed and developing countries

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Abstract

A *theory-based* approach to strategic decision-making under uncertainty recommends decision-makers and entrepreneurs to formulate a theory behind their decision problems and to follow a structured framework to make decisions. Theoretical reasoning should enable actors to generate more comprehensive representations of the world, ground hypothesis testing in a clear framework, identify causal mechanisms and better interpret results from experimentation efforts. However, despite the abundance of theoretical research, limited empirical evidence of the effectiveness of such systematic approach to decision-making is available. Most of the evidence in entrepreneurial settings focuses on decision outcomes and performance, with few papers investigating mechanisms or intermediate outcomes that can affect the decision-making process.

This thesis contributes to the stream of research on theory-based approaches in entrepreneurial decision-making, and more generally to the literature about decision-making under uncertainty, by 1) proposing novel theoretical arguments for the channels through which a theory-based approach improves decision outcomes; 2) providing novel empirical evidence on the matter leveraging three distinct field experiments conducted with entrepreneurs in both developed and developing countries, the latter being a context widely understudied in the strategy literature.

Particularly, the three chapters are devoted to the examination of entrepreneurs' perceptions and their ultimate connection to outcomes, analyzing whether and how they are affected by the application of a theory-based approach to decision-making. Entrepreneurs' perception of their ideas, the environment in which they act, as well as self-perceptions in relation to that environment are important mechanism that despite their importance for decision-making processes have not been widely studied yet in the literature. The goal of this thesis is to disentangle the effects that following a theory-based approach has on different dimensions of entrepreneurs' perceptions and ultimately on business outcomes.

Each chapter studies different aspects of the decision-making process and different types of perceptions. The first chapter develops a theoretical framework explaining how a theory-based approach affects entrepreneurs' perceptions of their projects' value, and how this change in perceptions leads to a better selection process with respect to entrepreneurs not following a structured approach to decision-making. Results also show how this process ultimately results in better business outcomes for entrepreneurs following a theory-based approach. The second chapter compares again these two groups of entrepreneurs, focusing on pivoting activities and business model changes. Results show how entrepreneurs following a theory-based approach introduce changes that are more customer-centric, and how this leads to a different update process on their beliefs about project's value and related uncertainty. The third chapter leverages the unique setting of an emerging economy, Tanzania, to study entrepreneurs' perceptions of ability to deal with potential challenges to business development and how they relate to performance and uncertainty perceptions. Results show how entrepreneurs trained to follow a theory-based approach perceive themselves as better able to deal with potential challenges when compared to entrepreneurs trained with a structured approach solely based on experimentation, ultimately isolating the positive spillovers related to the theoretical element of decision-making.

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Acknowledgments

The journey towards this PhD has been a long one, but I am grateful to have embarked on it. These five years have been terrific and made me grow exponentially as a person and as a researcher. In these five years, I learnt what does it mean to be intellectually challenged and how to become more resilient. I learnt how to deal with my frustrations and unmet expectations, and how to focus on the process rather than on the outcomes. The latter aspect is, I believe, one of my biggest achievements.

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During this journey, I was lucky not to conduct research just sitting alone in front of my computer. In these years I worked closely with scholars from all over the world, I managed large field experiments with entrepreneurs, worked directly with leading companies, and had the great

opportunity to teach at master's and executives' levels since my second year of studies. All these aspects made my path towards the PhD unique and extremely satisfactory on a personal level.

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"If you're not scared, you're not taking a chance.
And if you're not taking a chance, what the hell are you doing?"
Ted Mosby

Introduction

Scholars in strategy and entrepreneurship have been interested in decision-making processes under conditions of uncertainty for decades. Recently, a vibrant debate has risen within both academics and practitioners on which approaches should be followed by decision-makers and entrepreneurs when making such type of decisions (e.g., Zellweger and Zenger, 2022). Within the entrepreneurial realm, alternative methodologies have been proposed, each of them leveraging peculiar aspects of the uncertainty concept. For instance, one of the most popular approaches in the practitioners' world is the "Lean startup" approach (Ries, 2011), which emphasizes that entrepreneurs can mitigate uncertainty by conducting multiple validation rounds with experimental processes based on market and customer feedback. The "Lean startup" is a peculiar example of an *action-based* approach (Ott et al., 2017), where experimentation is employed as a "learning by doing" strategy. Approaches based on frequent experimentation have however been recently criticized (e.g., Felin et al., 2019) for being too focused on hypothesis testing and not devoting enough attention to generating a holistic understanding of the causal logic behind business experiments.

Starting from the suggestion to combine the *action* with a *cognition* element that emphasizes the advantages of "thinking before doing" (Ott et al., 2017), an emerging stream of research advocates for strategizing through *theory-building* (Camuffo et al., 2022; Felin & Zenger, 2017; Ehrig & Schmidt, 2022; Zellweger and Zenger, 2022). Theories should indeed enable strategists and entrepreneurs to generate abstract yet logical representations of the world, articulate hypotheses directed at testing the causal mechanisms underlying the value being created by a business proposition (Felin & Zenger, 2017). This ultimately guides the choice of experiments to conduct (Camuffo et al., 2022) and the interpretation of the evidence collected (Ehrig & Schmidt, 2022).

Empirical evidence on the effectiveness of such theory-based approaches in the entrepreneurial setting is growing, but it is still at its early stages (Zellweger & Zenger, 2022). The goals of this thesis are to: 1) expand the empirical basis supporting the effectiveness of theory-making, and related experimentation, for strategy and decision-making processes under uncertainty; 2) propose novel theoretical arguments of why it should be the case.

Importantly, the focus of all three chapters is not on entrepreneurial outcomes per se, rather on the study of potential mechanisms and intermediate outcomes through which a theory-based reasoning could act. Specifically, the three chapters are devoted to the study of entrepreneurs' perceptions, and their ultimate connection to outcomes, and how they are affected by the application of a theory-based approach to decision-making. Indeed, entrepreneurs' perception of their ideas, the environment in which they act as well as self-perceptions in relation to that environment are important mechanism that despite their importance for decision-making processes (e.g., Kahneman and Tversky, 1974; Kahneman et al., 2019; Shepherd et al., 2015) have not been widely studied with respect to these systematic approaches to decision-making. The goal of this thesis is to disentangle the effects that following a theory-based approach has on different dimensions of entrepreneurs' perceptions and ultimately on business outcomes.

In all the three chapters, I operationalize the theory-based approach with the "scientific approach" to decision-making proposed by Camuffo et al. (2020). A scientific approach to decision making combines *action* and *cognition* elements (Ott et al., 2017) suggesting to decision-makers and entrepreneurs the adoption of a systematic decision-making routine (Novelli and Spina, 2022). Such routine starts with the formulation of a *theory* over the strategic problem to be solved, including the definition of assumptions about the environment and the development of logical connections between the problem and the solution devised. These assumptions and potentially causal relationships are then translated into formal predictions or *hypotheses*. These first two steps constitute the *cognitive* part of the approach. Then, other two steps refer directly to the *action* element. Specifically, decision-makers conduct *tests* that can support or reject the hypotheses defined in the first phase. Test results are finally *evaluated* in light of the initial theory and are used as feedback to potentially revise the cognitive representation of the problem initially developed. Finally, a strategic decision is made. By employing this approach in an iterative way over time, it is argued that decision-makers develop an accurate understanding of the structure and the distribution of outcomes in the environment, being able to gauge the effectiveness of the identified solution under different contingencies.

To study the relationships between the adoption of the scientific approach, entrepreneurs' perceptions and business outcomes, all studies are based on randomized field experiments. Experiments have been conducted with entrepreneurs in both developed and developing countries, specifically in Italy (Chapters 1 and 2) and Tanzania (Chapter 3). In all settings, we offered a free-of-charge entrepreneurial training program to entrepreneurs developing novel start-ups or innovative ideas. Entrepreneurs were randomly assigned to two main experimental conditions in all studies. Specifically, experiments in the first two chapters assigned entrepreneurs either to a training based on the prescription of the "scientific approach" or to a standard entrepreneurship training where neither theorizing nor hypothesis testing was mentioned. Instead, in the last chapter, entrepreneurs were exposed to two trainings both based on the concept of experimentation and hypothesis testing. However, in one treatment, such concepts were taught only after having introduced theory-based reasoning. Therefore, in the last chapter the only difference between the two trainings is the presence of the "theory-building" element.

The three chapters study different entrepreneurs' perceptions and related outcomes, as explained below.

Chapter 1, titled "*Scientific decision-making and project selection*", focuses on entrepreneurs' perceptions of their ideas' potential value.
As a starting point, this chapter leverages on data from two distinct randomized control trials (RCTs) conducted in Italy to corroborate results from Camuffo et al. (2020), which found that entrepreneurs following a scientific approach were more likely to terminate their projects. Having found consistent evidence, two research questions are asked: (1) What mechanisms affect termination rates following the use of a scientific approach? (2) Is a tighter selection also associated

with a better balance between type I and type II errors? To answer these two questions, the chapter proposes a theoretical framework, guiding the empirical analysis. This framework identifies two effects. First, compared to the control group, entrepreneurs following a scientific approach make an earlier and faster downward adjustment in their assessment of the project's expected values, which raises the odds of project termination (the *estimation effect*). Second, the framework predicts that, conditional on selection, scientific entrepreneurs perform better and grow faster (the *performance effect*).

Results from the estimation thus show how entrepreneurs' perceptions of ideas' potential value change as an effect of the intervention and how they ultimately affect the decision to terminate projects earlier. However, it might be that this tighter selection process induced by the scientific approach leads to adverse outcomes, such as the ruling out of ideas that would have turned out to be successful. Indeed, while a tighter selection process likely reduces false positives, it might be that it increases the rate of false negatives in an excessive way. While it is not possible to retrieve a precise counterfactual of what would have happened to terminate projects were they not terminated, this empirical issue is addressed by providing novel evidence based on different approaches. Among others, we collected additional data on the long-term success rate of projects participating in the RCTs and asked two highly qualified professionals to evaluate the pre-training pitch of the projects developed by entrepreneurs in the two RCTs. Overall, there is no evidence that entrepreneurs trained with a scientific approach terminate better projects than control entrepreneurs. This provides a sufficient condition to argue that the tighter selection done by treated entrepreneurs is a better selection: treated entrepreneurs exhibit a higher expected value given selection without terminating better projects.

Chapter 2, titled "*Updating strategy and beliefs: experimental evidence on entrepreneurial pivoting*", focuses on the phenomenon of entrepreneurial pivoting and how entrepreneurs' perceptions change following such activities. Specifically, the chapter studies whether and how entrepreneurs adopting a scientific approach update their beliefs about the prospects of their idea and how this is related to the uncertainty they perceive when compared with entrepreneurs not following such approach. The theoretical framework proposes that pivoting activities conducted by scientific entrepreneurs have two direct consequences on perceptions and beliefs. First, such activities should lead to an increase in the beliefs about an idea's expected value since the pivoting activity is backed by more thought-through information and knowledge about the direction to take. Second, since scientific entrepreneurs can potentially see more strategic patterns of development compared to entrepreneurs not following such approach, the perceived uncertainty around the idea's potential value should increase after the pivoting activity is conducted.

These propositions are tested on one of the two experiments employed in Chapter 1, leveraging unique data on pivoting. Results show how pivoting activities conducted by scientific entrepreneurs led to an increase in the expected value of the idea with respect to control entrepreneurs, but do not support the proposed increase in perceived uncertainty. Exploratory analyses on potential mechanisms reveal that entrepreneurs following a scientific approach conduct pivoting activities that are more focused on customers and value propositions aspects of the business model, rather than focused on operational aspects of the company, when compared to entrepreneurs not following the approach. Finally, analyses show that pivoting activities are correlated to improvements in performance metrics, such as revenue, profits and activated customers. Specifically, entrepreneurs that pivoted at least once perform better, regardless of the treatment group to which they belong.

Chapter 3, titled "*Entrepreneurship Training and Founders' Perceptions of Ability: A Randomized Control Trial with Entrepreneurs in Tanzania*" studies the implications of adopting a scientific approach grounded on theory-building on entrepreneurs' perceptions ability. The chapter leverages data from a field experiment conducted in Tanzania, with a peculiar sample of entrepreneurs active in the agricultural and farming sectors. Specifically, we compare the adoption of a scientific approach based on both cognition and action elements, with a scientific approached based solely on the action element of experimentation. To reinforce such difference, throughout the chapter the two approaches are respectively labelled theory-and-evidence-based and evidence-based.

To study perceptions of ability, the chapter identifies different factors that entrepreneurs in emerging economies could identify as challenging and ultimately increase their perceptions of uncertainty. These factors are then distinguished between *environmental* and *project-related* ones. The former are institutional factors and/or other characteristics of the economic environment in which entrepreneurs act, which could be perceived as challenging since entrepreneurs have limited control over them. The latter are factors related to the unique business proposition developed by entrepreneurs, which could be directly mitigated by the entrepreneur, by developing relevant skills associated to business modelling or market research. Survey and interview instruments collect data on both entrepreneurs' perceptions of the relative importance of such factors as sources of challenges and on entrepreneurs' perceived ability to deal with them. The theoretical framing argues that the theory-and-evidence-based training, thanks to the cognitive element preceding experimentation, has a more positive impact on entrepreneurs' perceived ability when compared to a training where only the experimentation element is emphasized.

The empirical analysis starts with a rich description of the agricultural entrepreneurial environment in Tanzania as represented by the sample at disposal. Then, results show how entrepreneurs trained with the theory-and-evidence-based approach increase their perceived ability more than entrepreneurs trained with the evidence-based approach, being this effect persistent over time. The effect is mostly driven by an increase of the perceived ability scores over *project-related* factors. Exploratory analyses on the relationship between perceived abilities, perceptions of control over future events, and performance measures find positive correlations, suggesting that entrepreneurs with higher levels of perceived ability also perceive uncertain environments as more controllable and perform better.

Overall, the three Chapters explore different entrepreneurs' perceptions, how they are affected by the adoption of a theory-based approach to decision-making under uncertainty, operationalized through the scientific approach to decision-making (Camuffo *et al.*, 2020), and how this impacts decisions or business outcomes. The key take-away from this thesis is that of generally positive spillovers of a theory-based approach on entrepreneurs' perceptions compared to decision-making approaches based on experimentation alone or not following any type of structured framework, which can ultimately explain the positive effects of such approach found in previous research. Entrepreneurs trained to follow a theory-based approach, while becoming more conservative about the potential value of their ideas, make better decisions when deciding to continue pursuing their projects or terminate them, improving the ratio between false positives and false negatives (Chapter 1). Better performance might be driven by better pivots. Results show that entrepreneurs trained to follow a theory-based approach make pivots that are more customer-centered: this leads to an improvement in their perceptions about the expected value of their ideas once they change their course of actions, which is higher than the one experienced by entrepreneurs following a non-structured approach to decision-making (Chapter 2). Finally, theory-based entrepreneurs become more confident about their abilities to deal with potential challenges, particularly those related to the specific project they are working on. The latter results are found in a highly uncertain environment such as the one of an emerging economy, allowing to extend theories and empirical evidence in an often understudied context (Chapter 3).

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1

Scientific decision-making and project selection

with Alfonso Gambardella (Bocconi University) and Elena Novelli (Bayes Business School)

ABSTRACT

In this chapter, co-authored with Alfonso Gambardella and Elena Novelli, we explore the mechanisms and implications associated with the adoption of a scientific approach to decision making. By using data from two randomized control trials involving early-stage start-ups, we show that decision makers adopting a scientific approach make more conservative estimates of the value of their projects, leading to a tighter project selection. We show that, conditional on their decision to keep projects active, decision makers adopting a scientific approach outperform those not following this approach. At the same time, we do not find that they generate more false negatives with respect to the control group, which suggests that tighter selection does not come at the cost of discarding good projects. We conclude that the scientific approach improves performance by creating a better balance between type I and type II error.

1. Introduction

One important strategic decision for firms is the selection of new projects, that is the assessment of new projects to decide whether to pursue or terminate them. This process is a challenging one. The data paint a striking picture, with 90% of innovative projects failing (Fisher, 2014) Further evidence shows that a large proportion of entrepreneurs developing new projects fail within ten years, with quite a few failing already in their first year (National Business Capital, 2020). Part of the reason is that decision makers involved in project selection face an uncertain decision-making process along multiple dimensions (Folta, 1998; McGrath, 1997).

One way to deal with uncertainty is to use a structured decision-making process, and make decisions based on a "scientific" approach (Ashraf et al., 2021; Camuffo et al., 2020; Zellweger & Zenger, 2022). Decision makers following this approach develop a theory of the business idea underlying the project, articulate it into testable hypotheses, design tests, and evaluate test results in a disciplined way. This process resembles the one followed by scientists in exploring new phenomena. Prior research that has explored the use of similar approaches has reported that they are associated with higher project termination rates and higher performance conditional on keeping projects alive (Camuffo et al., 2020; McDonald & Eisenhardt, 2020).

However, previous research on this topic has not fully elaborated nor provided direct evidence of the mechanisms that connect the use of this approach with its outcomes. This is not surprising, given the research-design challenges that filling this gap involves. It requires an exogenous shock that induces decision makers to reason and make decisions in a scientific way, allowing a comparison with decision makers not adopting this approach. In addition, it requires observing the decision-making process steps in detail and not only the outcomes originating from the process. In this paper, we overcome both issues by leveraging original data from two new randomized control trials (RCTs) involving 382 early-stage start-ups in Italy. In these RCTs the treatment consists of teaching a sample of entrepreneurs to adopt a scientific approach in their decision making, keeping the other half in a control condition. To study project selection, we focus on entrepreneurs of early-stage start-ups. This ensures that individuals undergoing the treatment are key decision makers and that we can closely observe their decisions on an innovative project (i.e., the business proposition of the start-up).

As a starting point, we use our novel RCT data to verify whether we observe tighter project selection (i.e., higher termination of projects) associated with the use of a scientific approach, in line with prior studies (Camuffo et al., 2020). Having found consistent evidence, we ask two research questions: (1) What mechanisms affect termination rates following the use of a scientific approach? (2) Is a tighter selection also associated with a better balance between type I and type II errors? A thorough assessment of the performance of a scientific approach needs to answer both questions because while a tighter project selection may reduce the pursuit of false positive projects, it may also increase the rate of false negatives.

To answer these two questions, we develop a theoretical framework, which guides our empirical analysis. This framework identifies two effects. First, compared to the control group, entrepreneurs following a scientific approach make an earlier and faster downward adjustment in their assessment of the project's expected values, which raises the odds of project termination. We call this the *estimation effect*. Second, our framework predicts that, conditional on selection, scientific entrepreneurs perform better and grow faster. We call this the *performance effect*.

We empirically estimate this model leveraging our novel and unique data from the RCTs, in which we asked entrepreneurs to provide their own expectation of the value of their projects and their perceived probability of terminating them. These two pieces of information are key to separately identify the *estimation* and *performance* effects. If our treatment affected both an "action" and "performance conditional on the action", we could not separately identify the two effects of the treatment. In other words, we could not separate its effect on the estimation of performance, which affects the action, from its effect on conditional performance. We develop an estimation framework in which we show the conditions under which we can leverage entrepreneurs' predictions to identify these two effects separately even if the models that generate performance or its expectation differ, and we exploit the uniqueness of our data to estimate them empirically. Our findings show that scientific entrepreneurs provide a lower estimate of the value of their project after the beginning of the training program, which leads to a tighter selection process. Conditional on remaining active, we find that firms led by scientific decision makers produce higher revenues.

Next, to claim that the tighter selection process induced by the scientific approach is a "better" process compared to the control group, we need to show that the higher performance conditional on selection (which likely leads to a reduction in false positives) is not offset by an excessive increase in false negatives. This task entails theoretical and empirical challenges. Theoretically, we cannot determine the optimal trade-off between false positive and false negatives without attaching a measure of value or utility on the outcomes. We can work with good approximations such as revenue or growth for projects that are not terminated, but one cannot have an equally good measure for the terminated projects because their foregone revenues or values are not observed, which is also the main empirical challenge.

We address these issues by providing evidence based on four approaches. First, we compare the pattern of funding received and cumulative revenues over time of all treated and control firms, including those that eventually terminate. Second, we asked two highly qualified professionals to evaluate the pre-training pitch of the projects developed by entrepreneurs in the two RCTs. Third, we study termination and selection using a business simulation game. Finally, leveraging the results of our estimation, we study the performance of entrepreneurs who terminated under two opposite extreme scenarios. Overall, we do not find evidence that treated entrepreneurs terminate better projects than control entrepreneurs. This provides a sufficient condition to argue that the tighter selection done by treated entrepreneurs is a better selection: treated entrepreneurs exhibit a higher expected value given selection without terminating better projects.

This paper makes three unique contributions. First, our model and unique data on entrepreneurs' own assessment of their projects contribute to strategy research and to the important debate regarding how decision makers select strategic opportunities (Agrawal et al., 2021; Gans et al., 2019). Within this context, we provide direct evidence of the mechanisms that connect the use of a scientific approach to its outcomes. Specifically, we show that – in addition to having an impact on performance – a scientific approach affects choices by leading decision makers to be more conservative in their evaluations of the options available. This offers novel insights about the mechanisms through which decision-making approaches that combine cognition with action contribute to strategy definition and performance (Levinthal, 2017; McDonald & Eisenhardt, 2020).

Second, this paper contributes to strategy research by exploring the full trade-off associated with a tighter selection process, and not just the effect on performance conditional on selection. We show that the scientific approach – despite leading decision makers towards more conservative project estimates – does not make them significantly more likely to wrongly discard good projects. This represents a relevant insight for research about the use of causal inference processes for strategy formation within organizations (Ryall & Sorenson, 2021; Zellweger & Zenger, 2022).

Third, we make a methodological contribution by providing a possible solution to the general problem of obtaining a separate identification of *estimation* vs *performance* effects. Our paper highlights that these effects can be identified by asking for predictions before actions, and by making reasonable assumptions.

The chapter is structured as follows. Section 2 provides some background information about the scientific approach to organizational decision making. Section 3 details the estimation framework. Section 4 describes our methodology and data. Section 5 reports the estimation results. Section 6 provides additional evidence about performance conditional on selection (section 6.1), including new data about the long-term performance of the scientific approach, and we provide evidence that treated firms do not suffer from a higher rate of false negatives (section 6.2). Section 7 offers concluding reflections.

2. Background

2.1 A scientific approach to decision-making

Prior literature in strategy and organization has shown that decision makers often make decisions following their gut feelings as opposed to using structured approaches that systematically take all available information into account (Bennett & Chatterji, 2019; Ryall & Sorenson, 2021). At the same time, some scholars have documented the benefits that decision makers can derive from the use of well-defined approaches that support managerial and entrepreneurial decision making, such as the use of structured managerial practices (Bloom & Van Reenen, 2007; Ott et al., 2017; Yang et al., 2020).

Within this context, prior literature has emphasized two main classes of approaches (Ott et al., 2017). On the one hand, cognition-based approaches to decision-making hinge on the development of cognitive structures and mental models to understand markets, firms, and strategies (Csaszar & Laureiro-Martínez, 2018; Felin & Zenger, 2009; Gary & Wood, 2011; Walsh, 1995). The logic of these approaches is that the environment and its future states cannot be predicted or known, but an understanding of the relationship between market characteristics and strategic choices such as project selection can lead to superior outcomes. On the other hand, action-based approaches to decision-making hinge on the idea that – in the face of an environment that cannot be predicted (Eisenhardt, 1989) – taking actions and then adjusting those actions based on the feedback obtained by the environment can lead to valid organizational decisions. Action-based approaches, include, for instance, trial and error learning and heuristics (Bingham & Davis, 2012; Bingham & Eisenhardt, 2011; von Hippel & Tyre, 1995), and experimentation (Ries, 2011; Thomke, 1998).

More recent studies have advanced the idea that these two types of approaches can be successfully combined in a ”decision weaving” process that can actually lead to acquiring knowledge about the environment and use that knowledge as a guide for action (Eisenhardt & Ott, 2017; Ott et al., 2017). For instance, Gavetti & Rivkin (2007) provide a detailed description 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. McDonald & Eisenhardt (2020) elaborate on the benefits of deliberate learning, and of testing the cognitive assumptions underlying a business model before committing to it. They show that such an 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 & Katila (2020) show how teams that engage more 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.

Camuffo et al. (2020) focus on a specific way in which a cognition-based approach and an action-based approach can be combined to select projects, which they refer to as a "scientific approach" to decision making, and which is the focus of this paper. A scientific approach to decision making starts with a cognitive approach to the problem that the project aims to solve, which includes the definition of assumptions about the environment and a theory on the relationship between the problem and the solution devised. These assumptions and causal relationships are then translated into formal predictions or "hypotheses". This initial phase is complemented with an action-based approach to the problem, consisting in conducting tests that can support or reject the hypotheses defined in the first phase. Test results are carefully examined and used as feedback to revise the cognitive representation of the problem initially developed. By employing this approach in an iterative way over time, the decision maker develops an accurate understanding of the structure and the distribution of outcomes in the environment, being able to gauge the effectiveness of the identified solution under different contingencies.

2.2 A stylized example

We illustrate the use of a scientific approach to project selection in practice with a stylized example. Consider a decision maker facing a new project, such as the development of an innovative product or service, or the launch a new business. Assume she starts with an intuition coming from observation of real-world phenomena, spotting a problem that requires an innovative solution for it to be solved. Our decision maker will evaluate whether this project is worth the development efforts and this assessment will be made at regular intervals throughout the life of the project (Bingham & Eisenhardt, 2011; Gans et al., 2019; Kirtley & O'Mahony, 2020; Lieberman et al., 2017). Based on this assessment, she will decide on project selection, i.e., whether to maintain the project active or to terminate it.

Along the way, her assessment on the value of the project will be based on considerations regarding the multiple potential scenarios she could face in the environment in which she operates, over which there is uncertainty. This uncertainty could originate, for instance, from the fact that she is not yet familiar with customers' preferences in the environment she targets; or from the fact that these preferences might be subject to change. She will also consider the choices she can make to deal with the multiple scenarios she might be facing. At the very early stage of her process, choices could regard the basic features of the project. At later stages, they could be linked to the project implementation and could include, for example, the development of different versions of the same product, service, or business model, or the implementation of alternative marketing strategies.

Of course, every choice she envisions might affect the value of the project under different scenarios, and she needs to make these choices in the face of uncertainty. Suppose for instance that our entrepreneur's project is about developing an innovative service for car-sharing, but there is uncertainty regarding the extent to which cars are going to be relevant in the medium term in the context in which she is operating. If the context in which she operates is going through a massive drop in the use of cars and an increase in the use of bikes, the choice of pursuing such car-sharing project could have a negative value. Instead, if renting cars is a valuable option in the context in which she operates, the choice of pursuing such car-sharing project idea could have a high value. Depending on her prior on the scenario more likely to manifest and what value she envisions her choices to have, she could decide to terminate the project, or to pivot to a new version of the project, or to simply continue the development of the project along its natural trajectory.

If our entrepreneur approached project selection in a scientific way, she would start by developing a theory about the problem that the car-sharing service addresses and the way in which it addresses it, and how the value of each choice would change under different relevant scenarios. She would then decompose the theory into core hypotheses regarding the scenarios she is facing and the value of choices in those scenarios. For instance, relevant hypotheses could be: “Car transportation in large cities is highly valued by families” or “The majority of adults living in a large city believe that owning a car in a large city is not practical due to the high fixed costs and the limited use per person”, or “The majority of adults living in a large city consider sharing cars a viable option”. She will test such hypotheses by collecting relevant information from a representative group of target customers. She will then evaluate the results obtained from the test against her theory. This will lead to a decision about whether to maintain the project active or terminate it, if she believes that no choice that she could implement would lead to achieve value under the scenarios that she expects to be more likely to occur.

2.3 Estimation and performance effects

Camuffo et al. (2020) show that entrepreneurs who employ a scientific approach terminate their projects more frequently and faster than other entrepreneurs, make more focused changes to their projects and perform better. However, research in this area still lacks a precise understanding of the mechanisms underlying the relationship between the use of the approach and its main outcomes (more frequent project termination and superior performance). Moreover, we do not know whether this higher rate of project termination also implies that decision makers discard potentially good projects. In other words, we need to understand whether the tighter selection process generates a positive net value.

In this paper we fill these gaps by elaborating on two main mechanisms. First, prior literature has explained the widely spread phenomena of excess entry in a market and delayed exit as a consequence of cognitive biases, such as overestimation and overconfidence (Åstebro et al., 2007; Chen et al., 2018; Chen et al., 2022; Gutierrez et al., 2020; Zhang & Cueto, 2017). By developing theories, scientific entrepreneurs focus on the relevant assumptions behind their projects, which translates in the formulation of more structured expectations about the probability of success and value estimation. This is complemented by the design of higher quality tests that can provide them with objective signals about the extent to which their theory and hypotheses are supported by data. Relating signals back to theory leads to a validation of the theory or to a rejection of it. This results in more objective updates of the probabilities of success that produces a more conservative expectation of the value of the project, contrasting entrepreneurs' tendency toward overconfidence. We call this effect the *estimation* effect. A more conservative assessment of projects is likely to lead to a reduction in the rate of *false positives,* that is projects that are not terminated despite not delivering much value.

For instance, if the hypothetical entrepreneur we introduced in the previous section collected a negative signal on people's willingness to share cars due to hygiene concerns in a pandemic world, she would be more likely to form a negative value expectation and terminate the project. This effect is likely to lead scientific entrepreneurs to terminate their projects more often than non-scientific entrepreneurs, a result in line with qualitative research that suggests that factual grounding speeds decision-making, reduces emotional conflict and facilitates de-escalation of commitment (Eisenhardt, 1989; McDonald & Eisenhardt, 2020; Raffaelli et al., 2019; Sleesman et al., 2018).

The second effect of a scientific approach is that it improves the ability of scientific entrepreneurs to better identify the more valuable development trajectory for the business project, ultimately leading to higher performance and value. We call this the *performance* effect. The development of a theory and its articulation into hypotheses leads to a clear identification of the core elements or the problem faced and the relationships between them. This facilitates a quicker and more efficient search of the solution space, as it leads actors to identify ex-ante the characteristics of the solution (e.g. Camuffo et al., 2020; Felin et al., 2020). The subsequent test of hypotheses validates the theory, providing decision makers with useful feedback to improve the quality of their projects (Gross, 2017).

For example, if our entrepreneur obtained a positive signal on her hypotheses that car transportation in large cities is highly valued by households with young children who cannot use other types of transportation such as bikes easily, she would quickly understand that this will also make the service appealing to households that include the elderly and could change the development trajectory towards this direction. This effect is likely to lead scientific entrepreneurs to perform better, conditional on the fact that they do not terminate their project.

To disentangle and identify the *estimation* and *performance* effects, in the next section we develop a decision-making framework and subsequently estimate it with a multi-equation simultaneous maximum-likelihood model using data from two Randomized Control Trials. We will then turn to the analysis of the net effects of the selection process.

3. Estimation framework

We study project selection by focusing on early-stage start-ups. This is a particularly convenient setting for the study of project selection as these firms tend to focus on one single project (the main business idea underlying the launch of the start-up) and therefore firm performance and project performance coincide. Our estimation framework starts with a performance equation for firms that do not terminate their activity. We model the realized performance (v) of the project as:

$$v = a + \theta T + \sigma \epsilon \tag{1}$$

where $a = \gamma X$ summarizes the linear impacts γ of a set of controls X recorded at the baseline period. We assume that the realized value of the project is a function of the controls X, a stochastic term ϵ with zero-mean and unit variance, a parameter $\sigma > 0$ that represents the standard deviation of the full stochastic term $\sigma\epsilon$, and a dummy variable T that takes value 1 if the entrepreneur employs a scientific approach to decision making (treated group) and 0 otherwise (control group). Hence, θ identifies the *performance* effect.

Our model postulates that entrepreneurs evaluate their projects and form expectations of their potential value and probability of success over time. Denote these expectations by $\hat{v}$. We assume that entrepreneurs decide to keep developing their projects if these expectations are higher than their outside option w. Therefore, in our framework, these estimations are crucial as the decision between continuing with the development of the project or terminating it is based on the evaluation of that expectation with respect to an individual outside option.

Our RCT compares decision makers trained in the use of the scientific approach with decision makers who receive a more standard training in entrepreneurial decision-making (the control group in our RCT). Accordingly, we identify four points in time in the entrepreneur's decision-making process: (i) the baseline, before the training (0 – the Baseline Evaluation), (ii) during the training (E – the Early Evaluation), (iii) later in time after the training (L – the Late Evaluation), and (iv) the exact time of the decision whether to remain active or terminate the business (F – the Final Evaluation). Specifically, we consider as Late Evaluation the last available data point before the decision to terminate, or if the entrepreneur never terminates the project within the observation window, the end of our observation window. As we will see we do not observe the exact date of the Final Evaluation, but we estimate it from our model.

Hence, we develop four equations:

$$\hat{v}_0 = c + c_0 + \sigma_0 \epsilon \tag{2}$$

$$\hat{v}_E = c + c'_0 + c_E + (c_{ET} + \theta)T + \sigma_E \epsilon \tag{3}$$

$$\hat{v}_L = c + c'_0 + c_L + (c_{LT} + \theta)T + \sigma_L \epsilon \tag{4}$$

$$\hat{v}_F = c + c'_0 + c_F + (c_{FT} + \theta)T + \sigma_F \epsilon \tag{5}$$

The baseline evaluation (2) happens before the training and therefore it depends on factors independent of the training, such as education levels, age, or previous startup experience, which we include in the vector c_0, while c represents a constant term.

Once the intervention starts, it influences the evaluation. Equations relating the early (3), late (4) and final (5) evaluations include c, which is the constant term, c'_0 that identifies constant idiosyncratic factors and any other factor that may vary because all entrepreneurs now undergo one or the other form of training (scientific or control group), and c_J ($j = E, L, F$) that identify contemporaneous factors affecting the value estimation.

In addition, we assume that the intervention has two effects on the project evaluation made by entrepreneurs, the *performance* effect θ and the *estimation* effect c_{jT} (which is not restricted to be constant over time). They cannot be identified empirically without adding some structure to our model. Therefore, we assume that entrepreneurs trained with the scientific approach learn about new opportunities prompted by this approach during the training, and thus before the Early evaluation, while the estimation effect may vary over time. This is a natural assumption in that the effects of the scientific approach are likely to manifest themselves immediately during the training because they are absorbed during the lectures and can be applied concomitantly. Moreover, it is at these early stages that entrepreneurs define the core features of the project, whereas later they spend relatively more time developing it. In contrast, information that affects predictions is likely to unfold more gradually over time.

Thus, we first build on the previous steps and generalize the decision-making process as:

$$\widehat{v_j} = c + c'_0 + c_j + (c_{jT} + \theta)T + \sigma_j\epsilon \geq w_j \qquad (6)$$

where j represents the different time periods, and w_j represents the entrepreneur's outside option that we assume varies over time and we represent as $w_j = w_{j-1} + b_j$. This condition is verified if and only if:

$$\epsilon \geq \frac{w_j - c - c_0' - c_j - \left(c_{jT} + \theta\right)T}{\sigma_j} \equiv z_j \tag{7}$$

We cannot observe either the final performance or the evaluation made by entrepreneurs who terminate their projects at the time F in which they make this decision. We only observe the outcome of this decision, i.e., whether they terminate the project. Hence, for F, we consider the following equation based on a latent model for the probability of maintaining the project active:

$$\Pr(Stay) = \Phi\left(\frac{-w_F + c + c_0' + c_F + (c_{FT} + \theta)T}{\sigma_F}\right) \tag{8}$$

We can now retrieve the structural parameters of interest. Specifically, from (7), we rewrite z_0, z_E, and z_L for the first three data points (0, E and L) as

$$z_0 = \frac{w_0 - c - c_0}{\sigma_0} \tag{9}$$

$$z_E = \frac{w_E - c - c_0' - c_E - (c_{ET} + \theta)T}{\sigma_E} \tag{10}$$

$$z_L = \frac{w_L - c - c_0' - c_L - (c_{LT} + \theta)T}{\sigma_L} \tag{11}$$

Since $w_j = w_{j-1} + b_j$ for all $j = E, L, F$, we can substitute w_j in all the three equations. Finally, plugging (11) into (8), (10) into (11), and (9) into (10), we obtain:

$$z_E = \frac{\sigma_0 z_0 + b_E - (c_0' - c_0) - c_E - (c_{ET} + \theta)T}{\sigma_E} \tag{12}$$

$$z_L = \frac{\sigma_E z_e + b_L - (c_L - c_E) - (c_{LT} + c_{ET})T}{\sigma_L} \tag{13}$$

$$\Pr(Stay) = \Phi\left(\frac{-\sigma_L z_L - b_F + (c_F - c_L) + (c_{FT} - c_{LT})T}{\sigma_F}\right) \tag{14}$$

In the next section we describe the data and methodology used to estimate the model and the coefficients of interest.

4. Methodology and data

4.1 Experimental design

To estimate the model outlined in Section 3 we leverage data from two field experiments, delivered in the context of a business support program that was offered to entrepreneurs in Milan and Turin (Italy). Both Randomized Control Trials (RCTs) shared the same structure, type of intervention, and data collection process. The two RCTs were held asynchronously.

Both programs were advertised nationally over multiple offline and online channels. The advertisement campaign lasted for several weeks to ensure recruitment of at least 100 entrepreneurs per batch. The campaign promoted the 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 startups ensured that participants into the programs were highly involved in the decision-making process and that they focused on one project. To apply, entrepreneurs were required to fill in an online survey and complete a telephone interview. In total, the data from the first RCT (Milan) includes 250 entrepreneurs, and the second (Turin) 132[1].

Entrepreneurs were assigned to either a treatment or a control group through simple randomization. Considering both RCTs, we allocated 192 entrepreneurs in the control group and 190 in the treated group. We checked that the randomization was successful with a set of balance checks across groups (Tables A1 and A2 in the Supplementary Materials). Then, each group was broken down into smaller groups and assigned to an instructor, thus creating different groups of entrepreneurs. To avoid potential biases due to instructors' teaching style, each instructor was in charge of teaching one treated and one control classroom.

[1] Both experiments have been pre-registered on the AEA RCT Registry.

Entrepreneurs in both groups attended the same number of sessions. All the sessions were highly experiential and the division in small classes ensured that instructors provided feedback to each participant. Both groups of entrepreneurs were exposed to (1) general managerial frameworks (such as the balance scorecard or the Business Model Canvas), which would support a cognition-based approach to decision making, and (2) to data gathering techniques (such as interview techniques, surveys and A/B testing), which would support an action-based approach to decision making. The treatment group was taught to apply this content using a scientific approach, i.e., combining cognition and action and make decisions in a scientific way. Specifically, treated entrepreneurs learnt to develop a theory of the problem that their project (i.e., their business) aimed to solve, to develop hypotheses that flow logically from the theory, and to use the evidence gathering techniques to test those hypotheses and relate the results back to the theory. For instance, in one of the first sessions, both groups were exposed to the Business Model Canvas (BMC), a widely used tool in entrepreneurship, which helps entrepreneurs graphically schematize a firm's business model. Entrepreneurs in the control group were exposed to this method and simply invited to apply it to their business, as it typically happens in any class in which such a method is taught. Instead, treated entrepreneurs were taught to use the BMC as a starting point for the development of their theoretical conceptualization of the project. Each component of the BMC was translated in hypotheses to be tested. Later in the module, entrepreneurs were exposed to different testing designs. Entrepreneurs in the control group were generally encouraged to apply these techniques to the problems they were facing in their business. Treated entrepreneurs were explicitly encouraged, instead, to use those techniques to test the hypotheses developed in the previous sessions, to closely assess the results and compare the results with the theory originally envisioned.

Contamination between treatment and control groups was prevented by scheduling sessions in different days or times of the week. Moreover, the research team ensured that acquaintances were not allocated to different groups.

4.2 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 purposefully trained by the research team and were responsible of conducting monthly telephone interviews with entrepreneurs. Overall, for each entrepreneur we collected the baseline and up to 18 data points.

Each phone interview was based on a standardized semi-structured interview script, including both open and closed-ended questions. Inquired topics included business performance, decision-making practices and any change introduced to the project. Each interview was recorded and stored in an encrypted storage space, while RAs were also instructed to encode qualitative answers into quantitative information.

Each entrepreneur was interviewed up until the end of the data collection period or up until the time they declared to have terminated the development of their project. Thus, for terminated projects we have information only up to the communication of such termination (what we consider to be the Late data point). For firms that did not terminate their project before the end of our observation window, we have information up to 66 weeks after the beginning of the study.

4.3 Data and estimation technique

We used data on all firms that participated in the program (N = 382) in the three data points considered in the model. The *Baseline* period refers to the period before the training. The *Early* period corresponds to 8-weeks after the beginning of the training. The *Late* period means that, for entrepreneurs that maintained their project active, we have the full set of information (i.e., up to week 66). Instead, for entrepreneurs that terminated their projects before the end of the full observation window, we have information up to the data point prior to which they declared that they terminated the project, which we treat as our "last available" data point. Note that the chronological timing of this last available data point is not directly relevant to us, because we focus on the actions that firms take just before termination or at the end of the period if they did not terminate. In our framework, the key element of interest is the information before this action and not whether this happened chronologically sooner or later.

To identify selection, i.e., entrepreneurs whose projects were still active at the end of our investigation period, we created a dummy variable that takes value 1 for entrepreneurs whose projects are still active and 0 for those who instead terminate their project at any point in time. For the former, we measure overall performance by computing the log of revenues at the last data point. We also check the robustness of results by computing the average of the revenue growths between each collected data point.

To measure entrepreneurs' perceived project value and estimation of future value, we rely on survey and interview data, which recorded relevant variables. First, we asked entrepreneurs to provide a predicted probability of project termination at each of the three data points (on a scale from 0 to 100). Second, we asked entrepreneurs to indicate the minimum and maximum value they associate with the project (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". We compute the average between the minimum and the maximum to retrieve our measure of estimated value, and finally take the logarithm of such resulting measure.

Finally, as to capture idiosyncratic factors that could affect both the project value and entrepreneurs' estimations, we employ baseline data on: team size (number of people in the founding team), team average age, team average weekly hours worked, team average years of experience with startups and the team-average highest level of education achieved by the team members (where 5=PhD,4=MBA, 3=MSc, 2=BA, 1=high school, 0=otherwise).

Table 1.1 includes some descriptive statistics about these variables by treatment group. Randomization checks at the baseline with detailed variable description are available in the Supplementary Materials.

Table 1.1 – Descriptive Statistics

	Treatment		Control		Total	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
Revenues (log, Active project = 1)	2.02	3.78	1.05	2.69	1.48	3.25
Average Revenue Growth (Active project = 1)	0.11	0.21	0.06	0.15	0.08	0.18
Active project (Dummy)	0.55	0.50	0.68	0.47	0.62	0.49
Probability of Termination (Baseline)	0.17	0.20	0.21	0.21	0.19	0.20
Probability of Termination (Week 8)	0.17	0.23	0.16	0.19	0.16	0.21
Probability of Termination (Last)	0.25	0.29	0.29	0.29	0.27	0.29
Estimated Project Value (Baseline - log)	4.16	0.29	4.12	0.30	4.14	0.29
Estimated Project Value (Week 8 - log)	4.06	0.40	4.11	0.30	4.09	0.35
Estimated Project Value (Last - log)	4.00	0.48	4.00	0.40	4.00	0.44
Startup Experience (years)	1.34	3.12	1.20	2.32	1.27	2.75
Team Size (Baseline)	2.33	1.49	2.24	1.38	2.29	1.43
Education	1.91	0.79	1.99	0.91	1.95	0.85
Age	31.17	8.48	31.08	7.62	31.13	8.05
Hours Worked (Baseline)	13.24	19.27	12.91	19.28	13.07	19.25

Note. Descriptive statistics on both baseline characteristics and outcomes, by treatment group. N = 382. For balance checks and related tests, please refer to Tables S1.1 and S2.2 in the Supplementary Materials.

By assuming a cumulative normal distribution, we can estimate the value of $z_J \; \forall \, j = \{0, E, L\}$ in our model by simply calculating the inverse of the latter given the predicted probabilities of termination p_j. Since $p_j = \Phi\left(\frac{w_j - c - c_0' - (c_{jT} + \theta)T}{\sigma_j}\right) = \Phi(z_j)$, we can retrieve z_j as:

$$z_j = \Phi^{-1}(p_j) \tag{15}$$

We cannot know the z estimate at the exact time in which the decision has been taken (what we labelled F). Therefore, we employ a selection model where we include as our selection variable the estimate z_L, and we rely on a latent estimation for such probability. If we were to only estimate the first two equations of the structural model described above, this could be done with a standard Heckman model where the exclusion restriction would be satisfied by the inclusion in the selection equation of the estimate z_L from (15) evaluated in the late period. This would allow us to estimate the *performance* effect θ conditional on the decision to keep the project active. However, relying solely on such two equations does not allow us to retrieve the *estimation* effect.

The opportunity to leverage data on the entrepreneurs' estimation of the potential value of their projects enables us to retrieve all the parameters of interest and be able to separate the *estimation* effect from the *performance* effect. Particularly, we leverage on the first two post-training data points (E and L) and consider these predicted values for two additional equations. It is thus the availability of the own estimations by entrepreneurs that allows us to estimate empirically both (3) and (4) and ultimately retrieve the two variances σ_E and σ_L that allow us to estimate the variance σ_F from (8). This additional step allows us to identify the *estimation* effect in the all the data points we are considering. By estimating the three variances, we can subtract θ from the estimated coefficients on T in (14) and (12) and finally compute the *estimation* effect for (13).

We thus end up with the following model to be estimated, made up of six equations:

$$v = a + \theta T + \sigma \epsilon \tag{1}$$

$$\Pr(Stay) = \Phi\left(\frac{-\sigma_L z_L - b_F + (c_F - c_L) + (c_{FT} - c_{LT})T}{\sigma_F}\right) \tag{14}$$

$$z_L = \frac{\sigma_E z_e + b_L - (c_L - c_E) - (c_{LT} + c_{ET})T}{\sigma_L} \tag{13}$$

$$z_E = \frac{\sigma_0 z_0 + b_E - (c_0' - c_0) - c_E - (c_{ET} + \theta)T}{\sigma_E} \tag{12}$$

$$\hat{v}_L = c + c'_0 + c_L + (c_{LT} + \theta)T + \sigma_L \epsilon \tag{4}$$

$$\hat{v}_E = c + c'_0 + c_E + (c_{ET} + \theta)T + \sigma_E \epsilon \tag{3}$$

We estimate these equations through a multi-equation conditional mixed-process estimator using the `cmp` user-written command in STATA (Roodman, 2011). The fitted algorithm is a modified version of a seemingly unrelated regressions estimator. In other words, it employs a maximum likelihood (ML) estimator with the assumption that the errors from the different, independent, equations are distributed according to a joint normal distribution. The `cmp` estimator allows us to model a simultaneous equation framework where endogenous variables in a multi-staged process appear both on the right and left end sides of six empirical equations representing the structural model described in the previous subsection. We estimate the following set of empirical equations, linked to the structural equations above:

$$
\begin{aligned}
&Eq.(1): \; v = \alpha_v + \beta_v X + \theta T + D + \epsilon_v \\
&Eq.(14): \; \Phi(\alpha_F + \gamma_F z_L + \beta_F T + D) \\
&Eq.(13): \; z_l = \alpha_L + \gamma_L z_E + \beta_L T + \epsilon_L \\
&Eq.(12): \; z_E = \alpha_E + \gamma_E z_0 + \beta_E T + \lambda_E X + D + \epsilon_E \\
&Eq.(4): \; \hat{v}_L = \alpha_{v_L} + \beta_{v_L} T + \lambda_{v_L} X + D + \epsilon_{v_L} \\
&Eq.(3): \; \hat{v}_E = \alpha_{v_E} + \beta_{v_E} T + \lambda_{v_E} X + D + \epsilon_{v_E}
\end{aligned}
$$

where D is a set of dummies for RCT and class instructors, X is a set of controls recorded at the baseline period as described above and the α represent constant terms of each equation. All the equations are linearly estimated, but the selection equation (14), which is estimated instead with a probit. Again, equations are estimated simultaneously assuming a joint normal distribution of the error terms. Since the intervention is administered at the classroom level, we cluster standard errors by classroom.

