SMALL CHANGES WITH BIG IMPACT: EXPERIMENTAL EVIDENCE OF A SCIENTIFIC APPROACH TO THE DECISION-MAKING OF ENTREPRENEURIAL FIRMS

June 2020

Preliminary version

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Abstract

Identifying the most promising business ideas is key to the introduction of novel firms, but predicting their success can be difficult. We argue that if entrepreneurs adopt a scientific approach by formulating problems clearly, developing theories about the implications of their actions, and testing these theories, they make better decisions. In particular, this approach helps entrepreneurs make more precise predictions of the value of their idea and to spot new ideas with higher expected returns. We also examine the mechanisms with which the scientific approach works. Specifically, we posit that scientific entrepreneurs are more precise initially, and less precise later on because they envision new version of their business idea that are worth assessing. Using a field experiment with 250 nascent entrepreneurs attending a pre-acceleration program, we provide evidence consistent with these mechanisms. We teach the treated group to formulate the problem scientifically and to develop and test theories about their actions, while the control group follows a standard training approach. We collect 18 data points on the decision-making and performance of all entrepreneurs for 14 months. Results show that increased precision in the assessment of the value of the business idea of treated entrepreneurs raises the probability that they close their start-ups. Scientific entrepreneurs are also more likely to see new opportunities with higher positive outcomes which prompt them to pivot to these new ideas and perform better.

Keywords: scientific approach, entrepreneurship, field experiment.

Section 1. Introduction

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

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

Extant studies on this topic converge on the iterative nature of the process entrepreneurs go through as they evaluate and develop their business ideas (Baron and Ensley, 2006), but do not clarify how this process of strategic change and pivoting should be conducted. Emerging streams in entrepreneurship such as effectuation (Sarasvathy, 2001) and bricolage (Baker and Nelson, 2005) propose that entrepreneurs should rely on non-predictive techniques given the high uncertainty surrounding the creation of a new venture. Proponents of these approaches argue that entrepreneurs should 'make do' with what they have at hand and improvise to win over stakeholders that will co-create new products and markets with the entrepreneur (Wiltbank et al., 2006). Effectual and bricolage approaches are attempts to acknowledge the bounded rationality of the entrepreneur and embrace the uncertainty of the environment by setting aside predictions and focusing on controlling the environment. Instead, other scholars suggest structured and disciplined processes of idea evaluation and development can mitigate fallible judgement (Hogarth and Karelaia, 2012) and reduce the cognitive biases that affect entrepreneurial decision-making (Murray and Tripsas, 2004; Camuffo et al., 2020; Cohen et al., 2018; Kahneman et al., 2019). Drawing on the latter stream of research, we propose that entrepreneurs can better understand whether their business idea is valuable when they formulate problems clearly, develop theories about the implications of their actions, and test these theories rigorously. In conducting these actions, labelled 'a scientific approach to decision-making', entrepreneurs also become better equipped to gather and interpret valuable signals from customers and other stakeholders that contribute to pivots of the initial business idea (Furr, 2009; Camuffo et al., 2020).

In this study, we first develop a theory of the implications of the scientific approach to decision-making for early-stage entrepreneurs. We propose that scientific entrepreneurs develop and test theories that help them to frame the problems they face as they start new businesses more effectively. In doing so, they decompose problems into sub-problems, and identify solutions geared towards increasing the value of the business. The use of theory and tests has two main implications. First, they enable entrepreneurs to predict the value of their business with greater precision. Second, they help them to identify new problems and their solutions that enhance the value of their business. These two effects have opposite implications on the perceived distribution of the value of the business idea. Greater precision makes the distribution of value more concentrated around its expected value. New problems and solutions raise the spread of the perceived distribution because they are innovations and therefore raise uncertainty with respect to the status quo. We argue that the adoption of the scientific approach affects how entrepreneurs collect and interpret information, change the perceived distribution of the value of their business idea and consequently impacts the decisions they make. In particular, we theorize that an increase in precision increases the likelihood to cease all activities related to the business (exit). An increased vision of new directions for their business idea implies that scientific entrepreneurs pivot in a focused manner (i.e. they know where to go, and do not need to pivot multiple times).

We provide evidence consistent with this framework by conducting a randomized controlled trial (RCT) with 250 nascent entrepreneurs attending a pre-acceleration program that teaches how to go from an initial business idea to product launch. We randomly assign entrepreneurs to either a treatment (being taught how to use a scientific approach when developing a business idea) or a control group (being taught how to develop a business idea). We collect detailed data about their performance and decision-making over 14 months to investigate how a scientific approach impacts the development of these business ideas. We first replicate the results of a previous study (Camuffo et al., 2020) with a different, and larger sample. Consistently with Camuffo et al. (2020), we find that treated entrepreneurs are more likely to close their business than entrepreneurs in the control group, they are more likely to pivot, and they enjoy higher revenue. However, we extend the contributions of Camuffo et al. (2020) by theorizing and providing evidence consistent with the mechanisms that we propose.

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

Section 2. A scientific approach to decision-making

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

Extant literature suggests there are two fundamental approaches to decision-making in early-stage entrepreneurship. The first is akin to trial and error (Dencker et al., 2009), and it normally involves experimenting sequentially with various methods until entrepreneurs achieve some results. This search strategy is normally 'blind' or only guided by prior assumptions and beliefs, and consequently entrepreneurs often run the risk of engaging in confirmatory search (Shepherd et al., 2012). An alternative approach, which has been called 'purposeful' (Murray and Tripsas, 2004), or 'scientific' (Camuffo et al, 2020), is more systematic and structured. We define this scientific approach as a discipline, a set of behavioral routines – similar to those used by scientists – that 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 and Zenger, 2009; Felin and Zenger, 2017). Also, the framing of the problem and the articulation of a theory is associated with the decomposition of the problem into sub-problems that represent the specific factors or determinants of the value of the business (Nickerson 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. Hypotheses are testable and falsifiable inasmuch as they clearly define the contingencies in which they are not false (or are definitely false) and can produce good, actionable evidence and validated learning (Eisenmann et al., 2011).
3. The empirical testing of hypotheses, based on facts and data appropriately collected and rigorously analyzed, ideally through experiments (Murray and Tripsas, 2004; Kerr et al., 2014). 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).
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 and Klein, 2012; Pfeffer and Sutton, 2006), as well as critical appraisal of evidence.

