When Innovators Act Like Scientists:
A Field Experiment of UK Entrepreneurs

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This version: April 2021

ABSTRACT

Entrepreneurs operate in environments characterized by high degrees of uncertainty that is endogenous to firm action. In these contexts, recent research shows that firm performance benefits from systematic decision-making approaches. However, it is not clear if all entrepreneurs benefit equally from these approaches. To address this gap, we conduct a 9-month field experiment with 261 UK entrepreneurs. Our sample includes both entrepreneurs that have already registered their company and entrepreneurs that have not yet done so. This allows us to distinguish between firms that are more or less established. We use the experiment to train half of the participants on using a more systematic - "scientific" - approach to decision-making, and half of them on the same content but without a scientific approach to decision making. Our results show that registered firms that are trained to use a more scientific decision-making process generate higher revenue and higher revenue from innovation. While these firms incur in higher costs, they also achieve higher productivity.

INTRODUCTION

A fundamental question for research in strategy concerns the extent to which managerial approaches can make a positive impact on firm-level performance. This question is particularly relevant in innovation-based settings such as entrepreneurial ones, where firms have to form their strategy in environments characterized by high uncertainty along multiple dimensions such as technology (McGrath, 1997; Folta, 1998; Gans and Stern, 2003) and market preferences (Sarasvathy, 2009; Foss and Klein, 2012; Kirtley and O'Mahoney, 2020). The resolution of these uncertainties is often endogenous to action (Gans and Stern, 2017; Ott and Eisenhardt, 2020). An emerging stream of research suggests that the use of systematic decision-making approaches can have a positive impact on an innovative firm performance. Proponents of these approaches identify four key components of effective systematic decision-making: (a) a clear formulation of the problem under investigation (Felin and Zenger, 2017; Camuffo et al., 2020); (b) the development of clear predictions of the key dimensions of the problem that needs to be addressed (Felin et al., 2019; Camuffo et al., 2020; Felin et al., 2020) (c) the systematic collection of evidence to validate those predictions (Bloom, 2012; Ries, 2012; Camuffo et al., 2020; Ghosh et al., 2020); and (d) a disciplined assessment of the feedback collected (Murray and Tripsas, 2004; Camuffo et al., 2020). The key tenet of these related streams of research is that these four components help firms resolve the uncertainty associated with entrepreneurial choices and, in doing so, lead to the formation of superior decisions. Recognizing the synergies associated with the use of these practices in combination, Camuffo et al. (2021) refer to an approach that employs all of these steps as to a "scientific approach to innovation management".

But under what conditions and to what extent is the use of a "scientific" decision-making approach associated with superior performance in innovative settings?

Despite the important insights from prior contributions, little is known about the boundary conditions of this type of approach. This is partly due to two fundamental issues that restrict the advancement of research in this area. First, limited conceptual work has investigated the boundary conditions that determine the effectiveness of systematic approaches to decision making. Second, despite the substantial interest that these types of decision-making approaches have generated within the scholarly and practitioner communities, there is very limited empirical evidence on their performance implications. This is because this area of research is still nascent, but also because of the inherent challenges related to monitoring the use of these approaches and their performance within firms. The limited evidence available on this topic is based on studies with firms at relatively advanced stage in their journey (Bloom and VanReenen, 2012; Pillai et al., 2019). However, it is difficult to generalize results from studies focusing on mature firms to earlier-stage firms which face a different set of challenges. As Kirtley and O'Mahoney (2020) note, few studies examine firms that are less established. In addition, results on the performance implications of these approaches among less established firms are generally inconclusive (Karlan et al., 2015; Bruhn et al., 2018; Camuffo et al. 2020a and 2020b) or focused on relatively narrow performance metrics (Koning et al., 2020). As a consequence, we lack an understanding of when systematic decision-making approaches result in superior performance.