From the estimated coefficients of the regressions, we can retrieve all the parameters of interest that belong to our theoretical model. Specifically, the *performance* effect is straightforwardly the estimated coefficient θ of the treatment dummy in the first model. All the other theorized parameters have instead to be computed leveraging the estimated variances and coefficients from the econometric models. Particularly, the computation entails a non-linear combination of different estimated parameters. We conduct such computation using the `nlcom` routine on STATA.

Retrieving the OLS variances from (3) and (4), we can estimate the variance of the model related to the decision (selection equation) from (14) and we compute all the structural coefficient related to the *estimation* effect at different points in time from the other equations. Recall that in all equations but the performance equation, the estimated coefficient of the treatment dummy captures both hypothesized effects. Thanks to the estimation of variances, we can subtract the estimated *performance* effect θ from such coefficients and finally retrieve the correct estimation for the *estimation* effect. Table 1.2 details the calculations.

Table 1.2 – Parameters Computation

Parameter	Computation	Equations employed
θ	θ	1
σ_E	*OLS variance*	3
σ_L	*OLS variance*	4
σ_F	$-\frac{\sigma_L}{\gamma_F}$	14, 4
c_{ET}	$\beta_{v_E} - \theta$	3, 1
c_{LT}	$\beta_{v_L} - \theta$	4, 1
c_{FT}	$\beta_F \sigma_F + c_{LT}$	14, 4

Note. This computation strategy leverages on the straightforward calculations from (3) and (4). An alternative computation strategy is shown in the Supplementary Materials

Before computing the full-fledged structural estimation, we also estimate a three-step extended selection model where we only leverage the entrepreneurs' prediction of the project value rather than on both the latter and the predicted probability of project termination.

First, we account for selection by running a simple Heckman selection model using the predictions at the last available data point to identify the selection equation, always controlling for baseline characteristics. This step is a different way of modelling the first two equations in the full theoretical model. Differently from that, we directly employ the prediction about the project value rather than relying on the perceived probability of project termination. However, since our theory explains how entrepreneurs' value estimations should be a function of the treatment, such identification might be subject to endogeneity. We thus add a third equation, instrumenting the late predictions with the baseline, exogenous, prediction of project value. In the final step, to disentangle the *estimation* effect of the treatment, we add a fourth equation introducing entrepreneurs' value estimations in the early period, thus setting up a recursive instrumentation structure. To run this stepwise estimation, we also rely on the `cmp` command in STATA

4.4 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., 2019). To prevent this problem, we designed a series of monthly events focused on entrepreneurial challenges and issues. These events were offered to both treatment groups and did not include any additional manipulation. They were offered free of charge to ensure the highest attendance rates. The only requirement for obtaining access the events was continued participation in the data collection.

Across the two RCTs, 10% of the entrepreneurs dropped out of the program, despite they did not terminate their project. In the main analyses that we performed, we input missing values of the "attritors" using their last available data point, considering them as entrepreneurs with an active project. This relies on the conservative assumption that both the project performance and the entrepreneurs' assessment did not change after they left the program.

Nevertheless, in the Supplementary Materials we show tests for selective attrition, comparing baseline characteristics of "attritors" with active projects, by treatment group. Moreover, as a robustness check, we re-estimate all the models only considering compliant units, reducing the sample size to 344 observations. Results are available in the Supplementary Materials and are fully consistent with the main estimations.

5. Results

5.1 Extended selection model

Table 1.3 reports the results of the four-equations extended selection model. In the Supplementary Materials we also report the results of the first two steps of the model.

Table 1.3 – Extended Selection Model

	(1) Performance Equation	(2) Selection Equation	(3) $\hat{v}_L$	(4) $\hat{v}_E$
Treatment Dummy	1.046**	-0.280**	0.0432	-0.0585**
	(0.440)	(0.120)	(0.0430)	(0.0267)
$\hat{v}_L$		1.874***		
		(0.320)		
$\hat{v}_E$			1.103***	
			(0.361)	
$\hat{v}_0$				0.256***
				(0.0690)
Startup Experience (Baseline)	0.221***	-0.0289	0.00451	0.00466
	(0.0765)	(0.0251)	(0.00815)	(0.00515)
Team Size (Baseline)	0.306*	-0.0591	0.0106	0.00187
	(0.169)	(0.0400)	(0.0126)	(0.0135)
Education (Baseline)	0.280	-0.00824	-0.00708	-0.0346*
	(0.237)	(0.0737)	(0.0224)	(0.0204)
Age (Baseline)	-0.0855***	0.0147*	0.00251	0.00283
	(0.0239)	(0.00866)	(0.00288)	(0.00242)
Hours Worked (Baseline)	0.00800	0.00574	-0.00189	0.00205**
	(0.0127)	(0.00531)	(0.00157)	(0.000862)
Constant	1.769***	-7.457***	-0.655	3.103***
	(0.686)	(1.413)	(1.505)	(0.317)
Correlation	-0.199***			
	(0.0751)			
RCT Dummies	Yes	Yes	Yes	Yes
Mentor Dummies	Yes	Yes	Yes	Yes
Observations	382	382	382	382

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *Note.* The performance equation is estimated through an OLS conditioned on the selection equation, estimated through a probit model. The last two equations are estimated through OLS. Standard errors clustered at the classroom level (K = 24).

The coefficient on the intervention dummy from the performance equation suggests that projects of entrepreneurs exposed to a scientific approach have revenues of 104 pp higher than those of entrepreneurs in the control group (*performance* effect). The large magnitude of the coefficient is driven by the fact that only few firms experience a sizeable revenue growth over time. Thus, in the Supplementary Materials, we show results of the same model estimated on revenues trimmed at the 99th percentile, leading to a drop of three potential outliers. Results are consistent but more conservative: the *performance* effect is estimated to be around 0.76 (i.e., firms in the treated group have revenues that are 76 pp higher). Moreover, we run an alternative estimation in the

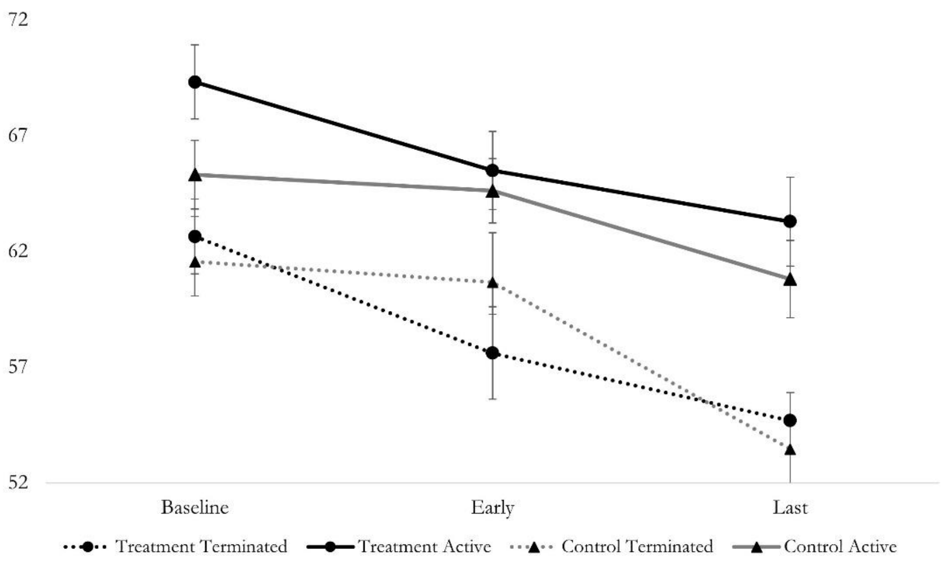
Supplementary Materials, using the average or the revenue growth between each data point as dependent variable, rather than the plain revenues at the last data point. Results are consistent and show how treated entrepreneurs experience an average growth that is around 6 pp higher than the one in the control group.

Regarding selection, in the model in Column (2), the dependent variable is a dummy taking value 1 if the project is still active at the end of the observation window. The negative coefficient of the intervention dummy signals that treated entrepreneurs are more likely to terminate their projects, a result consistent with Camuffo et al. (2020). The significant correlation ($\rho = -0.199$) between these first two equations highlights the need for controlling for selection when analyzing performance. The negative correlation aligns with our theoretical expectations that entrepreneurs overestimate the value of their projects, as it implies that entrepreneurs with projects with higher perceived evaluations are associated with lower realized performance.

Columns 3 and 4 in Table 3 highlight the *estimation* effect. At the baseline, the evaluation of the average project is the same across the two groups (due to random allocation), thus we should see no differences in the average evaluation other than due to the treatment. The negative and significant coefficient of the treatment dummy in the *Early* equation ($\beta = -0.059, SE = 0.027$), indicates that scientific entrepreneurs decrease their project value estimates early. The non-significant coefficient of the treatment dummy in the *Late* equation ($\beta = 0.043, SE = 0.043$) suggests that the *estimation* effect appears for earlier evaluations rather than later ones. These results are not surprising if we think that in the *Late* period, all entrepreneurs –regardless of their treatment status—should reach more accurate estimations of the value of their projects as the market provides a natural form of feedback. This positive, non-significant, coefficient might also be the result of entrepreneurs considering the positive performance effect in their late evaluation as this will have already manifested at this point. Our full-fledged structural estimation allows us to accurately disentangle these two effects.

To provide additional evidence in support of this early-stage *estimation* effect, we look at the estimates made by entrepreneurs on the potential value of their projects at different points in time (on a 0-100 scale). In Figure 1.1, we compare the averages of entrepreneurs' estimations across four groups defined by two dimensions: whether the entrepreneur belongs to the treatment (versus control) group and whether they terminated the project (vs maintained the project active) within the observation window.

Figure 1.1 – Entrepreneurs' evaluations of projects



Note. Entrepreneurs' estimation of their project value over time (scale: 0-100). We show the data for the three main data points: Baseline (pre-intervention), Early (8 weeks from the first lecture of the training), Last (last available observation in our dataset). We consider four groups, according to the project allocation into the treatment group (vs. control group) and the final decision of terminating the project (vs. maintaining it active) made by the entrepreneur. Error bars represent standard errors.

Figure 1.1 shows a set of interesting patterns. First, projects that were not terminated show higher estimation value than those that were terminated, in line with the idea that entrepreneurs, on average, terminate the projects that they expect to have lower value. This confirms that our measure captures consistent predictions, given the final decision made by entrepreneurs. Second, for both groups, value estimates are progressively lower over time. As entrepreneurs collect more information, they revise their estimate of the value of a project accordingly and correct a potential initial overestimation. Third, the figure shows that the downward sloping path differs between treated and control entrepreneurs. In line with the econometric results, treated entrepreneurs reached a lower estimation earlier, both in the case in which their final choice was to maintain the project active and in the case in which they choose to terminate it. Instead, the estimates of control entrepreneurs tend to remain similar between the baseline and the *Early* period, and become lower only later.

5.2 Full estimation results

We now focus on the full-fledged structural estimation, to clearly disentangle both theorized effects. Table 1.4 reports the results of the parameters estimation based on our theoretical model.

Table 1.4 – Estimated parameters

	Parameter	Std. Err	z-score
$\boldsymbol{\theta}$	1.12	0.455	2.46
$\boldsymbol{\sigma_E}$	0.34	0.032	10.72
$\boldsymbol{\sigma_L}$	0.43	0.039	10.83
$\boldsymbol{\sigma_F}$	1.56	1.078	1.45
$\boldsymbol{c_{ET}}$	-1.17	0.453	-2.58
$\boldsymbol{c_{LT}}$	-1.13	0.440	-2.57
$\boldsymbol{c_{FT}}$	-1.84	0.411	-4.47

Note. Parameters retrieved after ML estimation of the six equations described in Section 4. Parameters and their standard errors are retrieved using the *nlcom* routine in Stata 16. All estimated equations include dummies for RCT and instructor, with standard errors clustered at the classroom level (K = 24). Full estimation results of the six equations model are reported in the Supplementary Materials.

Our estimation results show a positive and significant coefficient θ (1.12), which represents our *performance* effect. On average, "scientific entrepreneurs" experience an increase in revenues of around 110 percentage points compared to the control group, conditional on the decision to maintain the project active. This result is in line with the extended selection model described in the previous subsection. As before, we also run a robustness check with the trimmed version of the dependent variable. Results, available in the Supplementary materials, show a more conservative - but still positive - estimate of the effect (0.84).

The three variance estimates, $\sigma_E, \sigma_L, \sigma_F$ grow in magnitude as entrepreneurs get closer to the final decision. Interestingly, this suggests that at the outset of the process entrepreneurs have simple representations of their problems that neglect many stochastic elements associated with the decision. This is in line with Barrero (2022) who shows that the realized distribution of sales growth across firms exhibits a greater spread than the predictions made by managers who ignore stochastic factors that only manifest themselves *ex-post*. Thus over time, as these factors manifest themselves, decision makers realize that their business performance depends on new stochastic factors that they ignored in the earlier periods. The variance related to the decision equation is around five times the variance experienced in earlier stages (1.56 vs 0.34), consistently with the idea that at the time in which the decision is finally made there is a larger variance in the project's perceived value, leading to the termination of less valuable projects.

Parameters c_{ET}, c_{LT}, c_{FT} identify the *estimation* effects in the decision periods of our framework. Differently from the extended selection model estimation, we leverage the model structure to clearly separate them from the *performance* effect. Results show that treated entrepreneurs are more likely to reduce their estimate of the value of the business ideas at each one of the three stages. Particularly, and consistently with the results of the extended selection model, the *estimation* effect materializes already at an early stage, i.e., eight weeks after the beginning of the training. This effect is persistent over time, signaling a more conservative approach of treated entrepreneurs when estimating the future value of their ideas.

In the Supplementary Materials, we report the results of the six equations estimated via `cmp` and an alternative computation of the parameters. To test the robustness of the results, we run several checks. First, we re-estimate our models excluding attritors from the sample. Second, we include additional controls in all empirical equations to consider imbalances between groups prior to the training. Third, we re-estimate the model leveraging a trimmed version of the revenue variable. Then, we compute the predicted values $\hat{v}$ as the average of the logs from the perceived minimum and maximum values stated by entrepreneurs, rather than taking the logarithm of the average. Then, we employ z lagged one-period as an alternative measure for z. We also re-run the full model adding lags of $\hat{v}$ in (4) and (3). Finally, we conduct the same analyses using the average revenue growth over time rather than the simpler revenue variable. Results, reported in the Supplementary Materials, are all consistent with our main analyses.

6. The trade-off between false positives and false negatives in projects selection

We next focus on understanding whether the tighter selection of scientific entrepreneurs is also associated with a better balance between type I and type II error. Scientific entrepreneurs are more conservative in their assessment of projects, and this makes them more likely to discard *false positive* projects compared to the control group. Although this is a welcomed outcome, this paper aimed to provide some evidence regarding whether the scientific entrepreneurs' tendency toward more conservative evaluations is also leading to an increase in *false negatives* compared to the control group. To address this important question, we start by testing the robustness of our RCTs' main results by providing additional evidence for the performance effect associated with the scientific approach conditional on selection. We then focus on *false negatives*. Because the value of terminated projects cannot be directly observed, we use data from multiple sources to compare the value of terminated projects by treatment and control entrepreneurs.

6.1 Performance conditional on selection: additional evidence

6.1.1 Additional RCT Evidence

As an additional way to obtain a relatively objective assessment of the value of projects we examine whether firms have received financing from external investors over time. In our data collection efforts during the RCTs, we asked entrepreneurs whether they received external financing (for instance, from venture capitalists or business angels) at any data point. Importantly, investors were blind to the treatment – at most, investors could have been aware that entrepreneurs were taking part into a business support program. We create a dummy taking value 1 if the entrepreneur indicated that they received funding within the observation period, and 0 otherwise. In Table 1.5 we report, the share of projects having received external financing, distinguished by intervention (treatment vs. control) and final decision (project termination vs. maintaining the project active).

Table 1.5 – Share of projects receiving external financing

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

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

Looking at the results for active projects at the end of the observation window, we find that 20% (21 firms out of 104) of treated entrepreneurs received external financing, which corresponds to twice the 10% (13 firms out of 131) recorded for the "control" group. These numbers reinforce the intuition that active projects of scientific entrepreneurs tend to be of higher quality, with a reduction of *false positive* projects taking place.

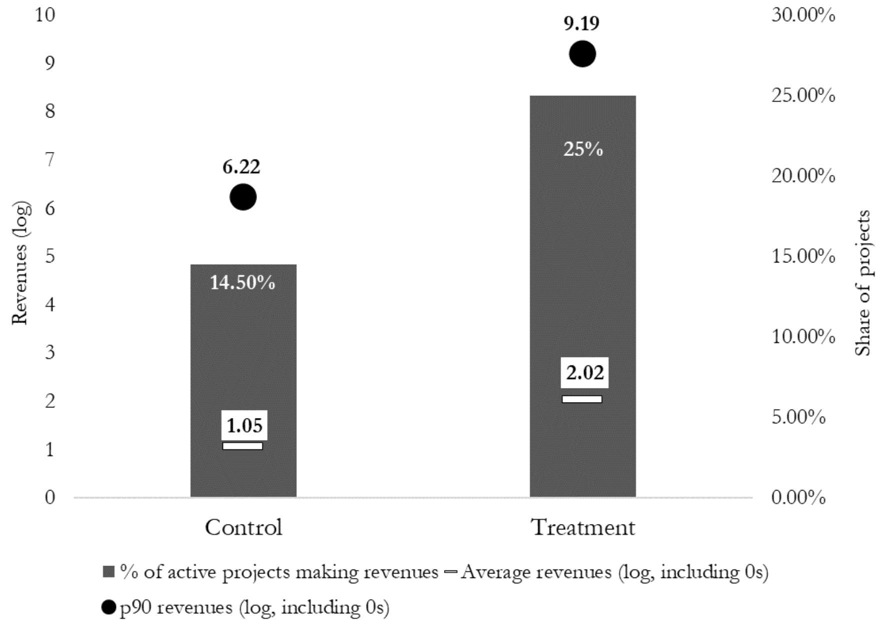
In the Supplementary Materials, we report the results of both a linear probability model and a Heckman model using as dependent variable the dummy for external finance. Results validate the statistical significance of the difference reported in Table 1.5, confirming that projects of scientific entrepreneurs are more likely to have received external support, also given the tighter selection process. Again, this provides further robust evidence that the scientific approach helps selecting the best projects ex-ante, using a different, objective, and externally generated dependent variable to measure performance.

In addition, we provide additional evidence on the distribution of revenues across treatment groups and termination decisions. In both RCTs all projects started the program with no revenues. The distribution of revenues at the end of the observation window is very skewed, with few projects having positive values. For active projects, we created a dummy variable taking value 1 whether a firm shows positive revenues at the end of the observation period. Figure 1.2

summarizes the share of projects making revenues together with the average and 90th percentile of the revenue (log) distribution by treatment group.

Looking at the average revenues of all active projects, including those with no revenues, Figure 1.2 shows a higher average for scientific entrepreneurs. Whereas the medians for both groups are set to 0, the figure shows that the value of 90th percentile is higher for scientific entrepreneurs. Results are consistent if we instead look at the average revenue growth over time, as shown in the Supplementary Materials. Moreover, focusing on the extensive margin, only 14.5% of projects still active on the market in the control group (namely, 19 out of 131) made revenues, versus the 25% (26 out of 104) of those in the scientific group.[2]

Figure 1.2 – Additional evidence on revenues



Note. The columns indicate the share of projects with positive revenues, conditional on the entrepreneur's decision to maintain the project active (right axis). The white bar and the black dot indicate, respectively, the 90th percentile and the average of the distribution of revenues (including 0s), conditional on the decision to maintain the project active (left axis).

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[2] We also run a Probit with a Heckman selection model (*heckprobit*) using as a dependent variable the dummy recording positive revenues. Results, in line with the idea that the probability of making revenues conditional on the decision to maintain the project active is significantly higher for scientific entrepreneurs, are available in the Supplementary Materials.

6.1.2 *Longer-term survival rates: Additional data collection*

A limitation of the previous findings is that they only enable us to assess project performance during the limited time window of the observations covered by our experiment.

To address this limitation, we conducted an additional data collection in February and March 2022, which is respectively five and four years from the beginning of the first and second RCTs to determine which of the projects in our sample is still active. The survival rate of startups projects in the context under investigation is generally low, hence survival can be considered an alternative measure of performance[3]. We recruited a research assistant (RA) and provided them with a list comprising the startup's name and the founder's name for the 382 firms in our sample. To avoid biases in the research process, the RA was blind to the type of intervention the entrepreneur went through during the training program. We asked the RA to search online for information about the founder and the startup, to understand whether the firm was still active. The search was performed on standard research engines (e.g., Google), on LinkedIn and on the official Italian chamber of commerce firm registry.

We considered a startup as still active if clear references to its activities were found online. These references include, among others, the existence of a website, clear references to the startup in the founders' LinkedIn profiles and activities, registration to the Chamber of Commerce or recent press coverage. This data collection led to the identification of 68 active projects out of 382 (17.8%) as of March 2022. This percentage is lower compared to the official statistics on the number of active startups within a similar time horizon[3]. However, these statistics refer to established and registered companies rather than projects at the very early stage of development as those participating to the two RCTs. We also note that we relied on the assumption that a project that is

[3] *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

still active would have an online presence. Official Italian statistics report that 79% of business with at least 10 employees have a website, making this a reasonable assumption[4]. Moreover, to make sure we are also capturing projects without an official website, we also record the project's presence on LinkedIn and other social media. We acknowledge, however, that we might not capture those projects that after 4 or 5 years are still in a pre-launch phase nor projects that have been eventually developed under a different name than the one recorded in our database. In any case, whereas this measure might give a conservative estimate of the total number of active projects, we believe it is nevertheless a good proxy.

When splitting the sample between treatment and control conditions, we find that of these 68 active projects, 42 were part of our treatment group (22 in Milan RCT; 20 in Turin RCT), whereas only 26 were part of our control group (13 in each RCT). Comparing these numbers to the number of projects in our original sample, we obtain that 22% of the projects of treated entrepreneurs are still active versus the 14% of control ones. To corroborate further these results, we report in Table 1.6 in the next page the marginal effects from two probit regressions. Model 1 includes RCT and mentor dummies, plus a set of baseline controls. Model 2 conditions the regression on the firms active at the end of the RCT.

[4] ISTAT. *Database:* Rilevazione sulle tecnologie dell'informazione e della comunicazione nelle imprese. Last access: 16.06.2022

Table 1.6 – Marginal effects on success variable (2022)

	(1) Active in 2022	(2) Active in 2022
Treatment Dummy	0.081**	0.160***
	(0.037)	(0.056)
RCT Dummy	Yes	Yes
Mentor Dummy	Yes	Yes
Controls	Yes	Yes
Observations	382	235

Note. Average marginal effects (AME) from probit regressions. DV = Dummy variable recording whether the project is still active (based on evidence of online presence) as of March 2022. Controls include information recorded at the RCT baseline period: team average age, team size, team average education, team average startup experience, team average industry experience and team average managerial experience. Standard errors are not clustered at the intervention level, given the longer time-horizon. Results are fully robust also to clustered standard errors. Model 1 refers to the whole sample of firms, while Model 2 conditions the estimation of projects declared to be active at the end of the RCT observation window. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Results from Model 2 show that – among projects that were not terminated during the RCT observation period – scientific ones have a significantly higher probability of remaining active in the long term. This evidence further corroborates the idea of a better project selection by scientific entrepreneurs. It suggests that projects that were maintained active by scientific entrepreneurs have performed better in the longer term, corroborating the robustness of the *performance* effect. It also signals that the tighter selection process has ruled out many *false positive* ideas that, instead, were retained by control entrepreneurs during the RCT period. Interestingly, these results also show that scientific entrepreneurs terminate earlier because they make more conservative estimates of the value of their projects, and in the longer term this tighter selection has a beneficial effect in that it leads to a higher survival rate. We focused on these 68 active projects and identified those that received external financing during the observation period: 43% of the active startups that were allocated to the treatment group did so compared to only 19% of those in the control group. Whereas we acknowledge that external financing could be one of the reasons of this higher success rate, the fact that we observe a similar share of projects in the treatment and control group receiving financing for projects that were eventually terminated is notable.

Overall, these patterns in the data support the idea of both the *estimation* and *performance* effects of the scientific approach taking place. Entrepreneurs following such approach to decision making were able to understand earlier the nature of their projects, terminating potential bad ones earlier than control entrepreneurs whose termination rate rather kept increasing over time. Looking at longer-term survival rates, chances of their projects being still active are higher for treated entrepreneurs. This could mean that treated entrepreneurs, when compared to control ones, were better able to develop their projects given the initial tighter selection, bringing further evidence in support of the two mentioned effects.

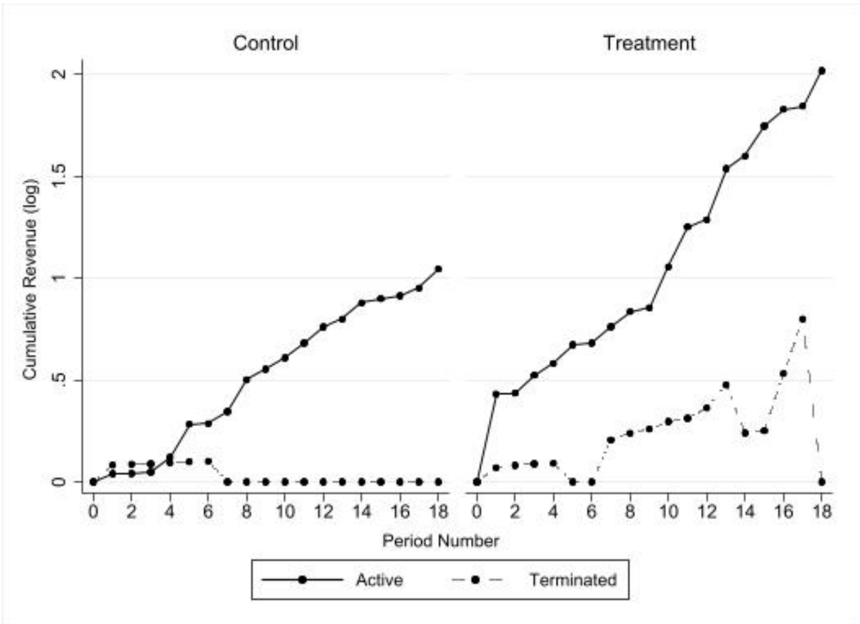
6.2 False negatives

6.2.1 RCT Evidence

To understand whether a scientific approach, which makes entrepreneur more likely to discard bad projects, might also lead to higher rejection of good projects in comparison with the control group, we start with evidence from our RCT data. We first look at the data on external funding received by the entrepreneurs in our sample. In Section 6.1.1 we looked at the funding received by the projects that did not terminate during the time horizons of our RCTs. When we look at the share of terminated projects, in the treatment group only 1% (1 project out of 86) of them obtained external finance before the decision to terminate. This share corresponds to 2% (1 project out of 61) for those in the control group. This suggests that projects terminated by treated entrepreneurs are not better than those terminated by control entrepreneurs. When looking at project terminated in the longer time (following the data collection described in Section 6.1.2), only 3% in the treatment group vs, 5% in the control group received external financing during the observation period. It suggests that, despite the treatment being associated with a tighter selection of projects, it did not lead entrepreneurs to a higher rate of *false negatives*, i.e., discarding potentially valuable projects.

Following the logic from Elfenbein et al., (2017), we also look at the projects revenue pattern distinguishing between terminated and active projects[5]. First, we leverage the panel structure of our database and look at data on revenues over time, computing for each project in the sample its cumulative revenue from the baseline to each observation in our panel. For active projects, we expect a growing trend. For terminated projects, we expect a noisier pattern, as their revenues naturally go to zero after their decision to terminate the project (and we conservatively set them as missing values in our database). We then compute the average for treatment and control group distinguishing between active and terminated projects. Figure 1.3 shows the pattern over time.

Figure 1.3 – Panel data on revenues



Note. The graph shows the revenues pattern by project allocation into the treatment group (vs. control group) and the final decision of terminating the project (vs. maintaining it active). For projects that were terminated, the value is set as missing after their decision to terminate, explaining the noisier pattern.

For active projects, Figure 1.3 shows that those in the treatment group perform better, in line with previous findings. Interestingly, projects in the treatment group that were terminated still made

[5]Elfenbein et al. (2017) run an experiment where they ask participants to deduce a firm type (high-profit vs. low-profit) and optimal exit time by looking at profit streams from period to period and at the information disclosed at each round of the game. By analogy, in our paper we consider terminated projects as "low-profit" ones, and active projects as "high-profit" ones and look at their revenue pattern at each of the 18 data points we collected.

some revenues, although revenues were lower than the ones of projects still active at the very same point in time. This is a signal that, on average, projects that were discarded performed worse than those that were not discarded, at least up to their termination decision.

When looking at the control group, our model suggests projects remaining active likely include *false positives*, but could also include projects that the treatment group might have discarded as *false negatives*. However, the facts that 1) the revenues of active projects of treated entrepreneurs are higher than that of control firms, and 2) that the revenues for terminated projects of treated entrepreneurs are always lower than the one of active projects of control entrepreneurs, suggests that overall, for treated entrepreneurs, the reduction in *false positives* more than compensates the potential increase in *false negatives*.

6.2.2 Professional Evaluation of Projects

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 entrepreneurs' projects. Evaluations were made by two senior consultants dealing daily with startups and innovation projects. We decided deliberately to rely on professionals' evaluations, rather than relying on crowdsourcing online communities, despite the larger cost incurred. This is because we believe the scores assigned by two experienced professionals to be more reliable and precise than those obtained by an online community not necessarily composed of professionals.

Our goal is to obtain an objective evaluation of the projects that were discarded as well as retained active in both groups. We asked the consultants to evaluate the pitches submitted by entrepreneurs at the baseline, that is, before the start of the training[6]. We assume that the baseline idea is a good

[6] We used 220 pitches for the RCT conducted in Milan, and 110 pitches for the RCT conducted in Turin. The missing pitches were unfortunately not available due to corrupted data in our storage space. We checked whether the firms for which we do not have the pitch 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

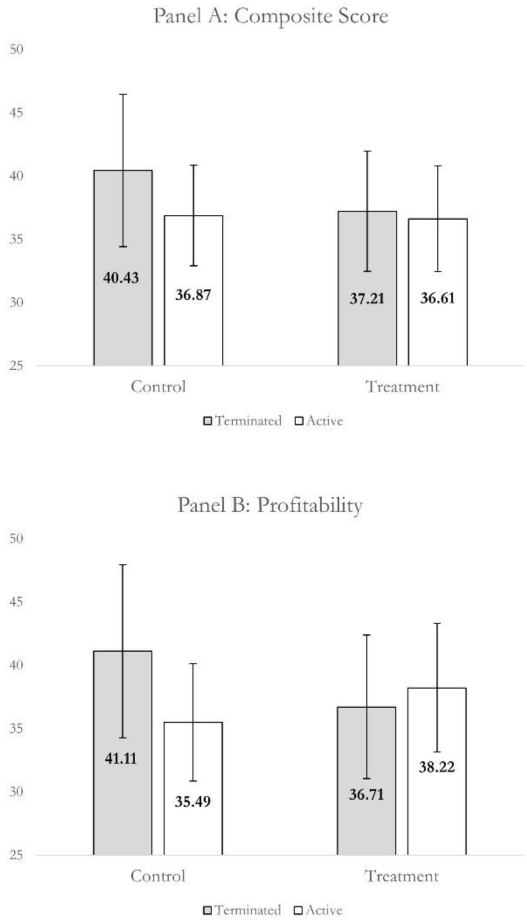
proxy of the potential success and future value of the project. The two evaluators were blind to the treatment and to whether the project was still active or not. To make sure they were not able to retrieve other information than those included in the pitches, we anonymized all the pitch decks by removing the project name and any personal contact or name related to the founding team. The evaluation has been made on three main elements, on a scale from 0 to 100 for each of them: 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). We averaged these three scores to create a "composite" expert evaluation score ranging from 0 to 100. In the following analyses, we also look at the profitability score alone, as it is the one which is more directly comparable to the potential monetary value of the project.[7]

Figure 1.4 in the next page reports the averages for both the expert evaluation and profitability scores, by group and based on whether the project was terminated or remained active during the RCT period.

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.

[7] We checked the robustness of the expert evaluations by comparing the averaged evaluation score between two groups of projects: those receiving external financing during the RCTs observational window (N = 32) and those not receiving any external financing (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 not being a significant difference at conventional levels, the qualitative evidence points towards a reliable evaluation made by the experts, who evaluated with higher scores project that were indeed funded during the RCTs periods. Evaluators were blind to any outcome/characteristics/treatment of the evaluated projects, including their financing status.

Figure 1.4 – Expert evaluations (Panel A = composite score; Panel B = profitability score)



Note. Figure 1.4 reports the group averages of the expert evaluations scores. Experts were asked to evaluate each project on three dimensions, on a scale from 1 to 100: 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" instead 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

Interestingly, the project evaluations made by entrepreneurs (represented in Figure 1.1) are significantly higher than those made by these external experts. This reinforces our initial intuition that entrepreneurs tend to overestimate their project's value at the baseline and the correction in the entrepreneur's evaluation that we observe over time is due to the *estimation* effect induced by the scientific approach. Coming back to the trade-off between *false positive* and *false negative* rates, Figure 1.4 shows that the score that experts gave to projects terminated by treated entrepreneurs is not significantly higher than those in the control group. On the contrary, projects terminated by entrepreneurs in the control group received the highest scores. This suggest that scientific entrepreneurs have not discarded a higher rate of *false negative* projects compared to the control group. This is also valid if we look at the median scores. For instance, the median on the "Composite score" for treated entrepreneurs that terminated their projects is 30, versus the 36.7 scored by projects terminated by control entrepreneurs. Looking at active projects, treated entrepreneurs are associated with a median score of 33.3, versus 30 for control ones.

Combined with all the previous evidence, these results suggest that the selection induced by the scientific approach has a net "positive" effect. In other words, we do not find strong evidence suggesting that the solid reduction in *false positives* that we documented so far is compensated by a parallel increase in *false negatives*.

6.2.3 Business Simulation Game

To further corroborate our results, we run an additional experiment using a business simulation game with Master of Science (MSc) students. Business games are widely used in entrepreneurship and strategy education, and are claimed to provide a high value in the whole education process (Fox et al., 2018). We leverage the potential of a real-life computer simulation for our research purposes, trying to replicate the results found in a real-life setting.

The game simulates the decision-making process of an early-stage startup. The player, in the co-founder role, makes predictions on the potential value of the startup's project and ultimately decides whether to launch it or to terminate it. To learn more about the project potential, the player can choose to engage in several activities that mimic the real-life experience of an early-stage entrepreneur. For instance, she can brainstorm with the virtual co-founders and develop a theory of the project and related hypotheses using the business model canvas and/or can validate her assumptions by running virtual interviews or questionnaires. The game includes a time dimension, and market conditions change as the game "days" go by: the player receives updates about this in the form of short virtual newspaper articles. Once the player makes her termination vs. launch decision, the game ends. The performance is evaluated based on a different set of metrics, including market performance and "scientific" performance (based on whether the player has used a scientific approach to decision making, developing a theory with hypotheses and testing them).

Following again the experiment run in Elfenbein et al. (2017), we force the simulation game to only have two types of scenarios: a good and a bad one. In the good scenario, the underlying project to be evaluated by the player is a potentially profitable one. In this case, the best decision for the player is to launch the project. In the bad scenario instead, the underlying project to be evaluated is not a potentially profitable one. In this case, the best decision is to terminate the project. Given the nature of the game, the ultimate profitability of the idea also depends on the specific choices that the player makes during the game. However, what is important for our testing is that such choices cannot change the fundamental value of the project, which will be generally low in the bad scenario and high in the good scenario.

In the context of a lecture involving different Master of Science (MSc) programs at the home institution of two of the authors, we asked students to play this game. Students who participated were all enrolled in their first year of studies and belonged to three different programs. Only students in one of these programs had previously attended a course on scientific decision-making; thus, we considered them as our treated group (N = 28). Students in the other two MSc programs did not attend such course and thus we considered them to be our control group (N = 50). For game-related technical reasons, we randomized the in-game scenario (good vs. bad) before students came to class, stratifying by MSc program. The distribution of conditions was quite balanced, with 54% and 60% of students in the control and treated group respectively being assigned to the good scenario.

Students played for a maximum of 60 minutes and had to make their final decision by this time window. To incentivize players and reproduce the monetary incentives of an entrepreneurial activity, we offered three 20€ gift cards (one per each MSc program) to the top players based on their performance in the game. To avoid biases, we introduced the game to students without any explicit reference to the "scientific approach". We mentioned that the main goal was to make the best decision based on their evaluations of the project, not suggesting any path or methodology to follow when making such evaluation.

Our outcome variable is a dummy taking value 1 if the player decides to terminate the project. Based on the evidence from our RCTs, our expectation is that treated students will terminate more often regardless of the underlying idea. Second, we would like to have further confirmation about the positive trade-off between the rate of *false-positives* and *false-negatives*. By comparing the two groups within each scenario, we expect that the treated students terminate projects relatively more often in the bad scenario than in the good scenario.

Results suggest how treated players are more likely to decide to terminate their projects (8 out of 28 in the treated group; 6 out of 50 in the control group). Despite our small sample size, a two-tailed t-test on the termination dummy between the two groups shows a significant difference (two-tailed, $t = -1.84$; $p = 0.068$; $M1 = 0.12$; $M2 = 0.29$)[8]. Interestingly, in the *bad* scenario, where the best decision would be to terminate, treated players are three-times more likely to decide to do so (4 out of 7 in the scientific group; 3 out of 20 in the control group). In the *good* condition, where the best decision would be to launch the startup, treated players are only two-times more likely to choose termination as their final decision (4 out of 13 in the scientific group; 3 out of 24 in the control group). Thus, qualitatively, it seems that the reduction in the *false-positive* rate more than compensates the increase in the *false-negative* one. Moreover, the better ability of treated players in

[8] Alongside acknowledging the fact that this experiment is underpowered, we also acknowledge the limitation of using a business simulation game as a testing tool. Indeed, a simulation game cannot reproduce the affection mechanisms and emotional dynamics that real-life entrepreneurs might display when it comes to the development of their own business idea.

discriminating between projects when compared to the control group is also signaled by the constant share of players belonging to the latter that decide to terminate.

This evidence is aligned with all the data presented in the previous subsections. As a final step, in the next section we go back to our estimated model and compute results for two simulated scenarios.

6.2.4 Model Estimation: Additional Insights

Let us consider the first two equations of our formal model: the *performance* equation (equation (1)) and the *selection* equation (equation (14)). The former has been estimated through a linear regression, while the latter using a probit model. Since this is a selection model, we retrieve the correlation coefficient ρ between the two equations and the Mills' ratios from the selection equation for entrepreneurs who maintained the project active and those who terminated their projects.

Using the computed variances of the performance equation (σ) and of the selection equation (σ_F), we can compute for each entrepreneur in our sample the expected value of the correction in the value equation by treatment condition and by decision to terminate the project. Mathematically, for entrepreneurs who maintained their project active, this corresponds to:

$$correction = \rho \times \frac{\sigma}{\sigma_F} \times \frac{\phi(x\beta)}{\Phi(x\beta)} \tag{17}$$

Instead, for entrepreneurs who terminated, this corresponds to:

$$correction = -\rho \times \frac{\sigma}{\sigma_F} \times \frac{\phi(x\beta)}{(1 - \Phi(x\beta)} \tag{18}$$

The intuition behind this analysis is that the correction provides us with a measure of the extent to which the value of projects needs to be adjusted due to the selection. A positive value of the correction suggests that entrepreneurs using a scientific approach underestimated the value of the project; a negative sign suggests that scientific entrepreneurs overestimate the value of the project. A positive difference in the correction between the terminated and the active projects suggests that the underestimation of those who terminate is higher than the overestimation of those who maintain their project active. We are interested in the difference between projects of control and treated entrepreneurs.

We compute these differences in Table 1.7, where we make the conservative assumption that the value model for entrepreneurs whose projects remained active and those who terminate their projects is identical. We call this the *lower bound* condition.

Table 1.7 – Lower-bound: Same model for terminated and active

	Terminated	Active	Difference
Control	0.56 *(0.14)*	-0.26 *(0.11)*	0.822
Treatment	0.43 *(0.14)*	-0.36 *(0.12)*	0.796
Difference	0.127	0.102	**0.026**

Note. Standard Deviation in Parentheses

The negative ρ coefficient estimated through the model leads to a negative correction for active projects. Whereas it can be challenging to interpret such coefficient in the light of the Heckman selection model, the negative direction signals that, on average, entrepreneurs overestimate the value of their projects resulting in a negative correlation when looking at realized performance. This effect could be mostly driven by the weakest bias reduction provided by the control group, given the results from our estimation for treated entrepreneurs. Importantly, the difference-in-difference calculation leads to a number close to zero and not statistically significant (0.026). This suggests that there is not a significant difference between projects of treated and control entrepreneurs when it comes to the balance between overestimated and underestimated projects.

However, our theory and empirics also suggest that scientific entrepreneurs perform better on average due to what we called the *performance* effect. We thus relax the assumption that the value model does not change depending on whether projects were discarded or not and rather assume that the value model is different according to the decision taken. This assumption will lead us to what we call our upper-bound condition. Under this assumption, we subtract the *performance* effect θ to the correction coefficient for scientific entrepreneurs who terminate their projects. We subtract the estimated *performance* effect since the performance model we estimated already considers the treatment effect for scientific entrepreneurs. The negative correction signals the existence of a bias reduction also for entrepreneurs that terminated their projects.

We report these results in Table 1.8. The difference-in-difference estimation becomes 1.143, suggesting that the selection results in a lower reduction of value for projects of treated (vs. control) entrepreneurs. Bad ideas are effectively ruled out, without a substantial increase in the *false negative* rate.

Table 1.8 – Upper-bound: Different model for terminated and active

	Terminated	Active	Difference
Control	0.56 *(0.14)*	-0.26 *(0.11)*	0.822
Treatment	-0.68 *(0.14)*	-0.36 *(0.12)*	-0.321
Difference	1.245	0.102	**1.143**

Note. Standard Deviation in Parentheses

These cases represent two extremes, one where the selection induced by the scientific approach is particularly positive (the *upper-bound*) and one where the approach leads to some adverse selection processes (the *lower-bound*), but close to zero.

Despite these results should be interpreted with caution as they are based on assumptions, we believe they provide encouraging suggestive evidence of a well-balanced trade-off between the extent to which scientific entrepreneurs discard bad projects at the expense of good projects: in the worst-case scenario (*lower bound*) these two effects essentially compensate each other; in the best-case scenario (*upper bound*) the positive effect dominates the negative one.

Overall, these results provide robust evidence that ideas that were selected by scientific entrepreneurs had a performance advantage with respect to those selected by the control group. This reinforces our argument that the tighter selection process enacted by scientific entrepreneurs, who become more conservative earlier about their ideas' potential, leads to a sizeable reduction of the *false-positive* rate. Moreover, the evidence supports the idea that the increase in *false-negatives* had not been so pronounced as to counterbalance the robust decrease in *false-positives*, providing a sufficient condition to this claim.

7. Conclusions

In this first chapter we explored the implications of the adoption of a scientific approach to decision making. Our framework and empirical estimations predict that entrepreneurs following this approach are more likely to terminate their projects, following what we call an *estimation* effect that generates more conservative estimates of the value of their projects. Treated entrepreneurs perform better given the tighter selection, an effect that we called *performance* effect. In addition, we do not find evidence that scientific entrepreneurs wrongly discard good projects significantly more than control entrepreneurs. All this enables us to conclude that, unconditionally, scientific entrepreneurs perform better. Moreover, additional long-run data, which we collected four to five years after the RCT, suggest that the selection process and the performance effects induced by the scientific approach have long-term benefits as well.

Our paper is not free of limitations. First, our results could not be generalizable to other countries or entrepreneurial ecosystems. However, this is attenuated by the fact that we estimate our models across two distinct RCTs. Second, our RCTs encompass entrepreneurs at very early stages of project development and with different levels of project novelty. Other research (Rindova & Courtney, 2020; von Hippel & von Krogh, 2015) suggest that entrepreneurs with highly novel projects might follow different procedures to gather additional knowledge, not necessarily linked to hypothesis testing and ex-ante problem formulation. The extension of our results to these other types of firms is an open question for future research.

Overall, we believe that these findings might inform existing research on strategic decision making, particularly in innovative and entrepreneurial contexts characterized by uncertainty. Our model and unique data on entrepreneurs' own assessment of their projects enabled us to clarify the effects of approaches to decision making that combine cognition with action (Levinthal, 2017; McDonald & Eisenhardt, 2020). Notably, one of these effects corresponds to an improvement in entrepreneurs' ability to ideally correct their own estimations in earlier phases of the project evaluation, reaching more conservative predictions. These results also contribute to research in this area by introducing the scientific method as a useful de-biasing tool.

Our results can be relevant for policy and practice. Educating entrepreneurs to follow a scientific approach to decision-making can lead to a better selection process, effectively discarding projects that will perform poorly and doing so earlier. This can generate resource savings and avoid wasting time and money on projects that would likely fail as highlighted by official statistics on startup survival rates. Moreover, teaching entrepreneurs and students to think in scientific terms helps them to devise better strategies and development trajectories, ultimately resulting in higher performance.

Two questions that this chapter leaves open are to understand what could drive the *performance* effects of treated entrepreneurs and how entrepreneurs' perceptions evolve over time as a function of the alternative decision of *pivoting*, that is to introduce systematic changes to the business model. Chapter 2 leverages data from the experiment conducted in Milan (N = 250) to understand the relationship between pivoting activities, beliefs and performance of both treated and control entrepreneurs.

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2

Updating strategy and beliefs: experimental evidence on entrepreneurial pivoting

with Chiara Spina (INSEAD)

ABSTRACT

In this chapter, co-authored with Chiara Spina, we study pivoting activities of entrepreneurs and how they impact their beliefs and performance. Indeed, identifying promising business ideas is key to the introduction of novel firms, and research shows that entrepreneurs frequently pivot during the process of idea identification. 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 positively update their beliefs, identifying changes leading to more promising development patterns of their ideas. We test these predictions with a field experiment with 250 nascent entrepreneurs attending a pre-acceleration program, where we taught the treated group to formulate the problem scientifically and to develop and test theories about their actions, while the control group followed a standard training approach. Results show how treated entrepreneurs who pivot positively update their beliefs on the potential value of their ideas, and pivot when they perceive higher uncertainty. We also show that pivots conducted by entrepreneurs taught to follow a scientific approach focus more on customer desirability. The paper provides novel evidence on pivoting activities and contributes to the growing literature on how entrepreneurs learn and adapt over time.

1. Introduction

In the previous Chapter, we investigated how a scientific approach to entrepreneurship makes entrepreneurs likely to terminate their projects by generating more conservative estimates of the value of their projects. Given this tighter selection, results showed also that entrepreneurs trained to follow the prescription of the scientific approach performed better. This chapter seeks to explore the dynamics of entrepreneurs' perceptions on the idea value, also introducing a measure for uncertainty, and to find a potential mechanism associated to the *performance* effect by investigating pivoting activities conducted by entrepreneurs. To do so, we leverage unique data on pivoting from one of the experiments analyzed in Chapter 1.