There is evidence (Bennett and Chatterji, 2017; Camuffo et al., 2020) that the majority of entrepreneurs do not behave in a scientific manner. We expect that entrepreneurs who use this approach will make better predictions, and will act accordingly, as detailed in the next section.

Section 3. Theory

3.1. Building blocks

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

In our framework, entrepreneurs predict the present value v of their business idea. Because they do not observe future performance, they do not observe v when they make the decision whether to develop their business idea. Thus, the way they form this prediction is important. In line with prior research (Parker, 2006; Cassar, 2014; Czasar, 2018), entrepreneurs typically identify the factors needed for their business idea (such as customer segments, features of their product, etc.) and weigh them to predict its future value. They can do it in many different ways, ranging from gut feelings to more rational approaches, and use these factors to make predictions. Even though we do not claim that entrepreneurs form their predictions in a strictly mathematical form, it is helpful for our understanding to describe the value of the entrepreneurs' business as a linear combination $v = v_1 + v_2 + v_3 + \ldots v_n + \varepsilon$, where v_1, v_2, v_3, …, v_n are the contributions of each factor to total value, and ε is a term that captures all the other factors that may affect value but that the entrepreneurs are unable to predict. The entrepreneurs' prediction is $\hat{v} = \hat{v}_1 + \hat{v}_2 + ... + \hat{v}_n$ where $\hat{v}$ is the expected v and $\hat{v}_1$, $\hat{v}_2$, … $\hat{v}_n$ are the expected unit contributions of each factor. For example, entrepreneurs could envision that gender affects the size of the potential market segment they target which may affect the value of their business idea. In the linear combination presented above, $\hat{v}_1$ is the predicted magnitude of the effect of a higher share of women in the market.

While this formulation is reminiscent of a linear regression, we emphasize that our approach is broader. Entrepreneurs identify the factors that determine value and their contribution to value in fuzzier or more refined ways.. Our representation is a benchmark, and entrepreneurs may either work on the wrong model (or with such a generic and fuzzy model that *de facto* they do not have a model) or they might make wrong or coarse predictions. Our framework argues that the scientific approach helps to build models that identify factors with larger effects on value and that generate more precise predictions.

We study the early phase of the entrepreneurial decision-making process. In this phase, entrepreneurs explore and develop ideas about their products or business models before they commit resources to their venture. They go through exploration cycles, meaning that they gather information about the value of their idea, and choose one of the three possible outcomes: i) close the firm because they expect that they cannot develop a profitable idea; ii) continue to develop the current idea; iii) pivot (i.e. change their idea), starting a new exploration cycle. It is reasonable to assume that they explore one idea at a time because of limited resources (Gans et al., 2019).

When they make this decision, entrepreneurs do not observe the value of the current idea, nor of the potential future ideas they could develop. However, they know that if they keep pursuing an idea and develop it, they will gain more information about v, and they will eventually observe it. In addition, all entrepreneurs have an opportunity cost x (e.g. the foregone salary as employees) such that they will close the firm if in the future they discover that $v < x$ (assuming they have to quit their job to keep pursuing their idea). Therefore, when they have to decide whether to commit to a business idea, entrepreneurs know that they will earn x if $v < x$ and v if $v \geq x$. This implies that a probability distribution of v with the same mean and fatter tails has a higher expected value than a distribution with slimmer tails. This is because high realizations of v occur with higher probabilities than the distribution with slimmer tails; conversely, the negative realizations, which make the fatter distribution less appealing, do not occur because entrepreneurs realize x instead of the low realizations of v to the left of x.

3.2 Implications of the scientific approach

The adoption of a scientific approach affects this decision-making process. We focus on three elements: precision, modification of ideas, and exhaustion of idea potential. It is important to point out that the theoretical framework presented below reflects the iterative process entrepreneurs go through and it include a dynamic that develops over time. In particular, we expect the precision effect to be relevant at the outset of an exploration cycle, and the modification of ideas, and exhaustion of idea potential to affect choices if entrepreneurs decide not to close their business at the outset of the cycle.

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

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

The next element is the process that leads to the modification of ideas during the firm's exploration cycles. After entrepreneurs make the initial decision that they should not close their firm, they can leverage well-defined frameworks and theories help the entrepreneurs who adopt the scientific approach to interpret signals in a more precise manner. At the same time, tests are an important source of signals. Rejection of some hypotheses and acceptance of others may induce entrepreneurs to rethink their business models. For example, failing to accept some hypotheses implies that they have to focus on radically different target markets, change the value proposition or that they should weigh differently other factors, in the end realizing that the idea they should pursue is different from the one that they originally conceived. The evidence on these patterns is systematic. Camuffo et al. (2020) 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'Mahoney (2020) find that when start-ups pivot they do not discard all the accumulated knowledge or the previous features of their products or business models. They *pivot* in the most literal sense - they stand on some of their past knowledge, and turn to some new factors that change their overall product or business (see also Ries, 2011; Furr and Dyer, 2014; Hampel et al., 2019).