In this paper we address both issues with a 9-month randomized control trial (RCT) with 259 UK entrepreneurial firms attending a strategy training program. Both treated and control firms undergo a strategy training course, where they are exposed to key strategy concepts and tools for a total of 21 hours of training spread across 7 sessions. The treatment group, however, is taught to apply these concepts and tools following a systematic decision-making process labelled 'a scientific approach'. Entrepreneurs who learn about the scientific approach are taught in each session of the course to formally develop theories about the problems they face, develop predictions consistent with those theories, test those predictions, and systematically evaluate their results. Entrepreneurs in the control group learn about the same key strategy concepts and tools of the treated group, but they are free, instead, to apply them following their own intuition, rather than using the rigorous approach presented to the treatment group.

Our sample is unique in that it includes both more and less established firms: firms that have already registered their company and firms that have not yet done so. Registration is an important step as it requires to make a formal commitment on some strategic choices, such as the sector in which the firm operates. This offers the opportunity to test how firms respond differently to our treatment depending on the stage of their journey (more or less established). Results show that treated and registered firms have superior performance compared to other firms: they generate higher sales and higher sales from new products or services. Even though these firms incur in higher costs and employ more employees, they achieve higher productivity. We conduct a number of robustness checks and sensitivity analyses, and we consistently find support for the idea that the growth in revenue and productivity of registered firms is driven by an increased ability to create rather than transfer value. These results point to the fact that more established firms benefit to a larger extent from a scientific approach to decision-making.

The contribution of this study is threefold. First, we contribute to strategy research on managerial decision making, by showing that different types of firms do not benefit from the use of a scientific approach to decision making equally. This result leads to reconsider previous findings that have shown a positive association between systematic approaches to managerial decision making and performance among more established firms (Bloom and Van Reenen, 2007; Yang et al., 2020). They stimulate a due reflection on the relevant boundary conditions of systematic approaches to managerial decision making, reconciling previous mixed results on the relationship between these types of approaches and firm performance (Karlan et al., 2015; Bruhn et al., 2018; Camuffo et al. 2020a and 2020b). Second, our paper contributes to research on entrepreneurial strategy. Scholarly - as well as practitioner-oriented - work in this area advocates that experimentation is the most appropriate approach for early-stage entrepreneurial decision making (Bennett and Chatterji 2019; Ries, 2010). Our results show that firms at a very early stage of their entrepreneurial journey do not benefit from these approaches as much as more established firms do. This is in line with recent theoretical work that suggests that experimentation might be more fruitful for firms at a more advanced stage of their strategy definition (Gans et al., 2019; Gans et al., 2020). It is also consistent with what suggested by Pillai et al (2019), that provide initial empirical evidence that, however, focuses only on established firms. We therefore provide unique evidence in this direction. Third, the results of this study provide crucial insights for governments and institutions looking to foster firm growth through programs that support innovation. The many initiatives that offer training with a view to stimulate growth and productivity have often produced limited results (Lerner, 2009). This study puts forth a possible explanation - that only some firms benefit from training programs within a limited time window. Awareness of which firms benefit from training is the starting point to more efficiently select firms that are admitted to these programmes, or to identify alternative forms of support for firms that do not benefit from training programs.

THEORY

A Scientific Approach to Decision Making and the Performance of Entrepreneurial Firms

A series of recent studies in strategy and entrepreneurship provides relevant insights on systematic decision-making approaches to entrepreneurial action. Collectively, these studies advance the idea that firm performance can improve when entrepreneurs deliberately employ routines based on structured processes of problem framing and information gathering. This is expected to generate relevant feedback that fosters learning and mitigates the biases and bounded rationality problem that typically affects entrepreneurs' decision-making process (Cohen et al., 2019; Camuffo et al., 2020; Yu, 2020). It is also expected to discipline entrepreneurs, leading them to avoiding decisions that are inconsistent with the feedback gathered, an issue consistently observed in various settings (Parker, 2006; Bennett and Chatterji, 2019; Chen et al., 2020). More specifically, four interrelated streams of research have emphasized the relevance of key processes underlying these systematic approaches.