When it comes to the choice of the business model to adopt, 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., 2019), or even family and friends (Bennett & Chatterji, 2019). This iterative 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 full-fledged start-up (Aldrich & 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 their business idea because 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's founders realized their company could not compete with Apple and a new direction was needed. As they thought about in which direction to go, they reflected on which aspects of their technology they could use to create a potentially successful product. They leveraged a messaging application they developed internally and turned it into Twitter, a micro-blogging platform. This iteration represented a significant change in strategy—also called a *pivot*—which allowed Twitter's owners to avoid a potentially costly mistake. Similar pivots also marked the early days of other tech companies such as Instagram, PayPal, and Slack (Kirtley & O'Mahony, 2020). To avoid pursuing unpromising ideas, these entrepreneurs had to understand what elements of their business ideas were likely to work and in which direction they should turn to achieve better outcomes.

Although this example shows how cognition and pivoting are intertwined processes, scholars have typically studied them separately (Shepherd and Gruber, 2021). As a result, the logic of pivoting has been rarely studied, despite its importance for theory and its prominence among practitioners (Chen et al., 2022). Extant studies on this topic converge on the exploratory (Shermon & Moeen, 2022) and iterative nature of the process entrepreneurs go through as they evaluate and develop their business ideas (Baron & Ensley, 2006; Chen et al., 2021) and note that pivoting is a crucial yet difficult choice for entrepreneurs. Research on pivoting highlights that entrepreneurs often resist pivoting because the initial vision for their business is perceived as a key part of their identity (Grimes, 2018), and as vital in mobilizing support from stakeholders (McDonald & Gao, 2019). More broadly, studies on pivoting point out that entrepreneurs do not always update their beliefs in light of feedback or new information received (Crilly, 2018; Leatherbee & Katila, 2020; Parker, 2006), frequently resulting in pivots that take place late as last resort remedies to visibly failing courses of action (Eisenmann, 2021; Wood et al., 2019). But limited theory and research have addressed how this trap might be avoided, leaving unanswered important questions about the cognitive process through which entrepreneurial beliefs are affected by new information, and whether different approaches to decision-making result in different pivoting and performance outcomes. Our goal in this study is to shed light on these aspects.

Drawing on the growing literature on pivoting (Chen et al., 2021; Kirtley & O'Mahony, 2020; Leatherbee & Katila, 2020; McDonald & Gao, 2019), we elaborate theoretically and show empirically the process of pivoting entrepreneurs go through as they develop their ideas, depending on the type of approach to decision-making they use. Specifically, we analyze how entrepreneurs adopting a "scientific approach" to decision-making (Camuffo et al., 2020) update their beliefs about the prospects of their idea and how this is related to the uncertainty they perceive when compared with entrepreneurs not following such an approach. As described in Chapter 1, applying a scientific approach implies following a structured and disciplined processes of idea evaluation and development that can mitigate fallible judgement (Hogarth & Karelaia, 2011) and reduce the cognitive biases that affect entrepreneurial decision-making (Camuffo et al., 2020; Cohen et al., 2019; Kahneman et al., 2019; Murray & Tripsas, 2004). Entrepreneurs following such an approach can better understand whether their business idea is valuable because they formulate problems clearly, develop theories about the implications of their actions, and systematically test these theories. This disciplined process of information gathering enables entrepreneurs to be more precise in collecting and interpreting feedback from the environment (Zellweger & Zenger, 2022) and, at the same time, to identify more promising variations of their business ideas because they gather and assess information about determinants of value for their business more systematically. Coherently with the above expectations, Chapter 1 has shown how entrepreneurs following a scientific approach became more conservative when estimating the potential value of their ideas, a mechanism leading to a tighter selection process. In this paper, we propose that pivoting activities conducted by these entrepreneurs have two direct consequences for their beliefs about the potential value of their ideas and the perceived uncertainty associated with those ideas. First, pivoting activities conducted by entrepreneurs following a scientific approach should lead to an increase in the beliefs about an idea's expected value. This results from the fact that the pivoting activity is backed by more thought-through information and knowledge about the direction to take. Second, since these entrepreneurs can potentially see more strategic patterns of development when compared to entrepreneurs not following such an approach, the perceived uncertainty around the idea's potential value should increase after the pivoting activity is conducted.

We tested these propositions through one of the two randomized controlled trials (RCT) employed in Chapter 1. Specifically, we leverage unique data from the RCT conducted in Milan with 250 nascent entrepreneurs attending a pre-acceleration program that teaches how to go from an initial business idea to product launch. We randomly assigned 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 collected detailed data about pivoting, decision-making, and performance over 14 months to investigate how a scientific approach impacts the development of these business ideas. Coherently with our theory, results show how pivoting activities conducted by treated entrepreneurs led to an increase in the expected value of the idea with respect to control entrepreneurs. However, we do not find support for the proposed increase in perceived uncertainty following a pivot. We also explore potential mechanisms and find that treated entrepreneurs pivot with a focus more on customer segments and value propositions than operational aspects of the company compared to controls, suggesting that they prioritize different aspects of their business model. We also tested whether pivoting activities results in improvements in performance metrics, such as revenue, profits and activated customers. We find that entrepreneurs that pivoted at least once during the observation window perform better, regardless of the treatment group to which they belong.

This chapter makes its contribution at the nexus of entrepreneurship, organization theory, and strategy. Our primary contribution is to show how applying a structured approach changes both the way entrepreneurs pivot and how that activity impacts their beliefs. Specifically, this study provides a better understanding of a fundamental choice such as a pivot and the role that learning and beliefs update play in this process. Moreover, it has implications for the growing body of literature on learning for early organizational forms (Assenova, 2020; Cohen et al., 2019; Hallen et al., 2020; Yu, 2020), confirming the important role accelerators play in educating entrepreneurs and showing that the type of content that is taught to entrepreneurs matters.

2. Background and theory

2.1 Pivoting in early-stage entrepreneurship

Literature on decision-making highlights that entrepreneurs make a series of decisions in an environment characterized by unclear product demand, undefined product characteristics, and rapid changes (Ozcan & Eisenhardt, 2009). To navigate this environment, entrepreneurs pursue various actions to learn about the prospects of their idea (Bennett & Chatterji, 2019). As noted by Chen et al. (2018) and McDonald and Gao (2019), entrepreneurs are also resource constrained, and thus exploring and learning about their idea before they commit resources to their venture is crucial. This process of learning underpins the critical decisions entrepreneurs make and is usually iterative (Ott & Eisenhardt, 2020), with entrepreneurs gathering information about the prospects of their idea through exploration cycles (Chen et al., 2021). An exploration cycle can terminate with three different choices: (a) continue to develop the business idea; (b) abandon the business idea, if the entrepreneur does not see value in pursuing it further; or (c) change the business idea and begin a new exploration phase. In the latter case, the entrepreneur decides to make changes to the business idea (pivot) and to further explore the effectiveness of those changes in improving the prospects of their idea.

In this study, we focus on pivoting, defined as a change that impacts the development of an early-stage idea (Camuffo et al., 2020; Cohen et al., 2019; Kirtley & O'Mahony, 2020). The term pivot has been popularized by Eric Ries (2011) and borrows a key concept from basketball: When players plant one foot into the ground and change direction by rotating the other foot. Likewise, pivoting among entrepreneurs implies that entrepreneurs retain some elements of their business idea (also called planting, see Cohen et al., 2019) but change others. For early-stage entrepreneurs, pivots can be identified with changes made to the underlying business model (Frederiksen & Brem, 2017; Pillai et al., 2020; Ries, 2011). However, not all components of the business model have the same relevance and importance (Hampel et al., 2020), and pivots can greatly vary in their quality (Kirtley & O'Mahony, 2020). For instance, changing the value proposition of a business means embarking in a more profound transformation than what is implied by changing a business' key partners.

Regardless of the type of pivot conducted, previous research has shown in a variety of geographies and contexts that entrepreneurs often make poor decisions when going through exploration cycles (Åstebro et al., 2007; Camerer & Lovallo, 1999; Elfenbein et al., 2017), which include missed and inefficient pivoting activities (Wood et al., 2019). Empirical evidence suggests that entrepreneurs do not frequently pivot (Denoo et al., 2022; Grimes, 2018; Kirtley & O'Mahony, 2020), and when they do, their pivoting choices are affected by a host of cognitive barriers that prevent effective learning. Grimes (2018) notes that the entrepreneurs and their business ideas are closely linked to the point that some entrepreneurs consider their business idea part of their identity, a concept called "psychological ownership". Negative feedback on the idea can be perceived as negative feedback on the founder, ultimately making them resistant to exploring alternative options. Crilly (2018) digs deeper into the choices behind pivoting and through a qualitative study with tech founders provides initial evidence of the fixation and inability to pivot among entrepreneurs. This is due to the use of maladaptive "defense mechanisms," whereby entrepreneurs disregard information that does not fit with their current logic or even reject information that conflicts with it. This finding is consistent with research that finds that entrepreneurs rarely update their beliefs even in light of new information (Parker, 2006), and that selective interpretation of new information is a key bottleneck in changing business models (Chesbrough, 2010), as entrepreneurs tend to engage in confirmatory search (Shepherd et al., 2012). Evidence from qualitative studies also shows that founders often pivot only after receiving a poor market response after introducing new products or services (Eisenmann, 2021) or observing the outcomes of experimentation at the industry level (Pillai et al. 2020). Taken together, these studies emphasize the difficulty of making good choices in an environment characterized by uncertainty and confusion about key features of products and markets because of cognitive processes linked to inefficient beliefs update.

While research has started to document the process of pivoting and the barriers to change faced by entrepreneurs, far fewer studies have identified remedies to these issues, as also noted by Shepherd and Gruber (2021). Cohen et al. (2019) find that consultation with mentors and external experts is effective in addressing the bounded rationality issues faced by entrepreneurs and seems to counteract the tendency to fixate since it facilitates the process of information update and pivoting. Grimes (2018) and Wood et al. (2019) speculate that structured processes of information gathering and elaboration are likely to help entrepreneurs to more seriously consider the suggestions and evidence offered in the feedback received from the environment. These considerations point to the fact that effective pivoting could be linked to less-explored learning processes that emphasize the role of prediction and cognition in guiding decision-making. This includes studies on cognitive representations (Ott & Eisenhardt, 2020), mental models (Csaszar, 2018; Zuzul & Tripsas, 2020), and theories (Ehrig & Schmidt, 2022; Felin & Zenger, 2017) that highlight the importance of prediction and cognitive structures as effective starting points for learning in entrepreneurship. Recent qualitative evidence shows the importance of incorporating both thinking and doing in the entrepreneurial setting (McDonald & Eisenhardt, 2020) to guide "purposeful" learning (Murray & Tripsas, 2004). In line with these studies, Camuffo et al. (2020) provide initial empirical evidence of a "scientific" approach to decision-making that combines a thinking component (theory and hypotheses) and a doing component (testing) in a field experiment with entrepreneurs taught different approaches to decision-making. This literature suggests that prediction and action play an important role in the iterative exploration that leads to entrepreneurs learning new insights about their business. In this paper, we build on this stream of work and examine the consequences of a scientific approach to decision-making on the pivoting activities of early-stage entrepreneurs, as detailed in the following sections.

2.2 A scientific approach to decision-making

We begin by defining the scientific approach, as done in Chapter 1 (Section 2.1), before describing how we expect to impact the pivoting process of entrepreneurs. Consistently with Camuffo et al. (2020), we define a scientific approach to decision-making as a discipline, a set of behavioral routines—like those used by scientists—that entrepreneurs follow to develop their ideas and assess their value. This discipline 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 grounded on a general understanding of the problem, its solutions, and implications. Entrepreneurs who adopt a scientific approach formulate theories about them that are novel, simple, falsifiable, and generalizable (Felin & Zenger, 2009, 2017; Zellweger & Zenger, 2022). 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 et al., 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 derived from the theory that enable 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 (Ehrig & Schmidt, 2022). Hypotheses are testable and falsifiable since they clearly define the contingencies in which they are not false (or are definitely false) and can produce actionable evidence and validated learning (Shepherd et al., 2012; Leatherbee and Katila 2020).

3. The empirical testing of hypotheses, based on facts and data appropriately collected and accurately analyzed, ideally through experiments (Kerr et al., 2014; Murray & Tripsas, 2004). These tests use valid and reliable metrics and allow entrepreneurs to assess whether the specific determinants predicted by the theory are valuable and possibly identify causal relationships (Davenport, 2009; Koning et al., 2022; Thomke, 2020).

4. The open, critical, and independent analysis and interpretation of the outcomes of the tests. The honest and thorough evaluation of the evidence gathered through tests requires individual and collective judgement (Foss & Klein, 2012; Pfeffer & Sutton, 2006), as well as critical appraisal of evidence.

Previous research has provided initial evidence that a scientific approach to decision-making leads to more pivoting on key dimensions of the business model, such as the key value proposition (Camuffo et al., 2020). However, current research does not examine what happens when considering also changes to other components of the business model, such as the cost and revenue structure, but more importantly does not look at differences in the process of beliefs update and learning that entrepreneurs go through, as recently noted by Chen et al. (2021). We focus on these important aspects in the next section.

2.3 Implications of the scientific approach on pivoting activities and belief updating

We propose that a scientific approach to decision-making reveals more precise information about entrepreneurs' business ideas thanks to its systematic approach to cognition and action (Eisenhardt and Bingham, 2017). This allows decision-makers to form more accurate estimates of the value of their ideas and to correct an unpromising business trajectory by pivoting. In the context of nascent entrepreneurship, acquiring knowledge about the potential outcomes of a business idea is particularly important since it can reduce the fundamental uncertainty entrepreneurs face (Delmar and Shane, 2003) by generating information about the ultimate value of a business idea. While it is very difficult to determine ex-ante the value of a business idea, entrepreneurs form beliefs about its potential value (Felin and Zenger, 2009; Gans et al., 2019) and update this information as they assess the idea and learn from the environment (Chen et al., 2021). This process of belief updating entails an estimation of both the expected value of the business idea and the perceived uncertainty around its realization (Kerr et al., 2014). Ultimately, entrepreneurs decide to pivot when they realize the current business idea does not represent an option with a sufficiently high payoff (Hogarth & Karelaia, 2011) and they envision options believed to result in more positive and likely outcomes (Kirtley & O'Mahony, 2020).

Prior research on this topic also emphasizes that pivoting is a very difficult choice for entrepreneurs (McDonald & Gao, 2019), who often resist changing key elements of their idea (Grimes, 2018; Hampel et al., 2020; Kirtley & O'Mahony, 2020). Two issues in the context of entrepreneurship make pivoting especially challenging. First, pivoting implies that entrepreneurs receive feedback from their environment that prompts them to change their business ideas. However, research shows that entrepreneurs often disregard feedback from the environment to follow their original intuition (Blume & Covin, 2011) and tend to dismiss information that does not fit with their current course of action (Crilly, 2018; Parker, 2006). Second, even when entrepreneurs consider the feedback received from the environment, this tends to provide ambiguous information (Joseph & Gaba, 2020), which results in a lack of clarity on where to pivot to. Consequently, entrepreneurs tend to engage in "local search," exploring market opportunities closely related to their initial idea or own experience (Gruber et al., 2013; Rosenkopf & Nerkar, 2001).

By the same token, entrepreneurs who do not adopt a scientific approach are less likely to understand promising directions in which to pivot from the information gathered from the environment. The lack of a theoretical framework prevents them from interpreting the information collected against a logical model of value creation and translating it into actions (Zellweger & Zenger, 2022). When faced with disconfirming evidence, they either do not have alternative hypotheses or are less able to generate new ones from the feedback received (Ehrig & Schmidt, 2022). Moreover, because they conduct less valid tests, they are less able to make informed decisions (Cao et al., 2021). Ample anecdotal evidence shows that entrepreneurs who do not adopt a scientific approach do not conduct tests that can accept or reject hypotheses (Cao et al., 2021; Maurya, 2022). Often, these entrepreneurs do not use falsifiable statements to understand what to do. Consequently, the information they collect is too generic to lead to meaningful conclusions or help them envision new business opportunities. For example, these entrepreneurs tend to conduct surveys in which they ask potential customers whether or not they like the entrepreneurs' product, but they do not set thresholds to conclude whether a given percentage of positive responses represents evidence that validates interest in that product (Maurya, 2022). Wood et al. (2019) conducted an experiment with a mix of entrepreneurs and executives and found that entrepreneurs tended to either remain "fixated" on their initial ideas or pivot too quickly and frequently when they realized their business was not performing as well as anticipated. The authors suggest that "formalizing an architecture" around pivoting decisions could improve their effectiveness. This suggestion is consistent with studies that have shown that increased access to sources of external information (Cohen et al., 2019) and practices that increase feedback quality such as structured prototyping (Grimes, 2018) can facilitate this revision process and improve the quality of the business ideas of the entrepreneurs (Perry-Smith & Mannucci, 2017).

In this sense, the scientific approach serves as an architecture for decision-making by providing well-defined frameworks and tests to interpret external feedback and decide where to pivot to (Wuebker et al., 2021). When entrepreneurs use a scientific approach, they clearly frame the problem faced through a well-articulated theory, which provides clarity around what elements of their business ideas are linked to performance. This allows them to choose the determinants of *value of their business idea* in logical and rigorous ways (Felin & Zenger, 2017), making them more likely to focus on relevant factors that affect value as they develop their business idea (Ehrig & Schmidt, 2022; McBride & Wuebker, 2022). The use of a more complete representation of the structure of the process of value generation and of "causal logic" is associated with more effective search strategies (Csaszar, 2018; Gary & Wood, 2011; Ott & Eisenhardt, 2020). This increased clarity in thinking is coupled with a more rigorous approach to data collection.

Koning et al. (2022) and McGrath (2010) note that experimentation is especially effective when driven by hypotheses. In addition, scientific entrepreneurs use a structured approach to data collection and testing, which reduces the extent to which they collect feedback from biased samples (Cao et al., 2021). The rejection of some hypotheses and acceptance of others may induce entrepreneurs to rethink their business models and consider an overarching logic of value creation (Felin et al., 2019). For example, failing to accept some hypotheses implies that entrepreneurs must focus on target markets or value propositions that are different from what they originally conceived but consistent with the key tenets of their thinking around value creation (Ott and Eisenhardt, 2020). The evidence on these patterns is systematic. Camuffo et al. (2020) report the story of a company, Inkdome, that finds evidence against its original business idea—a search engine to find tattoo artists online—and pivots to a service that evaluates the quality of tattoo artists. Kirtley and O'Mahony (2020) found that when start-ups pivot, they do not discard all the accumulated knowledge or the previous features of their products or business models. Effective pivots require *pivoting* in the most literal sense: Entrepreneurs stand on some of their past knowledge and turn towards new factors that change their overall product or business (Furr et al., 2014; Hampel et al., 2020; Ries, 2011).

When it comes to belief updating, if the pivoting activities conducted by entrepreneurs following a scientific approach incorporate better knowledge and information compared to those conducted by entrepreneurs not following such an approach, they should be associated with a positive update of entrepreneurs' beliefs about their idea's value. In the case of a pivot, this improved predictive capacity should make entrepreneurs pursuing a scientific approach better able to identify more valuable ideas and patterns of development. Therefore, a positive update of beliefs about the value of the idea following a pivot signals that the pivot is perceived to positively change the course of action of the company. Laureiro-Martinez et al. (2010) use the example of Thomas Edison's activities at Menlo Park to show the benefits of a scientific approach to entrepreneurship. In bringing his inventions to market, Edison experimented on the basis of pre-defined observations and hypotheses and solved problems by pivoting based on feedback from the environment, subsequently making positive updates in terms of idea value. This argument is also consistent with behavioral research that finds that cognitive pitfalls can be largely attenuated when individuals follow structured processes of organizational decision-making (Denrell et al., 2003; Tetlock, 2000) and take time to think about their strategy (Eisenhardt & Sull, 2001). Research in this area also notes that the ability to change direction coupled with structured decision-making processes plays a key role in obtaining positive outcomes, particularly in uncertain and ill-structured contexts such as the ones faced by entrepreneurs (Laureiro-Martínez & Brusoni, 2018). We summarize these arguments in the following proposition:

Proposition 1. Entrepreneurs following a scientific approach to decision-making perceive a higher idea value after pivoting than entrepreneurs not following such approach.

The points above suggest that when assessing a business idea, entrepreneurs who adopt a scientific approach systematically gather signals that help them envision new options to change or revamp their business. These new options stem from a more systematic search, suggesting new factors that determine business value and that are consistent with the overarching logic of how a business generates value (Zellweger and Zenger, 2022). Indeed, in a context of high uncertainty such as the one faced by early-stage entrepreneurs, explorative behavior coupled with cognitive flexibility is deemed to be a better fit (Laureiro-Martínez et al., 2010). When pivoting, entrepreneurs decide to explore a potentially new path of development that has been identified. Research considers pivoting activities as a way to correct a potentially faulty course of action (Crilly, 2018; Leatherbee & Katila, 2020): this should consequently lead to a business model that is perceived as less uncertain. However, another stream of literature considers pivoting to be a restructured course of action subject to further testing (Shepherd & Gruber, 2021) or simply a choice between alternative courses of action (Pillai et al., 2020). From the perspective of a scientific approach to entrepreneurship, the pivoting decision follows a process in which the entrepreneur has evaluated more systematically the possible strategic developments when compared to control entrepreneurs, choosing the one that is deemed most profitable. While this backbones Proposition 1, choosing a novel trajectory path also means that entrepreneurs have not yet theorized and tested the new version of the business idea as much as the previous one: The new version of the idea is more uncertain, and entrepreneurs can estimate its expected value less precisely compared to that of the previous version. We argue this is the case for two main reasons. First, when comparing two versions of the business idea (the initial one versus the new idea generated by the pivot), scientific entrepreneurs realize that the initial idea has been theorized and tested while the novel one is still subject to more exploration (Ehrig and Schmidt, 2022). Second, we argued that scientific entrepreneurs chose a pivoting trajectory from a larger roster of potential changes, discovered thanks to the more systematic search strategy they adopt (Eisenhardt & Bingham, 2017; Zellweger & Zenger, 2022).

Conversely, entrepreneurs who do not adopt the scientific approach do not identify new determinants of value nor as many potential alternatives as the entrepreneurs who adopt the scientific approach. Thus, their business ideas tend to change based on gut feelings (Sosna, 2012) or available evidence, which is often not systematic (Bennett & Chatterji, 2019; Forbes, 2005) and thus likely to produce untargeted variation with trial-and-error pivoting (McBride & Wuebker, 2022). This untargeted search process conducted by control entrepreneurs should not lead to an increase in perceived uncertainty following the pivot. Rather, we expect either a decrease or no change with respect to the periods preceding the pivot. We summarize our arguments in Proposition 2:

Proposition 2. Entrepreneurs following a scientific approach to decision-making experience an increase in uncertainty after pivoting that is not experienced by entrepreneurs not following such approach.

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

Mimoto, a scooter sharing service whose founders attended the scientific training of our RCT, provides a good illustration of our theoretical framework. The three co-founders initially envisioned a service that made electric scooters available for short-term rentals. The scooters could have been booked through an app and did not need to be locked in any specific drop-off point. The entrepreneurs first decomposed the problem they faced and understood that their value proposition depended on three main factors: (a) the ideal target market is university students because this population is willing to use scooters, has a frequent need to commute and an ability to pay, but still cannot afford to own a car; (b) scooters have to be large and solid to ensure drivers' safety; (c) the service is ideal for larger cities because the advantage of scooters is to reduce commute time when there is traffic. When the co-founders tested these three hypotheses with a representative sample of 600 respondents, they rejected the first two hypotheses because university students were not interested in this service and many users (particularly women) were not comfortable maneuvering large, solid scooters. However, they had a theoretical framework that suggested that their service was valuable for users who could not afford to buy their own vehicle but had some disposable income that they preferred to spend on shared vehicles rather than public transports. Their logic also suggested that the key characteristics of the scooters mattered. Thus, they pivoted to young professionals as a key target because of their willingness to pay and because they are likely to benefit from faster mobility in city traffic, and to lighter but equally safe scooters.

These changes were not obvious ex-ante. The process required a deep rethinking of the business model and the collection and testing of new data, which took about one year. Note also the dynamics of the process. Mimoto's founders built on the hypothesis they accepted (focus on cities with traffic) and devised new solutions building on the hypotheses they rejected (university students and large, solid scooters) by considering under what conditions their theory of value creation held. It took some time to test the new hypotheses because there were important uncertainties to solve. While it is now clear that young professionals and lighter scooters are good solutions, the founders did not precisely understand these elements when they rejected the initial hypotheses. They had initial ideas, hypothesized different solutions, and collected data to revise and test the theory. The value of the original idea was clearly more precise, but they understood that the expected value was smaller. The new idea was promising and seemed to have a higher expected value, but it implied higher uncertainty. A hypothetical non-scientific entrepreneur would have probably envisioned fewer promising changes to the initial idea, exploring the space quasi-randomly or starting with marginal changes close to the factors rejected. Such marginal changes are less likely to increase the expected value of the idea and lead to a positive beliefs update.

3. Methodology and data

3.1 Experimental design

Our research embeds a field experiment into a pre-acceleration program or "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 who have a business idea but 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). The experiment described in this section is one of the two employed in the previous chapter, leveraging on unique data about pivoting activities. We provide here additional details on the specific sample under study.

Participants in the 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, events), resulting in a total of 272 applications, out of which we selected into the intervention 257 start-ups. Seven start-ups abandoned the program before its start, so our final sample consisted of 250 participants. All the participants were early-stage entrepreneurs interested in launching a new business and applying to the program with a specific business idea. Most participants applied as founding teams (average team-size 2.2 people) where the average age was 31.4 years. Team members on average had a bachelor's degree and expected to start making revenue in about 11.4 months from the beginning of the pre-acceleration program. There was also a higher percentage of males among participants (78%), which is in line with statistics on gender distribution in entrepreneurship reported from the Global Entrepreneurship Monitor (2019/2020 report) for Italy. Start-ups operated in a wide range of sectors, from Software to Hospitality. The most represented sector in our experimental sample was Leisure, followed by Fashion, Food, Finance, and Software. Taken together, these five sectors accounted for 59% of the sample. While there were some traditional bricks-and-mortar businesses, most of the applicants (75.7%) intended to use Internet-enabled technologies to bring their product or services to the market. Based on data from the Global Entrepreneurship Monitor and conversations with start-up mentors and advisors, this sample is representative of the population of Italian entrepreneurs based on entrepreneurs' demographic characteristics (gender, age, education) and of the sectors they operate in. We used a statistical software package to randomly assign each start-up to one of the two arms of the experiment (treatment and control groups). We checked that the treatment (125 start-ups) and control groups (125 start-ups) were balanced on several key covariates that might affect the absorption of the intervention and its subsequent outcomes. Randomization checks are available in the supplementary materials for Chapter 1, being the experiment in common between the two chapters. 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, start-up potential (measured by an independent third party), the self-estimated expected value of the project, and the projected number of months to revenue. Given the number of checks, we are confident that the randomization was successful in producing balanced groups at baseline.

Following best practices (Baird et al., 2016), we pre-registered the randomized controlled trial and the two propositions tested in the paper. 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 focused 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. 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 taught 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 they 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 observing the lectures.

The course comprised eight sessions over the span of several days (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 learned about tools that are widely used in entrepreneurial education such as the Business Model Canvas (BMC) and Minimum Viable Product (MVP). 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 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. Each session combined a lecture to illustrate key concepts with an interactive activity so that entrepreneurs could apply the content of the lecture to their business idea right away. For instance, in the first lesson, all entrepreneurs learned about the BMC first and then worked on compiling the BMC for their business idea. Treated entrepreneurs were taught to use the BMC as a basis for their theory and to use it to articulate key assumptions that would be tested later. Control entrepreneurs were taught to use the BMC as a representation of the key elements of their business, aspects that would be tested later. Similar, subtle, differences were consistently implemented in each session. We also took several 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.

3.2 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 several 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 included a mix of open- and closed-ended questions following an interview protocol. 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 period. 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 and changes in their BMC, 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. All interviewers were extensively trained on the interview protocol and received clear guidelines and examples for the coding of each variable.

The first telephone interview took place 8 weeks after the training program began. We then collected data every 2 weeks until week 18 (the training program ended in week 12), and every 4 weeks until week 66. We collected 18 data points for the variables defined in the next section for most start-ups. We do not have 18 data points if entrepreneurs abandoned the business idea or the pre-acceleration program—in these cases we only have data up to the period before they abandoned. Attrition patterns are described in the supplementary materials.

3.3 Measures

3.3.1. 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.

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 the 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 to the nine BMC elements (value proposition, customers, channels, customer relationships, key partners, key activities, key resources, costs, and revenue streams). In each observation period, entrepreneurs could have performed pivoting that changed one or more elements of the BMC. To categorize these changes, we followed two approaches. First, we considered changes to the core value proposition or to the customer targets as *core* changes. Ideally, these are fundamental changes to the business idea. Conversely, we labeled as *operational* changes to the other seven categories of the BMC. It is important to note that when an entrepreneur declares to have pivoted, she could have made both *core* and *operational* changes in the same period of data collection. Consequently, we coded a categorical variable that registers whether, at any point in time, an entrepreneur 1) made no changes/pivots, 2) made *operational* changes only, 3) made *core* changes only, 4) made *both* types of change. We then coded two dummy variables. The former takes value 0 if the entrepreneur made no changes at all, 1 if she made changes to the *core* elements. The other instead takes value 1 if she made a change of any type. We used the latter variable in most of our econometric specifications.

The second categorization is taken from the practitioners' world. Popular work by Osterwalder (Bland & Osterwalder, 2019; Osterwalder et al., 2014) divides the nine BMC blocks in three categories: *desirability* (value proposition, customer segment, channels, customer relationships); *feasibility* (key resources, key activities, key partnerships); *viability* (revenue and cost structures). Desirability refers to customer-oriented aspects of the BMC: blocks related to the offer given to customers and the channels used to reach them. Feasibility refers to operational aspects of the BMC, namely whether the necessary resources and activities have been considered for the realization of the idea. Viability refers to the economic sustainability of the idea, entailing the revenue stream and the cost structure.

3.3.2. Dependent variables

Expected Idea Value: We define the expected idea value perceived by the same entrepreneurs as the expected potential of the idea in terms of revenue outcomes. To anchor the response, we asked entrepreneurs to indicate their minimum and maximum expected idea value on a scale between 0 and 100 where we clarified that 0 corresponded 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 in terms of revenue". We computed the expected idea value as the mid-point between the minimum and the maximum values reported by entrepreneurs. The same variable was employed in Chapter 1. We analyzed the change of the expected idea value between two consecutive observation periods.

Range: We used this variable as our main measure for uncertainty, defined as the variability of the expected idea value. We computed it as the difference between the maximum and the minimum value of the business perceived by the entrepreneurs at each moment in time. Similar to the expected idea value, we analyzed the change between two consecutive periods.

Revenues and profits: We used revenue and profits as measures of performance. During each telephone interview, we collected the cumulative revenue generated by each start-up and the cumulative costs sustained. Understandably, not all firms in our sample reached the revenue stage in the 66-week observation window. Only 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. We compute profits as the simple difference between revenues and costs.

Activated Customers: As for revenues and costs, we asked entrepreneurs how many customers they had activated in each observation period. Activation metrics are very common in the start-up environment, where they act as an early measure of performance (Maurya, 2022).

Table 2.1 defines all the variables that we used in our analyses and reports descriptive statistics.

Table 2.1 – Descriptive statistics

Cross-Section	Description	N	Mean	SD
Any Pivot (Dummy)	Dummy = 1 if any pivoting activity has been conducted during the observation window	250	.672	0.477
Core Pivot (Dummy)	Dummy = 1 if a *core* change has been introduced during any of the pivoting sessions	250	.552	0.502
Operational Pivot (Dummy)	Dummy = 1 if an *operational* change has been introduced during any of the pivoting sessions	250	.472	0.502
Feasibility Change (Dummy)	Dummy = 1 if a feasibility change has been introduced during any of the pivoting sessions (within pivoters)	168	.452	0.502
Economic Viability Change (Dummy)	Dummy = 1 if an economic viability change has been introduced during any of the pivoting sessions (within pivoters)	168	.357	0.493
Desirability Change (Dummy)	Dummy = 1 if a desirability change has been introduced during any of the pivoting sessions (within pivoters)	168	.905	0.329
Revenues (last period, log)	Logarithm of revenues at the last datapoint (only for start-ups still active in the market)	125	1.733	3.430
Customers Activated (last period, log)	Logarithm of customers activated at the last datapoint (only for start-ups still active in the market)	125	1.874	2.256
Profits (last period, €)	Revenues minus total costs at the last datapoint (only for start-ups still active in the market). Winsorized at 99th percentile by treatment group.	122	-3538.63	13749.44
Panel				
Any Pivot (Dummy)	Dummy = 1 if any pivoting activity has been conducted in a specific period	3299	.117	0.321
Core Pivot (Dummy)	Dummy = 1 if a *core* change has been introduced in a specific period	3299	.072	0.258
Operational Pivot (Dummy)	Dummy = 1 if an *operational* change has been introduced in a specific period	3299	.068	0.252
Expected Idea Value	Self-perceived value of the idea, from 0 to 100. Missing if the start-up terminates or is an attritor.	3651	62.394	19.477
Range	Range of the self-perceived value of the idea. Missing if the start-up terminates or is an attritor.	3651	32.853	21.050
Revenues (log)	Logarithm of revenues. Missing if the start-up terminates or is an attritor.	3303	.629	2.168
Customers Activated (log)	Logarithm of customers activated. Missing if the start-up terminates or is an attritor.	3297	.881	1.693
Profits (€)	Revenues minus total costs at the last datapoint. Missing if the start-up terminates or is an attritor. Winsorized at 99th percentile by treatment group.	3293	-1757.45	7754.71

3.4 Econometric Approach

Our estimation strategy builds on a preregistration plan but considers several variables that were not anticipated, specifically when looking at different types of pivoting. We clearly distinguish between pre-registered and exploratory analysis when reporting our results, following best practices outlined by Banerjee et al. (2020). To corroborate the two propositions, we ran first-differences OLS models where the dependent variable is the difference of the expected value between two consecutive periods or the range of values measure. This model allows us to understand the change in both entrepreneurs' expected idea value and related uncertainty by treatment group and pivoting activity. We ran models separately by treatment group and models interacting the first-differenced treatment and pivot indicators. Regressions always included period dummies to account for unobservable but common heterogeneities over time and clustered standard errors at the start-up level given the panel structure of the data and the level of randomization used. In the exploratory analyses, we ran Linear Probability (LPM) and Probit models, analyzing pivoting activities by treatment group in a cross-sectional fashion to understand different pivoting behaviors between treatment groups. Accordingly, we clustered standard errors at the level of administration of the intervention, namely the classrooms in which entrepreneurs were allocated. To correct for the low number of clusters, we also re-estimated p-values through wild bootstrapping. Finally, to analyze the relationship between pivoting activities and performance by treatment group, we ran Pooled-OLS models regressing the logarithm of revenues, activated customers or team size on the treatment indicator and its interaction with the overall pivoting status.

4. Results

4.1 Pivoting and belief update

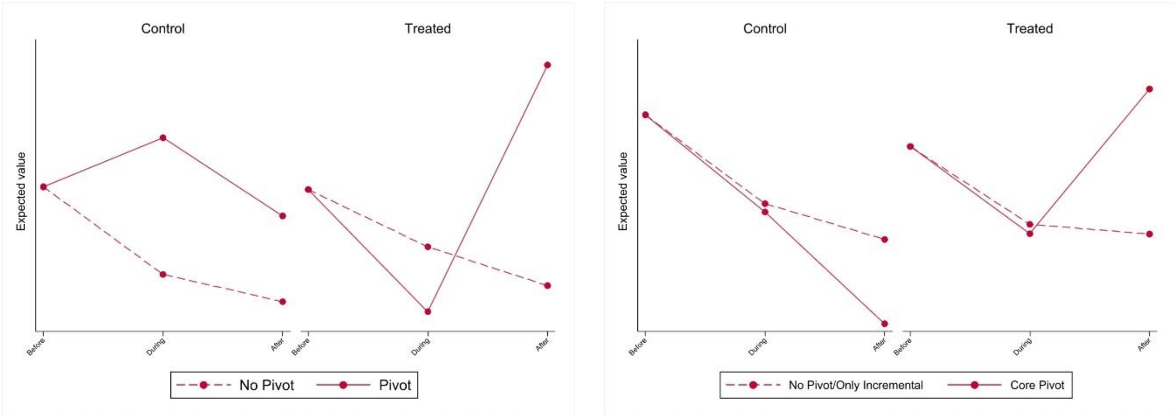
The first proposition theorized that treated entrepreneurs that pivot should perceive a higher expected value of their business idea in the period following the pivot, thus positively updating their beliefs. To test it, we analyzed the delta of the reported expected idea value between two consecutive periods. Specifically, we grouped entrepreneurs by their pivoting status using a dummy variable taking value 1 in the period in which a pivot of any kind happens. Figure 2.1 shows changes in the expected idea value conditioning on pivoting and treatment group, examining the period in which the pivot was recorded compared to the subsequent one[9]. Panel A reports the trends distinguishing by pivoters versus non-pivoters, including in the former category entrepreneurs that

[9] As an example, suppose that an entrepreneur makes a *core* change in period 5. For that specific entrepreneur, the period before the pivoting activity would be period 4, while the period immediately after would be period 6. We consider the difference between the pivoting period and the one before that (5 with respect to 4) and the difference with the subsequent period (6 with respect to 5).

made any type of change to their business model; Panel B adopts a more conservative definition, considering as pivoters only those entrepreneurs that made changes to the *core* elements of their business model (i.e., value proposition or customer segment). To ease the comparison, we re-scale the averages by the level at the period before the pivot was conducted.

Figure 2.1 – Pattern of expected idea value following a pivot

Panel A Pivoters vs non-pivoters **Panel B** Core pivoters vs other/non pivoters



Note. Figure 2.1 shows the expected idea value in the periods during and after a pivoting activity has been conducted, regardless of the specific observation period of the event. To ease the comparison, values have been rescaled to the "Before" value of the pivoters-treated group. Panel A shows the trend looking at pivoters versus non pivoters; Panel B only considers as pivoters those entrepreneurs introducing *core* changes (i.e. value proposition and/or customer segment) to their business models.
Panel A, observations: Non pivoters/control = 1,368; Pivoters/control = 185; Non pivoters/treated = 1,292; Pivoters/treated = 200
Panel B, observations: Non pivoters-other/control = 1438; Core pivoters/control = 115; Non pivoters-other/treated = 1371; Core pivoters/treated = 121.

Both panels in Figure 2.1 show that on average entrepreneurs who do not pivot decrease the expected value of their ideas over time. However, as predicted by Proposition 1, a positive belief update is recorded for treated entrepreneurs in the period following the pivoting activity. Specifically, Panel A shows that entrepreneurs in the control group increased their belief with respect to the period before the pivoting, that is however downward corrected after the pivoting activity. The exact converse is true for the treated group, which approached the pivoting with a marked belief downgrade but positively updating it after the pivoting takes place. A similar pattern is shown in Panel B, where we considered as pivoters only those entrepreneurs making *core* changes. While control entrepreneurs had a decreasing pattern of belief updating regardless of the pivoting activity, treated entrepreneurs who introduced *core* changes consistently made a positive update. Overall, the results indicate that treated entrepreneurs introduced changes to their BMC elements after becoming more conservative about the potential value of their idea and decided to change the course of action to another one that was linked to a positive belief update, very much like in the MiMoto's example in section 2.4.

Table 2.2 in the following page shows the results of the econometric models for the overall pivoting activities. As outlined in Section 3.4, we estimated first-difference models where the dependent variable is the difference in the expected idea value between two consecutive periods. We estimated the models using both the difference between the period preceding the pivot and the one in which the pivot happened, as well as the difference between the period in which the pivot happened and the following one. Given the first-difference structure, we included as regressors the first-differences of the pivoting dummy and estimated the models separately by treatment group (Columns 1–4). We then pooled the observation and also compute the first-differences of the interaction between the pivoting and the intervention dummy (Columns 5–6). Finally, we also report the results of the pooled model conditioning on entrepreneurs that were active for the whole period of observation and for which we have a full panel of observations, thus dropping those entrepreneurs who decided to terminate their project (Columns 7–8)[10].

[10] In the supplementary materials, we also report results for a model where we take the first-difference of the dependent variable only, using as regressors the full interacted set of pivoting and treatment dummies. Results are consistent with the models presented in the main text. As explained in section 4.2, we also re-run the models considering different pivoting categorizations.

Table 2.2 – Regression results for expected idea value

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Group	Control		Treated		All		All (Survived start-ups)	
Period	During	After	During	After	During	After	During	After
Pivot (FD)	0.838	-0.865	-0.887	1.144^	1.095	-0.670	1.421	-1.742^
	(0.914)	(0.855)	(0.901)	(0.663)	(0.915)	(0.813)	(0.910)	(0.939)
Pivot X Treatment (FD)					-2.222^	1.584	-2.877^	3.082**
					(1.301)	(1.001)	(1.473)	(1.144)
Observations	1,553	1,445	1,491	1,386	3,044	2,831	2,253	2,131
Unique IDs	112	111	112	107	224	218	133	133
R-squared	0.007	0.009	0.014	0.011	0.008	0.006	0.013	0.015
Period dummies	YES	YES	YES	YES	YES	YES	YES	YES

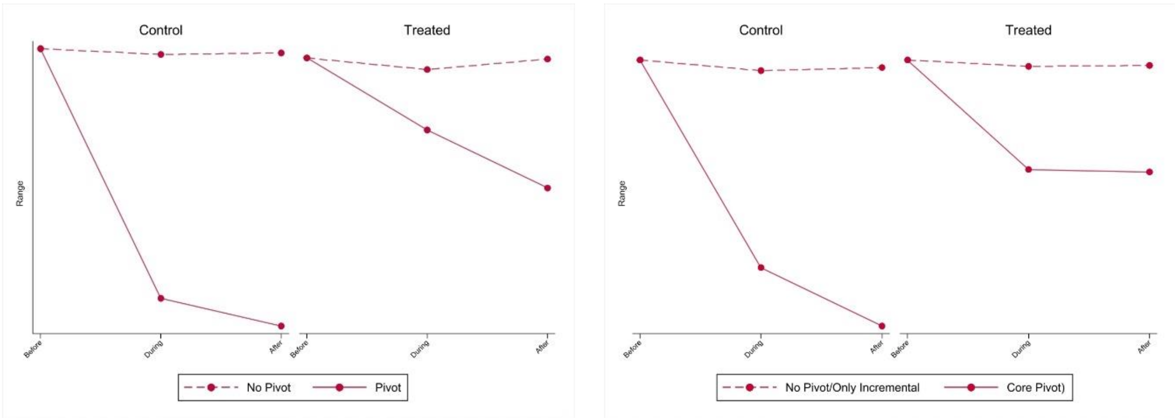
Note. DV: first-difference of expected idea value
All models report a first-difference OLS regression with period dummies and standard errors clustered at the entrepreneur level.
Column 1–2 report the regression for the control group, using the first-difference (1) and the forwarded first-difference (2). Columns 3–4 replicate the models for the treatment group. Columns 5–6 report the results for the full sample, adding the first-differenced interaction as a regressor. Columns 7–8 replicate the last two columns but conditioning on the decision of entrepreneurs to never terminate their project, as to have a full panel of observations. Attritors are excluded from the sample.
*** p<0.001, ** p<0.01, * p<0.05, ^ p<0.1

Regression results presented in Table 2.2 provide support for Proposition 1. A positive beliefs update in the period following the pivot is recorded only for treated entrepreneurs, while a negative coefficient is associated to entrepreneurs in the control group. Specifically, considering the control mean of the dependent variable for non-pivoters, treated entrepreneurs increase their expected value by roughly 2.6% with respect to control entrepreneurs. Moreover, both the significance and the effect size increase when looking at the subsample of entrepreneurs who are always active on the market (Columns 7–8), which reinforces the idea that treated entrepreneurs who pivoted might have chosen a more successful path of development when pivoting. In the Supplementary Materials we also report the expected values at the baseline period (before the interventions took place) and at the last available observation (i.e., up to the period in which start-ups are observed), by pivoting and treatment status. Results show how on average entrepreneurs across groups tend to lower their beliefs, but that this reduction is smaller for treated entrepreneurs who pivoted, coherently with results in Table 2.2, and higher for those who did not pivot, coherently with the results in Chapter 1.

Proposition 2 stated that treated entrepreneurs would perceive a higher uncertainty following a pivot, particularly if the associated changes were related to the *core* elements of the BMC. We operationalized uncertainty as the difference between the lower and upper bound of the expected idea value requested from entrepreneurs at each data point (labelled as *range*). Figure 2.2 shows how *range* changes over time by pivoting status and treatment status. As in the previous figure, Panel A reports the trends distinguishing between pivoters and non-pivoters; Panel B considers as pivoters only those entrepreneurs making *core* changes to their business models.

Figure 2.2 – Pattern of range of expected idea value following a pivot

Panel A Pivoters vs non-pivoters **Panel B** Core pivoters vs other/non pivoters



Note. Figure 2.2 shows the range of the expected idea value in the periods during and after a pivoting activity has been conducted, regardless of the specific observation period of the event. To ease the comparison, values have been rescaled to the "Before" value of the pivoters-treated group. Panel A shows the trend looking at pivoters versus non pivoters; Panel B only considers as pivoters those entrepreneurs introducing *core* changes (i.e. value proposition and/or customer segment) to their business models.
Panel A, observations: Non pivoters/control = 1,368; Pivoters/control = 185; Non pivoters/treated = 1,292; Pivoters/treated = 200
Panel B, observations: Non pivoters-other/control = 1438; Core pivoters/control = 115; Non pivoters-other/treated = 1371; Core pivoters/treated = 121.

The graphs show how entrepreneurs in both groups reduced the uncertainty around their expected idea value before pivoting. However, the decrease is more marked for the control group when compared to the treated group, also when looking at *core* pivots only (Panel B).

We report regression results in Table 2.3 where we compare pivoters and non-pivoters, irrespective of the type of changes introduced.