Entrepreneurs who do not adopt the scientific approach are less likely to see these factors from signals. The lack of general frameworks prevents them from interpreting signals and translating them into actions. In particular, when they find that some factors do not contribute to value as much as they expected, they either do not have alternative hypotheses or are less able to generate new ones from what they observe. The hypotheses formulated by scientific entrepreneurs are, instead, part of a more general framework that laid out the implications of different contingencies. For example, non-scientific entrepreneurs do not have a logical framework suggesting alternative target markets. Moreover, because they do not conduct rigorous tests, they are less able to make informed decisions. Ample anecdotal evidence shows that entrepreneurs who do not adopt a scientific method do not conduct tests that can accept or reject hypotheses (Ries, 2011; Maurya, 2013; Koning et al., 2019). Often, these entrepreneurs do not use falsifiable statements to understand what to do. As a consequence, the information they collect is too generic to lead to meaningful conclusions. For example, these entrepreneurs tend to conduct surveys in which they ask potential customers whether they like or not their product, but they do not set thresholds to conclude whether a given percentage of positive responses represents evidence that validates interest in their product (Maurya, 2013).

Viewed collectively, the points above show that while assessing a business idea, the entrepreneurs who adopt a scientific approach systematically gather signals that help them envision innovations and new options to revamp or change their business. New options, in turn, suggest new determinants or new combinations of determinants of business value. Overall, this generates a new model of v that features some of the factors of the previous business idea, and some new factors. However, entrepreneurs have not yet theorized and tested the new factors with the same depth of the previous factors, and more generally they have not yet theorized and tested the new version of the business idea as much as the previous one. The new model then yields more volatile predictions about *v* than the previous model.

Entrepreneurs who do not adopt the scientific approach do not identify new determinants of value as the entrepreneurs who adopts the scientific approach. Thus, their model tends to remain unchanged or to change based on the available evidence, which is not systematic, and thus likely to produce random variation. As a consequence, the distribution of value is likely to be as volatile as the current model. We therefore argue that scientific entrepreneurs see new options to change their business ideas that raise the volatility of the perceived distribution of value more than non-scientific entrepreneurs. When entrepreneurs foresee valuable changes to their business idea, they are likely to pivot –adjusting their idea and turning it into something significantly different from their initial idea. Entrepreneurs decide to pivot when they foresee that the changes they might make to their idea represent valuable factors. This leads to a higher wedge between the spread of the modified idea vis-à-vis the past distribution of value. Thus, during an exploration cycle, when they have to choose whether to close the firm, pursue the current idea, or pivot, entrepreneurs consider if the distribution that yields the highest expected value is higher than their opportunity cost. If the expected value is lower than their opportunity cost, they close the business. If it is higher, and the current idea yields what seems to be the best performance outcome, they pursue it, otherwise they pivot to a new version of the idea. To summarize, if the mean of the distribution does not change, a higher volatility implies a higher expected value. Other things being equal, entrepreneurs who adopt a scientific approach are more likely to close the firm than non-scientific entrepreneurs, as discussed in Proposition 1. If they perceive a higher increase in volatility between the future and current ideas, they are more likely to pivot.

Another important aspect to consider is the exhaustion of idea potential. Entrepreneurs, in fact, operate in a bounded space. In particular, they explore business ideas within their domain of expertise or within a topic or category they are interested in (Durand & Paolella, 2013), which implies that the space the can explore is limited (Hill & Birkinshaw, 2010). It follows that there is a finite number of factors they can consider and test and to which they might pivot. Moreover, even if the recombination of factors can result in increasing returns, exploration within a limited space ultimately hits diminishing returns. Other things equal, entrepreneurs who adopt a scientific approach envision more quickly promising factors and their combinations thanks to their theory and tests. However, because the space they can explore is bounded, they exhaust this space earlier. They quickly envision the potentially valuable changes they can make to their ideas. Conversely, entrepreneurs who do not adopt this approach envision less promising factors within their explorable space, continue navigating this space, and are therefore more likely to pivot several times.

A simple way to represent this distinction is to consider the marginal benefit of pivoting. As shown in Figure 1, the benefit of an additional pivot decreases as the number of pivots increases given that the explorable space is limited. However, the marginal benefit of pivoting for scientific entrepreneurs is high when they have not yet pivoted, and falls rapidly after a few pivots. The curve representing the marginal benefit of pivoting for non-scientific entrepreneurs is flatter. If the former curve cuts the latter curve, the scientific entrepreneurs are more likely to pivot few times than to not pivot at all or pivot many times. The non-scientific entrepreneurs are either not likely to pivot because the marginal benefit of pivoting is not sufficiently high or they are more likely to pivot multiple times when the curve is higher than for scientific entrepreneurs. Thanks to theories and tests, when scientific entrepreneurs pivot they know better how to modify their ideas, and do not need to pivot several times.

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

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

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

In discussing the impact of a scientific approach on the decisions entrepreneurs make, we have been agnostic about whether the scientific approach generates better performance. However, our discussion suggests that it is reasonable to assume that the perceived distribution of the entrepreneurs who adopt the scientific approach yields outcomes closer to what they expect. If this is the case, they are more likely to abandon less promising ideas because they close the firm, and they are more likely to pursue better ideas either because they remove worse ideas by closing the firm, or because they improve their ideas through pivoting. We can then write the following proposition.

Proposition 3. *Scientific entrepreneurs perform better because they select better ideas or they pivot in ways that improve their ideas.*

3.3 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 because university students were not interested in this service and women did not want to use large and solid scooters. However, they had a framework that suggested to look for relatively young users and that the characteristics of the scooters matter. Thus, they turned to young professionals 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 test 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 for the problem-solution pairs they rejected (university students and large and solid scooters.) 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 right after they rejected the initial hypotheses. They had initial ideas, hypothesized different solutions, and collected data to revise and test the theory. The spread of the distribution of value of the original idea was clearly more precise, but they understood that the expected value was smaller. The new idea was promising, but it implied higher uncertainty. A hypothetical non-scientific entrepreneur would have probably envisioned less promising changes to his 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 value of the distribution.