A first stream of research emphasizes how the development of *theories* (Felin and Zenger, 2009; Zenger, 2015; Felin and Zenger, 2017), rules (Bingham and Eisenhardt, 2012) or mental representations (Czaszar and Laureiro-Martinez, 2018) of business problems and their context drive business innovation, performance heterogeneity, and superior strategy. A second, related stream of studies focuses on examining the importance of systematically developing *predictions* regarding the key dimensions of the problem that needs to be addressed. Predictions are central to clarify what makes a value proposition valuable and to purposefully generate feedback on it. Studies in this area show that a systematic collection of evidence guides subsequent actions and is conducive to superior performance (McGrath, 2001; Bingham and Eisenhardt, 2011; Leatherbee and Katila, 2020). A third stream emphasizes the importance of purposeful experimentation to *test* predictions and generate relevant feedback (McGrath, 1999; Murray and Tripsas, 2004; Kerr et al., 2014; Ott and Eisenhardt, 2017; Gans et al., 2019; Pillai et al., 2019; Shepherd and Gruber, 2020). This area has strong connections with topics popular among entrepreneurs and practitioners. As such, several toolkits aimed at supporting practitioners in experimenting have emerged (Osterwalder and Pigneur, 2010; Ries, 2011; Gruber and Tal, 2013; Furr and Dyer, 2014). These toolkits appear complementary (Shepherd and Gruber, 2020) as they tend to focus on different aspects of the experimentation process: how to identify new business ideas (Gruber and Tal, 2013), how to strategize after identifying the initial busines idea (Osterwalder and Pigneur, 2010), and how to experiment while searching for the right product-market fit (Ries, 2011). Furr and Dyer (2014), instead, focus on how established firms can benefit from a combination of these tools. A final stream of research in this domain emphasizes the importance of the systematic *evaluation* of the evidence that entrepreneurs naturally gather to make decisions (Bennett and Chatterji, 2019; Chatterji et al., 2019; Cohen et al., 2019; Camuffo et al., 2020a; Camuffo et al., 2020b).

Recently, some authors have proposed that the core processes described above (i.e., the elaboration of theory, the development of predictions, the collection of feedback via purposeful experimentation and the systematic assessment of evidence) are complementary and mutually reinforcing. They called attention on the importance of combining "*thinking and doing*" (Eisenhardt and Bingham, 2017, p. 247) and taking a holistic approach to decision making that involves the joint use of the four processes described above (Camuffo et al., 2020a; Camuffo et al., 2020b). Recognizing the similarity with the rigorousness of the approach used by scientists in the discovery process, these authors refer to this set of routines as a scientific approach to decision making. This approach is in contrast with what many entrepreneurs often do in their decision-making process. This typically includes using trial and error techniques (Sosna et al., 2010; Bingham and Eisenhardt, 2011), relying on intuition (Blume and Covin, 2011) and gut-feelings rather than structured approaches (Mitchell and Shepherd, 2012). Evidence shows that entrepreneurs often operate without a clear vision of what they intend to achieve, choosing what to do next based on feedback gathered through enquiries with non-representative samples (Forbes, 2005; Bennett and Chatterji, 2019).