Table 2.3 – Regression results for range of expected idea value

Group	(1) Control	(2)	(3) Treated	(4)	(5) All	(6)	(7) All (Survived start-ups)	(8)
Period	During	After	During	After	During	After	During	After
Pivot (FD)	-1.630	-0.389	1.649	-1.663*	-1.764^	-1.113	-2.036^	-0.320
	(1.069)	(0.944)	(1.265)	(0.805)	(1.061)	(0.978)	(1.102)	(1.127)
Pivot X Treatment (FD)					3.454*	0.266	2.266	-0.279
					(1.684)	(1.220)	(1.852)	(1.501)
Observations	1,553	1,445	1,491	1,386	3,044	2,831	2,253	2,131
Unique IDs	112	111	112	107	224	218	133	133
R-squared	0.050	0.011	0.029	0.020	0.031	0.006	0.035	0.004
Period dummies	YES	YES	YES	YES	YES	YES	YES	YES

Note. DV: first-difference of range
All models report a first-difference OLS regression with period dummies and standard errors clustered at the entrepreneur level.
Column 1–2 report the regression for the control group, using the first-difference (1) and the forwarded first-difference (2). Columns 3–4 replicate the models for the treatment group. Columns 5–6 report the results for the full sample, adding the first-differenced interaction as a regressor. Columns 7–8 replicate the last two columns but conditioning on the decision of entrepreneurs to never terminate their project so as to have a full panel of observations. Attritors are excluded by the estimation.
*** $p<0.001$, ** $p<0.01$, * $p<0.05$, ^ $p<0.1$

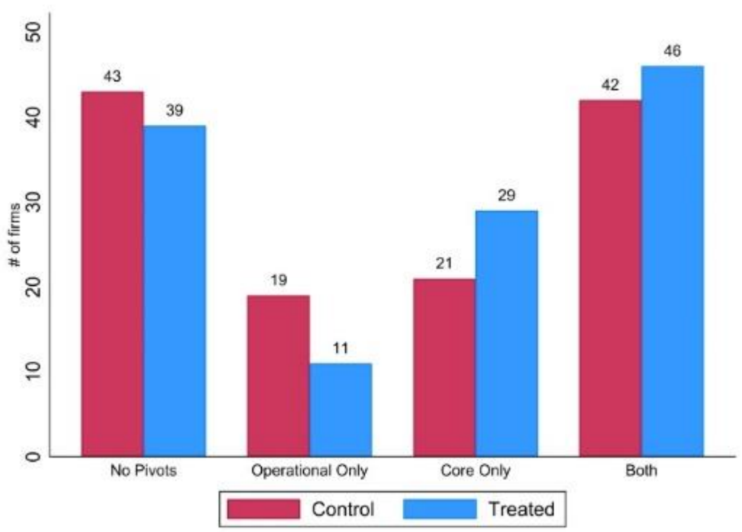
The regression results do not allow us to corroborate Proposition 2. Indeed, there are no statistically significant differences between treated and control entrepreneurs when it comes to the period after the pivot. A slight difference, albeit not statistically significant, is shown in Panel B, where a flat trend of perceived uncertainty around the potential value after *core* pivots is seen for treated entrepreneurs only. Nevertheless, what emerges from both the graph and the regressions is that while both groups reduced the perceived uncertainty before pivoting, treated entrepreneurs performed a milder reduction. In addition, treated entrepreneurs perceived higher uncertainty than those in the control group when they pivot compared to the period right before pivoting (Column 5), and this difference is statistically significant. Although not explicitly included in Proposition 2, this pattern is compatible with our theoretical argument. Indeed, this result is theoretically aligned with the idea that treated entrepreneurs perceive a higher variability of the potential value of the idea (compared with control entrepreneurs who pivot) even when they are trying to correct their course of action through pivoting. This could imply that control entrepreneurs performed pivots only when reaching a more stable expectation for their idea's value, making the pivot less valuable (in expectation), as shown in the first set of results. Conversely, treated entrepreneurs tend to approach pivoting with more uncertain expectations about the potential value, with the pivot leading to a better expected outcome over a longer horizon.

4.2 Exploration of pivoting activities

While in Section 4.1 we performed the analyses related to our pre-registered propositions, in this section we run exploratory analyses to examine what could drive the differences in terms of beliefs updating. We start with a description of the pivoting activities conducted by entrepreneurs in the two groups, showing basic patterns in the data. Among the 250 entrepreneurs participating in our study, 168 pivoted at least once during the observation window (67% of the sample). Rates of overall pivoting were similar across groups (*Control* = 66%; *Treated* = 69%; $p = 0.59$). Frequency of pivoting by observation period are reported in the Supplementary Materials.

Figure 2.3 shows the number of entrepreneurs pivoting according to the *core* versus *operational* classification, considering as pivoters those entrepreneurs who changed an element of their BMC at least once during the data collection window. In each period, entrepreneurs could have introduced *core*, *operational* or *both* types of changes to their BMCs.

Figure 2.3 – Number of entrepreneurs by pivoting category and treatment condition

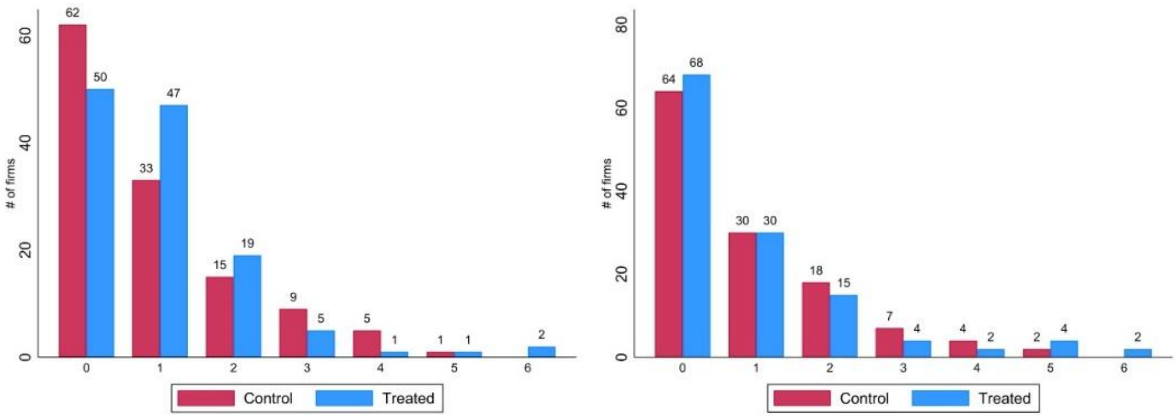


Note. Figure 2.3 displays the number of entrepreneurs in each pivoting category. "No Pivots" identifies entrepreneurs who never pivoted during the observational window; "Operational Only" identifies entrepreneurs who performed at least one operational change but no core changes across the whole observational window; "Core Only" identifies entrepreneurs who performed at least one core change but no operational ones across the whole observational window; "Both" identifies entrepreneurs who made both changes during the observation window. Attritors are assumed to have made no changes (N = 250).

Figure 2.3 shows that treated entrepreneurs were more likely to pivot by implementing *core* changes rather than *operational* ones[11], a result in line with Camuffo et al. (2020). This pattern indicates that treated entrepreneurs were more likely than control entrepreneurs to perform pivots where they change components related to the key value proposition or customer target of their business model. Conversely, they were less likely to introduce changes related only to the more *operational* components of their business models. This difference is also clearly shown in Figure 2.4, where we display the number of *core* pivots conducted per period. Interestingly, treated entrepreneurs were more likely to conduct fewer *core* pivots in each period: while 15 control entrepreneurs made 3+ *core* pivots, only 9 treated entrepreneurs did so.

Figure 2.4 – Entrepreneurs by number of pivots and treatment condition

Panel A Number of pivots (core) **Panel B** Number of pivots (operational)



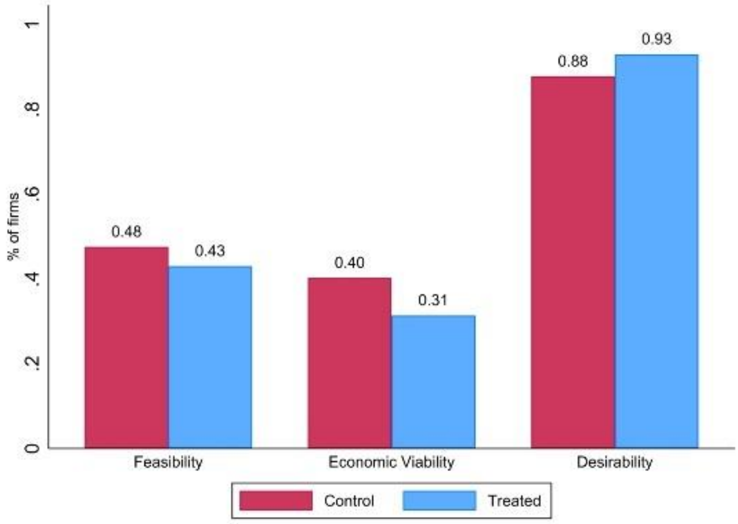
Note. Figure 2.4 displays the number of entrepreneurs by the number of pivots conducted across the whole observation period. Panel A shows the number of pivots in each period where *core* changes have been introduced; Panel B shows the number of pivots in each period where *operational* changes have been introduced. (N = 250).

We now consider only pivoting entrepreneurs (N = 168) and the more fine-grained categorization used by Bland and Osterwalder (2019). Figure 2.5 shows the share of pivoters falling in the three

[11] Table S2.2 in the Supplementary Materials shows the econometric results. The likelihood of making *core* changes is 9% higher for the treatment group, corroborating the results found in Camuffo et al. (2020). There is no significant difference when it comes to *operational* changes. Results are robust when excluding attritors, as reported in the same Table.

categories according to the business model aspect that changed at least one time during the observation window.

Figure 2.5 – Share of pivoting entrepreneurs, Bland and Osterwalder (2019) category



Note. Figure 2.5 displays the share of entrepreneurs by type of change, according to Bland and Osterwalder (2019) classification. "Feasibility" means changes to Key Resources, Key Activities or Key Partners have been made. "Economic Viability" means that changes to Revenue Stream or Cost Stream have been made. "Desirability" means that changes to Channels, Customer Relationship, Customer Segment or Value Proposition have been made. Only pivoting firms (N=168) are considered.

This categorization allows us to grasp the different focus of changes between the two experimental groups, that could help us explain the different pattens of beliefs updating found in Section 4.1. Treated entrepreneurs were significantly less focused on changes related to the *economic* aspect of their ideas[12], as if they realized that before making choices about the more operational parts of their activities, they needed to better understand the market and the desires of their customers, as suggested by their focus on changes related to the desirability of their idea. In other words, treated entrepreneurs tended to prioritize customer-centric problems rather than those related to the set-up of the entrepreneurial venture, in the spirit of a "customer first" orientation. In the Supplementary Materials we also report figures related to the number of BMC changes, which are

[12] Table S2.3 in the Supplementary Materials reports the econometric results. Treated entrepreneurs are about 8% less likely to have introduced changes related to the economic viability of their ideas with respect to the control group ($b = -0.084; p < 0.05$).

similar across groups. Especially with respect to *core* changes, this signals that the lower share of control entrepreneurs introducing those changes introduced more of them over time. Instead, while a higher share of treated entrepreneurs tended to make *core* changes, they did so only once or twice.

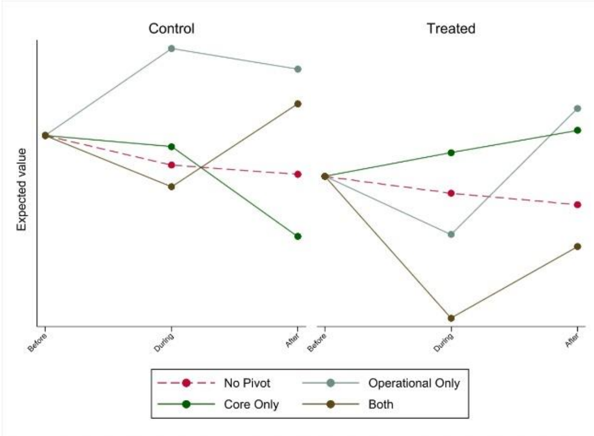
The key take-away from these results is that there is a significant difference between the two treatment groups not so much in terms of pivoting frequency, but rather on the specific focus of the pivots. These patterns are in line with our theoretical arguments and with the beliefs updating patterns found in Section 4.1. Indeed, the fact that a higher share of treated entrepreneurs focused on customer-centric changes aligns with the idea that entrepreneurs seek to gather more information about their customers and develop a value proposition that is more compelling for those customers if they follow a scientific approach. Focusing on customer-centric changes leaded to a more positive beliefs updating in terms of expected value of the idea, since entrepreneurs were possibly shifting the pattern of development towards a final solution that was deemed to be more promising in terms of market and customers' acceptance. At the same time, this different focus led to a milder uncertainty reduction when compared to control entrepreneurs. This could be explained by the broader exploration of the market conducted by treated entrepreneurs: while realizing that such pivoting activities were reducing the uncertainty around the idea, they also considered potential alternative paths of development and, more importantly, the necessity to further test and explore the novel implemented solutions, as illustrated in MiMoto's example.

To further reinforce these intuitions, we report in Figure 2.6 below the graphs for the beliefs update in both expected value and uncertainty over time considering the *core, operational* and *both* fine-grained categorization[13].

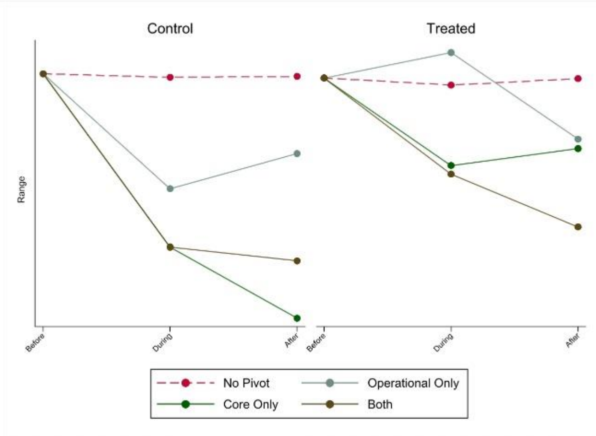
[13] Econometric results are reported in the Supplementary Materials.

Figure 2.6 – Pattern of expected idea value and range. Fine-grained categorization

Panel A Expected value



Panel B Range of expected value (uncertainty)



Note. Figure 2.6 Panel A shows the expected idea value in the periods during and after a specific pivoting activity has been conducted, regardless of the specific observation period of the event. Panel B shows the range of the expected idea value. To ease the comparison, values have been rescaled to the "Before" value of the core pivoters-treated group. The graphs use the fine-grained categorization between non pivoters; entrepreneurs who only implemented *operational* changes; entrepreneurs who only implemented *core* changes; entrepreneurs who implemented *both* type of changes. Observations: Operational-only/control = 70; Core Only/control = 72; Both/control = 43; Operational-only/treated = 79; Core Only/treated = 88; Both/treated = 33.

Panel A shows how the positive belief update on the idea's potential value following a pivot recorded for treated entrepreneurs was consistent across all types of pivoting activities. The decrease in the potential value in the period in which the pivot was conducted is marked for treated entrepreneurs that performed *both* type of changes.

A positive update is recorded for entrepreneurs conducting *both* changes across the two experimental groups, despite the negative overall update recorded for control entrepreneurs, driven by *operational* and *core* changes alone. This result is also linked to Kirtley and O'Mahoney (2020), which argue that successful pivoting activities are a consequence of interdependent changes. Finally, Panel B confirms the results of a reduction in perceived uncertainty on the idea value for all pivoting entrepreneurs, with a milder reduction for treated entrepreneurs. The latter is relatively more marked for entrepreneurs performing only *operational* changes: while control entrepreneurs decrease uncertainty perception, treated ones approach these pivots with a positive beliefs update.

4.3 Pivoting and performance

In this section we provide exploratory analyses on the consequences of pivoting on the performance of the business. Results so far have shown how treated entrepreneurs positively updated their beliefs on expected idea value, with a milder reduction of uncertainty. This could be a consequence of the different focus of the pivoting activities, which are directed toward customer-centric changes. Overall, the positive update indicates that the novel development path followed by treated entrepreneurs is expected to lead to better performance, or at least a better product-market fit. Therefore, we investigate if there is also a direct relation with outcomes beyond entrepreneurs' perceptions. We consider entrepreneurs as pivoters if they performed at least one pivot during the observation period and examine variation in key outcomes of interest depending on treatment and pivoting. Figure 2.7 in the next page shows the pattern of (logged) revenues (Panel A), cumulative profits (Panel B) and (logged) activated customers (Panel C).

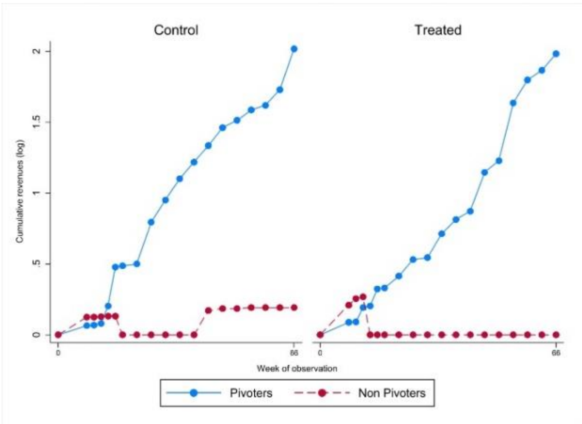
Overall, the share of startups making revenue is balanced between the two groups, with 12% of entrepreneurs in the treatment group (N=15) and 13.6% of the control group (*N*=17) achieving revenue. Differently from what studied in Chapter 1, we do not account for selection in this paper. What emerges from Figure 2.7 (Panel A) is that the startups making revenue are those that introduced changes to their BMCs. Panel B suggest that profits are lower for pivoting entrepreneurs in the treated group. This could be a signal of a stronger commitment to the project, since for early-stage startups it is quite rare to have positive net-profits in the first year of operations as initial investments typically exceed the revenues made. Moreover, when splitting between the fine-grained categories of pivoting (*operational* vs *core* vs *both*), performance effects are driven by entrepreneurs who performed only *operational* changes[14]. This is not highly surprising, since these might be startups with more promising business models, not needing a refinement of

[14] Results available in the Supplementary Materials.

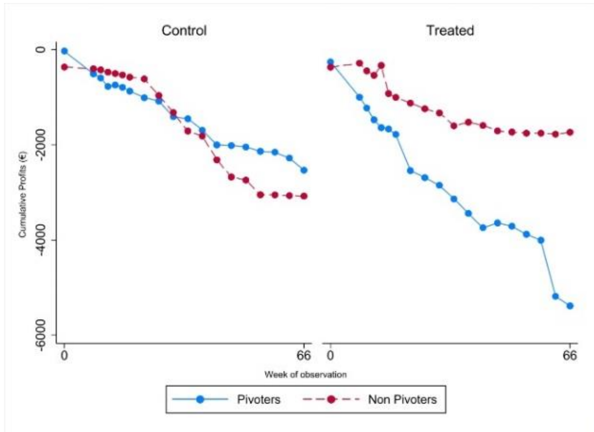
their core value proposition. Conversely, entrepreneurs who engaged in *core* changes make less revenues on average and are also less likely to be in the revenue stage when compared to firms making only operational changes.

Figure 2.7 – Entrepreneurs' performance by pivoting status

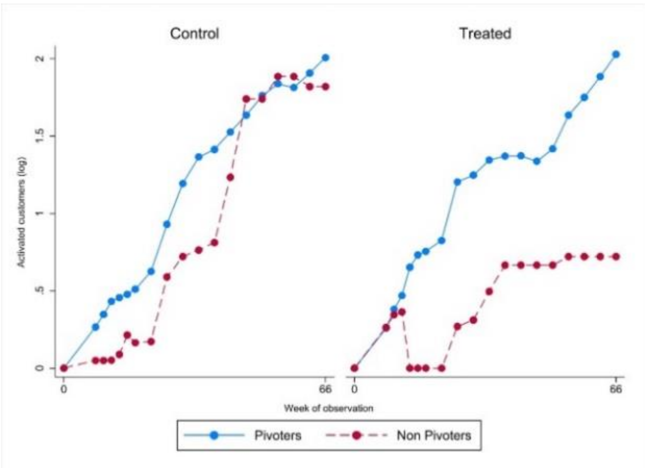
Panel A Cumulative revenues (logged)



Panel B Cumulative profits (€)



Panel C Cumulative activated customers (logged)



Note. Figure 2.7 Panel A shows the logged cumulative revenues over time, dividing between treatment group and pivoting condition. Panel B shows the profits made by entrepreneurs over time, winsorized at the 99th percentile of distribution by treatment. Profits are computed as cumulative revenue minus cumulative costs incurred over time. Panel C shows the logged cumulative number of activated customers over time. Observations for entrepreneurs that terminate their ideas are set to missing starting from the dropout period, explaining the potential noise in the pattern.

Nevertheless, we find no statistically significant differences between treated and control groups, as shown also by the regressions in Table 2.4.

Table 2.4 – Regression results for performance

	(1) Cumulative Revenues (log)	(2) Profit (€)	(3) Cumulative Activated Customers (log)
Pivot (Dummy)	0.532^	364.989	0.267
	(0.290)	(1,138.400)	(0.285)
Treatment (Dummy)	-0.402^	273.255	-0.452
	(0.215)	(1,304.943)	(0.318)
Pivot X Treatment	0.264	-1,296.791	0.481
	(0.439)	(1,713.036)	(0.390)
Observations	3,053	3,043	3,047
R-squared	0.086	0.055	0.184
Period Dummies	YES	YES	YES
Mentor Dummies	YES	YES	YES

Note. All columns report OLS regressions with period and mentor dummies; a control for the share of team members with an economics background (unbalanced at the baseline) is added. Standard errors clustered at the entrepreneur level.
Column 1 uses as DV the logged cumulative revenues over time. Column 2 uses as DV the cumulative profits in € over time, winsorized at the 99th percentile. Column 3 uses as DV the logged number of activated customers.
Once an entrepreneur terminates her project or leaves the program, the values are set to missing. Attritors leaving the program in the first week are excluded from the sample since the baseline period is excluded from the estimation.
*** p<0.001, ** p<0.01, * p<0.05, ^ p<0.1

Another useful metric to gauge the potential start-up performance is to look at the number of activated customers over time. From Figure 2.7, Panel C, there seem to be no differences between groups. However, a different pattern seems to exist within the treated group, with pivoters showing a stronger increase in the number of activated customers. This difference is not statistically significant, despite the estimation showing a large positive coefficient. As for the difference in revenue pattern, it is especially driven by entrepreneurs performing *operational* changes or conducting *both* type of changes. Overall, we find an initial performance effect in terms of short-term revenues for pivoting firms but no differences by treatment condition. However, the relatively short time span of observation, specifically if we consider that a higher share of treated entrepreneurs introduced more fundamental changes, does not allow us to reach a definite conclusion about the realized potential of the introduced changes.

5. Discussion and Conclusion

This chapter examined pivoting among early-stage entrepreneurs and how a scientific approach to decision-making affects pivoting and beliefs update in the process of new venture creation. Because entrepreneurs often start with ideas that need refinement and change (McDonald and

Eisenhardt, 2020), understanding in which direction to turn represents a fundamental challenge for new firms. Our study advances the idea that using a scientific approach is beneficial for entrepreneurs as they develop their idea and identify how to modify it. By examining the process of beliefs update underlying the decision-making and pivoting process, we contribute to research at the nexus of strategy, entrepreneurship, and organization theory by incorporating a scientific approach—one that combines cognition and action—into existing research on pivoting and learning in new ventures. We argue that entrepreneurs who use a scientific approach are able pivot to ideas that they perceive to offer higher value and higher uncertainty. Through an RCT with 250 entrepreneurs, we empirically show how the process of pivoting is linked to a positive beliefs update on the potential idea value for entrepreneurs who are taught to use a scientific approach. Conversely, we do not find any evidence that pivoting leads to an increase in uncertainty, as predicted by our theory. However, we find evidence for a significantly milder reduction in uncertainty for treated entrepreneurs with respect to the period preceding the pivoting activity. While this is not what our proposition predicted, we believe it is not far from our theoretical argument. Indeed, while our evidence shows that entrepreneurs who pivot tend to have lower levels of uncertainty, its reduction is stronger for control entrepreneurs than for treated ones. This implies that treated entrepreneurs perceive higher uncertainty relative to control entrepreneurs before pivoting, signaling that they are still aware that other patterns of development they could follow (or other contingencies over which they have superior information) could lead to a more variable outcome. Moreover, in line with Pillai et al., (2020) we find that pivoting happens generally after entrepreneurs lower their beliefs about idea value, and this is especially true for treated entrepreneurs. Arguably, this could be the result of better experimentation and better information that leads treated entrepreneurs to introduce changes only when a clear (negative) signal on the idea quality is observed.

Our results provide insights for research on learning in new ventures, as they show that a scientific approach helps entrepreneurs understand what elements to retain and what elements to change in their ideas thanks to synergies between thinking and doing. This suggests that the challenges of adopting a trial-and-error approach can be mitigated by structured search strategies that reduce noise in integrating outside knowledge, as in the case of entrepreneurs trained to use a scientific approach. These findings also provide an important empirical test of cognitive processes outlined only theoretically in research that models decision-making in entrepreneurship (Chen et al., 2021), as well as in conceptual papers that provide frameworks for entrepreneurial choices (Gans et al., 2019) and for scientific-like experimentation (Ehrig and Schmid, 2022; Zellweger and Zenger, 2022). Finally, this study has important implications for entrepreneurial education. As pre-accelerator programs are becoming increasingly popular at a global level (Hallen et al., 2020; Yu, 2020), similar initiatives can benefit from a better understanding of tools and approaches that help entrepreneurs in the difficult process of new venture creation.

By examining the pivoting focus, we explore how entrepreneurs tend to focus on different aspects of their venture and we find that treated entrepreneurs tend to focus more on core changes rather than operational ones and customer desirability rather than economic viability compared to the control group. This result is consistent with a prior study on a scientific approach to decision-making (Camuffo et al., 2020) that shows that entrepreneurs who learn about a scientific approach tend to pivot more at the core. Our results replicate this finding using a comparable design but a different sample, thus mitigating concerns related to the "replication crisis" that affects studies in social sciences (Duflo & Banerjee, 2017; Goldfarb & King, 2016).

While our evidence about beliefs update is interesting and points in promising directions, this study is not free of limitations. As in Chapter 1, we employ coarse, though effective, measures of the perceived distribution (range). This is largely because it is difficult to reliably measure distributions of value for early-stage entrepreneurs who face highly uncertain scenarios with limited prior information. Future research could develop more sophisticated measures to provide additional identification of these mechanisms. Moreover, we are only able to infer whether the introduced changes will be effective in terms of performance through belief updating, since the observed time span might be too short to fully leverage the impact of (especially) *core* changes to the business models and do not fully explain the *performance effect* found in Chapter 1. More nuanced metrics to gauge a start-up potential would be needed to clearly disentangle the performance effects of pivoting. Nevertheless, we show a positive short-term performance effect for pivoting start-ups with respect to non-pivoters across both experimental groups. As in most field experiments in social sciences, our design does not allow perfect identification. Given the high financial costs of running a similar field experiment, the sample is relatively small, limiting the experiment's power especially when we consider multiple pivoting categories. However, the fact that we have repeated observations over a reasonably long period of time mitigates this problem and strengthens our main findings.

We also see many fruitful opportunities for further research stemming from this study. Apart from extensions to other countries and industries (e.g., high-tech), we wonder what the effect might be when entrepreneurs 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. Moreover, this study embeds the intervention in a specific learning model. It would be valuable to understand what teaching approach and learning model (e.g., experiential, in presence vs. online, etc.) results in a better effect of the scientific approach. A similar study would allow us to understand how to scale similar interventions with a view to improve entrepreneurship education. Finally, it would be intriguing for future studies to evaluate the effects of the scientific approach vis-à-vis other approaches, such as effectuation.

Overall, these first two chapters point to the fact that, while the scientific approach has limitations, it also has potential. Chapter 1 showed the effects of the approach in terms of selection and performance, with Chapter 2 complementing the evidence on belief updating by an in-depth analysis of pivoting activities. In the last Chapter of this thesis, we extend the research on entrepreneurs' perceptions by studying how entrepreneurs perceive themselves as more or less able to deal with challenges to business development. We do so in the context of an emerging economy, Tanzania, leveraging on a novel field experiment where we isolate the effect of entrepreneurial theoretical reasoning when crafting business strategies.

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3

Entrepreneurship Training and Founders' Perceptions of Ability: A Randomized Control Trial with Entrepreneurs in Tanzania

with Francesca Bacco (Vrije Universiteit Amsterdam) and Audra Wormald (University of North Carolina Chapel Hill)

ABSTRACT

Entrepreneurs' perception of ability is a key driver of the decision to initiate new entrepreneurial ventures and a predictor of their performance. This chapter, co-authored with Francesca Bacco and Audra Wormald, studies whether the application of systematic approaches to decision-making increases entrepreneurs' perceptions of ability. Specifically, it analyses whether an approach grounded on theory-building as an antecedent to experimentation has a larger impact on perceptions when compared to an approach grounded solely on experimentation. The empirical analysis relies on a Randomized Control Trial conducted with 151 agribusiness entrepreneurs in Tanzania. Entrepreneurship is critically important in the developing world, and founders in these contexts operate under extreme uncertainty and with tremendous challenges. Yet, emerging economies remain underrepresented in the entrepreneurship and strategy literature, and existing training opportunities tend to focus on basic business skills rather than strategy-making. Our study shows that a strategy-based training grounded on theory-building has important effects on entrepreneurs' perceived ability to deal with different factors that may hinder the development of new ventures. Specifically, we find that training entrepreneurs to apply a theory-and-evidence-based approach to strategic decision-making increases their perceived ability to deal with uncertainty stemming from the development of a viable business model. Leveraging a novel categorization, we find this effect to be stronger for the perceived ability to deal with factors idiosyncratic to the projects developed by entrepreneurs. Finally, exploratory analyses show a positive relation between perceived abilities, perceptions of controllability of future events and business performance.

1. Introduction

Entrepreneurship is one of the main drivers of economic growth and poverty alleviation (Acs et al., 2008; Bruton et al., 2008; Sutter et al., 2019), and supporting entrepreneurs in emerging economies has become one of the strategies deployed to foster economic development. However, the economic, financial, and institutional landscapes of emerging countries are not as supportive of entrepreneurial endeavors as those in developed economies (Dutt et al., 2016; Mitchell et al., 2022). Entrepreneurs operating in emerging economies face barriers to innovation and business development related to resource scarcity, corruption, difficulties in accessing capital, and other institutional voids (Armanios et al., 2017; Bischoff et al., 2020; Khanna & Palepu, 1997; Mair et al., 2012). Navigating these environments can be difficult for entrepreneurs, who may not perceive themselves as sufficiently able to face the challenges associated with the development of a business within an unsupportive context. Prior research has shown that perception of ability plays a pivotal role in both the decision to start new businesses and the performance of these ventures (Arenius & Minniti, 2005; Shepherd et al., 2015; Townsend et al., 2010). Specifically, entrepreneurs with higher perceived abilities are more likely to pursue innovative entrepreneurial projects when located in contexts characterized by significant barriers to entrepreneurship (Amini Sedeh et al., 2021).

Entrepreneurs' abilities and perceptions of their abilities can be strengthened through entrepreneurial training initiatives (Bae et al., 2014). These initiatives are particularly salient in emerging economies, where approximately $1 billion is spent annually to train 4-5 million aspiring and active entrepreneurs (McKenzie, 2021). Typically, these trainings are focused on providing basic business skills, such as accounting practices, planning or inventory management (McKenzie & Woodruff, 2014, 2017). However, these initiatives typically do not address a critical task all entrepreneurs face: decision-making under uncertainty (McKenzie, 2021; McKelvie et al., 2011; McMullen & Shepherd, 2006). This lack of attention to strategizing under uncertainty is surprising, given the evidence that entrepreneurs following systematic approaches to decision-making make better decisions and have better performance (e.g., Camuffo et al., 2020; Harms & Schwery, 2020; Leatherbee & Katila, 2020).

Results from these studies are informative, but – aside from some notable exceptions (Carlson & Hager, 2022) – research studying the impact of such approaches has been conducted only in developed countries settings. Moreover, these studies have mostly focused on decisions (e.g., changes to business model or termination) and performance outcomes, leaving understudied other important determinants of decision-making and performance, such as entrepreneurs' perceptions of ability. Finally, while studies typically compare entrepreneurial trainings teaching systematic approaches with more traditional ones, there are no studies confronting two systematic approaches at the same time.

The goal of this chapter is to investigate how training entrepreneurs in an emerging economy to adopt a systematic approach to decision-making when developing new business ideas affects their perceived abilities. To accomplish this task, we conducted a field experiment to compare two prevalent approaches, based on the principles of the scientific method, which have been extensively discussed in both academic and practitioner literature, to determine which approach has more significant and persistent effects. In our experiment, entrepreneurs were randomly assigned to two training conditions: in the *evidence-based* approach, the training emphasizes quick validation of assumptions and business hypotheses with customer interviews, surveys and experimentation (Contigiani & Levinthal, 2019; Leatherbee & Katila, 2020; Ries, 2011); in the *theory-and-evidence-based* approach, the training emphasizes the role of developing a theory-of-value before engaging in hypothesis testing and experimentation (Camuffo et al., 2020, 2021; Ehrig & Schmidt, 2022; Zellweger & Zenger, 2021). The latter thus comprises both the action and cognition elements of the scientific approach, as discussed in previous chapters.

We conducted a randomized field experiment with 151 agri-business entrepreneurs in Tanzania. This setting is highly relevant to our study for several reasons as Tanzanian entrepreneurs face significant challenges that can hinder growth (Galperin & Melyoki, 2018). To design and deliver a free-of-charge entrepreneurship training on idea validation and strategy development, we partnered with a local entrepreneurial support organization. The training included six half-day, in-person sessions every other week for three months, and we collected data from entrepreneurs for about 13 months, including surveys and interviews across six different data collection rounds. As part of this data collection, we asked entrepreneurs about the challenges they faced in developing their businesses, and we measured their perceptions of ability in responding to several factors inherent in entrepreneurial activity that can become challenging and ultimately increase uncertainty (e.g., accessing financial capital or knowing customers' needs).

Our experimental results reveal that entrepreneurs trained with the *theory-and-evidence-based* decision-making approach report higher levels of perceived ability compared to entrepreneurs trained with the *evidence-based* approach. This effect persists even after the end of the training program. Following a pre-registered classification, we also find that this increase in perceived ability is stronger when related to factors that we categorize as *project-related* compared to the perceived ability towards *environmental* factors. Finally, additional exploratory analyses indicate a positive correlation between perceived ability and perceptions of control over future events as well as performance outcomes, suggesting that entrepreneurs with higher levels of perceived ability also perceive uncertain environments as more controllable and perform better.

Our findings contribute insights into entrepreneurship in emerging economies by providing a detailed account of entrepreneurial perceptions and business outcomes from an important yet underrepresented context (Foo et al., 2020; George, Corbishley, et al., 2016; George, Kotha, et al., 2016). Moreover, we contribute to the literatures on entrepreneurs' perceptions (e.g., Amini Sedeh et al., 2021; Arenius & Minniti, 2005; Townsend et al., 2010) and on systematic approaches to decision-making (e.g., Camuffo et al., 2020; Leatherbee & Katila, 2020) by showing that teaching entrepreneurs to apply a *theory-and-evidence-based* approach increases their perceived ability to deal with potentially challenging factors more than teaching entrepreneurs to follow an approach based solely on evidence gathering and experimentation. Altogether, our results show that entrepreneurs' perceptions of ability can serve as a central yet undertheorized mechanisms that underpins strategy formation under conditions of high uncertainty, which can have important implications for entrepreneurs' strategic choices as well as the outcome of those choices.

2. Conceptual framework

2.1 Entrepreneurship in emerging economies

Entrepreneurship is an important driver of economic growth and poverty alleviation in emerging economies (Foo et al., 2020; Sutter et al., 2019). However, entrepreneurs in these contexts face significant barriers and challenges to business development that can hamper the growth of existing ventures or the introduction of novel startups, products, or services. On the one hand, environmental factors – including difficulties in accessing capital due to a poorly functioning financial sector (Amini Sedeh et al., 2021; Bischoff et al., 2020) or limited access to basic services such as electricity, water or transportation due to underdeveloped infrastructure (Ajide, 2020) – can make the environment particularly hostile to navigate. These factors are compounded by institutional voids where critical structures and systems that enable market transactions are lacking or unreliable (Arrow, 1969; Dutt et al., 2016; Khanna & Palepu, 1997; North, 1990). Rampant corruption, poor regulations and inefficient judicial systems also limit entrepreneurial action and businesses' growth (Chakrabarty, 2009; Khanna & Palepu, 1997). On the other hand, access to specialized training opportunities is limited and opportunity costs are higher compared to developed economies, with entrepreneurs ultimately not having the right skills or mindset needed to cope with the challenges inherent to business development (Bruton et al., 2021; Sutter et al., 2019). These conditions make the entrepreneurial environment of emerging economies more challenging and uncertain than the ones faced by entrepreneurs in developed economies (Dutt et al., 2016; Mitchell et al., 2022).

2.2 Entrepreneurship training programs

A prominent question in the entrepreneurship and development economics literature is on how to foster entrepreneurial efforts and best support business development in such challenging settings. The most common answer has been to offer business training programs to both new and existing small firms in emerging economies (McKenzie, 2021). Indeed, an estimated yearly $1 billion is devoted to training entrepreneurs in developing countries, with the US administration alone spending $127 million in such training (Lyons & Zhang, 2018; McKenzie, 2021). The idea behind such effort is that entrepreneurs would benefit more from learning skills and techniques needed to manage their business, rather than, for instance, being subsidized with cash. As such, existing studies on training initiatives in emerging economies primarily focus on the effect of teaching entrepreneurs to apply basic business skills such as accounting practices, planning or inventory management (McKenzie & Woodruff, 2014, 2017; McKenzie, 2021).

While these initiatives are important, such training programs tend to overlook other critical skills relevant for strategic decision-making under uncertainty – such as idea assessment and business model choice (Carlson & Hager, 2022) – which are at the core of entrepreneurial activity (McKelvie et al., 2011; McMullen & Shepherd, 2006). This is particularly crucial in emerging economies settings, where uncertainty about market conditions is high. Indeed, entrepreneurs operating in these contexts might perceive that they lack the appropriate skill set to define a successful business offer, target the right customers, develop a business strategy, compete against alternative solutions in the same or similar industries or cope with difficulties in accessing capital and production inputs. Therefore, offering a training centered on strategy-based concepts could in principle help entrepreneurs in developing the skills needed to cope with an uncertain environment, ultimately increasing both actual entrepreneurial abilities and their perceptions of ability.

2.3 Entrepreneurs' perceptions of ability

Studying entrepreneurs' perceptions of ability is of paramount importance when evaluating entrepreneurial performance and efforts in emerging economies. Indeed, the study by Amini Sedeh et al. (2021) shows that entrepreneurs who display higher levels of perceived entrepreneurial abilities are less concerned and affected by barriers to innovation and entrepreneurship, suggesting that individual attributes and perceptions can act as "substitutes for the voids and barriers in institutions" (p. 17). In general, previous studies have shown that perceptions of ability are a key determinant of both entrepreneurs' decision to start a new venture and of business performance (Arenius & Minniti, 2005; Cassar & Friedman, 2009; Shepherd et al., 2015; Townsend et al., 2010). Similarly, perceptions of ability have been shown to be a stronger predictor of the decision to launch a novel business than venture's outcome expectations (Townsend et al., 2010). Moreover, higher perceived abilities have been related to higher tolerance for risk and higher propensity to embark on entrepreneurial activities (Keh et al., 2002; Simon et al., 2000; Zhang & Cueto, 2017).

These arguments have roots in social cognitive theory: high levels of self-beliefs and self-efficacy are important behavioral drivers that affect agents' actions and, in turn, their performance on tasks (Bandura, 1978, 2001). In the entrepreneurship context, perceptions of ability are strongly related to perceptions of uncertainty. According to Milliken (1987), uncertainty in decision-making is the "perceived inability to predict something accurately" (p. 136). Uncertainty can stem from the perceived inability to predict stakeholders' behavior, changes in the environment, or the consequences of actions undertaken by entrepreneurs themselves (Milliken, 1987). McKelvie et al. (2011) show that actions taken by entrepreneurs are strongly influenced by their perceptions of uncertainty, specifically when it comes to "uncertainties related to the outcomes of their own actions" (p. 286). Indeed, while uncertainty and its perception by entrepreneurs depend heavily on characteristics of the environment that are beyond individuals' control, scholars have highlighted that there are components of this uncertainty that are mitigable through the acquisition of knowledge and skills (Griffin & Grote, 2020; Packard & Clark, 2019).

Therefore, offering entrepreneurs in emerging economies a training focused on strategic decision-making under uncertainty could be a fruitful way to increase their ability perceptions and ultimately improve business outcomes. In general, previous literature has shown how entrepreneurship training and educational initiatives are important means through which entrepreneurs can increase their perception of ability and raise their entrepreneurial intention (e.g., Bae et al., 2014; Martin et al., 2013; Souitaris et al., 2007). However, there is no evidence about whether trainings centered on strategic decision-making are effective in increasing entrepreneurs' perceptions of ability. More importantly, we do not know yet which decision-making approach could be more effective in doing so, and whether this has positive spillovers in an emerging economy setting.

2.4 Systematic approaches to decision-making and perceptions of ability

Strategy and entrepreneurship scholars have highlighted different approaches entrepreneurs can be trained to apply to mitigate perceived uncertainty when making key strategic decisions (Ott et al., 2017). Training centered on strategic decision-making are designed to equip entrepreneurs with knowledge and tools that can help them mitigate the uncertainty inherent in the development of new business propositions. In this study, we focus on two approaches grounded on experimentation and scientific principles that have been developed in recent years. On the one hand, *evidence-based* approaches emphasize the role of evidence-gathering and experimentation in mitigating uncertainty (Leatherbee & Katila, 2020; Ries, 2011). Among these, the "lean start-up" framework (Contigiani & Levinthal, 2019; Ries, 2011) is a popular approach that posits that entrepreneurs can mitigate uncertainty through quick iterative cycles that entail building prototypes of their solution and collecting customer feedback. As such, entrepreneurs who learn to apply an *evidence-based* approach develop new ideas by articulating hypotheses based on early concepts of their proposition, and testing them right away through interactions with potential customers and other stakeholders.

On the other hand, *theory-and-evidence* based approaches suggest that entrepreneurs should first engage with the cognitive effort of developing a "theory-of-value" behind their business, and only then conduct experiments and gather evidence to test such theory (Camuffo et al., 2020; Ehrig &

Schmidt, 2022; Felin & Zenger, 2009, 2017). The theorization effort allows entrepreneurs to develop a more holistic understanding of the causal logic behind business experiments, overcoming a main limitation of *evidence-based* approaches (Felin et al., 2019). According to *theory-and-evidence-based* approaches, only after a theory has been developed will the entrepreneur articulate testable hypotheses centred on the causal mechanisms underlying the value being created by a business proposition (Felin & Zenger, 2017). Differently put, entrepreneurs who learn to apply a *theory-and-evidence-based* approach spend time thinking about the overall logic behind their business idea, building a "theory-of-value" prior to experimentation.

Despite evidence that both these approaches can positively impact performance outcomes (e.g., Camuffo et al., 2020, 2021; Harms & Schwery, 2020; Leatherbee & Katila, 2020; Thomke, 1998), previous studies did not analyse the effect on intermediate outcomes, such as perceptions of ability. Both *evidence-based* and *theory-and-evidence-based* approaches to strategic decision-making under uncertainty teach entrepreneurs to address customer-related or market-related uncertainty by collecting systematic evidence to test assumptions and hypothesis. As such, both approaches should be effective in increasing entrepreneurs' perceptions of ability and in mitigating uncertainty.

The key questions are whether the two approaches have similar or different effects, and whether such effects persist over time. The *theory-and-evidence-based* approach nudges entrepreneurs to follow a more structured protocol when compared to the *evidence-based* approach. As such, it might be that entrepreneurs trained to follow such approach, being more systematic and considering several contingencies as part of their strategy development, feel more discouraged and hence have a milder increase in perceived ability levels when compared to entrepreneurs trained to follow an *evidence-based* approach. On the other hand, the *theory-and-evidence-based* approach adds theoretical reasoning as a crucial antecedent to experimentation. By developing a theory behind their business propositions, entrepreneurs develop a more holistic representation of the business and identify key areas of uncertainty. Entrepreneurs who learn to theorize are indeed provided with a wider set of tools and skills to reflect critically on different courses of action, and visualize how different factors can contribute to strategy (Felin & Zenger, 2017). This increased awareness, in turn, can have implications for their perceived ability to cope with different sources of uncertainty and carry out entrepreneurial activities. Indeed, by feeling better equipped to deal with complex decisions in a complex and uncertain environment, perceptions of ability of entrepreneurs trained to follow a *theory-and-evidence-based* approach should be higher compared to entrepreneurs trained with an *evidence-based* approach.

Between the two effects, we hypothesize that the latter has a stronger impact, resulting in a larger increase and more persistent effect of the *theory-and-evidence-based* training on perceptions of ability when compared to the *evidence-based* one[15]. In the remainder of this study, we test this assertion and also analyze the relationship between perceptions of ability, perceptions of control over future events and performance outcomes.

3. Empirical methods

3.1 Experimental Design

We conducted a randomized field experiment with 151 small entrepreneurs located in three regions of Tanzania (Morogoro, Pwani, and Dar Es Salaam). We partnered with a local educational institution to design and deliver an entrepreneurship training program targeting entrepreneurs operating in the Tanzanian agricultural sector. The free-of-charge training lasted about three months and included six half-day (24h total), in person-sessions every other week from October to December 2021. The sessions were delivered by local instructors recruited by our partner and carefully trained by the research team.[16]

[15] This hypothesis was pre-registered prior to the study. The pre-registration is available at: https://osf.io/5w4h9/

[16] The "instructors' training" was conducted online. We provided about 32 hours of training, covering all materials instructors taught in class. We ensured that instructors absorbed and mastered the content of both approaches by running mock lecturing sessions, providing them with additional case studies and progress checkpoints and arranging dedicated Q&A sessions.

Participants to our training program included aspiring and early-stage entrepreneurs (we refer to these as *startups*) as well as entrepreneurs with established companies that wanted to develop a new project (we refer to these as *companies*). Entrepreneurs were allocated to two main experimental conditions – an *evidence-based* condition and a *theory-and-evidence-based* condition – and then randomly assigned to smaller groups of about 15 participants. Each instructor in charge of teaching was assigned two groups, one for each experimental condition. The training curriculum in both conditions had the same length and structure, including the same topics taught in the same order. Entrepreneurs in both conditions learnt how to validate a business idea using tools that are well known and widely used in entrepreneurship and strategy courses, such as the Business Model Canvas (BMC), Customer Personas, or Customer Journey. They both learned the two phases of Problem and Solution validation and learned how to interview customers and how to build an MVP. Differences between the two experimental conditions lie in the decision-making approach taught to entrepreneurs.

3.2 Differences between the training conditions

The experimental conditions were designed to isolate the role of theory development as an antecedent to experimentation and guiding framework of the whole decision-making process. Entrepreneurs in the *evidence-based* condition were trained to apply a methodology that emphasizes quick validation rounds of business model assumptions and hypothesis testing by collecting customer data (e.g., through surveys or interviews with customers) and running Minimum Viable Product (MVP) testing (Leatherbee & Katila, 2020; Maurya, 2016; Ries, 2011). Instead, entrepreneurs in the *theory-and-evidence-based* condition were taught to ground their whole decision-making process on the development of a "theory-of-value", being that a key antecedent to experimentation efforts (Camuffo et al., 2020; Ehrig & Schmidt, 2022; Zellweger & Zenger, 2021).

To clarify the distinction, we provide a short explanation of the first two sessions of the training program. During the first session, entrepreneurs in the *evidence-based* condition were encouraged to draft a first version of their BMC, articulate hypotheses based on it, and start testing those hypotheses against their target market right away. Entrepreneurs in the *evidence-based* training were also taught to keep developing hypotheses on different aspects of their business idea and conduct multiple validation rounds over time. During the second session, they learnt how to refine such hypotheses by the means of additional tools (e.g., Customer Persona) and how to falsify them through customer interviews. On the contrary, in the first session of the *theory-and-evidence-based* condition, hypothesis testing is not mentioned. Entrepreneurs learn how to develop a "theory-of-value" in the form of a logical "story" of their business idea. They identify key elements and create logical and causal connections between them, forming a holistic representation that goes from the observations about a phenomenon to the potential solution. During the second session, they are taught to refine their theories by the means of additional tools, and to leverage customer interviews to get deeper knowledge of the decision domain. Only in the third session, entrepreneurs in the *theory-and-evidence-based* condition are taught how to develop hypothesis and how to test them. We provide detailed examples and the training syllabus in Section S3.1 of the Supplementary Materials.