Section 4. Research design

4.1. The randomized controlled trial

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

Participants in our program are early-stage entrepreneurial firms, which are defined as those run by founders in the process of starting a business (Bosma et al., 2012). We issued a call for applications using multiple online (blogs, online communities) and offline channels (magazines, 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 have a bachelor degree and they expect to start making revenue in about 11.4 months from the beginning of the pre-acceleration program. There is 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 operate in a wide range of sectors, from Software to Hospitality. The most represented sector in our experimental sample is Leisure, followed by Fashion, Food, Finance and Software. Taken together, these five sectors account for 59% of the sample. While there are some traditional bricks-and-mortar businesses, the majority 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, on the basis of their demographic characteristics (gender, age, education) and of the sectors they operate in. We used a statistical software package (Stata) to randomly assign each start-up to one of the two arms of the experiment (treatment and control groups). We checked that the treatment (125 start-ups) and control groups (125 start-ups) were balanced on a number of key covariates that might affect the absorption of the intervention and its subsequent outcomes. We report the results of these randomization checks in the Online Appendix. This analysis confirms that the two arms of the experiment are balanced on key characteristics such as demographic variables (age, highest education level, work experience of the entrepreneurial team), industry, founding team size and composition, effort, startup potential (measured by an independent third party), the self-estimated expected value of the project (min, max, average), and the projected number of months to revenue. Given the number of checks, we are confident that the randomization was successful and resulted in balanced groups.

Following best practices (Baird et al., 2016), we pre-registered this randomized controlled trial on September 15, 2017. The intervention took place at the end of September 2017 and finished in December 2017 with the 250 participants attending a training program designed by the research team. Our pre-acceleration program focuses on market validation, with a series of activities aimed at testing the desirability of a product or service concept against a potential target market. These activities provide suitable information to help entrepreneurs assess the potential of their business ideas and are frequently taught in pre-acceleration programs. In order to offer engaging lessons and a valuable learning experience to participants, we divided the treated and control groups into smaller groups that were randomly matched with seven experienced instructors, recruited and trained for the purpose of this study. Since each instructor was teaching one group of treated entrepreneurs and one group of control entrepreneurs, we organized several 'train-the-trainer' sessions and conducted tests and simulations with the instructors to make sure that instructors were able to deliver the training material in accordance with our experimental design. We ensured that the instructors trained the start-ups in each group using the exact same content by providing all training material ourselves, and by 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 learnt about tools that are widely used in entrepreneurial education (such as the Business Model Canvas, and Minimum Viable Product). However, the treatment group was taught how to use each of these tools using a scientific approach. Throughout the training program, treated start-ups were taught to elaborate a theory behind their choices, and to articulate hypotheses and test them rigorously. The control group did not learn about the scientific approach, but followed the traditional approach to market validation used by entrepreneurs, which often relies on trial-and-error techniques. We took a number of measures to ensure the internal validity of our results and the soundness of our experiment. We avoided contamination by teaching treated and control start-ups in different time slots of the same day (morning and afternoon) to prevent them from meeting and discussing key elements of the treatment. For the same reasons, we kept communications about the program separate and discrete for the two groups.

4.2. Data collection procedure

We collected detailed information on all the participants with an extensive pre-intervention survey, which we used to randomly assign participants to treatment and control groups and to assess the pre-intervention levels of a number of covariates. During and after the intervention, we collected 18 data points through telephone interviews, following Bloom and Van Reenen's (2010) approach. Telephone interviews usually lasted for 30 minutes and were conceived as open-ended conversations with entrepreneurs. To guide these conversations, we created an interview protocol for interviewers. In the first part of the interview, entrepreneurs were asked to report changes in the entrepreneurial team and describe the activities they had been conducting in the last 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, as well as to provide estimates of the value of their idea. In collecting this information, we were also able to observe entrepreneurs who abandoned their business idea altogether or who decided to pivot to a different one.

The first telephone interview took place eight weeks after the training program had begun. We then collected data every two weeks until week 18 (the training program ended in week 12), and every four weeks until week 66. Our panel dataset includes 4500 observations for 250 firms over 18 periods. We collect 18 data points for the variables defined in the next section for most start-ups. We do not have 18 data points if entrepreneurs abandon the business idea or the pre-acceleration program – in these cases we only have data up to the period before they abandon.

4.3. Measures

4.3.1. Dependent variables

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

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

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

4.3.2. Independent variables

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

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

Range – This variable is the difference between the maximum and the minimum value of the business perceived by the entrepreneurs at each moment in time normalized by the mid-point between the maximum and the minimum (*Mean Value*). We define value as the discounted sum of expected future profits. In order to anchor the response, we ask 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 have one pre-intervention measure of *Range* (week 0) and 18 observations corresponding to the interviews during and after the training program. We can therefore compute *Range_lagged*, which is *Range* lagged one period. Also, *Av_Range* and *Av_Range_lagged* are the firm-specific average of *Range* and *Range_lagged* up to each week. In the result section we explain why we use this smoothed measure of the prediction.

Range_diff – This variable is equal to the difference between *Range* and *Range_lagged*. We also compute *Av_Range_diff* equal to the difference between *Av_Range* and *Av_Range_lagged*. This measure operationalizes the distance between the current perceived value of the business idea and perceived value of the business idea in the previous period.

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

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

Section 5. Results

5.1. Replication

We begin by replicating the results of Camuffo et al. (2020). In this paper we employ the same research design but a different and larger sample that includes 250 observations over 18 data points and 66 weeks vis-à-vis 116 observations over 16 data points and 48 weeks used by Camuffo et al. (2020) .