How a Scientific Approach to Decision-Making Works: An Example

To clarify how a scientific approach works, we provide one example related to an innovative firm that produces and sells vegetarian food. A scientific innovator would start with a clear theory of how his/her company can create value for customers. Vegetarian food is increasingly popular because it represents a healthier, more sustainable choice that does not affect animal welfare compared to meat products. Even if vegetarian food is highly nutritious, it is often not tasty. The entrepreneur believes he/she can offer value to customers by selling vegetarian food that is highly nutritious and tasty. This entrepreneur theorizes that younger consumers are the ideal target customer as they are more likely to care about a sustainable and healthier lifestyle and are willing to pay a premium for tasty vegetarian food. From this broader theory he/she derives testable hypotheses that his/her vegetarian food is as tasty as the non-vegetarian equivalent and that, if it is as tasty as non-vegetarian options, vegetarian food is more likely to be preferred by younger customers. To test these hypotheses, the entrepreneur could first test that his/her food is as tasty as the non-vegetarian version with a blind test. He/she could then sell vegetarian food using a pop-up stall where customers have the options to sample food before purchasing it and observe who is more likely to purchase food after tasting it to assess if it is younger or older consumers that prefer that type of food. The entrepreneur would then use this information to evaluate what to do next, for instance how to advertise the product. This information might in turn provide new ideas on what else to sell to customers based on the same theory.

The non-scientific entrepreneur, instead, sells the same product without a clear idea of the features valued by customers. In the absence of a theory, the entrepreneur is likely to make decisions based on what seems to work. This entrepreneur might also sell different types of vegetarian food but without a clear idea behind the reasons for selling them in the first place. This implies that he/she is likely to sell different types of vegetarian food that vary along a number of characteristics (i.e., produced with organic ingredients, gluten-free, etc.) because there is no intention to test precise hypotheses. If the entrepreneur finds that he/she sells more food produced with organic ingredients, he/she will not know if it is because of the taste, the preference for these ingredients or another feature. Even the evidence that naturally emerges from the data collected through sales is unlikely to be helpful in understanding what to do, because of the causal ambiguity given by the 'test' design. Overall, the non-scientific entrepreneur is less likely to have a clear assessment of what customers value, which might ultimately lead him/her to introduce new products or services by choosing randomly, rather than with a clear theory as a frame of reference. This implies that even the non-scientific entrepreneur might perform well when – serendipitously – selling their products or services. However, the lack of clear theory, hypotheses, and rigorous tests prevents him/her for learning about the reasons underlying how he/she creates value for customers, making the venture less likely to be successful in the long run.

A Scientific Approach to Decision Making for Registered and Unregistered Firms

We investigate the performance effects of the use of more scientific approaches to decision making and whether they are different for firms that are at different stages of their journey. This fills an important gap in prior research as the evidence from existing studies is mostly focused on firms at a relatively advanced stage of development. For example, Bloom and Van Reenen (2007) find that better management practices tend to be associated with higher productivity, profitability and other performance measures. Their results are based on a sample of medium-sized manufacturing firms with more than 50 years of age and more than 2,000 employees on average. These results are replicated in other settings through subsequent work. In a recent large study Yang et al. (2020) show that there is an association between firms that follow highly formalized, rigorous and deliberate processes and the achievement of a larger firm size and faster employment growth. Similarly, other studies show that deliberate approaches to learning relying on structure and codification are associated with superior performance in the context of acquisition integration, based on samples of large and experienced acquirers (Zollo and Winter, 2004; Heimericks, et al., 2012).

We know little about the performance implications of the use of these approaches for less established firms. Among the few studies, Karlan et al. (2015) conduct one RCT in urban

Ghana in which tailoring microenterprises received advice from an international consulting firm, cash, both or, neither. They find that, while all treatments lead to changed business practices and higher investment, they also lead to lower profits on average. Bruhn et al. (2018) conduct an RCT with 432 small and medium enterprises in Mexico, out of which 150 are randomly chosen to receive the treatment, which consists of access to consulting services. Results are mixed in that they show some positive effects on profits and ROA, which are, however, not robust to all econometric specifications and assumptions regarding outliers. Moreover, the authors find positive but not statistically significant point estimates on the short-term treatment effects for paid employees, log sales, and profits, and find negative but also not statistically significant point estimates on sales, log total employees, and log of firm assets.