3.3 Application process and randomization

We advertised a call for application to the training program through online and offline channel in April 2021, leaving it open for three months. We targeted two types of entrepreneurs: early-stage entrepreneurs developing a novel business idea (*startups*) and entrepreneurs with running companies developing an innovative project (*companies*). Entrepreneurs were required to be located in the regions of Morogoro, Dar es Salaam and Pwani, for cost and logistical reasons. Applicants were asked to complete an application survey and a phone interview with purposefully trained Research Assistants (RAs)[17]. We recruited 202 applicants, 130 startups and 72 companies. We

[17] All Research Assistants received about 12 hours of training administered online by the three authors before conducting these interviews. The aim of this training was to explain the research protocol, data collection methods, and coding procedures to the RAs. We ensured that the RAs mastered the content of the training by conducting both in-class as well as at-home exercises, and providing personalized feedback and additional examples. Moreover, we created a direct communication tool (*i.e.,* a group chat on a mobile application) between the RAs and the research

could not admit to the training 37 applicants that were located outside the three targeted regions, reducing the valid applicant pool to 165 entrepreneurs. Each applicant indicated a preferred training location (Morogoro or Dar es Salaam), since we offered parallel training sessions in both locations to ease travelling and maximize compliance. We randomly allocated entrepreneurs within location to different experimental conditions, given capacity constraints (90 slots in Morogoro, 60 in Dar es Salaam). After randomization, we took two steps to ensure the internal validity of our study. First, to minimize contamination risks, we allocated entrepreneurs who declared knowing each other (and thus more likely to potentially exchange training materials and discuss outside classrooms) to the same treatment condition.[18] Second, we made three manual adjustments, not affecting the research design.[19] The final allocation included 151 entrepreneurs: 76 in the *evidence-based* condition (33 in Dar-es-Salaam, 43 in Morogoro), and 75 in the *theory-and-evidence-based* condition (31 in Dar, 44 in Morogoro). The remaining 51 entrepreneurs were allocated to a *control* group that did not follow any training but agreed to provide data in exchange for access to three post-training events that were organized to lower attrition in the data collection process. Since this *control* group is non-random and suffers from selection bias (37 entrepreneurs were automatically moved in this group based on their location), we cannot make causal claims when comparing it to the two training conditions. Nevertheless, we use its data as a comparative benchmark without making any causal claim.

Section S3.2 in the Supplementary Materials shows balance checks both within and across locations. The two experimental groups are well balanced on almost all the observable variables at

team to solve issues or questions in real time. Additional meetings were held throughout the program to verify the quality of data collection efforts.

18 Moving participants after the randomization lowered the risk of randomization failures. If by chance people belonging to a pair/group of friends were already allocated to the same experimental condition, we did not make any change.

19 These manual adjustments occurred from misunderstanding of instructions by three entrepreneurs regarding their allocation, resulting in their showing up for the wrong sessions. Specifically, one entrepreneur not admitted to training showed up to Session 1 for the *evidence-based* group, one entrepreneur assigned to *theory-and-evidence-based* training showed up to the *evidence-based* session, and one entrepreneur assigned to the *evidence-based* training showed up for the *theory-and-evidence-based* session..

the baseline, with only minor unbalances which we control for in all models. Despite the difference in locations, also the *control* group appears to be balanced on observables. However, due to the non-random selection of entrepreneurs in the *control* condition, our causal inferences are centered on comparing entrepreneurs across the two training conditions only (N = 151). Section S3.3 in the Supplementary Materials discusses attrition and non-compliance issues.

3.4 Data Collection Process

Our data collection process lasted from April 2021 (baseline) to July 2022 (last interview conducted) and included six data collection rounds. To keep participants engaged with the data collection, we organized three events after the training program ended. We provided all participants that completed the program and participated to the data collection an official certificate. Notably, events were not part of our treatment and as such all participants were invited to attend, including those in the *control* group.

At each round of data collection, entrepreneurs completed a questionnaire followed by a phone interviewed conducted by RAs. The questionnaire asked for information on the project status, performance, perceptions of abilities and entrepreneurs' traits. Phone interviews were focused on entrepreneurs' decision-making activities and additional, qualitative information about their business goals and challenges faced. Considering the *control* group too, we collected 972 online surveys and 944 interviews over time, corresponding to a 76% response rate for the survey and a 73% response rate for the interviews. Considering only treated entrepreneurs (N = 151), the above rates increase to 83% and 79%. Moreover, 77% of treated entrepreneurs replied to at least 5 out of 6 survey sessions and 72% to at least 5 out of 6 interviews. As a robustness check, we also run analyses on the subsample of respondents replying to at least 5 datapoints.

3.5 Main variables: entrepreneurs' perceptions

Our pre-registered analysis is centered on entrepreneurs' perceptions of ability to deal with potential challenges faced during the development of their business ideas. In the questionnaire, we showed entrepreneurs a list of nine factors including: 1) Accessing inputs (e.g. new equipment, land, machineries); 2) Government policies and regulation (e.g. taxation, bureaucracy, support programs); 3) Accessing reliable infrastructure (e.g. internet, electricity, office spaces); 4) Accessing financial capital; 5) Accessing workforce; 6) Identifying the right customers/market; 7) Knowing who my competitors are; 8) Knowing what my customers want; 9) Developing my business strategy.

As we detail in Section 4, these factors largely overlap with challenges mentioned by entrepreneurs in the phone interview, where an open-ended question was asked by RAs. Nevertheless, these nine factors were chosen both by relying on existing surveys (e.g., the Global Entrepreneurship Monitor), but mostly by discussing them with the local Tanzanian team. In addition, we ran a pilot survey and gathered qualitative feedback from a small sample of entrepreneurs and students from the local partner, validating the importance of the nine factors presented in the questionnaire.

We took a further step and pre-registered a categorization of these factors into *project-related* and *environmental* ones. Specifically, factors 1 to 5 are categorized as *environmental*, while factors 6 to 9 are categorized as *project-related*. Importantly, this distinction was not mentioned to entrepreneurs in the questionnaire or to RAs. This categorization reflects the idea that these factors, when perceived as challenging by entrepreneurs, represent sources of uncertainty. As highlighted by McKelvie et al. (2011), uncertainty does not stem only from characteristics of the environment and uncertainty perceptions are influenced by actors' skills and expertise. Specifically, our goal was to distinguish between factors that are in principle controllable by the entrepreneur, that is directly mitigable, from those that are instead an intrinsic characteristic of the environment. In this sense, our list of nine factors comprises both items intrinsic to the environment (e.g., the reliability of the infrastructure) and items that are idiosyncratic to the business proposition of each entrepreneur and their abilities (e.g., knowing their customers' needs or competitors). While the boundary between the two might be blurry, the pre-registration ensures that the categorization is not driven by empirical results.

For each of the nine factors, we asked entrepreneurs to rank their ability in dealing with them as challenges on a scale from 1 (not able at all) to 7 (very able). Our main dependent variable, *perceived ability*, is the average of the nine scores. The Cronbach alpha for internal consistency, considering all six observation periods, is of 0.77. We then build two separate ability indicators, again as averages, but for the two subsets of factors pertaining to the *project-related* (alpha = 0.82) vs *environmental* (alpha = 0.70) categorization.

We also asked respondents to indicate, among the nine displayed, the top-3 challenging factors at each point in time. We use this information to build the *share of environmental challenges*, as the ratio of the top-3 sources of challenges that fall within the *environmental* category.

To measure perceptions of control over future events, we borrow from established scales in the entrepreneurship literature about locus of control and illusion of control (Keh et al., 2002; Simon et al., 2000). We measure *perceived control* as the simple average of four 1-7 (Disagree-Agree) items: 1) I could succeed at making this business a success, even though many others would fail; 2) If I am in charge, my skills would be the most important determinant of success of my new business; 3) I can accurately forecast when larger competitors will enter the market; 4) I can accurately forecast the most relevant future trends related to my business idea. Our goal was to capture the extent to which entrepreneurs perceive themselves as able to deal with uncertain future events, in line with the conceptualization by Milliken (1987). Cronbach alpha for the composite score is of 0.76.

Finally, we complemented quantitative information from survey data with qualitative evidence collected through phone interviews conducted by the RAs. In the phone interview, entrepreneurs were asked to explain what goals they wanted to achieve with their venture, and then asked up to three challenging factors they thought would prevent them from achieving those goals, without any pre-defined list to choose from. We manually classify them in broader categories to gather qualitative evidence on the context under analysis, as discussed in Section 4.

3.6 Additional variables: performance

We run exploratory analyses on performance using collected data on revenue and profits. Specifically, we consider the cumulative revenue and profit made by entrepreneurs between the baseline and the last data point. Amounts were converted from the local currency to US$. We also consider the average amount of revenue and profit recoded between each datapoint as an alternative outcome. To avoid the impact of outliers, and given our relatively small sample size, we winsorize both variables at the 95th percentile of the within-period distribution and exclude from our analyses four outlier firms that showed exceptionally high revenue (3 in the *theory-and-evidence-based* group and 1 in the *evidence-based* group).

3.7 Independent variable and additional variables

Since the goal of the experimental design is to compare entrepreneurs in the *evidence-based* condition with those in the *theory-and-evidence-based* condition, our main independent variable *theory-and-evidence-based condition* is a dummy taking value 1 when entrepreneurs are in the latter condition. This allows us to retrieve the intent-to-treat (ITT) effect. In all specifications, we add controls related to variables unbalanced after randomization. Controls include dummies for *tertiary education*, *gender* and *whether another training course has been attended in the past*, *number of hours worked on the business project* at the baseline, and entrepreneurs' self-reported *likelihood of introducing major changes at the baseline*. We also add a dummy controlling for the *type of firm*, i.e., startup or company, and dummies for *instructors*.

Table 3.1 provides descriptive statistics on the sample (Panel A) and for the variables described in this section at the baseline (Panel B). For balance checks please refer to Section S3.2 of the Supplementary Materials.

Table 3.1 – Sample descriptives

Panel A: sample characteristics

Entrepreneur characteristics	Evidence-based	Theory-and-evidence-based	All (treated)	All (with control group)
Gender = male (dummy)	68%	56%	62%	66%
Tertiary education (dummy)	78%	81%	79%	83%
Business degree (dummy)	.12%	6.7%	9.3%	11%
Other business course (dummy)	63%	63%	63%	61%
Respondent age	31.4	32.9	32.1	32
Work experience (years)	4.9	6.5	5.7	5.7
Work experience in agriculture (years)	2.9	3.3	3.1	3.2
Managerial experience (years)	3.2	3.5	3.3	3.6
Entrepreneurial experience (years)	3.7	4.0	3.8	3.9
Working full time in company (dummy)	57%	57%	57%	58%
Respondent is founder (dummy)	90%	95%	92%	93%
Company/Startup characteristics				
Share of startups	66%	64%	65%	64%
For-profit business (dummy)	92%	95%	93%	92%
Registered business (dummy)	37%	29%	33%	35%
Founding team size	1.9	2.0	1.9	2.1
Total employees (with founders)	6.4	7.4	6.9	7.1

Panel B: main variables

Baseline values	Evidence-based	Theory-and-evidence-based	All (treated)	All (with control group)
Perceived ability (all factors)	4.6	4.3	4.452	4.4
Perceived ability (project-related factors)	5.2	4.9	5.079	5.0
Perceived ability (environmental factors)	4.1	3.8	3.95	3.9
Share of project-related challenges	68%	72%	69%	69%
Perceived control	5.5	5.4	5.4	5.5
Revenue (95^{th} winsorized)	743.4$	985.1$	863.5$	914.1$
Profits (95^{th} winsorized)	-254.7$	-292.7$	-273.6$	-239.8$
Observations	76	75	151	202

4. Study context: agricultural entrepreneurship in Tanzania

Tanzania is one of the largest countries in East Africa, and one of the fastest growing economies in the Sub-Saharan Africa with a GDP growth of about 4.3% in 2021[20] (World Bank, 2022). This steady growth has granted the classification of Tanzania as a "lower middle-income country" according to the World Bank. However, its per-capita GDP ($1,136) is still lower than the average one for Sub-Saharan countries ($1,550). The main economic sector in the country is agriculture, which accounts for about 30% of the GDP and 65% of the workforce employment (Statista, 2023). Nearly half of the adult population in emerging economies is estimated to engage in entrepreneurial

[20] Macro-economic data retrieved from the World Bank (https://www.worldbank.org/en/country/tanzania/overview) and the Tanzanian Invest institutional website (https://www.tanzaniainvest.com/economy).

activities (United Nations Conference for Trade & Development, 2018) and Tanzania makes no exception with roughly 54% of the total employment accounted by "own account" workers (Statista, 2023).

Our dataset allows to gather novel information about the entrepreneurial environment in Tanzania, specifically related to the challenges faced by entrepreneurs and their business goals. Official statistics describe an environment that is not easy to navigate. For instance, the World Bank's "ease of doing business" indicator ranks Tanzania 141 out of 190 countries, and its entrepreneurial ecosystem is described to be growing, especially with respect to foreign direct investments in the last years, but faced with "significant challenges that can impede entrepreneurship" (Galperin & Melyoki, 2018: 51). The novel statistics we provide are not meant to be representative of the whole Tanzanian population of entrepreneurs. Indeed, our study has been conducted targeting three specific regions in Tanzania: Morogoro, Pwani and Dar es Salaam[21]. Nevertheless, they provide suggestive and unique evidence of the entrepreneurial environment, also given the lack of coverage of Tanzania in larger studies such as the Global Entrepreneurship Monitor.

We show data collected at the baseline, that is before the experiment took place, for all the 202 entrepreneurs that initially applied to our business training program, thus also including entrepreneurs in the non-random *control* group. Again, most of the entrepreneurs (165) declared to be resident in one of the three targeted regions, while 37 were living in other Tanzanian regions. As described in Table 3.1 in previous section, applicants to the program are mostly man (67%) and highly educated, with 83% declaring having tertiary education and 61% declaring having attended at least another business training course. The average age is of around 32 years old, and

[21] Morogoro and Pwani are rural regions, with respectively 2.2 and 1.1 million inhabitant and a population density of 31 and 34 people per squared km. Dar es Salaam is considered to be the economic center of the whole country, with a population of 4.3 million inhabitants and a population density of 3,133 people per squared km (Tanzanian Statistical Office, 2021).

they declare an average work experience of 5.7 years, of which 3.2 spent in the agricultural sector. Most entrepreneurs work full time on the startup idea or at the company presenting an innovative project. Only 15% of them declare not working full time on the project and not conducting other activities (e.g., studying or being employed in another entity). In basically all cases, the entrepreneur attending the program is also the founder of their company or startup.

When it comes to business characteristics, entrepreneurs in our sample are mostly working to develop for-profit entities that however operate informally: indeed, only 35% of the startups/companies are declared to be registered. The average founding team size is of 2 people, whereas the total number of employees averages around 7 people (including founders), according to baseline data. The focal offering under development in the course is a tangible product in around 50% of the cases, while purely service-based companies are the minority. Agricultural entrepreneurs in our sample offer products or a combination of products and services and operate in farm production, processing, marketing & logistics. The bulk of activities are about fruit and vegetable farming, maize cultivation, and chicken rearing, as shown in Figure 3.1, representing a word cloud of the most frequent words used by entrepreneurs to describe their business ideas during phone interviews with RAs.

Figure 3.1 – Word-cloud from business descriptions

To give some examples, one company that applied to the program produces around 10 liters of yoghurt per day and wanted to introduce new products and double its production capacity. Another entrepreneur described her business as a "horticultural farming and livestock keeping" company whose goal was to enter new markets and develop new products she could export. Another entrepreneur wanted to open a green bean farm after receiving advice from a friend. Her goal was to understand the right customer target (e.g., retailers or final customers) and which type of bean to produce. Other than pure farming ideas, examples of startups related to agricultural services include ideas such as a "farming park" where people could interact with animals and access veterinary services, the production of environment-friendly bags to replace plastic, or a small bakery focused on cake-production.

During the application process, entrepreneurs replied to a structured interview where we asked, among other information, what were their three main business goals and the three main challenges preventing them to reach their goals[22]. We manually coded such information into narrower categories, to better gauge what were their expectations and troubles. We start by analyzing goals: Figure 3.2 shows the share of entrepreneurs per goal category at the baseline observation round.[23]

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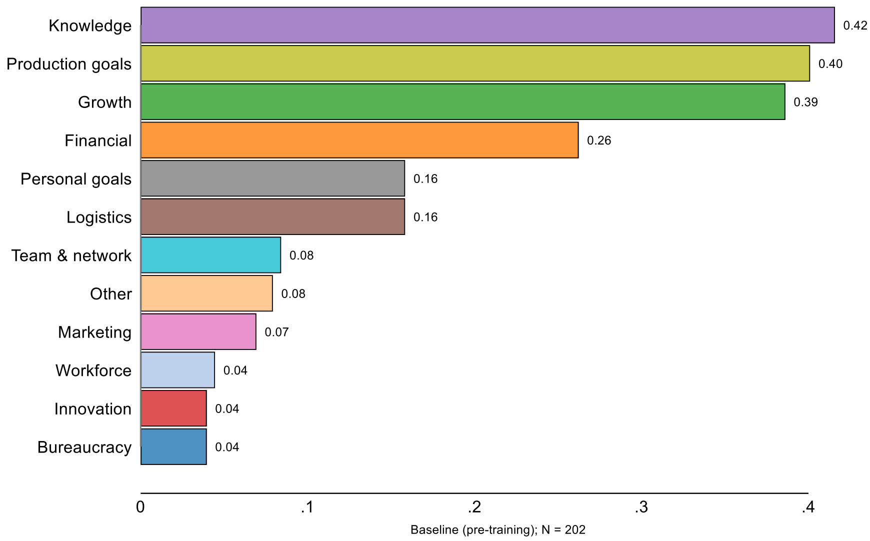
[22] Specifically, RAs asked an open-ended question to entrepreneurs to indicate "*the three most important things they would like to focus on with regards to their business idea in the next three months*" and the "*most important challenges that would prevent you from reaching these goals?*".

[23] We categorized goals as follows. *Production:* goals related to production and supply of materials/technologies; *Marketing:* goals related to marketing and advertising; *Workforce*: goals related to finding employees; *Logistics:* goals related to logistics (offices, transportation, infrastructure); *Knowledge*: goals related to skill updating, market/customer knowledge etc.; *Innovation:* goals related to the introduction of new processes/products/technologies; *Personal:* goals related to personal ambition; *Growth:* goals related to general firm growth (e.g. expanding market); *Financial:* goals related to obtaining finance; *Team and network:* goals related to team or network creation; *Bureaucracy*: goals related to business registration and other bureaucratic milestones.

Figure 3.2 – Share of entrepreneurs mentioning business goals

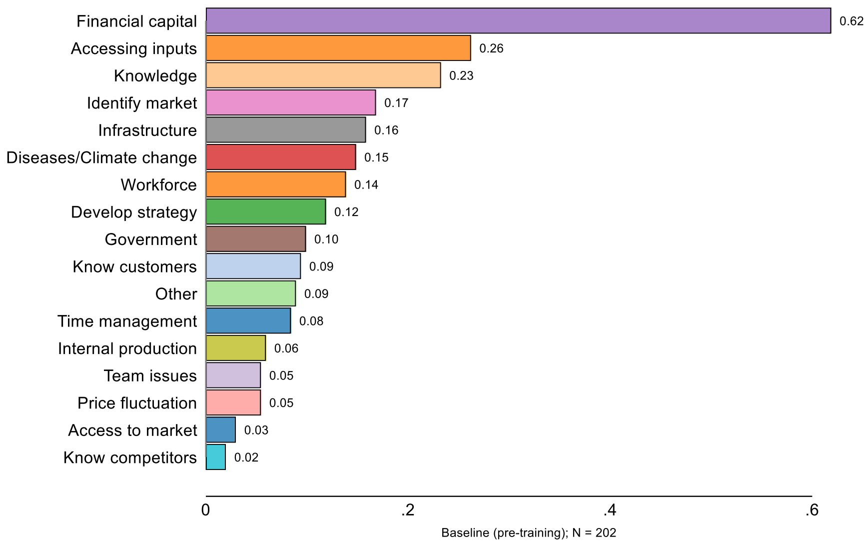


Entrepreneurs in our sample are mostly growth and knowledge oriented: they aim at kickstarting the activities, scaling-up or accessing new markets. Nevertheless, while the bulk of goals are related to operational aspects of the business (e.g., logistics, financials, marketing, production), 42% of entrepreneurs indicate skill upscaling and training as one of their top-3 goals. Despite the sample at our disposal declared to be highly educated, there is the need to obtain business- and agricultural-specific skills.

It is also interesting to compare entrepreneurs given their region of activity. Compared to the average results on the full sample, entrepreneurs in Pwani or Morogoro are more likely to focus on goals related to production (e.g., start farming; get quality seeds; execute projects) and less growth oriented (e.g., market expansion; increase customers; improve product; expand the business). Knowledge goals (e.g., do market research; increase skills; finalize idea; review business plan) are instead more common within Dar es Salaam entrepreneurs. This could reflect differences across regions in terms of education and business opportunities.

Figure 3.3 focuses on the challenges mentioned in the interviews. Again, we manually coded the transcriptions to identify narrower categories.

Figure 3.3 – Share of entrepreneurs per potential challenge (interview)



The most concerning challenge to business development is access to financial capital (mentioned by 62% of entrepreneurs, with a peak of 68% for entrepreneurs located in Morogoro and Pwani), followed by issues in accessing inputs and gathering the relevant knowledge needed to effectively run a business or properly conduct farming activities. Reading Figures 1 and 2 together offers a stylized picture of a vibrant and growing entrepreneurial environment that is however limited by challenges that can directly impede reaching the stated goals. Knowledge gathering is a clear example: 42% of entrepreneurs declared that to be one of their main goals, but 23% of them also stated how difficult it is to get proper training. Similarly, production goals are obviously at the top of the priorities, but difficulties in accessing inputs or gathering the necessary funding to kickstart operations can significantly hamper production efforts.

As explained in Section 3, we also developed a survey measure to understand the top-3 challenging factors faced by entrepreneurs, narrowing them down to a list of nine pre-determined factors. Figure 3.4 shows the share of entrepreneurs choosing each factor.

Figure 3.4 – Share of entrepreneurs per potential challenge (survey)

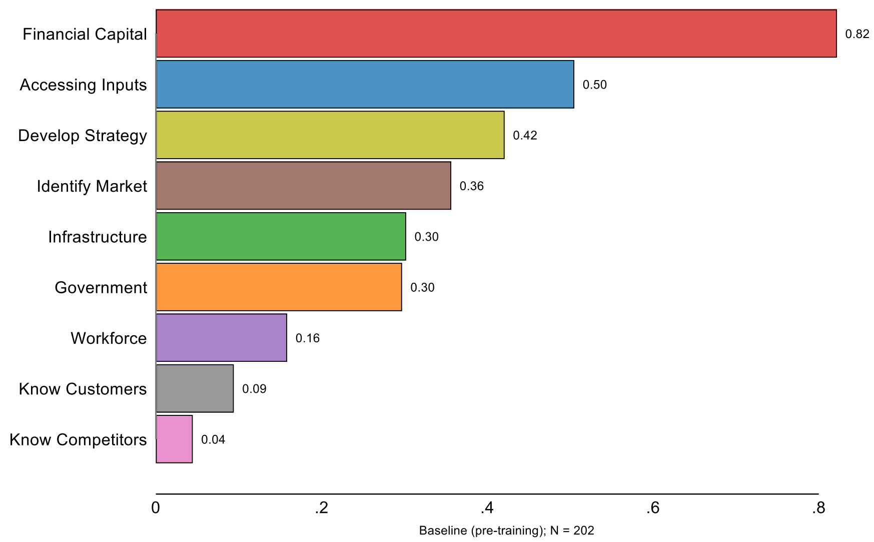


Figure 3.4 offers a representation coherent with Figure 3 based on the open-ended questions, thus offering a validation of the nine factors we chose to include in the questionnaire. Financial matters are deemed to be the most prominent barrier, followed by difficulties in accessing inputs and in developing their own strategy, the latter being referrable to the "knowledge" barrier. With that respect, following a pre-registered specification, we grouped these nine factors in two categories: *project-specific* factors and *environmental* factors.[24] Out of the three factors chosen by entrepreneurs as challenging in the baseline questionnaire, on average 70% (i.e., 2 out of 3) are related to *environmental* factors. This signals how factors perceived to be prominently difficult to address are mostly related to characteristics of the environment, rather than factors related to the development of the internal strategy.

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[24] We repeat here the categorization detailed in Section 3. *Environmental* factors: 1) Accessing inputs (e.g. new equipment, land, machineries); 2) Government policies and regulation (e.g. taxation, bureaucracy, support programs); 3) Accessing reliable infrastructure (e.g. internet, electricity, office spaces); 4) Accessing financial capital; 5) Accessing workforce.
Project-related factors: 1) Identifying the right customers/market; 2) Knowing who my competitors are; 3) Knowing what my customers want; 4) Developing my business strategy.
Importantly, we did not mention the distinction between the two categories in the survey.

The overall picture that emerges from our data is that of an entrepreneurial environment and ecosystem that are perceived as rich in opportunities. At the same time, entrepreneurs in our sample declared a lack of adequate access to both financial resources and production inputs, and a lack of sufficient knowledge on both the business strategy and agricultural/operational sides. Contrary to common knowledge, our data shows that government policies and regulations are not seen as the most prominent obstacles: the most complex matter in this area seems to be related to business registration, which comprises many different categories (i.e., local, national, or presidential registration). Indeed, as stated before, only 35% of entrepreneurs in our sample declares to have registered their businesses, with 65% running operations informally.

5. Econometric analysis

Studying entrepreneurs' perceptions of ability is important to understand entrepreneurs' attitude and behavior in a challenging context such as the one depicted in the previous section. We are primarily interested in understanding whether entrepreneurs trained to adopt a systematic approach to decision-making based on theoretical reasoning (the *theory-and-evidence-based* condition) increase their *perceived ability* to deal with potentially challenging factors more than entrepreneurs trained with a systematic approach solely based on evidence gathering (the *evidence-based* condition). We then study the relationship between entrepreneurs' *perceived ability,* their perceptions of control over future events (*perceived control)* and business performance.

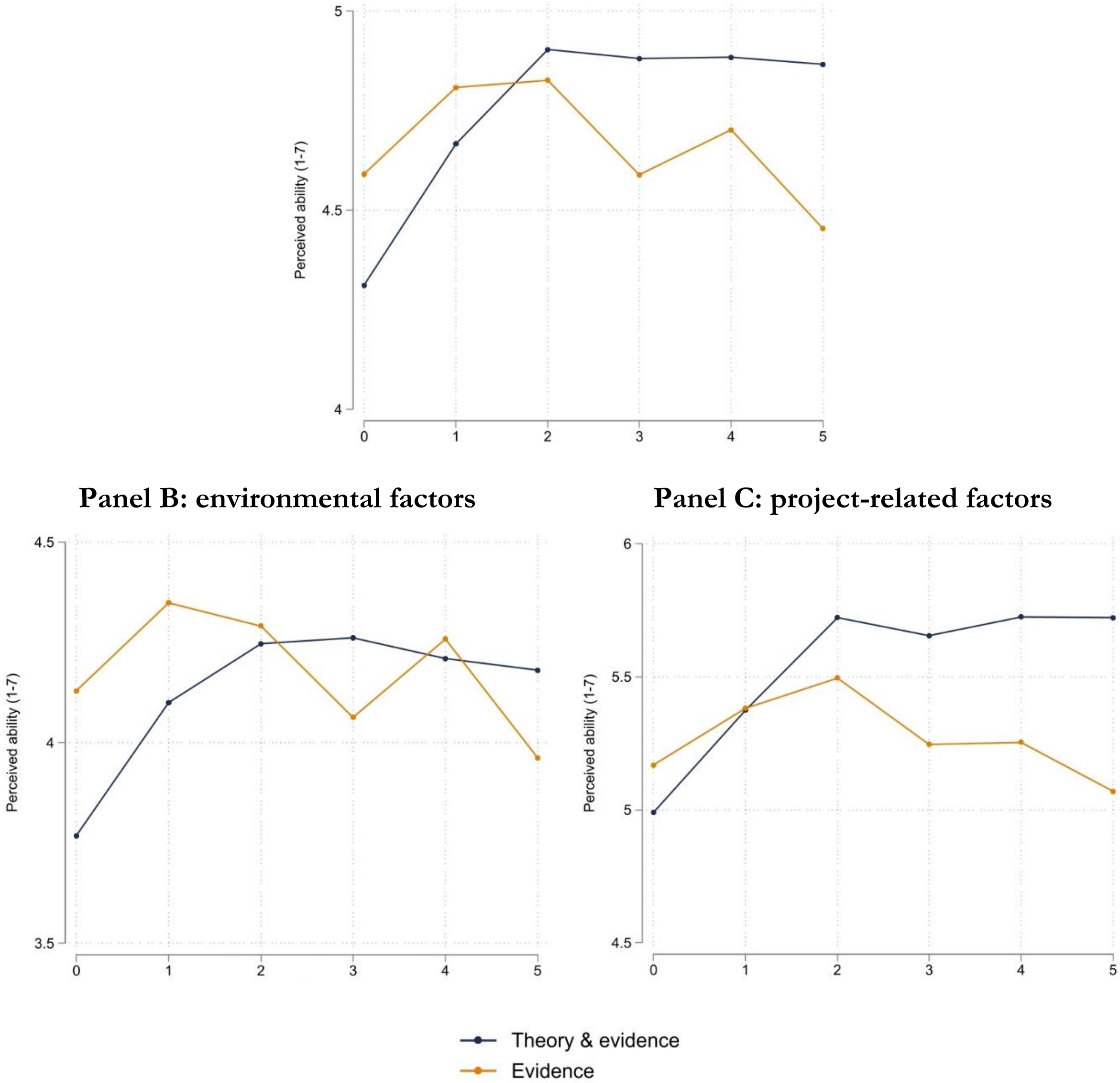
5.1 Systematic approaches and perceived ability

We begin by testing whether training entrepreneurs with a *theory-and-evidence-based* approach increases their *perceived ability* scores significantly more than for entrepreneurs trained with an *evidence-based* approach. Figure 3.5 displays the panel trend of the *perceived ability* variable considering all nine factors together (Panel A), *environmental* factors only (Panel B), and *project-related* factors only (Panel C).

Figure 3.5 – Entrepreneurs' perceived ability

Panel A: all factors

Panel B: environmental factors **Panel C: project-related factors**



The average *perceived ability* to deal with challenges stemming from *environment-related* factors is lower than the perceived ability to deal with challenges from *project-related* factors across all data points[25]. This is consistent with our categorization, considering that the former measure is related to factors outside entrepreneurs' direct control. Graphical results suggest that entrepreneurs trained with the

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[25] Taking baseline values as benchmark, the average perceived ability score (1-7 scale) for challenges stemming from project-related factors is 5.01, while the one for environment-related factors is 3.93 (two tailed t-test, $t = 10.77$, $p < 0.001$).. Looking at period 2, the average for the project-related ability is 5.55, while the environment-related perceived ability averages a significantly lower 4.24 (two tailed t-test, $t = 9.77$, $p < 0.001$).

theory-and-evidence-based approach report a higher *perceived ability* to deal with potential challenges arising from our list of factors. Even though we observe an increase in the perceived ability score across groups during the training (Panel A, periods 1-2) that seems to remain stable over time after the training for the *theory-and-evidence-based* condition (periods 2-5), results for the *evidence-based* condition are unclear and show higher fluctuations.

The latter seems particularly true for *project-specific* factor (Panel C). After the training (periods 2-5) entrepreneurs in *theory-and-evidence-based* condition report a significantly higher perceived ability score when compared to the *evidence-based* condition. This higher perception score seems to be persistent over time, while entrepreneurs in the *evidence-based* condition seem to experience a decrease of their perceived ability score over time and return to the baseline level at the end of our observation period (period 5).

Regression results in Table 3.2 confirm the differences between the two experimental conditions. For each *perceived ability* measure, the first two models are difference-in-differences regressions with respect to the baseline period. Model 1 considers all firms; Model 2 excludes entrepreneurs for which only baseline data is available through a fixed-effect regression. Model 3 consider only the post-baseline periods. Boundary analyses (Kling et al., 2007) are displayed.

Table 3.2 – Regression results on perceived ability

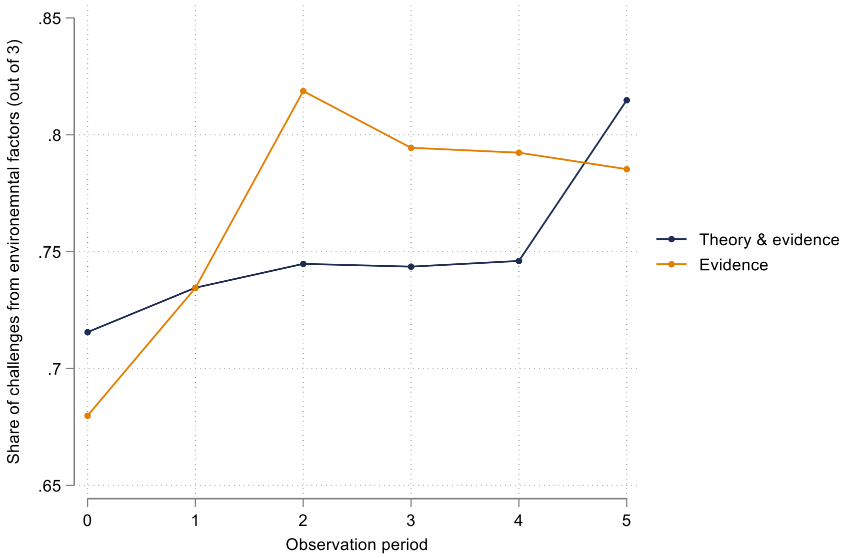
DV	All factors			Environmental factors			Project-related factors		
Model	(1) DiD	(2) DiD (FE)	(3) Post-baseline	(1) DiD	(2) DiD (FE)	(3) Post-baseline	(1) DiD	(2) DiD (FE)	(3) Post-baseline
Theory & evidence	0.48*	0.69**	0.19	0.41^	0.67**	0.03	0.57*	0.71**	0.39**
	(0.21)	(0.21)	(0.12)	(0.24)	(0.24)	(0.17)	(0.25)	(0.25)	(0.15)
Observations	752	736	601	752	736	601	752	736	601
R-squared	0.09	0.48	0.10	0.07	0.52	0.08	0.07	0.43	0.07
SE	firm	firm	firm	firm	firm	firm	firm	firm	firm
Controls	YES	NO	YES	YES	NO	YES	YES	NO	YES
Firm FE	NO	YES	NO	NO	YES	NO	NO	YES	NO
Period FE	NO	YES	YES	NO	YES	YES	NO	YES	YES
Boundary analyses (N=906)									
Lower bound	0.24	0.24	-0.05	0.12	0.12	-0.65^	0.27	0.27	0.09
Upper bound	0.65**	0.65**	0.37***	0.64**	0.64**	0.27^	0.79**	0.79***	0.62***

DVs: perceived ability scores (1-7)
Model 1 estimates a difference-in-differences regression with respect to the baseline value. Model 2 performs the same estimation, using firm and period fixed effects, thus dropping observations with baseline data only. Model 3 excludes baseline values. Controls include: education (dummy =1 if the entrepreneur has tertiary education), gender, hours worked at the baseline, firm type (startup or company), perceived probability of introducing major changes at the baseline and instructors dummies.
Standard errors are clustered at the entrepreneur (firm) level reported in parentheses. Boundary analyses report the coefficients on the treatment dummy from the same models, using as DVs the scores with attrition values replaced accordingly to Kling et al. (2007). Robustness checks and results with the non-random *control* group are reported in the Supplementary Materials.
*** p<0.001, ** p<0.01, * p<0.05, ^ p<0.1

The difference-in-differences results (Models 1 and 2) find a significant increase with respect to the baseline values for all the ability scores, regardless of the factors considered. The more robust results, however, significant also when focusing only on the post-baseline period, are found for the measure related to *project-related* factors. Compared to the *evidence-based* condition, entrepreneurs in *theory-and-evidence-based* condition experience additional increase in their perceived ability towards *project-related* factors of about 11% in the post-baseline period. In the Supplementary Materials (S3.4) we report robustness checks, also including the non-random *control* group, obtaining consistent results. Particularly, we find that differences with respect to the *control* group are more marked for the *theory-and-evidence-based* condition, especially when considering *project-related* factors. In the same section, we also report results of analyses conducted on the nine factors separately.

Next, we analyze whether there are differences with respect to the prominence of *environmental* factors with respect to *project-specific* ones, by looking at the share of the former in the top-3 challenging factors chosen by entrepreneurs in the questionnaire out of the nine proposed. Figure 3.6 shows how the share seems to be rather stable over time, with a slightly increasing trend for the *evidence-based* group in the first two periods. Nevertheless, we do not find evidence of significant changes in the prominence given to one or the other type of challenging factors by entrepreneurs. This signals how *environmental* factors seem to be the most prominent source of challenge among our entrepreneurs.

Figure 3.6 – Share of environmental factors on the top-3 challenging factors



Taken together, these results indicate that entrepreneurs that receive a *theory-and-evidence-based* training report a higher perceived ability to cope with potential challenges arising from *project-related* factors that can affect the development of their ventures, while this effect does not seem to hold as strongly for *environmental* factors over which entrepreneurs have a limited degree of control. Regardless of the change in perceived ability, over the whole observation period entrepreneurs in both experimental conditions consider as more prominent challenges stemming from *environmental* factors.

5.2 Exploratory analyses: Ability scores and perception of control

We now turn to an exploratory analysis to understand whether *perceived ability* scores are positively correlated with *perceived control* scores. This analysis speaks directly to our conceptual framing and serves the purpose of understanding whether entrepreneurs that perceive themselves as being better able to face potential challenges are also perceiving themselves as better equipped to predict and deal with uncertain future events. All regressions in Table 3.3 have *perceived control* score as the main dependent variable: Model 1 tests whether there are differences between the two experimental conditions using a difference-in-differences model with respect to the baseline. Models 2 and 3 run an OLS regression on the panel, using *perceived ability* scores as the main independent variables. Models 4 to 7 run first-differences regressions, to analyze whether changes in *perceived ability* scores are associated with changes in *perceived control* scores.

Table 3.3 – Perceived control and perceived ability

DV	Perceived control (1-7)						
Model	(1) DiD	(2) Pooled OLS	(3) Pooled OLS	(4) First Difference	(5) First Difference	(6) First Difference	(7) First Difference
Theory and evidence	0.12						
	(0.21)						
Ability (all)		0.27***		0.17**	0.16**		
		(0.05)		(0.06)	(0.06)		
Ability (project-related)			0.24***			0.10*	0.10*
			(0.04)			(0.05)	(0.05)
Ability (environmental)			0.04			0.06	0.06
			(0.04)			(0.05)	(0.05)
Observations	752	752	752	571	571	571	571
R-squared	0.07	0.14	0.16	0.04	0.05	0.05	0.05
SE	firm	firm	firm	firm	firm	firm	firm
Controls	YES	YES	YES	NO	YES	NO	YES
Period FE	NO	YES	YES	YES	YES	YES	YES

DVs: perceived control scores (1-7)
Model 1 estimates a difference-in-differences regression with respect to the baseline value, to check whether there are differences between experimental conditions. Models 2 and 3 perform a pooled OLS regression with period dummies correlating the perceived control scores with perceived ability scores. Models 4 to 7 perform first differences OLS regressions, with and without controls.
Controls include: education (dummy =1 if the entrepreneur has tertiary education), gender, hours worked at the baseline, firm type (startup or company), perceived probability of introducing major changes at the baseline and instructors dummies.
Standard errors are clustered at the entrepreneur (firm) level reported in parentheses. Results robust to the inclusion of the control group, and to alternative specifications (Appendix D.3).
*** p<0.001, ** p<0.01, * p<0.05, ^ p<0.1

Results show how there are no differences between the two experimental conditions (Model 1), implying that there are no direct effects of the *theory-and-evidence-based* training on the perceived control that entrepreneurs have over future events, with respect to the *evidence-based* condition. However, all the models correlating the *perceived control* and the *perceived ability* scores show positive correlations. From Model 2, a unit increase in the *perceived ability* score is associated with a 0.27 unit increase in the *perceived control* score (5% marginal increase in relative terms).

Interestingly, Models 3 and 7 show how this relationship is larger and statistically significant when considering the *perceived ability* to deal with challenges stemming from *project-related* factors. Theoretically, this points out to the fact that entrepreneurs perceive themselves as better able to deal with uncertain future events when feeling more able to deal with potential challenges stemming from "internal" problems (*project-specific*), rather than "external" ones (*environmental*). This implies that higher perceptions of control is not due to a potentially irrational belief in the controllability of exogenous factors, such as the presence of poor regulation. Rather, it is coherently associated with a larger confidence in one's skills towards endogenous factors, such as being better equipped to develop a business strategy. We discuss this result further in the discussion section.

5.3 Exploratory analyses: Ability scores and performance

Finally, we analyzed the relationship between *perceived abilities* and performance metrics. We run both cross-sectional and panel models. For the former, we consider as dependent variables the *total amount of revenue* and *profits* (US$) recorded by each entrepreneur between the first and the last post-baseline observations, and the *average revenue* and *profits* recorded between each observation period. The main independent variable for these cross-sectional models are *averages* of the *perceived ability* scores. For panel models, we regress *cumulative revenue* and *profits* in each period on the contemporaneous *perceived ability* scores. All performance measures have been winsorized at the 95th percentile of the within-period distribution and models exclude four outlier firms with exceptionally large revenue (three of which in the *theory-and-evidence-based* group). Tables 3.4 and 3.5 reports results for the cross-sectional and panel models respectively. We run models considering only treated entrepreneurs: in Appendix D.4 we re-run all the models including entrepreneurs in the control group.

Table 3.4 – Performance and perceived ability (cross-section)

DV	(1) Total revenue	(2)	(3) Average periodic revenue	(4)	(5) Total profit	(6)	(7) Average periodic profit	(8)
Ability (all)	2,146.20^		179.34		271.18		-76.08	
	(1,119.27)		(165.98)		(742.29)		(177.33)	
Ability (project-related)		2,104.72**		247.39^		584.80		10.01
		(799.60)		(0.05)		(462.33)		(0.94)
Ability (environmental)		320.87		-25.79		-200.91		-75.05
		(791.99)		(0.83)		(538.78)		(0.48)
Observations	116	116	130	130	116	116	130	130
R-squared	0.24	0.27	0.19	0.21	0.08	0.09	0.11	0.11
SE	robust	robust	robust	robust	robust	robust	robust	robust
Controls	YES	YES	YES	YES	YES	YES	YES	YES

DV: Models 1-2; total revenue from January 2021 to July 2022, winsorized at 95th percentile of the distribution. Models 3-4: average of period-by-period of observations revenue, between January 2021 to July 2022. Models 5-6, as for 1-2 but considering profits. Models 7-8 as for 3-4, but considering profits.
Number of observations: Models 1,2,5,6 have 116 observations since the estimation excludes outlier firms (4), non-respondents in the last period (29) and two entrepreneurs who terminated the project (2). Models 3,4,7,8 have 130 observations since the estimation excludes outlier firms (4), attritors never replying to any survey (16) and entrepreneurs for which we only have one datapoint after the baseline (1).
Models 1,3,5,7 include the overall perceived ability scores. Models 2,4,6,8 include the separate perceived ability scores.
Controls include a dummy for tertiary education, a dummy for gender, hours worked at the baseline, a dummy for the firm type (startup or company), a dummy for the preferred location of the training, logarithm of firm size as total number of owners and salaried employees, dummies for sector of activity, perceived probability of introducing major changes at the baseline, instructor dummies. Robust standard errors reported in parentheses. *** p<0.001, ** p<0.01, * p<0.05, ^ p<0.1

Table 3.5 – Performance and perceived ability (panel)

DV	(1) Cumulative revenue	(2)	(3) Periodic revenue	(4)	(5) Cumulative profit	(6)	(7) Periodic profit	(8)
Ability (all)	521.73^		174.73^		-66.91		21.91	
	(269.84)		(91.06)		(217.51)		(77.39)	
Ability (project-related)		364.86^		97.58		17.78		29.36
		(206.64)		(65.70)		(124.29)		(45.79)
Ability (environmental)		164.74		78.87		-81.87		-5.76
		(265.04)		(70.47)		(183.86)		(63.70)
Observations	728	728	570	570	728	728	570	570
R-squared	0.24	0.24	0.07	0.07	0.07	0.07	0.03	0.03
SE	firm	firm	firm	firm	firm	firm	firm	firm
Period dummies	YES	YES	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES	YES	YES

DV: Models 1-2; cumulative revenue over time, winsorized at 95th percentile of the period distribution. Models 3-4: revenue observed in each period, winsorized at 95th percentile. Models 5-6, as for 1-2 but considering profits. Models 7-8 as for 3-4, but considering profits.
Models 1,3,5,7 include the overall perceived ability scores. Models 2,4,6,8 include the separate perceived ability scores.
Controls include a dummy for tertiary education, a dummy for gender, hours worked at the baseline, a dummy for the firm type (startup or company), a dummy for the preferred location of the training, logarithm of firm size as total number of owners and salaried employees, dummies for sector of activity, perceived probability of introducing major changes at the baseline, instructor dummies. Clustered standard errors by entrepreneur (firm) reported in parentheses. *** p<0.001, ** p<0.01, * p<0.05, ^ p<0.1

Regression results show a positive correlation between the perceived ability measures and revenue, with larger and more statistically significant coefficients related to the ability to deal with *project-related* factors. When it comes to profits, the magnitude of the coefficients is lower and never statistically significant. Albeit these results are correlational and have low statistical power, they suggest that higher perceived ability to deal with challenges arising from different factors – specifically those that are *project-related*– can have positive implications for business outcomes.

Summing up the results described in this section, we found that the entrepreneurs in the *theory-and-evidence-based* condition perceive themselves as better able to deal with potential challenges, specifically those stemming from *project-related* factors. A higher perceived ability is positively correlated with both *perceived control* and business performance, suggesting that a training that improves entrepreneurs' perceptions can have positive spillovers.

6. Discussion and conclusion

This chapter represents one of the first and few attempts to provide evidence of the effects of a strategy-based training intervention to entrepreneurs in an emerging economy focusing on entrepreneurs' perceptions of ability, an outcome that has not been analyzed by similar experimental studies on the matter (e.g., Camuffo et al., 2020). Different from other studies in similar settings that provide either short courses on basic business practices or interventions of just a few hours or days (Carlson & Hager, 2022; Dimitriadis & Koning, 2022), we designed and delivered a training spanning three months that focused on strategic decision-making and followed-up with participants for several months after the training has ended.

Our intervention tested the effects of training entrepreneurs to apply different approaches to strategic decision-making under uncertainty. Consistently with our expectations, we find that entrepreneurs in the *theory-and-evidence-based* condition increase their perceptions of ability more than entrepreneurs in the *evidence-based* condition. Given our experimental design, this difference is attributable to the presence of the *theorizing* component. We propose that theory-building increases perceptions of ability to deal with potential challenges because it provides entrepreneurs with a wider set of tools and skills to reflect critically on different courses of action and their underlying logic. Differently put, learning to theorize provides entrepreneurs with the ability to craft different mental models of their ideas, evaluate their predictive value (Csaszar, 2018) and revise them as they develop their proposition into viable companies.

As such, entrepreneurs who receive the *theory-and-evidence-based* treatment might be better equipped to make sense of what works and what doesn't, but also why that is the case, which in turn can make them more confident in their abilities. Particularly, our results show that the *theory-and-evidence-based* treatment has a positive and persistent effect on entrepreneurs' perceived ability to deal with *project-related* factors (e.g., develop a viable strategy or identifying their competitors or customers) that increase uncertainty and can affect important business decisions. Results concerning entrepreneurs' perceived ability to cope with *environmental* factors are less clear and do not allow us to find consistent differences between experimental conditions when it comes to these factors.