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

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

The first column of Figure 2 shows the number of start-ups that exit during our time frame. As the figure shows, more start-ups in the treatment group than in the control group exited (59 vs 46). This result, which we also obtain in the regressions below, confirms the finding of Camuffo et al. (2020). The next columns of the figure show the number of start-ups that pivoted from 0 up to 5 times during the analyzed period for the treatment and control groups. Fewer start-ups in the treatment group pivoted 0 times (58 vs 68 – column 2). However, these start-ups were more likely than the control start-ups to pivot once (43 vs 29 – column 3). While the number of start-ups in the treatment and control group that pivoted twice is the same (17), fewer start-ups in the treatment group pivoted three or more times (7 vs 11). Regression analyses also confirm that treated start-ups are more likely to pivot once than never or multiple times. These patterns suggest that while the scientific entrepreneurs see new versions of their idea they can pivot to, they tend to stick to the new version, as if they were better at envisioning options they can pivot to. Camuffo et al. (2020) find that treated start-ups pivot more than the control group. However, with 116 start-ups and 48 weeks their sample did not produce many observations at the right tail. In their study, only two firms pivoted more than two times. In this study, we also find that treated firms are more likely to make one or two pivots as opposed to zero or many pivots. However, with more firms and a longer time span we show that in the right tail treated firms become less likely to pivot.

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

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

We now turn to the regression results. In all the regressions presented in this section, the main independent variable is the dummy for intervention (*Intervention*). All regressions include dummies for the instructors who trained the start-ups and the panel regressions include time fixed effects. Apart from controlling for time, time fixed effects control for the different length of the observation periods between some of our interviews, as discussed in Section 4.2. In all the regressions of this section, we cluster errors by instructor and intervention.

We start with the regression results for exit with respect to the intervention. The first two columns of Table 2 report cross-section results, respectively with a linear probability model and a probit model. The dependent variable (*Exit*) is a binary one and equal to 0 if the start-up did not exit, and to 1 if the start-up abandoned the business during our observation window. The next two columns report the results of a panel analysis of the 250 start-ups during the 18 periods of data collection. Finally, the last column shows the results of a survival regression that predicts the time of exit. All these regressions show that the intervention increases the likelihood that entrepreneurs cease all activities related to the firm. This is the same result presented by Camuffo et al. (2020) where their smaller sample produced a weaker statistical significance. The result in our study is more robust thanks to the larger sample employed. This finding is consistent with our framework that predicts that the scientific approach makes the entrepreneurs more precise and thus less likely to expect higher returns because of higher opportunities in the right tail. The panel and the survival analyses also suggest that the intervention brings forward the date in which they close the firm.

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

The first column of Table 2 provides the most immediate interpretation of the effect size. It shows that the intervention increases the probability to exit by 10% in the cross-section analysis. This is a sizable effect given that treated entrepreneurs exit earlier. At an individual level, these results imply that one entrepreneur out of ten could avoid wasting time, money and effort developing business ideas that are not as promising as they initially thought. At an institutional level, the adoption of the scientific approach as an 'accelerating philosophy' could improve the time to acceleration, freeing up a considerable amount of resources (roughly more than 10% without considering faster turnover).

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

Camuffo et al. (2020), that we also extend. We find, in fact, that treated start-ups are more likely to pivot one or two times, but we also show that they are less likely to pivot many times.

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

The effect sizes of the regressions are more complex to interpret in this case. However, at the individual level, a limited number of pivots allows entrepreneurs to explore ideas that would otherwise be lost (foregone options). At the same time, it helps to avoid redundant pivoting, saving a significant amount of resources. At the institutional level, acceleration programs could be more effective and efficient – redundant pivoting could be reduced by as much as 80% (one pivot instead of five).

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

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

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

5.2 Evidence of the mechanisms

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

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

Figure 5 shows the variations over time for *Range* and for *Av_Range*. *Av_Range* is smoother and less erratic because the average of the past values eliminates the more volatile components of this measure. For all start-ups *Range* and *Av_Range* decline initially. Since all our start-ups are at their very initial stage when they enter the RCT, it is natural that they become more informed, whether because of the training or the start of activities, and they become more precise. However, the start-ups in the control group stop becoming more precise earlier, and the two variables remain stable thereafter. The start-ups in the treated group increase their precision for longer, and then *Range* and *Av_Range* increase. This is consistent with our framework: initially, the scientific approach makes entrepreneurs more precise, and then they see more innovative and diverse potential changes to their ideas. Figure 5 also implies that, for the treated start-ups, the difference in range between two periods also declines and then increases more sharply, which is again consistent with our framework.

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

We provide evidence about the mechanisms by presenting the results of three sets of regressions for exit, pivot, and performance. In these regressions, we employ dummies for instructor and time fixed effects and use robust standard errors. Clustering by instructors and intervention produced similar but less precise estimates. This is probably due to the fact that we do not have enough clusters and we employ *Intervention* as the excluded instruments for all the regressions.

The first two columns of Table 5 show that a smaller *Av_Range_lagged* (which corresponds to greater precision) increases the probability that the entrepreneurs close their firms. Statistical significance is stronger in the IV probit than in the linear probability model. In the IV probit, at the mean value of the independent variables, a one standard deviation increase in *Av_Range_lagged* (which is equal to 0.394) reduces the probability of exit by 0.204. This is a sizable impact because with the IV probit estimates the probability of exit in that point of the sample is equal to 0.236. A one standard deviation increase of *Av_Range_lagged* then reduces this probability to 0.032. We employ *Av_Range_lagged* instead of *Range_lagged* to focus on the more systematic components of this measure. This variable is a prediction of the distribution of the future value of the firm. At each moment in time, our telephone interviews collect updates of this prediction, which always refer to the same variable: the future value of the firm. Thus, each exact measure declared in the interview may be affected by an erratic component that may depend on many factors, including the particular perception of the value at the moment of the interview or other similar contingencies of the interview or the interviewee. When we use *Range_lagged* instead of *Av_Range_lagged* we obtain similar second-stage results. In the first stage, the sign of *Intervention* does not change, but *Intervention* is a weaker instrument, which probably reflects the more volatile nature of the non-smoothed measure.