Entrepreneurs in the *evidence-based* condition seem to experience a positive effect of the training during the intervention, but this effect does not persist over time. Although our evidence does not allow us to identify the causes of this result, we can speculate on possible explanations. First, the *evidence-based* training aims at teaching entrepreneurs *what to do* as they develop a new idea (e.g., create a prototype early, collect feedback, revise, and restart) more than *how to think* about the causal mechanisms behind a successful business proposition. As such, entrepreneurs might tend to forget (or fail to apply) this behavioral advice relatively sooner or more easily compared to entrepreneurs who learn to make the thought exercise of stopping and thinking about their overall theory before making any decisions, explaining the non-persistent effects on perceptions of ability. Second, and relatedly, entrepreneurs who do not learn to make sense of their testing results against an overarching guiding framework may feel discouraged when results are different from what they expect and struggle to make sense of what to do next, which in turn can contribute to lowering their perception of ability and/or lead them to go back to their preferred way of operating.

We also find that exposure to the training has no significant effect on the relative importance entrepreneurs give to each type of factor in relation to each other, and that entrepreneurs consistently consider *environmental* factors (especially access to finance and production inputs) as most challenging to cope with over time compared to *project-related* factors. This signals how prominent these barriers are perceived by entrepreneurs that operate in an emerging economy context, where the uncertainty stemming from external contingencies is tremendously high.

Overall, these results demonstrate the value of providing strategy-based training to entrepreneurs operating in an emerging economy setting. Available studies have pointed at institutional intermediaries – such as business incubators, local cooperatives, and trade associations – as means through which entrepreneurs in low-income settings can access the resources they need to face different challenges as they develop new ventures (Armanios et al., 2017; Dutt et al., 2016; Sydow et al., 2022). These studies, however, do not touch upon the content of training programs these organizations might provide. Our research suggests that training entrepreneurs in developed economies to apply systematic approaches to decision-making – and particularly a *theory-and-evidence-based* approach that merges cognitive- and evidence-based elements – can help entrepreneurs navigate their challenging context by increasing their perceived ability to cope with different sources of uncertainty as they grow their businesses, and that this has implications for the success of their ventures. Second, existing research on systematic approaches to entrepreneurial decision-making and their effects on business outcomes is largely theoretical or case-based, with few experimental studies that focus predominantly on objective measures of decision outcomes or performance in the developed world (e.g., Camuffo et al., 2020, 2021). This is important, but leaves understudied potential mechanisms that drive those outcomes and does not allow to evaluate the effect of training entrepreneurs to apply these approaches in emerging economies, where, paradoxically, this type of training might be more needed. Our study is one of the first to study causal changes in entrepreneurs' perceptions as consequences of different trainings.

We now turn to the relationship between perceptions of ability towards challenging factors and the perceived control towards future and unpredictable events. Higher levels of perceived abilities are theoretically associated with higher predictability of events, and hence a mitigated perception of uncertainty (Milliken, 1987). Moreover, empirical studies showed how higher perceptions of control are associated with a higher tolerance towards risk (Keh et al., 2002). Our exploratory results show that higher degrees of perceived ability to deal with different factors inherent in entrepreneurial activity are associated with higher levels of perceived control towards future and unpredictable events. Interestingly, we find this correlation to be stronger and statistically significant only for the perceived ability related to *project-related* factors, that is those idiosyncratic to the business idea developed by entrepreneurs and that were, in principle, directly addressable. This result holds theoretical importance as it demonstrate that perceptions of control can stem from rational perceptions rather than irrational ones. One possible negative consequence of increasing entrepreneurs' perception of ability is that they may become irrationally overconfident in their capacity to deal with different factors even when these factors fall beyond their direct control. In our case, higher perceptions of control primarily correlated with perceptions of ability regarding environmental factors, which are potentially uncontrollable, could have signaled overconfidence. Our results indicate that this is not the case in our sample. We found that higher levels of perceived control were mostly associated with higher levels of perceived ability regarding project-related factors, which are indeed controllable by entrepreneurs. This suggests that entrepreneurs can mitigate uncertainty by developing valuable skills in handling problems they can directly control, such as knowing customer needs and preferences.

Finally, previous research found that entrepreneurs' ability perceptions are important mechanisms underpinning strategy formation under high uncertainty, and can affect key strategic decision such as the choice to fund a new venture and performance (Amini Sedeh et al., 2021; Gatewood et al., 1995; Shepherd et al., 2015; Townsend et al., 2010). We contribute to this debate by showing that higher levels of perceived ability are associated with higher revenue, albeit with low statistical power. As such, our results provide evidence on a possible pathway – designing training initiatives teaching entrepreneurs to apply a *theory-and-evidence-based* approach to decision-making – through which these perceptions of ability can be increased, which in turn can have positive implications for business outcomes.

Our results are not free from limitations. First, our experiment was affected by financial and logistical constraints that led to a non-random *control* group. This does not allow us to make any causal claim on the effect of attending the training per se (regardless of the approach) against not receiving any training at all. Second, our results might not generalize to entrepreneurs in other settings or sectors within Tanzania. Indeed, while our samples comes from the largest economic sector in the country, it might be that different dynamics and challenges are at play in different industries. Similarly, entrepreneurs' perceptions about potential challenges and predictability of future events might be different in more developed economies. Moreover, descriptive results show that entrepreneurs in our sample are well-educated on average. Our evidence does not allow us to state whether the same effects would hold for less educated entrepreneurs. Third, although we show that the nine factors chosen as potentially challenging in the questionnaire are representative of the general concerns among entrepreneurs, results could be different if alternative factors were included. Albeit our qualitative evidence from phone interviews mitigate this concern, this is a limitation of our empirical design. Finally, there might be alternative ways to measure entrepreneurs' perception of ability to cope with uncertainty arising from different challenges, which the scope of our study did not allow us to explore.

To conclude, this thesis explored different facets of entrepreneurs' perceptions and how they are affected by the adoption of a theory-based approach to decision-making under uncertainty, operationalized through the scientific approach (Camuffo *et al.*, 2020). The key take-away is that entrepreneurs trained to follow a theory-based approach, while becoming more conservative about the potential value of their ideas, make better decisions when deciding to continue pursuing their projects or terminate them (Chapter 1). The theoretical element is what allows entrepreneurs to make pivots that are more customer-centered and increase the expected value of their ideas once they change their course of actions (Chapter 2). Finally, theory-based entrepreneurs become more confident about their abilities in a highly uncertain context such as the one of an emerging economy (Chapter 3).

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Appendix

S1. Supplementary materials for Chapter 1, Scientific method and project selection

S1.1 Balance checks

Table S1.1 – Balance checks Milan RCT

Variable Name	Description	Treatment		Control		Difference	
		Mean	SD	Mean	SD	b	p
Age	Age (Team Average)	31.47	8.18	31.41	7.90	-0.06	(0.950)
Analytic Thinking	Agreement on a 1-10 scale with the following statements (Team Average): "Analyzing the situation and looking at the evidence is critical to our company's decision-making", "We carefully assess all the possible alternatives before making a choice for our company", "We prefer to gather all the relevant information before making a decision for our company", "Multiple elements are taken into account when making a decision for our company, pros and cons are carefully evaluated in every situation"	8.38	3.68	8.07	3.28	-0.32	(0.475)
Background: Economics	Team members with an economics background (%)	0.41	0.42	0.31	0.37	-0.10**	(0.046)
Background: Other	Team members with no economics backgrounds (%)	0.22	0.36	0.20	0.33	-0.02	(0.696)
Background: STEM	Team members with a STEM (Science Technology Engineering Mathematics) backgrounds (%)	0.38	0.40	0.49	0.41	0.11**	(0.032)
Certainty	Agreement on a 1-10 scale with the following statements (Team Average): "We are sure about our business model", "We are sure about our strategy"	5.93	1.94	5.61	1.91	-0.32	(0.191)
Consensus	Answer on a 1-10 scale to the following questions (Team Average): "To what extent do you and your team members have consensus on the long term objectives of the firm?", "To what extent do you and your team members have consensus on the short term objectives of the firm?", "To what extent do you and your team members have consensus on the survival strategy of the firm?"	8.85	1.67	8.86	1.66	0.00	(0.990)
Education	Highest educational level attained by team members (5=PhD, 4=MBA, 3=MSc, 2=BA, 1=high school, 0=otherwise; Team Average)	1.94	0.74	1.95	0.80	0.00	(0.969)
Experience: Entrepreneurial	Number of years of entrepreneurial experience (Team Average)	1.09	2.19	0.93	1.44	-0.17	(0.480)
Experience: Industry	Number of years of experience in industry (Team Average)	2.84	3.82	2.33	3.62	-0.51	(0.280)
Experience: Managerial	Number of years of managerial experience (Team Average)	2.29	3.69	2.27	4.18	-0.02	(0.971)
Experience: Work	Number of years of work experience (Team Average)	8.73	7.75	9.02	8.85	0.28	(0.788)
Full Time	Percentage of team members working full-time	0.57	0.43	0.62	0.42	0.05	(0.390)
Gender (Female)	Proportion of women in the team	0.27	0.37	0.25	0.36	-0.03	(0.541)
Hours: Total Weekly	Weekly hours dedicated to the company (Team Average)	10.17	9.65	10.96	11.45	0.78	(0.560)
Project Potential	Independent assessment of the value of the project	47.22	21.22	47.31	23.25	0.09	(0.975)
Project Value: Max	Maximum estimated value of the project (0 to 100)	85.08	16.29	85.67	16.16	0.59	(0.773)
Project Value: Mean	Estimated value of the project (mean, 0 to 100)	65.40	15.53	64.52	16.69	-0.88	(0.668)
Project Value: Min	Minimum estimated value of the project (0 to 100)	45.71	19.86	43.21	22.93	-2.50	(0.357)
Project Value: Range	Estimated value of the project (range, 0 to 100)	39.37	18.85	42.46	20.99	3.10	(0.221)
Intuitive Thinking	Agreement on a 1-10 scale with the following statements (Team Average): "We are prone to following our intuitions when making company-related decisions", "We consider feelings and intuitions rather than analysis in our startup decisions", "First impressions are important when making decisions", "It is important to rely on gut feelings and intuition when making decisions"	4.09	1.70	3.83	1.74	-0.25	(0.244)
Lombardy	Dummy variable taking value of 1 when the majority of team members comes from the Italian region of Lombardy, 0 otherwise	0.56	0.47	0.57	0.46	0.01	(0.883)
Months to Revenue	Number of months to revenue	11.52	5.80	11.51	5.85	-0.01	(0.987)
Part Time	Percentage of team members working part-time	0.08	0.18	0.08	0.17	0.00	(0.941)
Probability Termination	Probability of terminating the project	31.64	32.53	32.35	31.60	0.70	(0.863)
Team Size	Number of team members	2.25	1.46	2.28	1.37	0.03	(0.858)
Observations		125		125		250	

Table S1.2 – Balance checks Turin RCT

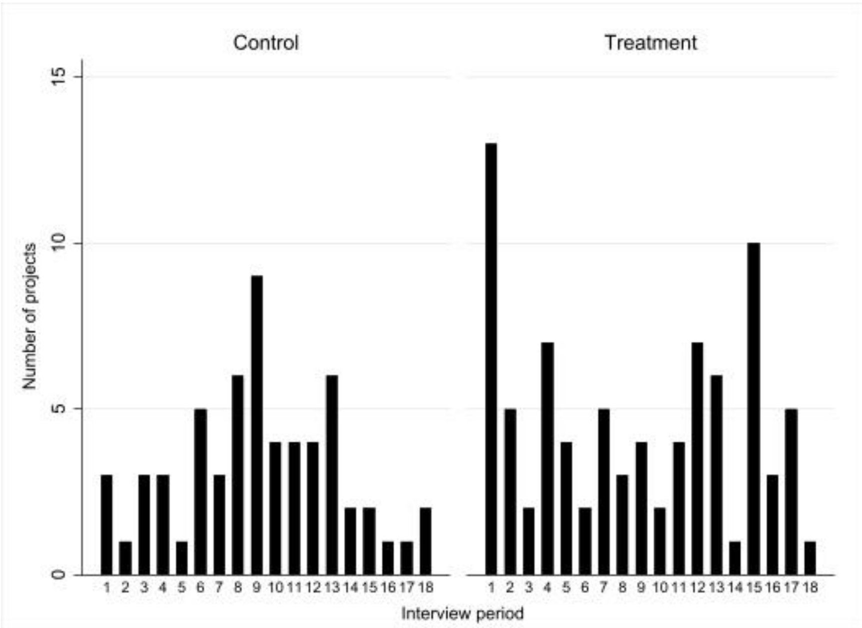
Variable Name	Description	Treatment Mean	Treatment SD	Control Mean	Control SD	Difference b	Difference p
Age	Age (Team Average)	30.58	9.07	30.48	7.09	-0.10	(0.943)
Analytic Thinking	Agreement on a 1-5 scale with the following statements (Team Average): "Analyzing the situation and looking at the evidence is critical to our company's decision-making", "We carefully assess all the possible alternatives before making a choice for our company", "We prefer to gather all the relevant information before making a decision for our company" and "Multiple elements are taken into account when making a decision for our company, pros and cons are carefully evaluated in every situation"	4.27	0.65	4.39	0.56	0.13	(0.234)
Background: Economics	Team members with Economics backgrounds (%)	0.19	0.32	0.21	0.36	0.02	(0.789)
Background: Other	Team members with no Economics/STEM backgrounds (%)	0.56	0.43	0.44	0.46	-0.12	(0.130)
Background: STEM	Team members with a STEM (Science Technology Engineering Mathematics) backgrounds (%)	0.25	0.37	0.35	0.45	0.10	(0.161)
Confidence	Agreement on a 1-5 scale with the following statements (Team Average): "We are confident in our entrepreneurial skills", "We are sure we are deploying the best strategy for our business", "We are confident in our ability to manage our business", "We master the competences necessary for our venture" and "We are sure there is no better business model for our project"	3.42	0.53	3.32	0.64	-0.10	(0.335)
Currently Studying	Number of team members enrolled in an education program at the time of training	0.26	0.30	0.22	0.30	-0.04	(0.429)
Education	Highest educational level attained by team members (5=PhD, 4=MBA, 3=MSc, 2=BA, 1=high school, 0=otherwise; Team Average)	1.86	0.88	2.07	1.08	0.21	(0.221)
Experience: Business Plan	Dummy taking value of 1 if the team had years of experience in business plan design, 0 otherwise	0.27	0.37	0.35	0.42	0.07	(0.282)
Experience: Entrepreneurial	Number of years of entrepreneurial experience (Team Average)	1.81	4.38	1.71	3.35	0.11	(0.873)
Experience: Industry	Number of years of experience in industry (Team Average)	2.88	5.65	2.99	5.01	0.10	(0.911)
Experience: Managerial	Number of years of managerial experience (Team Average)	1.56	2.71	1.73	3.74	0.18	(0.756)
Gender (Female)	Proportion of women in the team	0.33	0.39	0.25	0.35	-0.07	(0.256)
Hours: Total Weekly	Weekly hours dedicated to the company (Team Average)	11.26	9.85	11.62	12.32	0.35	(0.856)
Project Maturity	Maturity of the project (in months)	9.95	9.54	12.16	11.63	2.21	(0.234)
Project Potential	Independent assessment of the value of the project (two evaluators, average) based on five criteria: innovation, feasibility, sustainability, team competence, market size	48.85	12.05	49.17	12.77	0.33	(0.880)
Project Value: Mean	Estimated value of the project (mean)	66.24.82	18.89	63.54	16.06	-2.69	(0.380)
Intuitive Thinking	Agreement on a 1-5 scale with the following statements (Team Average): "We are prone to following our intuitions when making company-related decisions" and "We consider feelings and intuitions rather than analysis in our startup decisions"	2.79	0.86	2.71	0.98	-0.08	(0.604)
Later Stage	Dummy variable taking value of 1 if the firm is at a more advanced stage than others, 0 otherwise	0.14	0.35	0.10	0.31	-0.03	(0.554)
Locus of Control	Agreement on a 1-7 scale with the following statements (Team Average): "In most jobs you need a lot of luck to excel", "One typically earns what they are worth", "To make money you just need to know the right people", "To get a good position you need luck", "Income is mainly the result of hard work", "There is a direct relationship˜ between a person's abilities and the position he/she holds", "Many of the difficulties encountered at work concerns senior colleagues", "Generally, people who work well get rewarded", "Promotions are awarded to people who work well", "To find a good job, having a good network is more important than actual skills", "A well-trained person always finds a satisfycing job" and "To get a really good job you have to have high-level acquaintances"	3.85	0.67	3.78	0.70	-0.07	(0.556)
Months to Revenue	Number of months to revenue	12.42	11.20	14.63	10.51	2.21	(0.245)
Piedmont	Dummy variable taking value of 1 when the majority of team members comes from the Italian region of Piedmont and 0 otherwise	0.52	0.46	0.52	0.48	-0.00	(0.994)
Probability Pivot Project	Probability of changing the project	30.69	22.96	32.42	26.56	1.73	(0.690)
Probability Pivot Other	Probability of changing other components of the business model	51.60	22.46	52.58	26.13	0.98	(0.817)
Probability Pivot Problem	Probability of changing the problem and customer segment	33.75	22.68	34.42	25.20	0.66	(0.873)
Probability Termination	Probability of terminating the project	12.95	16.27	17.31	21.52	4.36	(0.191)
Risk-averse	Agreement on a 1-7 scale with the following statements (Team Average): "In important matters I never take unnecessary risks, which can be avoided", "In important situations I never deliberately chose to take risks I could have avoided", "I always try to avoid situations that put me at risk of getting into trouble with other people", "I am always very careful and I put safety first" and "I prefer to avoid doing things that expose me to criticism and liability"	4.21	1.00	3.95	1.04	-0.26	(0.150)
Risk-taker	Agreement on a 1-7 scale with the following statements (Team Average): "I can be pretty reckless and take some big risks", "I think I often act boldly and courageously", "I am a brave and daring person and I like to tempt fate˜ in various situations", "There is a direct relationship between a personOs abilities and the position he/she holds" and "I think I am often less cautious than other people"	4.04	1.10	3.98	0.90	-0.06	(0.716)
Scientific intensity: 1 Theory	Theory development score	2.87	1.34	3.02	1.21	0.15	(0.514)
Scientific intensity: 2 Hypothesis	Hypothesis development score	2.12	1.64	1.97	1.50	-0.15	(0.587)
Scientific intensity: 3 Test	Test score	1.32	1.71	1.28	1.67	-0.03	(0.906)
Scientific intensity: 4 Valuation	Valuation score	0.85	1.50	0.94	1.62	0.09	(0.750)
Self-efficacy	Agreement on a 1-7 scale with the following statements (Team Average): "I think I will always be able to achieve a goal even if I have to perform a difficult task", "Faced with new tasks and challenges, I am always confident that I will be able to complete them", "I am sure I will succeed", "When I have a goal, I almost always get better results than others", "When I take a test or an exam I am sure I can pass it successfully", "I am confident that my results will be recognized and appreciated by others", "I am not worried about difficult situations, because so far I have always managed to get by with my skills", "I never had any problem understanding and facing even the most complicated situations" and "I think I get the crux of the matter first"	5.43	1.08	5.56	0.95	0.13	(0.461)
Self-regulation	Agreement on a 1-7 scale with the following statements (Team Average): "People can count on me to meet the set and planned deadlines", "I can hardly say no", "I change my mind quite often", "Others would describe me as an impulsive person", "I wish I had more self-discipline", "I get carried away by my feelings", "I am not easily˜ discouraged", "Sometimes I canOt stop but do something, even though I know it is wrong", "I often act without thinking about all the alternatives", "I often do things that seem right in the present, even at the expense of future goals" and "When I pursue a goal I follow the original plan, even when I realize that it is not the best"	4.97	0.83	5.23	0.86	0.26*	(0.074)
Startcup	Dummy variable taking value of 1 if the firm takes part to a local competition, 0 otherwise	0.11	0.31	0.18	0.39	0.07	(0.244)
Team Size	Number of team members	2.54	1.61	2.18	1.39	-0.36	(0.173)
Observations		65		67		132	

S1.2. Estimation results

S1.2.1 Extended selection model: Full results

First, Figure S1.1 reports the number of entreprenerus terminating their projects by observation period and treatment condition. The graph shows how scientific entrepreneurs tend to terminate more frequently and earlier than the control group.

Figure S1.1 – Termination Frequency by Treatment and Observation Period



We report the results of the first two steps of the four-equations extended selection model reported in Table 1.3 of Chapter 1, estimated separately. Table S1.3 shows the results of the Heckman selection model with entrepreneurs' own predictions of project value at the Late stage ($\hat{v}_L$) used to identify the selection equation. Table S1.4 adds the intermediate equation that instruments $\hat{v}_L$ with the pre-training (baseline) evaluations $\hat{v}_0$.

Table S1.3 – Heckman selection model

	(1) Performance Equation	(2) Selection Equation
Treatment Dummy	1.100***	-0.382***
	(0.411)	(0.108)
$\hat{v}_L$		0.586***
		(0.148)
Startup Experience (Baseline)	0.218***	-0.0146
	(0.0774)	(0.0242)
Team Size (Baseline)	0.307*	-0.0400
	(0.171)	(0.0505)
Education (Baseline)	0.281	-0.0878
	(0.233)	(0.0868)
Age (Baseline)	-0.0881***	0.0277***
	(0.0246)	(0.00820)
Hours Worked (Baseline)	0.00687	0.00875*
	(0.0128)	(0.00507)
Constant	1.890**	-2.445***
	(0.744)	(0.755)
Correlation	-0.226***	
	(0.0698)	
RCT Dummies	Yes	Yes
Mentor Dummies	Yes	Yes
Observations	382	382

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Note. The performance equation is estimated through an OLS conditioned on the selection equation, estimated through a probit model. Standard errors clustered at the classroom level (K = 24).

Table S1.4 – Extended Heckman selection model

	(1) Performance Equation	(2) Selection Equation	(3) $\hat{v}_L$
Treatment Dummy	1.035**	-0.281**	-0.0213
	(0.436)	(0.120)	(0.0496)
$\hat{v}_L$		1.874***	
		(0.321)	
$\hat{v}_0$			0.282***
			(0.0690)
Startup Experience (Baseline)	0.221***	-0.0287	0.00966
	(0.0757)	(0.0250)	(0.00729)
Team Size (Baseline)	0.304*	-0.0591	0.0127
	(0.169)	(0.0400)	(0.0140)
Education (Baseline)	0.276	-0.00751	-0.0452**
	(0.239)	(0.0735)	(0.0230)
Age (Baseline)	-0.084***	0.015*	0.006**
	(0.0237)	(0.00868)	(0.00254)
Hours Worked (Baseline)	0.008	0.006	0.0004
	(0.0127)	(0.00532)	(0.00152)
Constant	1.735**	-7.454***	2.768***
	(0.685)	(1.414)	(0.321)
Correlation	-0.197***		
	(0.0732)		
RCT Dummies	Yes	Yes	Yes
Mentor Dummies	Yes	Yes	Yes
Observations	382	382	382

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Note. The performance equation is estimated through an OLS conditioned on the selection equation, estimated through a probit model. The last equation is estimated through OLS. Standard errors clustered at the classroom level (K = 24).

S1.2.2 Full estimation: Results

We report in Table S1.5 the results of the full `cmp` estimation, used to retrieve the model parameters shown in Table 1.4 in chapter 1. Table S1.6 and S1.7 show the alternative computation for the model parameters and the results.

Table S1.5 – Full estimation

Model	Performance Equation Eq. 1 OLS	Selection Eq. 14 Probit	z_L Eq. 13 OLS	z_E Eq. 12 OLS	$\widehat{v_L}$ Eq. 4 OLS	$\widehat{v_E}$ Eq. 3 OLS
Treatment Dummy	1.117** (0.455)	-0.452*** (0.122)	-0.175** (0.0799)	0.0499 (0.0861)	-0.0116 (0.0498)	-0.0497* (0.0265)
z_L		-0.274 (0.181)				
z_E			1.017*** (0.183)			
z_0				0.312*** (0.0410)		
Startup Experience (Baseline)	0.194*** (0.0754)			0.00486 (0.0195)	0.0112 (0.00723)	0.00757 (0.00517)
Team Size (Baseline)	0.297** (0.145)			-0.137*** (0.0442)	0.0231 (0.0146)	0.00954 (0.0134)
Education (Baseline)	0.243 (0.231)			0.123* (0.0641)	-0.0441* (0.0242)	-0.0311 (0.0208)
Age (Baseline)	-0.0805*** (0.0249)			-0.0245*** (0.00692)	0.00451 (0.00299)	0.00187 (0.00228)
Hours Worked (Baseline)	0.00996 (0.0126)			-0.000998 (0.00324)	0.000542 (0.00143)	0.00219*** (0.000849)
Constant	1.737** (0.762)	0.255 (0.296)	0.395 (0.357)	-0.317 (0.286)	3.931*** (0.141)	4.153*** (0.0598)
Correlation	-0.282* (0.145)					
RCT Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Mentor Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Equation $\ln(\sigma)$ (OLS only)	1.124*** (0.0789)		0.176** (0.0731)	-0.00586 (0.0364)	-0.849*** (0.0923)	-1.066*** (0.0933)
Observations	382					

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Note. Standard errors clustered at the classroom level (K = 24).

Table S1.6 – Alternative parameters computation

Parameter	Computation	Equations employed
θ	θ	1
σ_E	*OLS variance*	3
σ_L	*OLS variance*	4
σ_F	$-\dfrac{\sigma_L}{\gamma_F}$	14, 4
c_{ET}	$\beta_E \sigma_E - \theta$	3, 12
c_{LT}	$-\beta_L \sigma_L - c_{ET}$	4, 13, 12
c_{FT}	$\beta_F \sigma_F + c_{LT}$	14, 4, 13, 12

Table S1.7 – Alternatively estimated parameters

	Parameter	Std. Err	z-score
$\boldsymbol{\theta}$	1.12	0.455	2.46
$\boldsymbol{\sigma_E}$	0.34	0.032	10.72
$\boldsymbol{\sigma_L}$	0.43	0.039	10.83
$\boldsymbol{\sigma_F}$	1.56	1.078	1.45
$\boldsymbol{c_{ET}}$	-1.13	0.434	-2.62
$\boldsymbol{c_{LT}}$	-1.06	0.442	-2.40
$\boldsymbol{c_{FT}}$	-1.77	0.409	-4.33

Note. Parameters retrieved after ML estimation of the six equations described in Section 1.4 in Chapter 1. This alternative computation retrieves the parameters c_{ET} and c_{LT} from Eq. 12 and 13 rather than from Eq. 3 and Eq. 4. Parameters and their standard errors are retrieved using the `nlcom` routine in Stata 16.

S1.3 Attrition

In Table S1.8, we report tests on a subset of covariates to compare "attritors" with respondents by treatment conditions. We report the results of F-test for joint orthogonality, comparing all four groups, and t-tests comparing "attritors" and respondents within treatment.

Table S1.8 – Selective attrition tests

	Control Attritors	Control Respondents	Treated Attritors	Treated Respondents	F-Test
Startup Experience	0.842	1.251	0.286	1.425	0.982
	[0.258]	[0.188]	[0.163]	[0.243]	
Team Size	2.125	2.262	1.500	2.392**	1.856
	[0.284]	[0.106]	[0.251]	[0.114]	
Education	1.642	2.040**	1.964	1.911	1.807
	[0.151]	[0.071]	[0.259]	[0.059]	
Age	29.441	31.319	31.780	31.120	0.412
	[1.323]	[0.599]	[1.848]	[0.649]	
Industry Experience	2.028	2.637	3.810	2.780	0.527
	[0.894]	[0.319]	[1.243]	[0.340]	
Managerial Experience	1.083	2.226	1.571	2.076	0.741
	[0.371]	[0.327]	[0.650]	[0.261]	
Hours Worked	13.243	12.864	13.393	13.225	0.012
	[3.475]	[1.515]	[5.432]	[1.451]	
Predicted Value	65.896	63.875	67.036	66.244	0.681
	[3.170]	[1.288]	[5.285]	[1.191]	
Probability of Termination	0.168	0.215	0.220	0.166	1.865
	[0.039]	[0.016]	[0.062]	[0.015]	
RA Evaluation	44.229	48.493	40.750	48.339	1.004
	[4.270]	[1.551]	[5.604]	[1.382]	
Observations	24	168	14	176	

***p < 0.01, **p < 0.05, * p< 0.10

Note. Selective attrition tests, by treatment condition. T-tests are conducted comparing attritors and respondents within treatment condition. All variables are recorded at the baseline. RA Evaluation refers to an evaluation made by Program Assistants on the quality of the applicants' projects. For the definition of the different variables, please refer to the Balance Check tables.

The within-treatment comparison signals that there are differences between respondents and attritors in terms of education and team size. However, the comparison between respondents across conditions, does not reveal any significant difference, but for the Predicted Value, which is slightly higher for respondents in the treated group. Nevertheless, any of the F-tests for joint orthogonality is significant at conventional levels.

To ensure our main results are robust to attrition, we estimate our main models excluding those observations. Thus, we run the estimation on a sample of 344 ventures (Control = 168; Treated =

176). Table S1.9 reports the result for the four-step simplified model, while Table S1.10 reports the parameters from the full estimation model.

Table S1.9 – Extended selection model

	(1) Performance Equation	(2) Selection Equation	(3) $\hat{v}_L$	(4) $\hat{v}_E$
Treatment Dummy	0.947**	-0.248**	0.035	-0.049*
	(0.444)	(0.120)	(0.043)	(0.026)
$\hat{v}_L$		1.952***		
		(0.318)		
$\hat{v}_E$			1.002***	
			(0.383)	
$\hat{v}_0$				0.237***
				(0.077)
Startup Experience (Baseline)	0.224***	-0.019	0.006	0.003
	(0.083)	(0.025)	(0.007)	(0.005)
Team Size (Baseline)	0.311*	-0.046	0.017	-0.004
	(0.178)	(0.039)	(0.014)	(0.015)
Education (Baseline)	0.312	-0.008	-0.000	-0.032
	(0.258)	(0.074)	(0.022)	(0.022)
Age (Baseline)	-0.099***	0.011	0.003	0.003
	(0.026)	(0.010)	(0.003)	(0.003)
Hours Worked (Baseline)	0.009	0.006	-0.002	0.002**
	(0.016)	(0.006)	(0.002)	(0.001)
Constant	2.552***	-7.862***	-0.291	3.187***
	(0.844)	(1.357)	(1.599)	(0.352)
Correlation	-0.238***			
	(0.088)			
RCT Dummies	Yes	Yes	Yes	Yes
Mentor Dummies	Yes	Yes	Yes	Yes
Observations	382	382	382	382

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Note. The performance equation is estimated through an OLS conditioned on the selection equation, estimated through a probit model. The last two equations are estimated through OLS. Standard errors clustered at the classroom level (K = 24).

Table S1.10 – Alternatively estimated parameters

	Parameter	Std. Err	z-score
$\boldsymbol{\theta}$	1.06	0.458	2.31
$\boldsymbol{\sigma_E}$	0.34	0.036	9.59
$\boldsymbol{\sigma_L}$	0.43	0.043	10.00
$\boldsymbol{\sigma_F}$	1.27	0.687	1.85
$\boldsymbol{c_{ET}}$	-1.10	0.455	-2.41
$\boldsymbol{c_{LT}}$	-1.06	0.445	-2.39
$\boldsymbol{c_{FT}}$	-1.62	0.452	-3.59

Note. Parameters retrieved after ML estimation of the six equations described in Section 1.4 in Chapter 1, excluding attritors. Parameters and their standard errors are retrieved using the `nlcom` routine in Stata 16. All estimated equations include dummies for RCT and instructor, with standard errors clustered at the classroom level (K = 24).

S1.4 Robustness checks

S1.4.1 Additional controls

In this robustness check, we include two additional controls to the main estimation that resulted to be statistically different between the two treatment groups at the baseline. The dependent variable for the value equation is the log of revenues at the last data point, as in the analyses reported in the main text.

We add the variable *Self-regulation*, which accounts for the team-level discipline in organization and decision-making activities measured through a 11-item Likert scale. This variable is only available for the RCT conducted in Turin, with a statistical difference between treatment groups significant at 10% (see Table S1.2).

Second, we add the variable *Background: Economics*, which records the percentage of team members with a degree in economics. This variable is only available for the RCT conducted in Milan, with a statistical difference between treatment groups significant at 5% (see Table S1.1). We set at 0 the value of these two variables for the RCTs where they were not recorded.

Table S1.11 reports the results of the four-equation extended selection model with these additional controls. Estimates show a consistent *performance* effect, with a slightly lower magnitude estimated to be around an additional 91 pp in revenues for the treated entrepreneurs. The likelihood of the project being active at the end of the observation window is still lower for treated entrepreneurs. Consistently with the main results, treated entrepreneurs tend to estimate lower values when asked to estimate the value of their projects in the early data point.

Table S1.12 shows the model parameters from the full-fledged estimation. All the parameters estimated are consistent with what we find in the main analyses, with a smaller size of the *performance* effect.

Table S1.11 – Extended selection model

	(1) Performance Equation	(2) Selection Equation	(3) $\hat{v}_L$	(4) $\hat{v}_E$
Treatment Dummy	0.914**	-0.279**	0.060	-0.056**
	(0.405)	(0.113)	(0.046)	(0.027)
$\hat{v}_L$		1.860***		
		(0.327)		
$\hat{v}_E$			1.151***	
			(0.377)	
$\hat{v}_0$				0.244***
				(0.070)
Startup Experience (Baseline)	0.215***	-0.028	0.004	0.005
	(0.080)	(0.026)	(0.008)	(0.005)
Team Size (Baseline)	0.302*	-0.060	0.007	0.003
	(0.161)	(0.041)	(0.014)	(0.014)
Education (Baseline)	0.227	-0.014	-0.002	-0.037*
	(0.247)	(0.079)	(0.024)	(0.021)
Age (Baseline)	-0.075***	0.014*	0.002	0.003
	(0.023)	(0.008)	(0.003)	(0.002)
Hours Worked (Baseline)	0.009	0.005	-0.002	0.002**
	(0.012)	(0.005)	(0.002)	(0.001)
Background: Economics	1.101*	-0.024	-0.141**	0.022
(RCT Milan only, baseline)	(0.579)	(0.211)	(0.071)	(0.035)
Self-regulation	-0.556	0.102	0.039	0.039
(RCT Turin only, baseline)	(0.400)	(0.162)	(0.046)	(0.026)
Constant	1.199*	-7.371***	-0.789	3.150***
	(0.692)	(1.485)	(1.563)	(0.319)
Correlation	-0.180**			
	(0.091)			
RCT Dummies	Yes	Yes	Yes	Yes
Mentor Dummies	Yes	Yes	Yes	Yes
Observations	382	382	382	382

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Note. The performance equation is estimated through an OLS conditioned on the selection equation, estimated through a probit model. The last two equations are estimated through OLS. Standard errors clustered at the classroom level (K = 24).

Table S1.12 – Estimated parameters

	Parameter	Std. Err	z-score
$\boldsymbol{\theta}$	0.97	0.428	2.27
$\boldsymbol{\sigma_E}$	0.34	0.032	10.62
$\boldsymbol{\sigma_L}$	0.42	0.039	10.77
$\boldsymbol{\sigma_F}$	2.41	2.967	0.81
$\boldsymbol{c_{ET}}$	-1.02	0.427	-2.39
$\boldsymbol{c_{LT}}$	-0.97	0.413	-2.35
$\boldsymbol{c_{FT}}$	-1.92	0.902	-2.12

Note. Parameters retrieved after ML estimation of the six equations described in Section 1.4 in Chapter 1, adding two controls for unbalances at the baseline. Parameters and their standard errors are retrieved using the `nlcom` routine in Stata 16. All estimated equations include dummies for RCT and instructor, with standard errors clustered at the classroom level (K = 24).

S1.4.2 Trimmed revenues

We re-run the main specifications using as a trimmed version of the dependent variable (i.e., log of revenues at the last data point) at the 99th percentile. Since three firms are dropped, the sample size is of 379 observations and the average of the revenue variable drops from 1.48 to 1.34.

Table S1.13 reports the results for the extended selection model. Results are consistent with the main estimation, with a smaller coefficient on the intervention variable (the *performance* effect). This signals that the larger magnitude of the coefficient found in the main specification might be influenced by the presence of three well-performing companies. However, the estimated effect in this robustness test is still high in magnitude and significant, signaling that the detected effect is robust. Results on the *estimation* effect are consistent, also looking at Table S1.14 with the model parameters from the full-fledged model.

Table S1.13 – Extended selection model

	(1) Performance Equation	(2) Selection Equation	(3) $\hat{v}_L$	(4) $\hat{v}_E$
Treatment Dummy	0.764*	-0.293**	0.042	-0.060**
	(0.426)	(0.122)	(0.044)	(0.027)
$\hat{v}_L$		1.842***		
		(0.325)		
$\hat{v}_E$			1.103***	
			(0.363)	
$\hat{v}_0$				0.254***
				(0.069)
Startup Experience (Baseline)	0.237***	-0.028	0.004	0.005
	(0.072)	(0.026)	(0.008)	(0.005)
Team Size (Baseline)	0.273*	-0.059	0.011	0.002
	(0.166)	(0.040)	(0.013)	(0.014)
Education (Baseline)	0.295	-0.010	-0.007	-0.034*
	(0.239)	(0.074)	(0.022)	(0.020)
Age (Baseline)	-0.089***	0.015*	0.003	0.003
	(0.025)	(0.009)	(0.003)	(0.002)
Hours Worked (Baseline)	0.012	0.006	-0.002	0.002**
	(0.013)	(0.005)	(0.002)	(0.001)
Constant	1.959**	-7.323***	-0.657	3.114***
	(0.785)	(1.441)	(1.513)	(0.315)
Correlation	-0.188**			
	(0.081)			
RCT Dummies	Yes	Yes	Yes	Yes
Mentor Dummies	Yes	Yes	Yes	Yes
Observations	379	379	379	379

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Note. The performance equation is estimated through an OLS conditioned on the selection equation, estimated through a probit model. The last two equations are estimated through OLS. Standard errors clustered at the classroom level (K = 24).

Table S1.14 – Estimated parameters

	Parameter	Std. Err	z-score
θ	0.84	0.449	1.88
σ_E	0.35	0.032	10.66
σ_L	0.43	0.039	10.86
σ_F	1.58	1.079	1.47
c_{ET}	-0.90	0.447	-2.01
c_{LT}	-0.86	0.434	-1.98
c_{FT}	-1.59	0.410	-3.89

Note. Parameters retrieved after ML estimation of the six equations described in Section 1.4 in Chapter 1, dropping three outlier firms (N = 379) in terms of revenue distribution. Parameters and their standard errors are retrieved using the `nlcom` routine in Stata 16. All estimated equations include dummies for RCT and instructor, with standard errors clustered at the classroom level (K = 24).

S1.4.3 Alternative computations of predicted values

In the main analysis, to measure entrepreneurs' prediction of project values, we asked entrepreneurs to indicate the minimum and maximum on a scale between 0 and 100 where we clarify 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 in terms of revenue". We computed the average between the minimum and the maximum to retrieve our measure of estimated value, and finally take the logarithm of such resulting measure.

As a robustness check, Table S1.15 and Table S1.16 report the results of the extended selection model and the model parameters from the full estimation using an alternative calculation for the predictions. Specifically, we first compute the logarithm of the minimum and the maximum values from the survey, and then compute the average of such logarithms. Correlations between the two measures are *0.85* for $\hat{v}_0$; *0.81* for $\hat{v}_E$; *0.87* for $\hat{v}_L$.

Finally, in Table S1.17 we report the model parameters from an estimation where we use an alternative measurement for z, where - instead of considering the last available data point - we considered the previous one.

All results are fully consistent with the main models reported in Chapter 1.

Table S1.15 – Extended selection model – Alternative computations for predictions

	(1) Performance Equation	(2) Selection Equation	(3) $\hat{v}_L$	(4) $\hat{v}_E$
Treatment Dummy	1.056**	-0.257**	0.016	-0.080**
	(0.434)	(0.119)	(0.051)	(0.035)
$\hat{v}_L$		1.215***		
		(0.313)		
$\hat{v}_E$			0.998***	
			(0.254)	
$\hat{v}_0$				0.211***
				(0.072)
Startup Experience (Baseline)	0.213***	-0.008	-0.001	0.000
	(0.077)	(0.027)	(0.015)	(0.010)
Team Size (Baseline)	0.299*	-0.028	-0.011	0.008
	(0.168)	(0.044)	(0.017)	(0.017)
Education (Baseline)	0.270	-0.042	-0.022	-0.033
	(0.233)	(0.073)	(0.029)	(0.035)
Age (Baseline)	-0.082***	0.013	0.007*	0.002
	(0.024)	(0.010)	(0.004)	(0.003)
Hours Worked (Baseline)	0.009	0.006	-0.001	0.003*
	(0.012)	(0.006)	(0.002)	(0.002)
Constant	1.689**	-4.591***	-0.321	3.210***
	(0.699)	(1.196)	(1.013)	(0.318)
Correlation	-0.231***			
	(0.067)			
RCT Dummies	Yes	Yes	Yes	Yes
Mentor Dummies	Yes	Yes	Yes	Yes
Observations	382	382	382	382

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Note. The performance equation is estimated through an OLS conditioned on the selection equation, estimated through a probit model. The last two equations are estimated through OLS. Standard errors clustered at the classroom level (K = 24).

Table S1.16 – Estimated parameters - Alternative computations for predictions

	Parameter	Std. Err	z-score
$\boldsymbol{\theta}$	1.09	0.458	2.39
$\boldsymbol{\sigma_E}$	0.51	0.031	16.15
$\boldsymbol{\sigma_L}$	0.61	0.042	14.49
$\boldsymbol{\sigma_F}$	2.23	1.468	1.52
$\boldsymbol{c_{ET}}$	-1.15	0.459	-2.52
$\boldsymbol{c_{LT}}$	-1.14	0.435	-2.62
$\boldsymbol{c_{FT}}$	-2.14	0.525	-4.08

Note. Parameters retrieved after ML estimation of the six equations described in Section 1.4 in Chapter 1, using an alternative computation for entrepreneurs' predictions. Parameters and their standard errors are retrieved using the `nlcom` routine in Stata 16. All estimated equations include dummies for RCT and instructor, with standard errors clustered at the classroom level (K = 24).

Table S1.17 – Estimated parameters – Lagged value for predicted probability

	Parameter	Std. Err	z-score
$\boldsymbol{\theta}$	1.10	0.456	2.42
$\boldsymbol{\sigma_E}$	0.34	0.032	10.72
$\boldsymbol{\sigma_L}$	0.43	0.039	10.83
$\boldsymbol{\sigma_F}$	1.47	1.006	1.46
$\boldsymbol{c_{ET}}$	-1.15	0.454	-2.54
$\boldsymbol{c_{LT}}$	-1.12	0.441	-2.53
$\boldsymbol{c_{FT}}$	-1.76	0.409	-4.30

Note. Parameters retrieved after ML estimation of the six equations described in Section 1.4 in Chapter 1, using a lagged value for the last available predicted probability of termination. Parameters and their standard errors are retrieved using the `nlcom` routine in Stata 16. All estimated equations include dummies for RCT and instructor, with standard errors clustered at the classroom level (K = 24).

S1.4.4 Full model with lagged values of $\hat{\boldsymbol{v}}$

In Section 1.4.3 in Chapter 1, we outline the full set of equations used to estimate our theoretical model. Given the structure of the latter, in Equations (4) and (3), we do not include lagged values of $\hat{v}$ as controls. In this robustness check, we show that by adding $\hat{v}_E$ to the regressors in (4) and $\hat{v}_0$ to the regressors in (3) results are fully consistent with the ones reported in the main paper.

Table S1.18 in the following page reports the full results from the `cmp` routine, while Table S1.19 reports the estimated parameters.

Table S1.18 – Full estimation with lags of $\hat{v}$

Model	Performance Equation Eq. 1 OLS	Selection Eq. 14 Probit	z_L Eq. 13 OLS	z_E Eq. 12 OLS	$\hat{v}_L$ Eq. 4 OLS	$\hat{v}_E$ Eq. 3 OLS
Treatment Dummy	1.121**	-0.455***	-0.175**	0.0523	0.0408	-0.0575**
	(0.450)	(0.122)	(0.0800)	(0.0858)	(0.0440)	(0.0263)
z_L		-0.282*				
		(0.170)				
z_E			1.026***			
			(0.178)			
z_0				0.325***		
				(0.0402)		
$\hat{v}_E$					1.055***	
					(0.384)	
$\hat{v}_0$						0.228***
						(0.0730)
Startup Experience (Baseline)	0.194**			0.00503	0.00321	0.00490
	(0.0759)			(0.0194)	(0.00763)	(0.00544)
Team Size (Baseline)	0.297**			-0.136***	0.0130	0.00425
	(0.145)			(0.0438)	(0.0115)	(0.0134)
Education (Baseline)	0.243			0.123*	-0.0113	-0.0332
	(0.231)			(0.0637)	(0.0228)	(0.0208)
Age (Baseline)	-0.0810***			-0.0247***	0.00256	0.00230
	(0.0249)			(0.00677)	(0.00309)	(0.00233)
Hours Worked (Baseline)	0.00986			-0.000933	-0.00177	0.00193**
	(0.0126)			(0.00319)	(0.00149)	(0.000858)
Constant	1.751**	0.247	0.409	-0.298	-0.452	3.227***
	(0.764)	(0.289)	(0.352)	(0.284)	(1.601)	(0.331)
Correlation	-0.286**					
	(0.140)					
RCT Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Mentor Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Equation $\ln(\sigma)$ (OLS only)	1.124***		0.179**	-0.00587	-0.838***	-1.088***
	(0.0788)		(0.0722)	(0.0366)	(0.137)	(0.0912)
Observations	382					

*** p < 0.01, ** p < 0.05, * p < 0.1

Note. Full model estimated adding the lags of $\hat{v}$ to Equations (3) and (4). Standard errors clustered at the classroom level (K = 24).

Table S1.19 – Estimated parameters – model with lags of $\hat{v}$

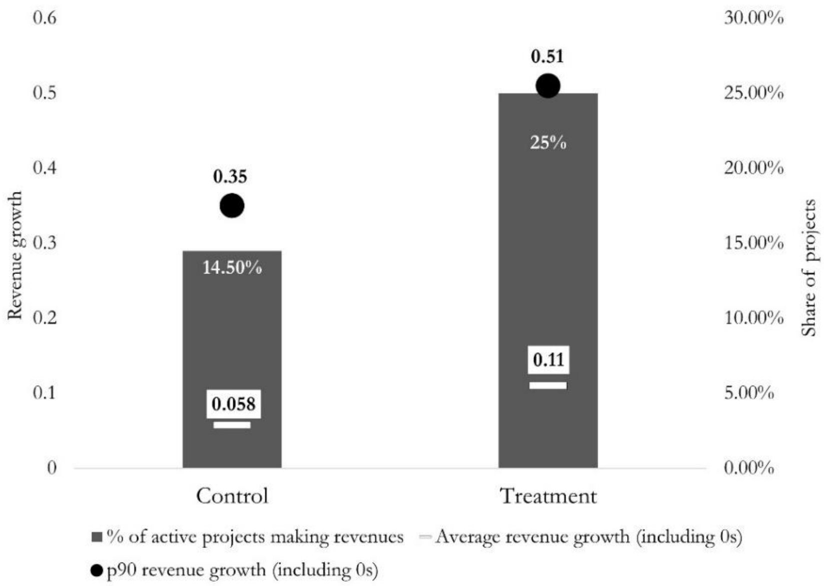
	Parameter	Std. Err	z-score
$\boldsymbol{\theta}$	1.12	0.450	2.49
$\boldsymbol{\sigma_E}$	0.34	0.031	10.96
$\boldsymbol{\sigma_L}$	0.43	0.059	7.29
$\boldsymbol{\sigma_F}$	1.53	0.962	1.59
$\boldsymbol{c_{ET}}$	-1.18	0.449	-2.62
$\boldsymbol{c_{LT}}$	-1.08	0.434	-2.49
$\boldsymbol{c_{FT}}$	-1.78	0.421	-4.22

Note. Parameters retrieved after ML estimation of the six equations described in Section 1.4 in Chapter 1 plus lags of $\hat{v}$ as in Table S1.18 of the Supplementary materials., Parameters and their standard errors are retrieved using the nlcom routine in Stata 16. All estimated equations include dummies for RCT and instructor, with standard errors clustered at the classroom level (K = 24).

S1.5 Results with Average Revenue Growth

In this subsection we report the results for the extended selection model and structural models when using the average revenue growth over time as dependent variable. First, Figure S1.2 shows the statistics pertaining to average revenue growth. The latter has been computed as the average of the growth of revenues between each data point in the sample (as simple difference between the log of revenues), only for firms remaining active for the whole observation window.

Figure S1.2 – Average revenue growth

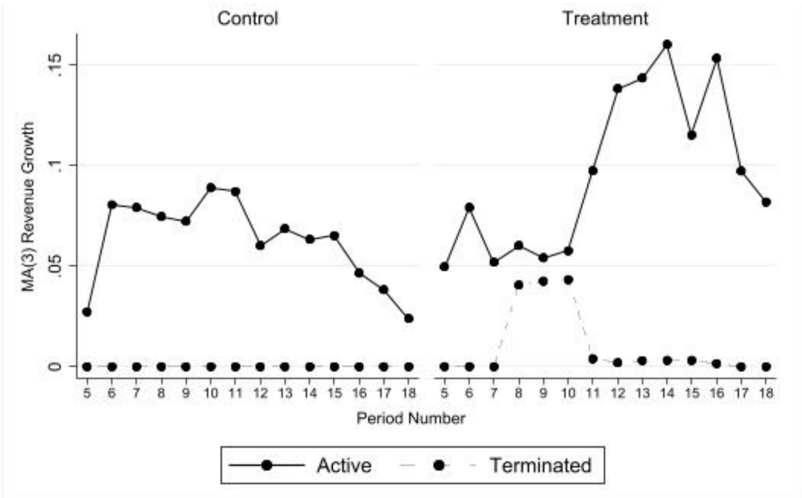


Note. The columns indicate the share of firms with positive revenues, conditional on their decision to stay operational (right axis). The white bar and the black dot indicate, respectively, the 90th percentile and the average of the distribution of average revenue growth over time (including 0s), conditional on the decision to stay operational (left axis).

Consistently with the figures on revenues discussed in the main text, treated firms have a higher growth rate when compared to control firms, both on average and at the 90th percentile. Figure S1.3 shows the revenue growth pattern using a 3-period moving average of the revenue growth by period, to corroborate the patterns found in Figure 1.3 of the main text.

Table S1.20 reports the results of the four-equations extended selection model, using as dependent variable the average revenue growth over time.

Figure S1.3 – Moving average (3 period) of revenue growth



Note. The graph shows a 3-period moving average of the revenue growth, by treatment and final decision of maintaining the project active or terminate. For firms that exited, the value is set as missing after their decision to terminate.

Table S1.20 – Extended selection model – average revenue growth

	(1) Performance Equation	(2) Selection Equation	(3) $\hat{v}_L$	(4) $\hat{v}_E$
Treatment Dummy	0.058**	-0.280**	0.043	-0.058**
	(0.024)	(0.120)	(0.043)	(0.027)
$\hat{v}_L$		1.874***		
		(0.320)		
$\hat{v}_E$			1.103***	
			(0.361)	
$\hat{v}_0$				0.256***
				(0.069)
Startup Experience (Baseline)	0.012***	-0.029	0.005	0.005
	(0.004)	(0.025)	(0.008)	(0.005)
Team Size (Baseline)	0.017*	-0.059	0.011	0.002
	(0.009)	(0.040)	(0.013)	(0.014)
Education (Baseline)	0.016	-0.008	-0.007	-0.035*
	(0.013)	(0.074)	(0.022)	(0.020)
Age (Baseline)	-0.005***	0.015*	0.003	0.003
	(0.001)	(0.009)	(0.003)	(0.002)
Hours Worked (Baseline)	0.000	0.006	-0.002	0.002**
	(0.001)	(0.005)	(0.002)	(0.001)
Constant	0.098***	-7.457***	-0.655	3.103***
	(0.038)	(1.413)	(1.505)	(0.317)
Correlation	-0.199***			
	(0.075)			
RCT Dummies	Yes	Yes	Yes	Yes
Mentor Dummies	Yes	Yes	Yes	Yes
Observations	382	382	382	382

*** p < 0.01, ** p < 0.05, * p < 0.1
Note. DV for performance equation = average revenue growth.
The performance equation is estimated through an OLS conditioned on the selection equation, estimated through a probit model. The last two equations are estimated through OLS. Standard errors clustered at the classroom level (K = 24).

The *performance* effect is still significant and estimated to lead to an additional average growth of 5.7 pp for treated entrepreneurs. The effect is quite sizeable given the averages shown in Figure S1.1. Table S1.21 instead reports the model parameters from the full estimation.

Table S1.21 – Estimated parameters - average revenue growth

	Parameter	Std. Err	z-score
$\boldsymbol{\theta}$	0.06	0.025	2.46
$\boldsymbol{\sigma_E}$	0.34	0.032	10.72
$\boldsymbol{\sigma_L}$	0.43	0.039	10.83
$\boldsymbol{\sigma_F}$	1.56	1.078	1.45
$\boldsymbol{c_{ET}}$	**-0.11**	**0.035**	**-3.18**
$\boldsymbol{c_{LT}}$	-0.07	0.048	-1.55
$\boldsymbol{c_{FT}}$	-0.78	0.453	-1.72

Note. Parameters retrieved after ML estimation of the six equations described in Section 1.4 in Chapter 1, using as dependent variable the average revenue growth over time. Parameters and their standard errors are retrieved using the `nlcom` routine in Stata 16. All estimated equations include dummies for RCT and instructor, with standard errors clustered at the classroom level (K = 24).

The *performance* effect is consistent with previous estimations and the same is valid for the different *estimation* effects, despite the substantial change in the nature of the dependent variable.

S1.6 External Financing and Revenue Dummy

We report here the results of two Heckman probits used to corroborate the performance results of active projects in the treated condition. Table S1.22 runs a selected model with the external financing dummy used in Section 6.1 of Chapter 1 as the dependent variable. Table S1.23 instead uses a dummy taking value 1 if the firm has made revenues, 0 otherwise. As selection variables, we use both the last available entrepreneurs' estimates of value and their last available predicted probability of termination.

Results confirm that, given the decision to maintain the project active, scientific entrepreneurs are more likely to have received external financing and to have made any amount of revenue during the RCT observation window.

Table S1.22 – Heckman probit on external financing

	(1) External Finance Dummy	(2) Selection Equation
Treatment Dummy	0.538***	-0.449***
	(0.142)	(0.107)
$\hat{v}_L$		0.335**
		(0.152)
Probability of Termination (last)		-1.023***
		(0.259)
Startup Experience (Baseline)	-0.008	-0.005
	(0.030)	(0.027)
Team Size (Baseline)	0.182***	-0.056
	(0.059)	(0.049)
Education (Baseline)	0.141	-0.079
	(0.108)	(0.089)
Age (Baseline)	-0.010	0.025***
	(0.013)	(0.008)
Hours Worked (Baseline)	0.002	0.009
	(0.005)	(0.005)
Constant	-0.788	-1.051
	(0.500)	(0.765)
Correlation	-1.569**	
	(0.678)	
RCT Dummies	Yes	Yes
Mentor Dummies	Yes	Yes
Observations	382	382

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Note. DV = dummy for external financing received during the RCT.
Standard errors clustered at the classroom level (K = 24).

Table S1.23 – Heckman probit on revenue dummy

	(1) Revenue Dummy	(2) Selection Equation
Treatment Dummy	0.504***	-0.477***
	(0.118)	(0.123)
$\hat{v}_L$		0.187
		(0.173)
Probability of Termination (last)		-1.037***
		(0.264)
Startup Experience (Baseline)	0.078**	-0.021
	(0.032)	(0.022)
Team Size (Baseline)	0.104*	-0.043
	(0.056)	(0.052)
Education (Baseline)	0.155	-0.097
	(0.096)	(0.080)
Age (Baseline)	-0.056***	0.021***
	(0.010)	(0.007)
Hours Worked (Baseline)	-0.002	0.008
	(0.005)	(0.005)
Constant	0.580	-0.299
	(0.376)	(0.732)
Correlation	-15.843***	
	(0.269)	
RCT Dummies	Yes	Yes
Mentor Dummies	Yes	Yes
Observations	382	382

*** p < 0.01, ** p < 0.05, * p < 0.1
Note. DV = dummy for making any revenue during the RCT.
Standard errors clustered at the classroom level (K = 24).

S2. Supplementary materials for Chapter 2, Updating strategy and beliefs: Experimental evidence on entrepreneurial pivoting

S2.1 Attrition

S2.1.1 Selective Attrition

We experienced attrition from participants. Specifically, 20 entrepreneurs out of 250 left the course before its end (8%): 14 of them left the program already at the first round of data collection, while other 6 left the program later in time. The attrition rate is slightly higher in the control group (14 entrepreneurs) rather than in the treatment group (6 entrepreneurs). Percentagewise, the rate in the control group amounts to 11% versus 5% of the treated group, being this difference significant at 10% (two-tailed t-test; $t = 1.87$; $p = 0.06$). The analyses on the cross-section of respondents in the main paper assumed that no changes were made by entrepreneurs that left the program. In the panel analyses, as not to input values or make assumptions about their activities, we excluded attritors from the sample. Table S2.1 reports results for the selective attrition test on a number of baseline covariates. Attritors are more likely to have a STEM background, but on average have a lower team-level education.

Table S2.1 – Selective attrition tests

	(1) Control Attritors	(2) Control Respondents	(3) Treated Attritors	(4) Treated Respondents	(1)-(2)	(1)-(3)	(1)-(4)	(2)-(3)	(2)-(4)	(3)-(4)	F-test for joint orthogonality
	Mean/SE				T-test (difference)						
Project Potential	45.714	47.514	38.333	47.672	-1.799	7.381	-1.958	9.180	-0.159	-9.339	0.361
	[6.871]	[2.186]	[10.775]	[1.922]							
Team Size	2.429	2.261	1.333	2.294	0.167	1.095	0.134	0.928*	-0.033	-0.961	0.950
	[0.416]	[0.128]	[0.211]	[0.136]							
Expected Value	67.679	64.032	59.500	66.681	3.647	8.179	0.998	4.532	-2.649	-7.181	0.925
	[4.162]	[1.615]	[5.418]	[1.329]							
Background: STEM	0.673	0.465	0.833	0.354	0.208*	-0.161	0.319***	-0.368**	0.111**	0.480***	5.460***
	[0.111]	[0.039]	[0.105]	[0.036]							
Experience: Industry	1.798	2.399	4.806	2.742	-0.602	-3.008*	-0.944	-2.407	-0.343	2.064	1.085
	[0.694]	[0.354]	[1.965]	[0.345]							
Experience: Entrepreneurial	1.015	0.918	0.167	1.141	0.097	0.848*	-0.126	0.751	-0.224	-0.975	0.703
	[0.271]	[0.142]	[0.167]	[0.205]							
Experience: Managerial	1.179	2.409	2.417	2.283	-1.230	-1.238	-1.104	-0.008	0.126	0.134	0.404
	[0.541]	[0.414]	[1.307]	[0.342]							
Age	28.565	31.769	30.333	31.532	-3.203	-1.768	-2.966	1.435	0.237	-1.199	0.702
	[1.558]	[0.766]	[2.857]	[0.756]							
Gender (Male)	0.786	0.750	0.833	0.720	0.036	-0.048	0.066	-0.084	0.030	0.113	0.348
	[0.085]	[0.034]	[0.105]	[0.035]							
Hours: Total Weekly	15.542	10.377	5.500	10.410	5.164	10.042	5.131*	4.877	-0.033	-4.910	1.522
	[3.922]	[1.037]	[1.722]	[0.898]							
Education	1.548	1.999	1.833	1.950	-0.451**	-0.286	-0.402*	0.165	0.049	-0.117	1.478
	[0.193]	[0.075]	[0.401]	[0.067]							
N	14	111	6	119							

S2.2 Ex-post data collection

Again, the panel analyses in the main paper excluded attritors as not to input information on both the dependent variables (e.g. expected value, range, revenues) and independent variables (i.e. the decision to pivot).

Nevertheless, we performed an additional data collection effort and re-contacted "attritors" entrepreneurs in September 2022, that is around 4 years after the end of the program.

We were able to successfully gather information for 7 out of the 20 attritors. We asked them whether they introduced any change to their BMCs in the period after their decision to leave the program or the data collection, as to corroborate our exploratory results on the pivoting activities. We also asked them if they were still active on the market (1 out of 7 is still active) and whether they made revenues in the fiscal years 2018 and 2019. Clearly, we couldn't ask them what their expected value at a specific month far in the past was, nor the precise time-period in which the change was introduced. Therefore, we only use this information to update the exploratory results on the pivoting activities, but do not make any assumption on the attritors' value when it comes to the panel regressions for the expected value and uncertainty measures.

Given this additional data for 7 attritors, we are left with missing information for 13 entrepreneurs. Since some of them did not drop already in the first data collection point, we use information for the observed periods to infer their pivoting status. Ultimately, we re-run the graphical and regression analyses with a sample of 241 entrepreneurs.

Looking at pivoting activities, two attritors performed one *operational* pivot after leaving the program, while one of them performed a *core* pivot. The other contacted ventures did not make any change. As in the main paper, Figure A2.1 shows the number of entrepreneurs according to the *core* versus *operational* classification, considering as pivoters those entrepreneurs that changed an element of the BMC at least one time during the whole observation window.

Figure S2.1 – Number of entrepreneurs by pivoting category and treatment condition

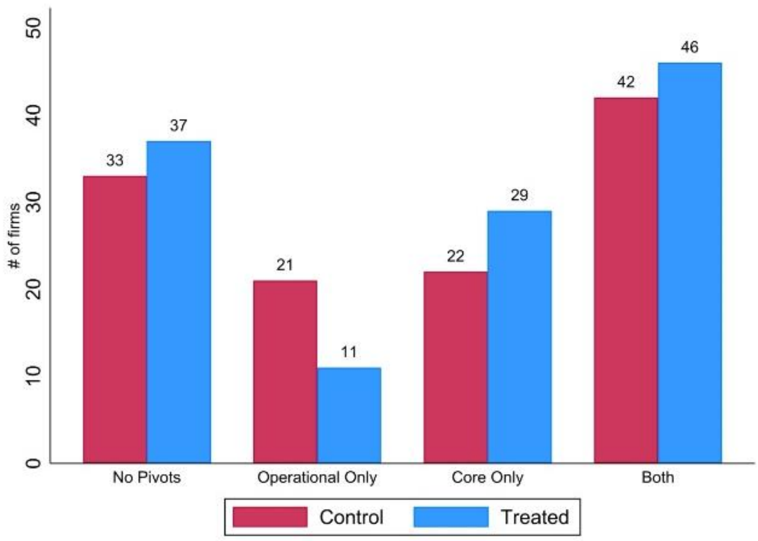


Figure S2.1 displays the number of entrepreneurs in each pivoting category. "No Pivots" identifies entrepreneurs who never pivoted during the observational window; "Operational Only" identifies entrepreneurs who performed at least one operational change but no core changes in the whole observational window; "Core Only" identifies entrepreneurs who performed at least one core change but no operational ones across the whole observational window; "Both" identifies entrepreneurs who made both changes during the observation window. Attritors in the first week are dropped from the sample, but for those for which we collected additional information in September 2022 (N = 241).

Dropping attritors leads to a consistent graph with respect to the main paper, with treated entrepreneurs more likely to perform *core* changes (see Table S2.2 in the next subsection for the regression results). Figure S2.2 instead shows the number of pivoting sessions conducted, by the type of changes introduced. Again, the Figure is consistent with the one reported in the main paper.

Figure S2.2 – Entrepreneurs by number of changes and treatment condition

Panel A Number of pivoting sessions (core) **Panel B** Number of pivoting sessions (operational)

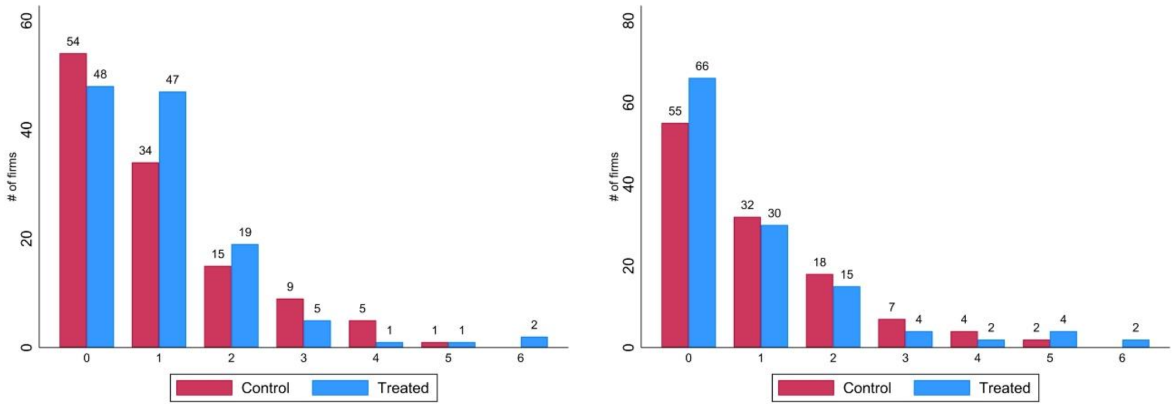


Figure S2.2 displays the number of entrepreneurs by the number of pivoting sessions conducted across the whole observation period. Panel A shows the number of sessions conducted where *core* changes have been introduced; Panel B shows the number of sessions conducted where *operational* changes have been introduced. Attritors in the first week are dropped from the sample, but for those for which we collected additional information in September 2022 (N = 241).

S2.3 An exploration of pivoting activities: additional results and regressions

S2.3.1 Frequency of pivoting by observation period

Figure S2.3 shows the frequency of pivoting sessions by observation period.

Figure S2.3 – Number of entrepreneurs making changes by week of observation

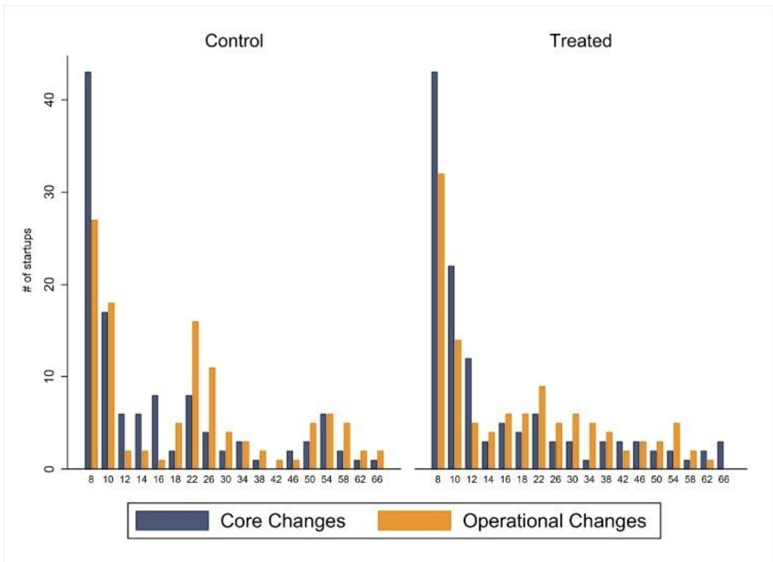


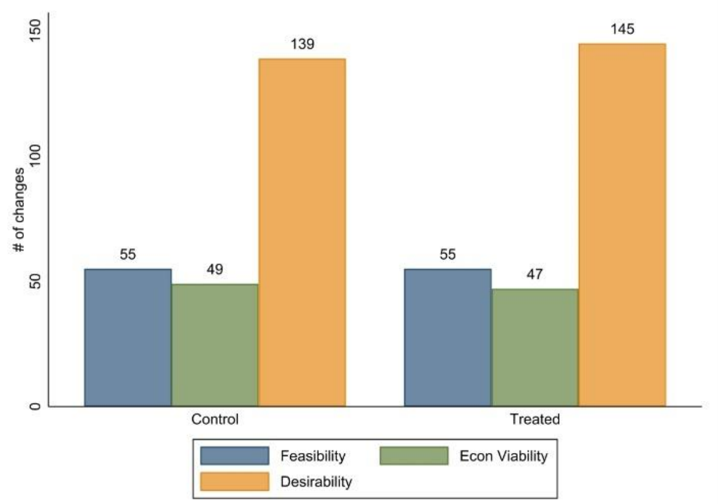
Figure S2.3 shows the number of entrepreneurs introducing *core* or *operational* changes by week of observation. The bulk of changes is introduced in the first weeks of observation, with a second peak halfway through the observation period.

The pattern of introduced changes has its peak in the first two weeks of observations, where *core* changes are more likely to be introduced by both treatment groups. *Operational* changes are also introduced progressively over time, with a second small peak around weeks 22-26 for both groups.

S2.3.2 Number of BMC changes

Figure S2.3 shows the total number of changes given the Bland & Osterwalder (2019) categorization. The total number of elements, regardless of which startup introduced them, is highly comparable between treatment groups. Since the number of entrepreneurs conducting pivoting sessions is similar across conditions, the graph indicates that the number of changes was comparable between groups.

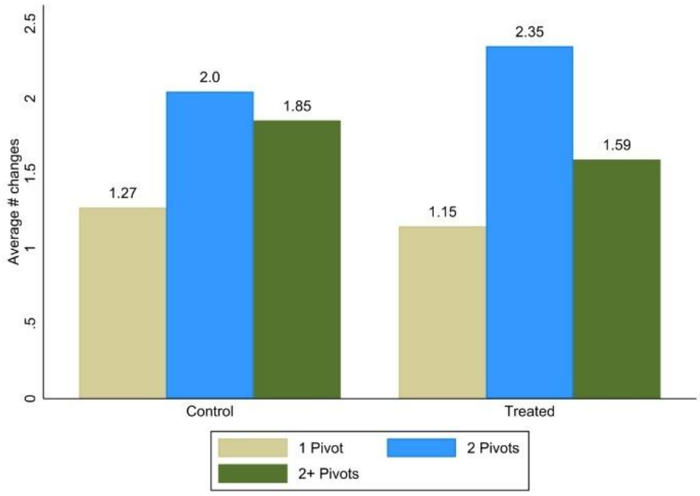
Figure S2.4 – Number of changes by Bland & Osterwalder (2019) category



Reading this graph together with Figure 2.2 in the main paper, suggests that the fewer number of control entrepreneurs introducing *core* changes made more changes in absolute terms, since the higher number of treated entrepreneurs performing that type of changes is responsible for a similar number of average changes.

Finally, Figure S2.5 shows the average number of BMC changes grouping entrepreneurs by the total number of pivoting sessions conducted. Specifically, we group those that conducted only one pivoting session, those that conducted two pivoting sessions and those that conducted more than two sessions during the observation period.

Figure S2.5 – Number of changes by number of pivoting sessions



Entrepreneurs performing only one pivoting session changed on average 1.2 elements of the BMC, in both experimental groups. The number of average changes increases for entrepreneurs performing two pivoting sessions, with a slightly higher average for the treatment group. Entrepreneurs changing their business model more than two times, did so by introducing fewer changes per session than those doing two sessions. The trends are similar in both groups, albeit with a more marked difference for the treated group. Overall, this signals that those entrepreneurs performing only one pivoting session were also those that changed the less and probably made a more focused pivoting activity.

S2.3.3 Regression results (Section 4.1)

We report here the results of the regressions related to Section 4.1 in the main paper. Table S2.2 shows the result for the likelihood of pivoting, by type of changes introduced. We run the regressions on the full sample of entrepreneurs, assuming no changes for attritors, as well for the subsample of compliers.

Table S2.2 – Probability of pivoting

VARIABLES	(1) Core Pivot	(2) Core Pivot (Probit)	(3) Core Pivot (Compliers)	(4) Operational Pivot	(5) Operational Pivot (Probit)	(6) Operational Pivot (Compliers)
Treatment	0.101**	0.267**	0.075*	-0.038	-0.095	-0.072
	(0.033)	(0.087)	(0.034)	(0.045)	(0.112)	(0.042)
	[0.047]	[0.009]	[0.16]	[0.60]	[0.40]	[0.29]
Control Mean	0.50		0.54	0.49		0.53
Observations	250	250	241	250	250	241
R^2 (LPM)	0.057		0.068	0.021		0.026
Mentor Dummies	YES	YES	YES	YES	YES	YES

Table S2.2 reports the results of the regressions for the probability of pivoting. Columns 1-3 use as dependent variable a dummy taking value 1 if a *core* change has been conducted during the observation window. Column 1 fits a LPM model. Column 2 repeats the exercise fitting a Probit model. Column 3 runs a LPM model removes attritors, keeping those for which additional information has been gathered. Columns 4-6 replicate the previous three columns using as dependent variable a dummy taking value 1 if an *operational* change has been conducted during the observation window. All specifications include mentor dummies and control for the share of team members with an economics background (unbalanced at the baseline). Standard errors clustered by classroom (reported in rounded parentheses). Due to the low number of clusters, we report in square brackets the more conservative p-values inferred from a Wild Bootstrapping inference with Webb weights and 9,999 repetitions.

Results show how treated entrepreneurs are 9% more likely to have performed pivoting sessions with *core* changes when compared to control entrepreneurs. There seem to be no difference instead when it comes to pivoting sessions entailing *operational* changes, albeit the negative estimated coefficient that turns to be statistically significant only in the model without attritors. Nevertheless, these results confirm that treated entrepreneurs make more fundamental changes to their business models when compared to control entrepreneurs.

Table S2.3 looks *within* pivoters (thus automatically excluding attritors) to understand the different focus of the introduced changes. Results show how treated entrepreneurs are significantly less likely to introduce changes to BCM quadrants related to the *economic viability* of their businesses, but significantly more likely to introduce changes related to the *desirability* of their offers. This confirms the intuition for which the *focus* of the pivoting activities is different by treatment group, with treated entrepreneurs that are more focused on customer-centric issues.

Table S2.3 – Bland & Osterwalder (2019) categories

	(1) Feasibility	(2) Feasibility (Probit)	(3) Viability	(4) Viability (Probit)	(5) Desirability	(6) Desirability (Probit)
Treatment	-0.030	-0.095	-0.084*	-0.234**	0.047	0.374^
	(0.049)	(0.132)	(0.031)	(0.088)	(0.029)	(0.199)
	[0.69]	[0.48]	[0.10]	[0.021]	[0.30]	[0.061]
Control Mean	0.48		0.40		0.88	
Observations	168	168	168	168	168	168
R^2 (LPM)	0.105		0.035		0.116	
Mentor Dummies	YES	YES	YES	YES	YES	YES

Table S2.3 reports the results of the regressions for the probability of making changes according to Bland & Osterwalder (2019) categorization. In each column, the dependent variable is a dummy taking value 1 if at least one change performed by entrepreneurs during any data point falls in the reference category. The first column for each variable fits a LPM model. The second column fits a Probit model. Only the subsample of pivoting entrepreneurs is considered.

All specifications include mentor dummies and control for the share of team members with an economics background (unbalanced at the baseline). Standard errors clustered by classroom (reported in rounded parentheses). Due to the low number of clusters, we report in square brackets the more conservative p-values inferred from a Wild Bootstrapping inference with Webb weights and 9,999 repetitions.

S2.4 Robustness Checks and exploratory results

S2.4.1 Exploratory results on pivoting

Table S2.3 reported results for the different focus of pivoting. Table S2.4 replicates the regressions but considering an Heckman (Probit) selection model to account for the selection into pivoting. To identify the selection equation, we use the perceived probability of pivoting at the baseline. Results are aligned with the ones in the main table, albeit being less statistically significant.

Table S2.4 – Heckprobit selection model for *strategyzer* categories regression

	(1) Feasibility	(2) Feasibility (Selection)	(4) Economic Viability	(5) Economic Viability (Selection)	(7) Desirability	(8) Desirability (Selection)
Pivot Probability		-0.008*		-0.008*		-0.007
		(0.004)		(0.003)		(0.004)
Treatment	-0.025	0.061	-0.156	0.091	0.371^	0.099
	(0.123)	(0.109)	(0.102)	(0.104)	(0.206)	(0.092)
Wald test	0.94		18.67***		80707***	
Observations	250	250	250	250	250	250
Mentor Dummies	YES	YES	YES	YES	YES	YES

Table S2.4 reports the results of selection models (Heckman Probit) for the probability of making changes according to the *strategyzer.com* categorization. In the first column of each group, the dependent variable is a dummy taking value 1 if at least one change performed by entrepreneurs during any data point falls in the reference category. The selection equation is specified on whether the startup has conducted at least one pivot. All specifications include mentor dummies and control for the share of team members with an economics background (unbalanced at the baseline). Standard errors clustered by classroom (reported in rounded parentheses). The Wald test of independent equations is reported.

S2.4.2 Panel regressions: additional specifications

We report here additional specifications for the regressions shown in Tables 2.2 and 2.3 in the main paper. Specifically, we re-estimate the models in Columns 1-4 in the main paper considering survived firms only and estimate the models in Columns 5-6 using as regressors the full interacted set of pivoting and treatment dummies without taking their first-difference.

Table S2.5 shows the results for the expected idea value measure; Table S2.6 the results for the range measure; All results are consistent with those in the main paper.

Table S2.5 – Regression results for expected idea value: additional specifications

	(1)	(2)	(3)	(4)	(5)	(6)
Group	Control (Survived startups)		Treated (Survived startups)		All groups (All startups)	
Period	During	After	During	After	During	After
Pivot (dummy)					1.459	-0.332
					(1.121)	(0.991)
Treatment					0.192	-0.059
					(0.275)	(0.239)
Pivot X Treatment					-1.320	2.306^
					(1.501)	(1.265)
Pivot (FD)	1.588^	-1.835^	-1.649	1.374^		
	(0.888)	(0.999)	(1.093)	(0.763)		
Observations	1,177	1,112	1,076	1,019	3,045	2,832
R-squared	0.015	0.019	0.022	0.024	0.007	0.008
Period dummies	YES	YES	YES	YES	YES	YES

DV: first-difference of expected idea value
All models include period dummies and standard errors clustered at the entrepreneur level.
Column 1-2 report the regression for the control group, using the first-difference (1) and the forwarded first-difference (2) for survived startups only. Columns 3-4 replicate the models for the treatment group, for survived startups only. Columns 5-6 report the results for the full sample, using as regressors the plain set of dummies and interactions without taking the first difference.
Attritors are excluded from the sample.

Table S2.6 – Regression results for range of expected idea value: additional specifications

	(1)	(2)	(3)	(4)	(5)	(6)
Group	Control (Survived startups)		Treated (Survived startups)		All groups (All startups)	
Period	During	After	During	After	During	After
Pivot (dummy)					-3.309**	-0.405
					(1.254)	(1.256)
Treatment					-0.120	0.313
					(0.299)	(0.256)
Pivot X Treatment					4.355*	-1.249
					(1.837)	(1.675)
Pivot (FD)	-1.650	0.129	0.006	-1.297		
	(1.046)	(1.056)	(1.388)	(1.011)		
Observations	1,177	1,112	1,076	1,019	3,045	2,832
R-squared	0.060	0.013	0.033	0.024	0.032	0.006
Period dummies	YES	YES	YES	YES	YES	YES

DV: first-difference of expected idea range
All models include period dummies and standard errors clustered at the entrepreneur level.
Column 1-2 report the regression for the control group, using the first-difference (1) and the forwarded first-difference (2) for survived startups only. Columns 3-4 replicate the models for the treatment group, for survived startups only. Columns 5-6 report the results for the full sample, using as regressors the plain set of dummies and interactions without taking the first difference.
Attritors are excluded from the sample.

S2.4.2 Regressions with fine-grained pivoting category

In this section, we re-estimate the first-differences model in the main paper using as regressors the first-differenced dummy considering the type of changes introduced, rather than the dummy grouping all pivoting activities together. These models are nevertheless less powerful, given the low number of events compared to the baseline of no-pivoting.

Table S2.7 shows the results for the (first differenced) expected value measure as the dependent variable.

Table S2.7 – Regression results for expected value: pivoting categories

	(1)	(2)	(3)	(4)	(5)	(6)
Group	Control		Treated		All	
Period	During	After	During	After	During	After
Operational Change (FD)	1.217	-0.481	-2.064	1.729*	1.465	-0.345
	(1.545)	(1.256)	(1.512)	(0.852)	(1.548)	(1.266)
Core Change (FD)	1.343	-1.584	0.952	-0.205	1.618	-1.339
	(1.304)	(1.106)	(1.195)	(0.979)	(1.296)	(1.042)
Both Changes (FD)	-0.699	-0.252	-2.786	3.076^	-0.410	-0.022
	(2.078)	(1.836)	(1.716)	(1.571)	(2.069)	(1.743)
Operational X Treatment (FD)					-3.693^	1.858
					(2.231)	(1.562)
Core X Treatment (FD)					-0.969	0.892
					(1.689)	(1.367)
Both X Treatment (FD)					-2.709	2.855
					(2.682)	(2.195)
Observations	1,553	1,445	1,491	1,386	3,044	2,831
R-squared	0.009	0.010	0.019	0.015	0.011	0.008
Period dummies	YES	YES	YES	YES	YES	YES

DV: first-difference of expected value
All models report a first-difference OLS regression with period dummies and standard errors clustered at the entrepreneur level.
Column 1-2 report the regression for the control group, using the first-difference (1) and the forwarded first-difference (2). Columns 3-4 replicate the models for the treatment group. Columns 5-6 report the results for the full sample, adding the first-differenced interaction as a regressor. Attritors are excluded from the estimation.
*** p<0.001, ** p<0.01, * p<0.05, ^ p<0.1

As expected, results show the same pattern displayed in Figure 2.4, Panel B in the main paper. The increase in expected value after the pivoting activity is especially marked for treated entrepreneurs only, especially when they introduce *operational* changes in conjunction with *core* changes.

Table S2.8 shows the results for the range measure. Looking at the fine-grained pivoting categories, the results seem to show a milder support for Proposition 2 when it comes to *core* changes, while the reduction in uncertainty is significant for treated entrepreneurs performing *operational* changes and goes contrarily to our expectations. Nevertheless, in the period when the pivoting is performed, treated entrepreneurs approach it with a higher perceived uncertainty when compared to control entrepreneurs as in the results reported in the main paper.

Table S2.8 – Regression results for range of expected value: pivoting categories

	(1)	(2)	(3)	(4)	(5)	(6)
Group	Control		Treated		All	
Period	During	After	During	After	During	After
Operational Change (FD)	-2.651	2.015	4.004^	-2.510*	-3.010	1.588
	(1.891)	(1.629)	(2.258)	(0.990)	(1.867)	(1.654)
Core Change (FD)	-0.465	-1.841	-0.416	-0.526	-0.517	-2.658
	(2.109)	(1.739)	(1.622)	(1.160)	(2.114)	(1.763)
Both Changes (FD)	-1.860	-2.020	1.453	-2.491	-1.912	-2.867
	(2.655)	(2.023)	(3.032)	(2.004)	(2.623)	(1.984)
Operational X Treatment (FD)					6.982*	-3.411^
					(2.971)	(1.938)
Core X Treatment (FD)					0.292	2.878
					(2.608)	(2.038)
Both X Treatment (FD)					3.499	1.239
					(4.035)	(2.702)
Observations	1,553	1,445	1,491	1,386	3,044	2,831
R-squared	0.051	0.017	0.033	0.022	0.033	0.010
Period dummies	YES	YES	YES	YES	YES	YES

DV: first-difference of range of expected value

All models report a first-difference OLS regression with period dummies and standard errors clustered at the entrepreneur level.

Column 1-2 report the regression for the control group, using the first-difference (1) and the forwarded first-difference (2). Columns 3-4 replicate the models for the treatment group. Columns 5-6 report the results for the full sample, adding the first-differenced interaction as a regressor. Attritors are excluded by the estimation.

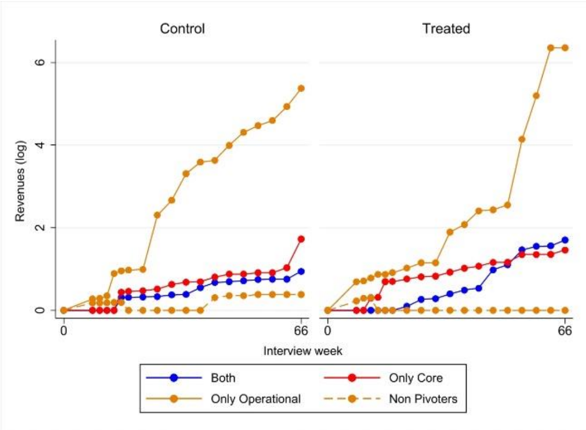
*** p<0.001, ** p<0.01, * p<0.05, ^ p<0.1

S2.4.3 Performance results with fine-grained pivoting category

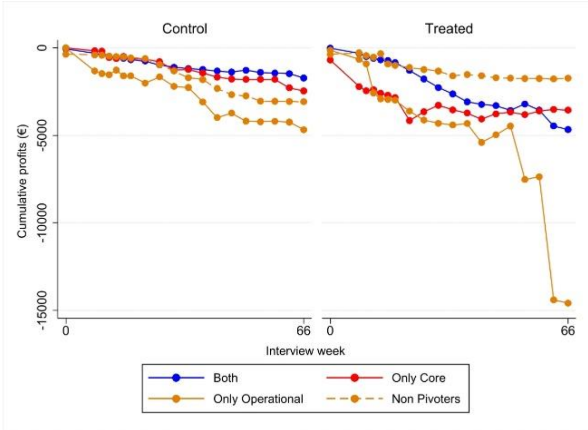
Figure S2.6 shows the performance outcomes by treatment allocation and the fine-grained pivoting category. Panel A displays (logged) cumulative revenues; Panel B cumulative profits; Panel C (logged) cumulative activated customers.

Figure S2.6 – Entrepreneurs' performance by pivoting categories

Panel A Cumulative revenues (logged)



Panel B Cumulative profits (€)



Panel C Cumulative activated customers (logged)

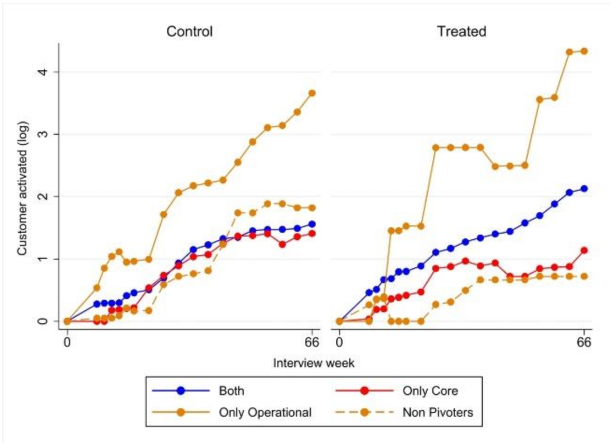


Figure S2.6 Panel A shows the logged cumulative revenues over time, dividing between treatment group and fine-grained pivoting condition. Panel B shows the profits made by entrepreneurs over time, winsorized at the 99th percentile. Profits are computed as cumulative revenue minus cumulative costs incurred over time. Panel C shows the logged cumulative number of activated customers over time. Observations for entrepreneurs that terminate their ideas are set to missing starting from the dropout period, explaining the potential noise in the pattern.

As explained in the main text, performance effects are mostly driven by entrepreneurs implementing only *operational* changes, as corroborated by regression results in Table S2.9.

Table S2.9 – Regression results on performance metrics: pivoting categories

VARIABLES	(1) Cumulative Revenues (log)	(2) Profit (€)	(3) Cumulative Activated Customers (log)
Operational Change (Dummy)	2.159**	-1,621.688	0.928^
	(0.696)	(1,473.753)	(0.475)
Core Change (Dummy)	0.253	961.122	-0.018
	(0.482)	(1,190.342)	(0.421)
Both Change (Dummy)	-0.051	912.439	0.102
	(0.250)	(1,181.111)	(0.303)
Treatment (Dummy)	-0.369^	193.692	-0.445
	(0.204)	(1,326.093)	(0.317)
Operational Change X Treatment	-0.233	-826.292	0.683
	(1.271)	(3,300.312)	(0.760)
Core Change X Treatment	0.417	-2,083.600	0.224
	(0.672)	(3,208.690)	(0.500)
Both Changes X Treatment	0.613^	-1,309.195	0.766^
	(0.356)	(1,569.329)	(0.430)
Observations	3,053	3,043	3,047
R-squared	0.159	0.224	0.054
Period Dummies	YES	YES	YES
Mentor Dummies	YES	YES	YES

All columns report a OLS regression with period and mentor dummies; a control for the share of team members with an economics background (unbalanced at the baseline) is added. Standard errors clustered at the entrepreneur level. Column 1 uses as DV the logged cumulative revenues over time. Column 2 uses as DV the cumulative profits in € over time, winsorized at the 99th percentile. Column 3 uses as DV the logged number of activated customers.
Once an entrepreneur terminates her project or leaves the program, the values are set to missing. Attritors leaving the program in the first week are excluded from the sample since the baseline period is excluded from the estimation.
*** p<0.001, ** p<0.01, * p<0.05, ^ p<0.1

S2.4.4 Expected value and uncertainty: baseline vs last available datapoint

Table S2.10 reports the average expected idea value and range by treatment group and pivoting status at the baseline (i.e. before the intervention) and at the last available datapoint. The latter means that if a start-up did not terminate, we observe its values up to the end of the observation period. If it terminated its activities, we consider the last available survey at our disposal.

Table S2.10 – Expected value and uncertainty: baseline vs last datapoint comparison

		Control			Treated		
		Baseline	Last	Delta	Baseline	Last	Delta
Non pivoters	Expected Value	65.49	59.62	-5.87	67.24	56.92	-10.32
	Uncertainty (range)	40.42	35.98	-4.44	39	36.51	-2.49
Pivoters	Expected Value	63.89	57.32	-6.57	65.92	62.17	-3.76
	Uncertainty (range)	43.54	30.37	-13.17	40.04	33.52	-6.52

Averages of expected idea value and uncertainty (range) by treatment group and pivoting condition. We label as pivoters those entrepreneurs that made at least one change during the whole observation period.
Observations: Control-non pivoters: 43; Control Pivoters: 82; Treated non-pivoters: 39; Treated pivoters: 86

Treated entrepreneurs who pivoted end up with the highest expected value, signaling that their pivoting activities led to more positive beliefs updating when introducing changes, as shown in the main text. Pivoting entrepreneurs seem also to reduce perceived uncertainty more than non-pivoting ones, with a milder reduction for treated ones. These differences, albeit qualitatively meaningful, are not however statistically significant at conventional level. A regression on the deltas indicates a more positive update for treated entrepreneurs who pivot ($\beta = 7.11$), but with a p-value greater than 10% ($p = 0.12$).

Results are even more marked when looking at the subsample of entrepreneurs that do not terminate. In this case, the average delta on expected value for treated entrepreneurs who pivot reduces to -2.38, compared to a reduction of -6.07 for control entrepreneurs who pivoted. A similar pattern is shown for the uncertainty measure.

Overall, these additional results suggest two main take-aways. First, both decision-making approaches made entrepreneurs more conservative about the potential value of their ideas. Second, this reduction in expectation seems to be less marked for treated entrepreneurs who pivoted. The latter is in line with the results reported in the main paper, that suggested a positive beliefs update following pivoting activities for treated entrepreneurs. Overall, this signals that, at least perception-wise, treated entrepreneurs are pivoting towards a more promising development trajectory with respect to entrepreneurs in the control group.

S3. Supplementary materials for Chapter 3, Entrepreneurship Training and Founders' Perceptions of Ability: A Randomized Control Trial with Entrepreneurs in Tanzania

S3.1 Details on the training curriculum and differences between experimental conditions

To isolate the role of having a theory-of-value to guide experimentation, we created two training conditions: *evidence-based* and *theory-and-evidence-based*. Entrepreneurs in both training conditions followed the same curriculum, and the syllabus shared with participants in both conditions can be found in Annex 1 at the end of the supplementary materials. Each training session reflected differences in the structure and content based on the experimental conditions. Table S3.1 documents the differences in Sessions 1 and 2 between the two conditions, and Figure S3.1 presents actual slides used in Session 1 for each experimental condition.

In Session 1, the *evidence-based* condition starts by developing a lean business model canvas (BMC) and falsifiable hypotheses based on the BMC (see Figure S3.1, Panels A & C). In Session 2, the entrepreneurs in this condition learn about early adopters and their pain points and are instructed to conduct customer interviews in order to test some of the hypotheses developed in Session 1. In contrast to the *evidence-based* condition, the first two sessions in *theory-and-evidence-based* condition were entirely devoted to the development of a theory-of-value for their business. In Session 1, the *theory-and-evidence-based* condition were taught to think of their theory-of-value in the form of a story, using a specific tool we developed called the "story tree" (see Figure S3.1, Panel D and Figure S3.2 for the template shared with entrepreneurs). This tool helped entrepreneurs find logical and causal connections between elements of their business proposition. In Session 2, these entrepreneurs learn to target customers based on their theory-of-value and to use customer interviews to further explore and refine their theory-of-value. Notably, there is no hypothesis creation or development at this stage of the training program for the *theory-and-evidence-based* condition. In each of the subsequent sessions, the entrepreneurs in the *theory-and-evidence-based* condition refer back to their "story tree," while the entrepreneurs in the *evidence-based* condition refer back to their BMC.