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

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

Table 6 reports the results of our analysis of pivots. In the first three columns, we employ IV Poisson rather than IV Probit because in the first two regressions some weeks include no cases in which the dependent variables is different from zero. Rather than selecting the relevant weeks, we show IV Poisson, and we run IV Poisson for all three columns to simplify comparison. At any rate, we obtain very similar results with IV Probit regressions that aggregate week dummies when there are no cases with no pivots, or in which we replace the week dummies with a higher order polynomial of time. Our theory predicts that treated firms are more likely to pivot a few times rather than zero or many times. The first column of Table 6 shows the results of a regression in which the dependent variable is equal to 1 for the observation in which the start-up pivots, if it pivots only once in the time frame of the study, and zero otherwise. Thus, the dependent variable will be equal to zero both for firms that do not pivot once and for the firms that pivot once for the observations related to the weeks in which they do not pivot. The second column shows the results of the analog regression in which the firm pivots once or twice in the time frame of the study. Finally, the third column shows the results in which the dependent variable is equal to 1 in any week in which any firm pivots, and zero otherwise.

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

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

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

Table 7 shows the results on performance, that we operationalize by measuring revenue. The first column shows that an increase in *Av_Range_diff* increases revenue. This result is consistent with our mechanism: a greater difference between current and past spread reflects the fact that entrepreneurs see new factors that increase the value of the idea. As discussed in the previous paragraphs, increases in *Av_Range_diff* increase pivots. At a broader level, this wider gap between current and past spread reflects the fact that entrepreneurs discover how to modify their idea on the basis of an improved understanding of the problem. This is implied by the fact that, as we have shown, *Av_Range_diff* increases with the intervention and scientific intensity. In regressions reported in the Online Appendix, we find that the dummies *Pivot (1 time)* or *Pivot (1 or 2 times)*, in lieu of *Av_Range_diff*, instrumented by *Intervention*, also raise revenue. However, the statistical significance is lower. This mirrors the general point that a greater *Av_Range_diff* increases performance because it is associated with the identification of new ways to change and perfect the business idea. As discussed in our theory section (Section 3.2), when these changes are particularly important, we observe a pivot, which is also what is recorded empirically in the analyses presented here. However, increases in *Av_Range_diff* may also capture innovation opportunities within the current idea that increase performance.

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

In this case as well, our result is conditional on the fact that *Intervention* does not have a direct impact on performance. In fact, if the scientific approach removes poor ideas because start-ups close their business, *Intervention* will have a direct effect. At the same time, the second and third columns of Table 7 show that scientific intensity, instrumented by *Intervention*, increases revenue and it also raises *Av_Range_diff*. At the same time, we cannot rule out that the scientific approach affects performance through the selection of better ideas. However, the second and third column of Table 7 use as the key independent variable scientific intensity, which should capture both selection and improvement effects. Still, *Intervention* might directly affect performance, but in this case we can rule out that the direct effect of *Intervention* is produced by effects other than the scientific approach. To address this problem, we rule out the fact that training on the scientific approach might provide entrepreneurs with greater enthusiasm or energy. In additional analyses reported in the Online Appendix, we estimated the effects of the number of hours worked by the entrepreneurs. We find that hours worked is not correlated either with intervention or revenue. Thus, overall, this evidence does not falsify Proposition 3.

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

Section 6. Discussion and Conclusion

This study offers a comprehensive framework and evidence of why and how a scientific approach improves entrepreneurial predictions and performance. In doing so, we connect this line of reasoning to the current debate in entrepreneurship, highlighting how the scientific approach might be thought of as a 'rational heuristic' – a set of behavioral routines that can mitigate decision biases (Zhang and Cueto, 2017) and improve the combination of thinking and doing that characterizes entrepreneurial ventures (Eisenhardt and Bingham, 2017; Ott et al., 2017). This study is also subject to limitations. As in most field experiments in social sciences, its design does not allow perfect identification. Given the high financial costs of running a similar field experiment, the sample is relatively small, which limits the power of the experiment. However, the fact that we have repeated observations over a reasonably long period of time mitigates this problem and strengthens our findings. Important open questions stem from the study of our mechanisms. We show how the scientific approach acts by affecting the prediction of the distribution of returns of the business idea. We clearly move beyond Camuffo et al. (2020) because we replicate their results, while extending their work in three important ways. First, we use a different and larger sample, that we observe for a longer period . In this study, we capture a proportion of early-stage Italian firms operating in a wide range of sectors, using a population that is similar to Camuffo et al. (2020). Given that findings of both studies align, our results show strong external validity with regards to this population and – we expect - for similar start-ups operating in other European countries. More research would be needed to establish if these results can be generalized to different settings such as high-growth tech firms, later-stage start-ups or start-ups in developing countries. Second, in replicating their results, we provide additional insights: scientific firms reach their goals with a few focused pivots. Third, this paper moves beyond an intention-to-treat-design and is able to provide evidence consistent with the comprehensive theory developed in section 3. While our evidence about the mechanisms is interesting and points to promising directions, it is preliminary. We employ coarse measures of the perceived distribution (spread). 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. Despite the effectiveness of these measures, future research could develop more sophisticated measures to provide additional identification of these mechanisms.