Table S3.1 – Comparison of content and structure for Sessions 1 and 2

SESSION 1

	Evidence-based	Theory-and-Evidence-based
Block 1	Course introduction: common mistakes entrepreneurs make	
Block 2	Introduce the Business Decision Process & business models	Introduce the Scientific Approach & theory-of-value
	Exercise: develop a business model canvas	Exercise: develop a story tree
Block 3	Identify assumptions + hypotheses	Introduce business models & connect to theory/story tree
	Exercise: create falsifiable hypotheses	Exercise: develop a business model canvas
At home	Continue developing a business model canvas & writing hypotheses	Continue developing a story tree & business model canvas

SESSION 2

	Evidence-based	Theory-and-Evidence-based
Block 1	Introduce customer identification (early adopters)	Introduce problem framing (using story tree + theory)
Block 2	Exercise: develop a customer persona	Exercise: develop a customer process map
	Introduce problem framing (early adopters' pain points)	Introduce customer identification (target customers based on story tree + theory)
Block 3	Exercise: develop a customer process map	Exercise: develop a customer persona
	Introduce customer interviews as a way to test hypotheses	Introduce customer interviews to explore & refine theory
At home	Keep developing tools & conduct 5 interviews	Keep developing tools & conduct 5 interviews

Figure S3.1 – Comparison of systematic approaches to decision making

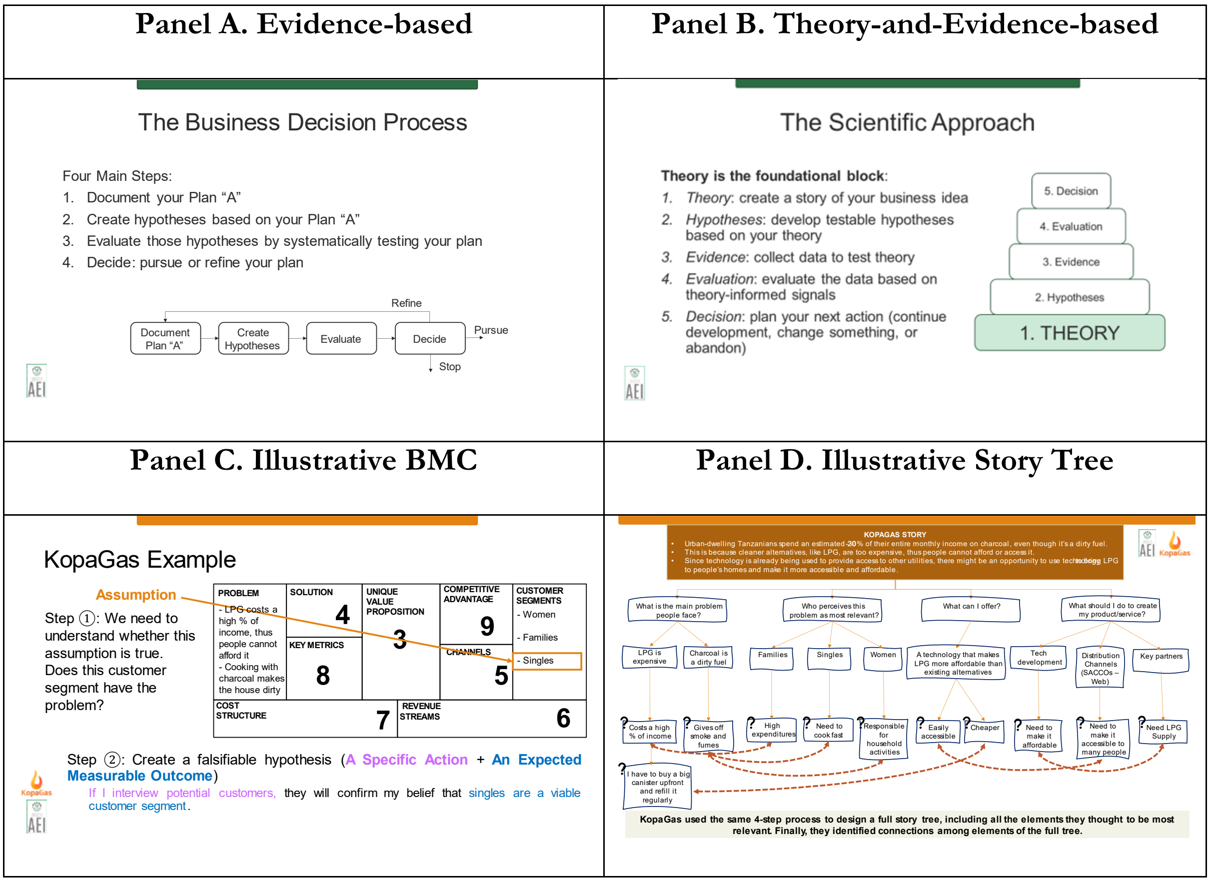
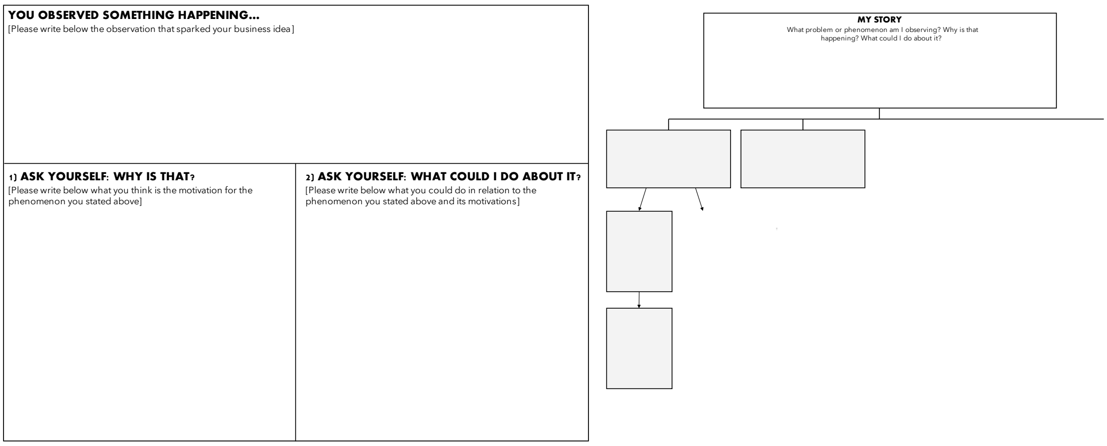


Figure S3.2 – The "story tree" template



S3.2 Additional details on randomization and balance checks

Table S3.2 reports balance checks for the three conditions, including the non-random *control* group. As reported in the main text, no major significant differences exist between the two experimental conditions. The only significant difference (at 10%) is related to the self-reported entrepreneurs' perceived probability of introducing major changes, which was recorded on a 0-100 scale in the baseline questionnaire. There are differences with respect to the non-random control group in terms of gender, tertiary education and hours worked on the business project.

Table S3.2 – Balance tables with control group

	(1) Control	(2) Theory-and -Evidence	(3) Evidence	T-tests			Normalized difference			F-test
Variable	Mean SE	Mean SE	Mean SE	(1)-(2)	(1)-(3)	(2)-(3)	(1)-(2)	(1)-(3)	(2)-(3)	
Respondents' age	33.294 (1.305)	32.853 (1.074)	31.421 (0.870)	0.441	1.873	1.432	0.048	0.225	0.169	0.852
Gender (% male)	0.784 (0.058)	0.560 (0.058)	0.684 (0.054)	0.22***	0.100	-0.124	0.469	0.223	-0.255	3.613**
Working full time (%)	0.608 (0.069)	0.573 (0.057)	0.566 (0.057)	0.035	0.042	0.008	0.070	0.085	0.015	0.118
Work experience (years)	5.669 (0.846)	6.507 (0.873)	4.908 (0.664)	-0.838	0.761	1.599	-0.120	0.129	0.237	1.121
Work experience in agriculture (years)	3.325 (0.444)	3.320 (0.438)	2.974 (0.386)	-0.085	0.262	0.346	-0.024	0.080	0.097	0.199
Managerial experience (years)	4.441 (1.011)	3.453 (0.495)	3.217 (0.438)	0.988	1.224	0.236	0.175	0.224	0.058	0.959
Entrepreneurial experience (years)	4.157 (0.477)	4.027 (0.490)	3.671 (0.448)	0.130	0.486	0.356	0.033	0.131	0.087	0.274
Tertiary education (%)	0.922 (0.038)	0.813 (0.045)	0.776 (0.048)	0.108*	0.145**	0.037	0.308	0.389	0.091	2.342*
Business degree (%)	0.176 (0.054)	0.067 (0.029)	0.118 (0.037)	0.110*	0.058	-0.052	0.348	0.166	-0.178	1.832
Firm type (=1 if startup)	0.627 (0.068)	0.640 (0.056)	0.658 (0.055)	-0.013	-0.030	-0.018	-0.026	-0.063	-0.037	0.064
For-profit business (%)	0.882 (0.046)	0.947 (0.026)	0.921 (0.031)	-0.064	-0.039	0.026	-0.237	-0.132	0.103	0.855
Perceived probability of termination	29.863 (5.207)	28.547 (4.177)	25.171 (3.539)	1.316	4.692	3.376	0.036	0.140	0.101	0.326
Perceived probability of major changes (0-100)	51.510 (4.760)	48.547 (3.792)	57.763 (3.955)	2.963	-6.253	-9.216*	0.089	-0.182	-0.272	1.454
Hours worked (from interview)	27.337 (3.110)	30.400 (2.795)	34.895 (2.838)	-3.063	-7.557*	-4.495	-0.131	-0.315	-0.183	1.610
Total revenues (US$ - winsorized 95th)	1063.804 (259.752)	985.131 (225.828)	743.436 (144.580)	78.672	320.367	241.695	0.041	0.210	0.147	0.647
Total costs (US$ - winsorized 95th)	856.135 (173.387)	1085.254 (191.395)	915.029 (164.251)	-229.12	-58.894	170.225	-0.153	-0.044	0.110	0.431
Number of owners (from interview)	2.686 (0.467)	2.040 (0.271)	1.895 (0.147)	0.646	0.792*	0.145	0.231	0.336	0.077	1.879
Number of salaried employees (from interview)	1.686 (0.345)	3.107 (1.342)	1.487 (0.326)	-1.420	0.199	1.620	-0.156	0.074	0.192	1.031
Number of other employees (from interview)	3.235 (0.843)	2.293 (0.497)	3.039 (0.818)	0.942	0.196	-0.746	0.186	0.029	-0.127	0.473
Idea stage (=1 if sales or pre-sales)	0.608 (0.069)	0.587 (0.057)	0.592 (0.057)	0.021	0.016	-0.005	0.043	0.032	-0.011	0.029
Months worked on the project	24.843 (3.932)	24.640 (4.080)	29.855 (4.669)	0.203	-5.012	-5.215	0.006	-0.139	-0.137	0.486
Other business courses attended (%)	0.569 (0.070)	0.627 (0.056)	0.632 (0.056)	-0.058	-0.063	-0.005	-0.118	-0.128	-0.010	0.293
Observations	51	75	76							
F-test of joint significance (F-stat)				0.854	1.125	0.874				

The value displayed for t-tests are the differences in the means across the groups. The value displayed for F-tests are the F-statistics. Standard errors in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Table S3.3 reports the balance tables within training location (i.e., Morogoro and Dar es Salaam), considering the two experimental conditions only. For entrepreneurs in Dar es Salaam, Table S3.3 shows significant differences (on the t-tests) between the two experimental conditions in terms of gender and perceived probability of introducing major changes. Table S3.3 also reports the normalized differences. Based on these and the rule of thumb of 0.25 in absolute values, we add controls for education (tertiary education and other business courses attended) and hours worked at the baseline to our regression models.

Table S3.3 – Balance tables by location (treated groups)

	Morogoro				Dar es Salaam			
	Theory-and -Evidence	Evidence			Theory-and -Evidence	Evidence		
	Mean SE	Mean SE	T-test	Normalized Difference	Mean SE	Mean SE	T-test	Normalized Difference
Respondents' age	32.068	29.488	2.580	0.331	33.968	33.939	0.028	0.003
	(1.311)	(1.002)			(1.820)	(1.421)		
Gender (% male)	0.591	0.605	-0.014	-0.028	0.516	0.788	-0.272**	-0.568
	(0.075)	(0.075)			(0.091)	(0.072)		
Working full time (%)	0.614	0.605	0.009	0.018	0.516	0.515	0.001	0.002
	(0.074)	(0.075)			(0.091)	(0.088)		
Work experience (years)	5.750	4.233	1.517	0.235	7.581	5.788	1.793	0.253
	(1.029)	(0.920)			(1.526)	(0.943)		
Work experience in agriculture (years)	3.568	2.907	0.661	0.166	2.968	3.061	-0.093	-0.031
	(0.632)	(0.574)			(0.567)	(0.490)		
Managerial experience (years)	3.295	2.640	0.656	0.162	3.677	3.970	-0.292	-0.073
	(0.690)	(0.527)			(0.699)	(0.729)		
Entrepreneurial experience (years)	3.250	3.767	-0.517	-0.142	5.129	3.545	1.584	0.347
	(0.401)	(0.679)			(1.019)	(0.542)		
Tertiary education (%)	0.841	0.721	0.120	0.289	0.774	0.848	-0.074	-0.189
	(0.056)	(0.069)			(0.076)	(0.063)		
Business degree (%)	0.045	0.070	-0.024	-0.104	0.097	0.182	-0.085	-0.243
	(0.032)	(0.039)			(0.054)	(0.068)		
Firm type (=1 if startup)	0.659	0.721	-0.062	-0.133	0.613	0.576	0.037	0.075
	(0.072)	(0.069)			(0.089)	(0.087)		
For-profit business (%)	0.909	0.907	0.002	0.007	1.000	0.939	0.061	0.346
	(0.044)	(0.045)			(0.000)	(0.042)		
Perceived probability of termination	33.227	25.326	7.902	0.238	21.903	24.970	-3.066	-0.091
	(5.345)	(4.692)			(6.597)	(5.473)		
Perceived probability of major changes	45.659	46.326	-0.666	-0.020	52.645	72.667	-20.022**	-0.626
	(5.101)	(5.148)			(5.650)	(5.181)		
Hours worked (from interview)	31.807	35.279	-3.472	-0.135	28.403	34.394	-5.991	-0.260
	(3.880)	(3.919)			(3.972)	(4.147)		
Total revenues (US$ - winsorized 95th)	865.325	655.608	209.717	0.131	1155.179	857.879	297.299	0.175
	(279.908)	(197.927)			(378.561)	(212.389)		
Total costs (US$ - winsorized 95th)	910.075	701.531	208.544	0.153	1333.895	1193.222	140.672	0.081
	(226.972)	(183.026)			(332.105)	(289.928)		
Number of owners (from interview)	1.818	1.884	-0.066	-0.042	2.355	1.909	0.446	0.198
	(0.288)	(0.174)			(0.515)	(0.255)		
Number of salaried employees (from interview)	1.659	1.302	0.357	0.104	5.161	1.727	3.434	0.279
	(0.519)	(0.521)			(3.156)	(0.326)		
Number of other employees (from interview)	2.091	1.953	0.137	0.050	2.581	4.455	-1.874	-0.222
	(0.442)	(0.385)			(1.035)	(1.802)		
Idea stage (=1 if sales or pre-sales)	0.659	0.698	-0.039	-0.082	0.484	0.455	0.029	0.058
	(0.072)	(0.071)			(0.091)	(0.088)		
Months worked on the project	23.432	30.977	-7.545	-0.204	26.355	28.394	-2.039	-0.051
	(3.972)	(6.930)			(8.188)	(5.952)		
Other business courses attended (%)	0.568	0.721	-0.153	-0.317	0.710	0.515	0.195	0.396
	(0.076)	(0.069)			(0.083)	(0.088)		
Observations	44	43			31	33		
F-test of joint significance (F-stat)			0.653				1.272	

The value displayed for t-tests are the differences in the means across the groups. The value displayed for F-tests are the F-statistics. Standard errors in parentheses ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

S3.3 Attrition and non-compliance

As is common in field experiments (*e.g.,* Ghanem, 2021; Molina Millán & Macours, 2017), we experienced cases of attrition and non-compliance. Specifically, 16 entrepreneurs (8 in the *evidence-based* condition; 8 in the *theory-and-evidence-based* condition) never replied to any data collection round after the baseline. We consider these entrepreneurs as "full" attritors (10% rate). Table S3.4 reports test for selective attritions, showing there are minor systematic differences between attritors across the two conditions and that respondents' subsamples are still balanced. This suggests a random attrition pattern that allows us to assume that analyses excluding attritors preserve internal validity (IV-R; Ghanem et al., 2019).

Table S3.4 – Selective Attrition Tests

Variable	(1) Theory-and-Evidence Attritors Mean/SE	(2) Theory-and-Evidence Respondents Mean/SE	(3) Evidence Attritors Mean/SE	(4) Evidence Respondents Mean/SE	T- Test (1)-(2)	(1)-(3)	(1)-(4)	(2)-(3)	(2)-(4)	(3)-(4)	F-test for joint orthogonality
Respondents' age	35.000	32.597	27.875	31.838	2.403	7.125	3.162	4.722	0.759	-3.963	1.072
	(4.268)	(1.099)	(2.030)	(0.934)							
Gender (% male)	0.500	0.567	0.500	0.706	-0.067	0.000	-0.206	0.067	-0.139*	-0.206	1.301
	(0.189)	(0.061)	(0.189)	(0.056)							
Working full time (%)	0.500	0.582	0.625	0.559	-0.082	-0.125	-0.059	-0.043	0.023	0.066	0.108
	(0.189)	(0.061)	(0.183)	(0.061)							
Work experience (years)	11.250	5.940	2.250	5.221	5.310*	9.000**	6.029**	3.690	0.720	-2.971	2.731**
	(3.539)	(0.867)	(1.146)	(0.722)							
Work experience in agriculture (years)	2.875	3.373	1.875	3.103	-0.498	1.000	-0.228	1.498	0.270	-1.228	0.441
	(1.329)	(0.466)	(1.231)	(0.407)							
Managerial experience (years)	6.500	3.090	1.688	3.397	3.410**	4.813	3.103*	1.402	-0.308	-1.710	2.213*
	(2.909)	(0.426)	(1.199)	(0.467)							
Entrepreneurial experience (years)	5.125	3.896	2.750	3.779	1.229	2.375	1.346	1.146	0.116	-1.029	0.461
	(1.394)	(0.524)	(1.760)	(0.460)							
Tertiary education (%)	0.875	0.806	0.625	0.794	0.069	0.250	0.081	0.181	0.012	-0.169	0.585
	(0.125)	(0.049)	(0.183)	(0.049)							
Business degree (%)	0.125	0.060	0.125	0.118	0.065	0.000	0.007	-0.065	-0.058	0.007	0.514
	(0.125)	(0.029)	(0.125)	(0.039)							
Firm type (=1 if startup)	0.625	0.642	0.875	0.632	-0.017	-0.250	-0.007	-0.233	0.009	0.243	0.628
	(0.183)	(0.059)	(0.125)	(0.059)							
For-profit business (%)	0.875	0.955	1.000	0.912	-0.080	-0.125	-0.037	-0.045	0.043	0.088	0.673
	(0.125)	(0.025)	(0.000)	(0.035)							
Perceived probability of termination	46.375	26.418	28.750	24.750	19.957	17.625	21.625*	-2.332	1.668	4.000	1.005
	(13.937)	(4.336)	(8.075)	(3.853)							
Perceived probability of major changes (0-100)	42.250	49.299	39.500	59.912	-7.049	2.750	-17.662	9.799	-10.613*	-20.412	1.936
	(13.684)	(3.949)	(13.067)	(4.101)							
Hours worked (from interview)	14.313	32.321	25.750	35.971	-18.01**	-11.438	-21.65**	6.571	-3.650	-10.221	2.176*
	(4.761)	(2.999)	(11.068)	(2.899)							
Total revenues (US$ - winsorized 95th)	102.538	1090.516	271.438	798.966	-987.978	-168.900	-696.428	819.08	291.550	-527.52	1.392
	(71.395)	(249.730)	(135.060)	(159.658)							
Total costs (US$ - winsorized 95th)	1414.568	1045.933	538.038	959.381	368.636	876.531	455.188	507.89	86.552	-421.34	0.461
	(717.480)	(198.086)	(379.144)	(178.064)							
Number of owners (from interview)	1.625	2.090	1.750	1.912	-0.465	-0.125	-0.287	0.340	0.178	-0.162	0.233
	(0.263)	(0.302)	(0.491)	(0.155)							
Number of salaried employees (from interview)	14.625	1.731	0.000	1.662	12.89***	14.625	12.96***	1.731*	0.070	-1.662	6.815***
	(12.136)	(0.356)	(0.000)	(0.359)							
Number of other employees (from interview)	2.625	2.254	2.375	3.118	0.371	0.250	-0.493	-0.121	-0.864	-0.743	0.246
	(1.335)	(0.536)	(1.194)	(0.905)							
Idea stage (=1 if sales or pre-sales)	0.375	0.612	0.625	0.588	-0.237	-0.250	-0.213	-0.013	0.024	0.037	0.559
	(0.183)	(0.060)	(0.183)	(0.060)							
Months worked on the project	42.875	22.463	29.000	29.956	20.412	13.875	12.919	-6.537	-7.493	-0.956	0.920
	(14.366)	(4.195)	(14.363)	(4.974)							
Other business courses attended (%)	0.625	0.627	0.625	0.632	-0.002	0.000	-0.007	0.002	-0.005	-0.007	0.002
	(0.183)	(0.060)	(0.183)	(0.059)							
N	8	67	8	68							

The value displayed for t-tests are the differences in the means across the groups. The value displayed for F-tests are the F-statistics.
Standard errors in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Second, we experienced non-compliance from some participants (8 *evidence-based*, 11 *theory-and-evidence-based*, excluding attritors[26]) who never attended any sessions but still replied to at least one data collection round after the baseline. Table S3.5 shows comparison tables for the subsample of compliers when compared to non-compliers, dropping attritors from the comparison (N = 135). Analyzing drivers of non-compliance, we found non-compliers to be less experienced, to perceive themselves as less skilled and more pessimistic in terms of business survival probability than compliers.

[26] There is no statistically significant difference in the proportion of non-compliers between the two training groups (Pearson chi2 = 0.6042; $p = 0.437$)

Table S3.5 – Compliers and non-compliers comparison

	(1) Compliers	(2) Non-Compliers	T-test	Normalized difference
Variable	Mean/SE	Mean/SE	(1)-(2)	(1)-(2)
Respondents' age	31.914	34.053	-2.139	-0.256
	(0.775)	(1.908)		
Gender (% male)	0.621	0.737	-0.116	-0.241
	(0.045)	(0.104)		
Working full time (%)	0.586	0.474	0.113	0.226
	(0.046)	(0.118)		
Work experience (years)	5.578	5.579	-0.001	-0.000
	(0.579)	(1.909)		
Work experience in agriculture (years)	3.293	2.895	0.398	0.111
	(0.338)	(0.757)		
Managerial experience (years)	3.052	4.421	-1.369	-0.374
	(0.310)	(1.188)		
Entrepreneurial experience (years)	3.940	3.211	0.729	0.181
	(0.391)	(0.619)		
Tertiary education (%)	0.802	0.789	0.012	0.031
	(0.037)	(0.096)		
Business degree (%)	0.078	0.158	-0.080	-0.281
	(0.025)	(0.086)		
Firm type (=1 if startup)	0.647	0.579	0.068	0.140
	(0.045)	(0.116)		
For-profit business (%)	0.948	0.842	0.106*	0.424
	(0.021)	(0.086)		
Perceived probability of termination	23.112	40.632	-17.520**	-0.522
	(3.037)	(8.170)		
Perceived probability of major changes	55.716	48.105	7.610	0.228
	(3.122)	(7.346)		
Hours worked (from interview)	34.297	33.316	0.982	0.041
	(2.234)	(5.908)		
Total revenues (US$ - winsorized 95th)	1012.253	524.889	487.364	0.284
	(167.160)	(230.392)		
Total costs (US$ - winsorized 95th)	1093.072	448.367	644.705*	0.418
	(151.011)	(145.342)		
Number of owners (from interview)	2.078	1.526	0.551	0.281
	(0.194)	(0.140)		
Number of salaried employees (from interview)	1.802	1.053	0.749	0.256
	(0.287)	(0.346)		
Number of other employees (from interview)	2.819	1.895	0.924	0.151
	(0.601)	(0.741)		
Idea stage (=1 if sales or pre-sales)	0.595	0.632	-0.037	-0.075
	(0.046)	(0.114)		
Months worked on the project	25.241	32.316	-7.074	-0.187
	(3.407)	(10.361)		
Other business courses attended (%)	0.690	0.263	0.426***	0.880
	(0.043)	(0.104)		
N	116	19		

Standard errors in parentheses ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

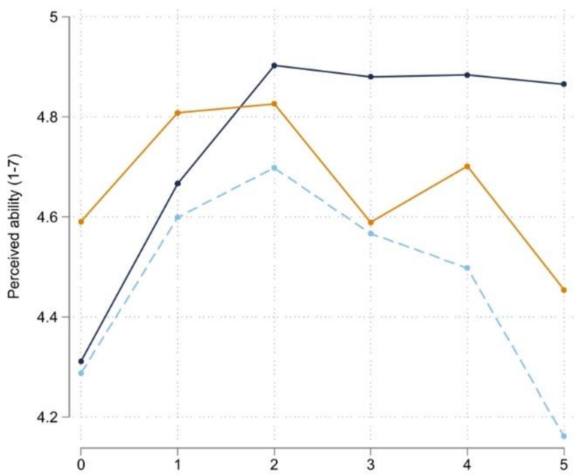
S3.4 Additional regressions and robustness checks

S3.4.1 Perceived ability

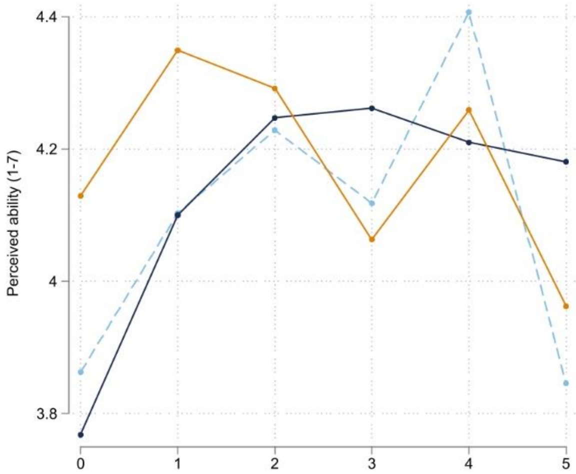
We report here graphs replicating main results in the paper for the *perceived ability* scores both including the non-random *control* group and also using only respondents replying to at least 5 surveys. Figure S3.3 includes the *control* group. Panel A shows the perceived ability measure over all potential challenging factors, while Panels B and C show the scores for the *environmental* and *project-related* factors.

Figure S3.3 – Perceived ability with *control* group

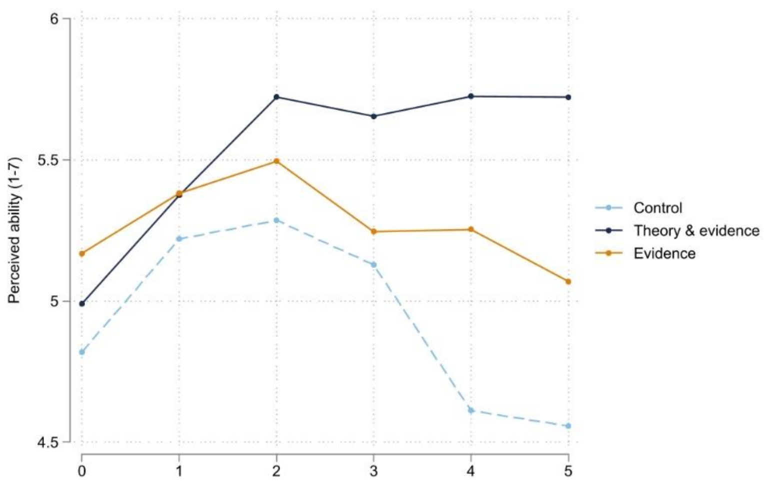
Panel A – All factors



Panel B – Environmental factors



Panel C – Project-related factors



Tables S3.6 to S3.8 reports robustness checks to the results of the regressions in Table 3.2 in Chapter 3. Table S3.6 uses as dependent variable the *perceived ability* for all factors. Tables S3.7 and S3.8 use, respectively, the *perceived ability* for *environmental* and *project-related* factors as dependent variables. In each table, Model 1 replicates the DiD model of Table 2 without controls; Models 2 and 3 only focus on respondents to at least five surveys or attending at least four lectures. Models 4 and 5 also include the *control* group, which becomes the baseline category. Model 6 runs DiD instrumental variable regressions, to study complier causal effects (CACE). Models 8 to 10 focus on the post-baseline periods; Model 11 runs CACE estimations on the post-baseline period.

Table S3.6 – Alternative specifications; perceived-ability (all factors)

Model/sample	(1) DiD (all)	(2) DiD (5+ datapoints)	(3) DiD (4+ lectures)	(4) DiD (with control)	(5) DiD (with control)	(6) DiD (CACE – IV)	(7) OLS (post-baseline; 5+ datapoints)	(8) OLS (post-baseline; 4+ lectures)	(9) OLS (post-baseline; with control)	(10) OLS (post-baseline; with control)	(11) CACE – IV (post-baseline)
Theory-and-evidence-based	0.45*	0.75**	0.76**	0.32	0.32	0.33	0.22^	0.21	0.34*	0.22	0.25
	(0.21)	(0.22)	(0.26)	(0.21)	(0.21)	(0.25)	(0.13)	(0.15)	(0.15)	(0.13)	(0.15)
Evidence-based	-	-	-	-0.13	-0.16	-0.46^	-	-	0.17	0.04	0.04
				(0.22)	(0.22)	(0.25)			(0.15)	(0.14)	(0.15)
Observations	752	673	565	967	967	948	557	469	765	765	765
R-squared	0.02	0.10	0.13	0.03	0.09	0.02	0.10	0.13	0.02	0.10	0.09
SE	firm	firm	firm	firm	firm	firm	firm	firm	firm	firm	firm
Controls	NO	YES	YES	NO	YES	NO	YES	YES	NO	YES	YES
Firm FE	NO	NO	NO	NO	NO	YES	NO	NO	NO	NO	NO
Period FE	NO	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES
Equality of coefficients (p-value)				0.03	0.02	.001			0.20	0.15	0.14

*** p<0.001, ** p<0.01, * p<0.05, ^ p<0.1

Table S3.7 – Alternative specifications; perceived-ability (environmental factors)

Model/sample	(1) DiD (all)	(2) DiD (5+ datapoints)	(3) DiD (4+ lectures)	(4) DiD (with control)	(5) DiD (with control)	(6) DiD (CACE – IV)	(7) OLS (post-baseline; 5+ datapoints)	(8) OLS (post-baseline; 4+ lectures)	(9) OLS (post-baseline; with control)	(10) OLS (post-baseline; with control)	(11) CACE – IV (post-baseline)
Theory-and-evidence-based	0.38	0.74**	0.68*	0.17	0.16	0.17	0.06	-0.08	0.07	-0.07	-0.08
	(0.24)	(0.26)	(0.29)	(0.25)	(0.25)	(0.30)	(0.18)	(0.21)	(0.17)	(0.17)	(0.19)
Evidence-based				-0.21	-0.24	-0.58*			0.05	-0.09	-0.10
				(0.26)	(0.25)	(0.28)			(0.17)	(0.16)	(0.18)
Observations	752	673	565	967	967	948	557	469	765	765	765
R-squared	0.01	0.08	0.12	0.01	0.06	0.02	0.09	0.12	0.01	0.06	0.07
SE	firm	firm	firm	firm	firm	firm	firm	firm	firm	firm	firm
Controls	NO	YES	YES	NO	YES	NO	YES	YES	NO	YES	YES
Firm FE	NO	NO	NO	NO	NO	YES	NO	NO	NO	NO	NO
Period FE	NO	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES
Equality of coefficients (p-value)				0.12	0.09	0.007			0.91	0.87	0.88

*** p<0.001, ** p<0.01, * p<0.05, ^ p<0.1

Table S3.8 – Alternative specifications; perceived-ability (project-related factors)

Model/sample	(1) DiD (all)	(2) DiD (5+ datapoints)	(3) DiD (4+ lectures)	(4) DiD (with control)	(5) DiD (with control)	(6) DiD (CACE – IV)	(7) OLS (post-baseline; 5+ datapoints)	(8) OLS (post-baseline; 4+ lectures)	(9) OLS (post-baseline; with control)	(10) OLS (post-baseline; with control)	(11) CACE – IV (post-baseline)
Theory-and-evidence-based	0.54*	0.76**	0.85**	0.52^	0.52^	0.52	0.42**	0.57***	0.68***	0.57**	0.65**
	(0.25)	(0.28)	(0.31)	(0.27)	(0.27)	(0.32)	(0.16)	(0.17)	(0.19)	(0.18)	(0.21)
Evidence-based				-0.02	-0.05	-0.30			0.32	0.20	0.23
				(0.28)	(0.28)	(0.30)			(0.20)	(0.19)	(0.20)
Observations	752	673	565	967	967	948	557	469	765	765	765
R-squared	0.03	0.08	0.10	0.04	0.08	0.01	0.07	0.09	0.05	0.08	0.09
SE	firm	firm	firm	firm	firm	firm	firm	firm	firm	firm	firm
Controls	NO	YES	YES	NO	YES	NO	YES	YES	NO	YES	YES
Firm FE	NO	NO	NO	NO	NO	YES	NO	NO	NO	NO	NO
Period FE	NO	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES
Equality of coefficients (p-value)				0.03	0.02	0.005			0.02	0.02	0.01

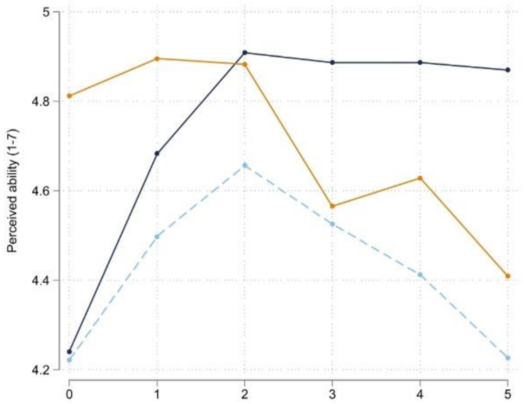
*** p<0.001, ** p<0.01, * p<0.05, ^ p<0.1

Results from robustness checks and with the non-random *control* group confirm those in the main paper. They show that the most consistent increase in *perceived ability* for the *theory-and-evidence-based* condition is found for the scores on *project-related* factors.

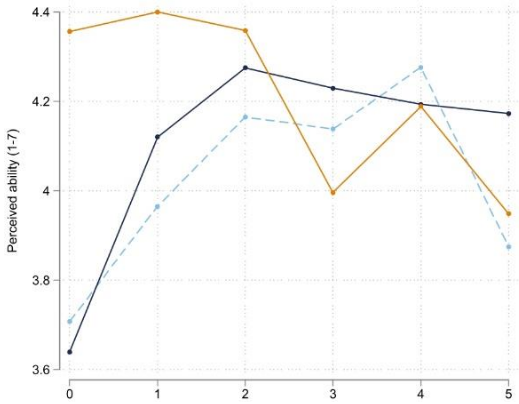
Figure S3.4 replicates Figure S3.3 but considering only "panel" respondents, i.e., those entrepreneurs that replied to at least five surveys. Results are fully comparable to the main ones.

Figure S3.4 – Entrepreneurs' perceived ability to deal with potential challenges ("panel" respondents)

Panel A – All factors



Panel B – Project-related factors



Panel C – Environment-related factors

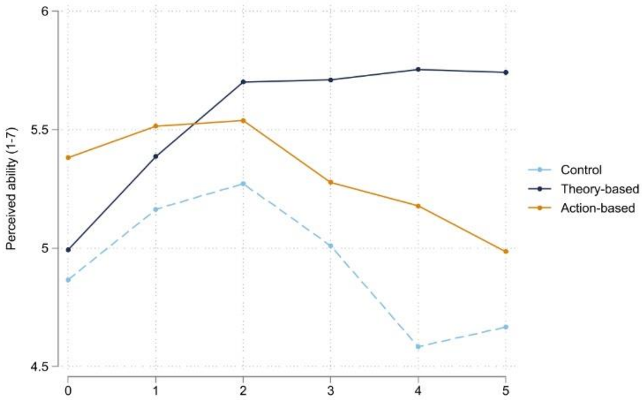
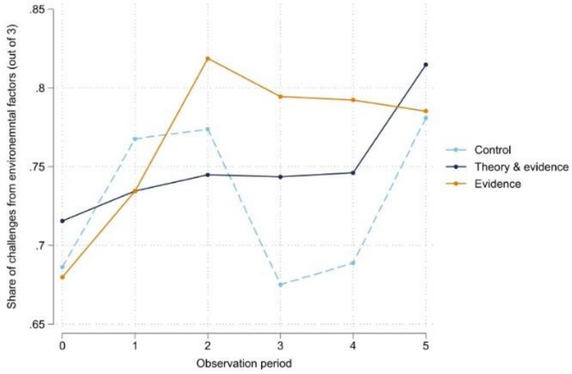


Figure S3.5 replicates Figure 3.6 in the main paper including the non-random *control* group. It shows that also control entrepreneurs are mostly concerned by challenges stemming from *environmental* factors.

Figure S3.5 – Share of *environmental* factors over time (with control group)



S3.4.2 Separate results on the nine potentially challenging factors

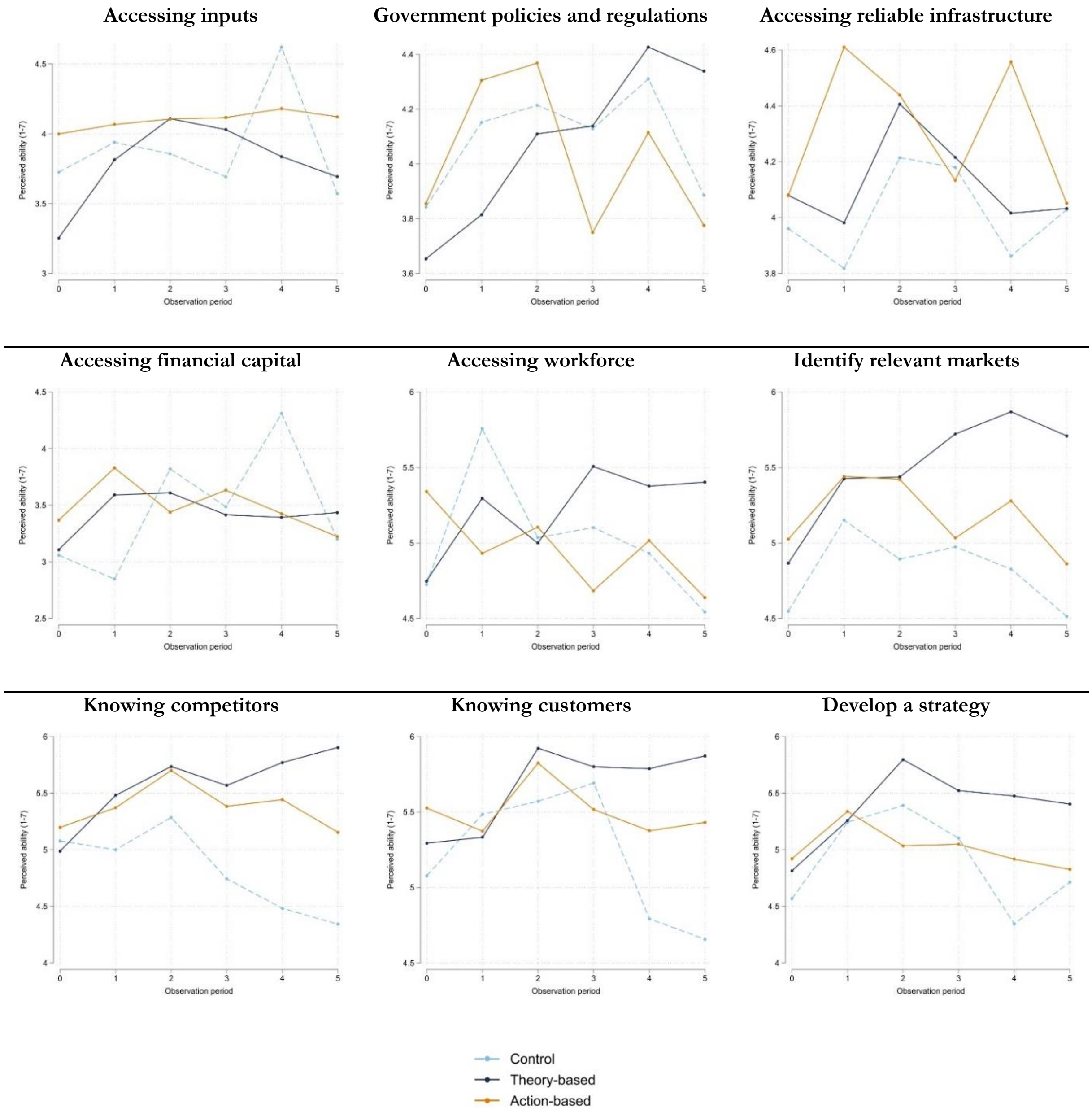
We report in this subsection results for the nine factors separately. Figure S3.6 below shows the perceived ability scores on all the nine potentially challenging factors displayed to entrepreneurs in the survey. Table S3.9 reports the result of difference-in-differences and post-baseline regressions comparing the two treatment conditions.

Table S3.9 – Regression results on perceived ability for all nine factors

	Accessing Inputs	Government policies	Infrastructure	Accessing financial capital	Accessing workforce	Identify relevant markets	Know competitors	Know customers	Develop strategy
Theory-and-evidence-based (DiD)	0.552	0.341	-0.189	0.257	1.065***	0.620*	0.539^	0.507^	0.603^
	(0.363)	(0.346)	(0.354)	(0.369)	(0.312)	(0.311)	(0.302)	(0.287)	(0.340)
Theory-and-evidence-based (post baseline)	-0.249	0.106	-0.146	-0.0989	0.542*	0.488**	0.351*	0.245	0.474*
	(0.220)	(0.249)	(0.220)	(0.246)	(0.214)	(0.169)	(0.161)	(0.179)	(0.182)
Observations	752	752	752	752	752	752	752	752	752

All models include controls. Controls include a dummy for tertiary education, a dummy for gender, hours worked at the baseline, a dummy for the firm type (startup or company), baseline perceived probability of introducing major changes and instructor dummies. Post-baseline models also include period dummies. Standard errors are clustered at the entrepreneur (firm) level reported in parentheses.

Figure S3.6 – Perceived ability on all nine potentially challenging factors



Both graphical and regression results show how entrepreneurs in the *theory-based* group significantly increased their perceived ability to deal with challenges stemming from *project-related* factors, as shown in the aggregate analyses. When it comes to *environment-related* factors, the most significant and stronger increase is recorded for the "workforce" factor, whereas little differences exist for the other four factors, explaining the noisier pattern found with the aggregate measure.

S3.4.3 Perceived ability and perceived control: robustness checks

Table S3.10 reports a battery of robustness checks for the specifications in Table 3.3 of the main paper. Models 1 and 2 replicate Model 1 in Table 3.3, focusing on panel respondents and on entrepreneurs attending at least four lectures. Models 3 to 8 replicate Pooled OLS and first differences regressions including observations from the control group.

Results consistently show a positive association between *perceived ability* and *perceived control*, particularly when considering the one over *project-related* factors.

Table S3.10 – Perceived control and perceived ability: robustness checks

	(1) DiD (5+ datapoints)	(2) DiD (4+ lectures)	(3) Pooled OLS (with control)	(4)	(5) First Difference (with control)	(6)	(7)	(8)
Theory-and-evidence-based	0.14	0.14						
	(0.22)	(0.23)						
Ability (all)			0.27***		0.18**	0.17**		
			(0.05)		(0.05)	(0.06)		
Ability (project-related)				0.24***			0.12**	0.12*
				(0.04)			(0.05)	(0.05)
Ability (environmental)				0.04			0.06	0.06
				(0.04)			(0.04)	(0.04)
Observations	673	565	752	752	701	701	701	701
R-squared	0.08	0.06	0.14	0.16	0.05	0.05	0.05	0.06
SE	firm	firm	firm	firm	firm	firm	firm	firm
Controls	YES	YES	YES	YES	NO	YES	NO	YES
Firm FE	NO	NO	NO	NO	NO	NO	NO	NO
Period FE	NO	NO	YES	YES	YES	YES	YES	YES
Model	DiD	DiD	OLS	OLS	OLS	OLS	OLS	OLS

S3.4.4 Perceived ability and performance: robustness checks

Tables S3.11 to S3.12 replicates results of Tables 4 and 5 in the main paper, considering also entrepreneurs belonging to the non-random *control* group. Results are qualitatively similar to the ones reported in the main paper, albeit being more dispersed and less statistically significant.

Table S3.11 – Performance and perceived ability (cross-section): with control group

DV	(1) Total revenue	(2)	(3) Average periodic revenue	(4)	(5) Total profit	(6)	(7) Average periodic profit	(8)
Ability (all)	1,582.50		219.11		333.70		-106.67	
	(962.63)		(160.87)		(672.92)		(154.83)	
Ability (project-related)		1,252.46^		181.06		360.09		-80.69
		(681.24)		(115.50)		(425.13)		(138.51)
Ability (environmental)		384.05		49.51		-5.56		-30.53
		(714.48)		(119.37)		(500.37)		(92.58)
Observations	151	151	176	176	151	151	176	176
R-squared	0.21	0.22	0.19	0.19	0.03	0.03	0.04	0.04
SE	robust	robust	robust	robust	robust	robust	robust	robust
Controls	YES	YES	YES	YES	YES	YES	YES	YES

Table S3.12 – Performance and perceived ability (panel): with control group

DV	(1) Cumulative revenue	(2)	(3) Periodic revenue	(4)	(5) Cumulative profit	(6)	(7) Periodic profit	(8)
Ability (all)	402.86		161.87^		-22.30		14.95	
	(266.31)		(94.88)		(241.44)		(80.44)	
Ability (project-related)		234.60		64.29		-60.91		-31.36
		(201.74)		(64.51)		(160.35)		(65.16)
Ability (environmental)		168.53		97.33		38.37		45.06
		(232.45)		(67.25)		(179.03)		(62.68)
Observations	943	728	724	724	943	943	724	724
R-squared	0.23	0.24	0.16	0.16	0.05	0.05	0.02	0.02
SE	firm	firm	firm	firm	firm	firm	firm	firm
Period dummies	YES	YES	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES	YES	YES

Annex 1 – Training syllabus

Mission & Content Summary

This training program addresses early-stage entrepreneurs developing their own business idea and small business owners or managers developing an innovative project within their existing entities. Specifically, the overarching goal of the program is to provide participants with a structured and rational decision-making framework to enable them to make better business decisions and ultimately improve the performance of their entrepreneurial or innovative projects. The course enables participants to learn key strategic skills and master practical decision-making tools to improve business practice. Participants will receive guidance from seasoned instructors and have the opportunity to discuss and network with fellow entrepreneurs. The small class size allows sessions to be highly interactive, with peer-to-peer discussion and personalized feedback from the instructor.

Learning Outcomes

At the end of this training program, participants will be able to:

- Master principles of business management
- Follow a structured approach to make better business decision
- Use widespread business tools to develop their business ideas (e.g., Business Model Canvas, Customer Personas, Customer Process)
- Run customer interviews and surveys
- Develop and test a Minimum Viable Product (MVP)
- Run A/B tests and analyses to develop better products or services
- Price their product or service according to existing pricing strategies

Class Structure

The training program includes **six sessions**, with a maximum duration of ~240 minutes (4 hours), including breaks and discussion times. Classes are taught by seasoned instructors, with experience in both academia and entrepreneurship. Each session is conducted in-presence in classrooms of about 15-20 entrepreneurs. Each class provides a mixture of face-to-face sessions, practical activities, peer-to-peer discussion times and role-play games. Practical applications of the different business tools to each participant's business idea are an integrative part of each session. Relevant business cases and real-life example for each business tool are provided.

Detailed Syllabus

Session 1: Introduction and Business Model Canvas

- Introduction to the course: program goals and practical information
- The mistakes of the entrepreneur: innovation and uncertainty
- Applying a structured approach to Decision-Making under uncertainty
- Business Models: definition
- Business Model Canvas (tool): what is it and how to complete it

Session 2: Customer Identification and Problem Framing

- Problem framing and validation: understanding in-depth the customer problem
- Customer Process (tool): what is it and how to use it
- Targeting the right people: understand who your customers are
- Customer Persona (tool): what is it and how to use it
- Running Customer Interviews

Session 3: Designing and Conducting Customer Surveys

- Customer Interviews: learn how to evaluate insights and results
- How to use insights to develop a better product or service
- Declaring expectations over Customer behavior and attitudes
- Developing Customer Surveys: best practices and common mistakes

Session 4: Evaluating Results and Creating MVPs

- Customer Survey: interpreting the results from questionnaires
- How to make business decisions based on survey results
- Moving from the Customer problem to the Solution: The Solution Validation phase
- The Minimum Viable Product (MVP): what is it and how to develop it
- Testing your MVP

Session 5: Solution Validation through A/B Tests

- Interpreting the results from MVP tests
- Using insights and test results to refine your product or service
- Evaluate alternative features of your product or service: the A/B Test
- How to make decisions based on test results

Session 6: Pricing Strategies, Recap and Final Pitch

- Getting your price right: pricing strategies
- Recap of the course
- Final Pitch: present your idea to your peers