We see many fruitful opportunities for further research. Apart from extensions to other countries and industries (e.g. high-tech), we wonder what the effect might be when entrepreneurs 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 given learning model. It would be valuable to understand what teaching approach and learning model (e.g. more or less experiential, in presence vs. online, etc.) results in a better effect of the scientific approach. A similar study would allow to understand how to scale similar interventions with a view to improve entrepreneurship education. Additionally, our study did not identify the micro-mechanisms that, at the individual level, drive the different predictions of scientific entrepreneurs (Busenitz & Barney, 1997). This could complement a more refined understanding of the mechanisms of the scientific approach. There is a vast body of literature about the corrections of perceptions, changes in predictive models and mitigation of biases (Astebro et al., 2014). However, this study did not collect data to examine the micro-foundations of the mechanism that lead scientific entrepreneurs to differ in how they perceive the variability of the value of their business idea, compared to non-scientific entrepreneurs.

Finally, it would be intriguing to evaluate the effects of the scientific approach vis-à-vis other approaches, such as effectuation. Future studies could examine the effectiveness of non-predictive techniques for early-stage entrepreneurs vis-à-vis the scientific approach.

This study contributes to a better understanding of how entrepreneurial decision making impacts key decision early on in the life of a start-up, such as exit and pivot. In exploring this topic in the context of a pre-accelerator program, we contribute to literature on early organizational forms and entrepreneurship in several ways. Firstly, our study shows that entrepreneurs benefit from using a systematic approach to decision making. We show 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. This adds to a new perspective to the current conversation focusing on external sources of information used by entrepreneurs in the early-stages of new venture creation (Chatterji et al., 2019; Cohen et al., 2019; Hallen et al., 2020; Yu, 2020) Secondly, our study contributes to entrepreneurship literature by providing a better understanding of important choices such as exit and pivot. As early-stage entrepreneurship represents the least understood part of entrepreneurship, we provide insights into the factors that help entrepreneurs assess the potential of new business ideas. Thirdly, this study also 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. Finally, this research has also implications for policy. As the quality of entrepreneurship in a country depends on a high number of early-stage firms moving from provisional ideas to fully-formed businesses (Lerner, 2009), governments can promote a better selection of entrepreneurial ideas thought training initiatives similar to the one we ran. In fact, exit and failure in early-stages are not necessarily negative if they allow to select and advance only truly profitable ventures. Overall, this study points to the fact that, while the scientific method has limitations, it also has potential. We are far from claiming that this potential makes it the best approach in entrepreneurial decision-making. However, this paper provides additional evidence that it represents a helpful way to approach business problems through mental frameworks that we test and possibly update.

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Table 1. Variable definitions and descriptive statistics

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

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

Table 2. Exit

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

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

Table 3. Pivot (cross-section)

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

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

Table 4. Performance

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

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

Table 5. Exit (mechanism, panel)

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

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

Table 6. Pivot (mechanism, panel)

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

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

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

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

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

Figure 1. Marginal benefits of pivots

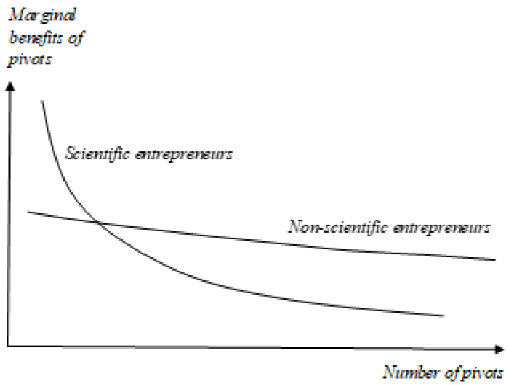


Figure 2. Number of exit and pivot

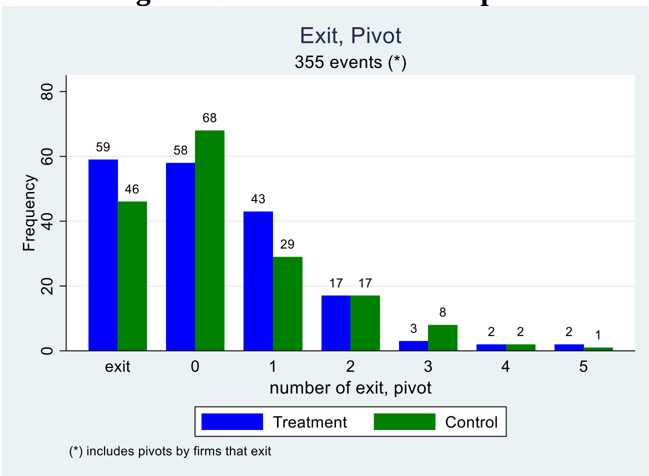


Figure 3. Average cumulative revenue (weeks 8-66)

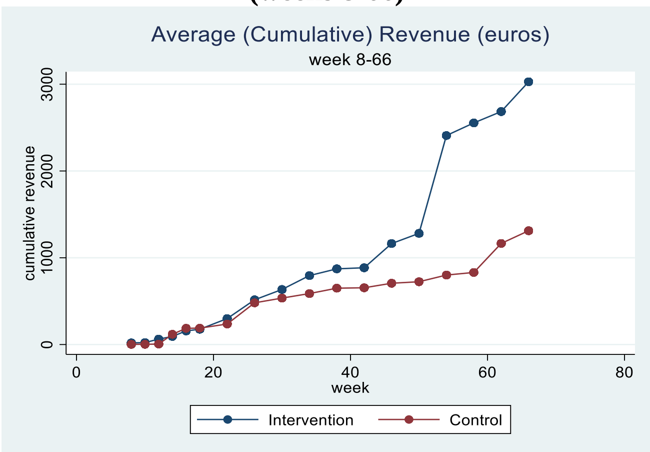


Figure 4. Mean Value

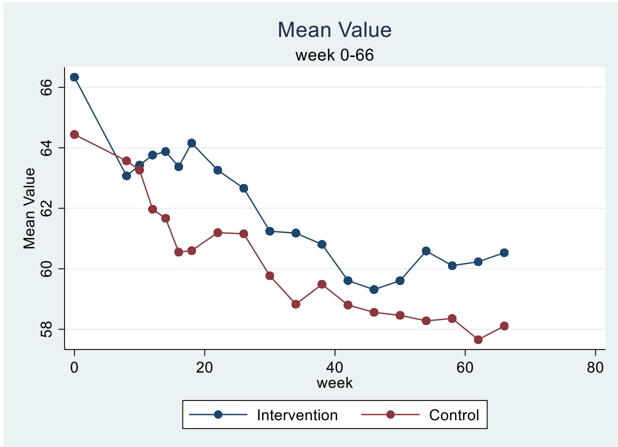
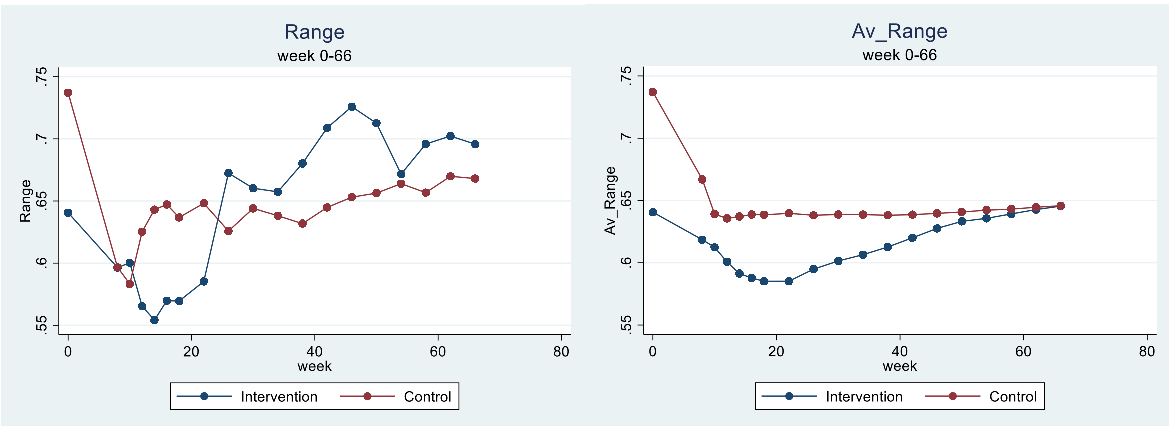


Figure 5. Range and Av_Range



Online Appendix A: Randomization checks on key covariates

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

Online Appendix B: A Description of Scientific Intensity

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

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

Element	**Dimension**	**Description**
Theory: this part of the interview aims to understand if the respondent has a theory, i.e. a cohesive story about the mechanisms underlying the problem and the building blocks that need to be in place for the business to be viable.	*Theory_Clear*	Score to quantify whether the theory is understandable
	Theory_Articulated	Score to quantify if the theory goes into details, i.e. whether the respondent can provide a high level of detail consistent with the main theory
	Theory_Alternatives	Score to quantify if the theory expressed by the respondent considers additional aspects not currently implemented by the company, but that could be implemented
	Theory_Evidence	Score to quantify if the theory is supported by data. Data could be industry reports or information gathered by the respondent itself
Hypotheses: this part of the interview aims to understand if the respondent has identified specific hypotheses based on their theory, i.e. propositions that logically flow from the theory but that have yet to be tested.	*Hypothesis_Explicit*	Score to quantify if the respondent can clearly articulate the fundamental hypotheses that make his/her business viable
	Hypothesis_Coherent	Score to quantify if the hypotheses are coherent with the theory elaborated earlier
	Hypothesis_Detailed	Score to quantify if the respondent is able to tell what he/she wants to learn in clear and concise terms
	Hypothesis_Falsifiable	Score to quantify if hypotheses are formulated in a way that allows the respondent to support it or refute it through tests
Testing: This part of the interview aims to understand if the respondent has tested their hypotheses based on their theory.	*Test_Coherent*	Score to quantify if the objective of the test is in line/coherent with the hypotheses expressed earlier
	Test_Valid	Score to quantify if the test measures what it is intended to measure
	Test_Representative	Score to quantify if the test uses a representative sample that accurately reflects the characteristics of the broader group targeted by the respondent
	Test_Rigorous	Score to quantify if respondents use the right type of test and with the right procedures
Evaluation: This part of the interview aims to understand if the respondent has analyzed the data collected and whether	*Val_Data*	Score to quantify if the evaluation is based on objective data – as opposed to making an assessment based on subjective perception
	Val_Measure	Score to quantify if the key measures used in the evaluation are consistent with what respondents identified as their priorities in the earlier questions

he/she is actually making use of their findings.	*Val_Sistematic*	Score to quantify whether the collection and analysis process are well-organized and systematic
	Val_Explanatory	Score to quantify if the respondent has clarity on the main findings of the tests and their implications for the business – e.g. what to do based on the findings

Online Appendix C: Additional analysis, Effect of pivot on performance (panel, 2SLS)

VARIABLES	(1) DV = Revenue	(2) DV = Revenue
Pivot (one time)	14,608.590	
	(0.203)	
Pivot (one or two times)		14,455.601
		(0.295)
Constant	3.908	-94.403
	(0.984)	(0.743)
Observations	4,500	4,500
R-squared	-1.195	-2.174
Dummies for instructors	Yes	Yes
Time FE	Yes	Yes
Clustered Errors	Robust	Robust

Robust pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Online Appendix D: Robustness check, Effect of number of hours worked on performance (panel, 2SLS)

VARIABLES	(1) Number of hours worked First stage	(2) Revenue Flow 2SLS
Intervention	0.035	
	(0.962)	
Number of hours worked		-110.111
		(0.272)
Constant	12.860***	2,070.439
	(0.000)	(0.253)
Observations	3,428	4,500
Dummies for instructors	Yes	Yes
Time FE	Yes	Yes
Clustered Errors	Robust	Robust

Robust pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1