In the context of an RCT with very early-stage start-ups, Camuffo et al. (2020) focus on a scientific approach to decision-making and find that treated entrepreneurs are more likely to pivot to alternative ideas and to terminate their projects early. However, the effect of the treatment on firm performance shows a higher degree of variability. In the context of early-stage firms, Koning et al. (2020) investigate the use of experimentation on the performance of high technology start-ups. They find that the use of A/B testing increases performance on some specific metrics such as including page views and new product features, but overall younger start-ups perform worse when using A/B testing, whereas firms with more experienced managers perform better than other firms. This points to the fact that it is difficult to design rigorously and interpret unambiguously the results of tests, as also confirmed by anecdotal evidence by Luca and Bazerman (2021).

While the evidence presented so far is informative, it does not provide a clear picture on the boundary conditions of the use of systematic approaches to decision-making and in particular if they can help more and less established firms equally. In this paper, we fill this gap by focusing on the distinction between registered and unregistered firms as a fundamental milestone in entrepreneurial firms' journey and investigating how these two types of firms respond to a treatment that teaches them the use of a scientific approach to decision making. Registration represents a crossroad in the evolution of an entrepreneurial idea: registering a firm is a straightforward and inexpensive process in many contexts, but it requires firm owners to clearly define the nature of the business, separate their own finances from the company finances, and take on some accounting responsibilities. It is therefore likely to take place when an entrepreneur has achieved sufficient clarity on at least some of the key strategic choices faced. Remarkably, this does not depend on the age of the firm, as there is high variance in terms of when entrepreneurs choose to register their company. Put differently, registration has more to do with the maturity of the firm than with its age.

We propose that more established firms - i.e., registered firms - benefit more from the use of a scientific approach compared to less established ones. Holding other conditions constant, such as the underlying quality of the idea, or the size of the firm, we posit that two key characteristics distinguish registered firms from unregistered ones. First, their value proposition tends to be more clearly defined, as the registration process requires entrepreneurs to specify key characteristics of their firms such as their sector of operation. We suggest that this added focus makes the application of the method more effective and efficient irrespective of the quality of the underlying idea. The registration – and focus associated with it - supports a better definition of the theory, hypothesis, test design and evaluation of the results, and consequently it is likely to lead the entrepreneur to make better decisions. The second characteristic that sets registered firms apart from others is higher contextualization. Registered firms do not examine the problem only in hypothetical terms; they look at it in the context of an existing company, potentially with running operations. This makes them better able assess the problem "in action", embedded into a specific context which provides them with a better opportunity to learn from the real-life feedback that they gain when they apply the scientific approach.

More specifically, entrepreneurs that employ a scientific approach frame the problem they face and evaluate alternative options through the use of a theory. This helps them understand more clearly what the key dimensions of the problem are and what they should focus their attention on (Camuffo et al., 2020a, 2020b; Felin et al., 2020). The higher degree of focus that likely characterizes registered firms, which operate under a more clearly defined value proposition, reinforces this mechanism. As a result, the theory developed by registered firms is likely to be more precise and thorough than the one developed by unregistered firms. This is consistent with organizational research that suggests that some degree of structure facilitates entrepreneurial decision-making processes by showing entrepreneurs what to pay attention to and what the most promising course of action is (Davis et al, 2009). In a similar vein, Gans et al. (2019) note that some form of "*commitment to one particular strategic alternative*" (p.744) leads to superior focus and exploitation of one trajectory as opposed to additional search.

Similarly, more established firms will benefit more from the articulation of their theory into clear, falsifiable, predictions (Felin and Zenger, 2016) as a way to modularize the problem into smaller, decomposable and more addressable blocks, which reduces the level of causal ambiguity (Felin et al., 2020). The increased focus facilitates the process of identification of the key blocks that are developed into hypotheses. In the highly uncertain entrepreneurial settings, it contributes to narrow down the range of possible options available to entrepreneurs, thus simplifying the number of possibilities available to them.

Entrepreneurs who use a scientific approach also gather feedback through rigorous tests, which can help distinguish between good and bad projects (Thomke, 2003; Murray and Tripsas, 2004; Bingham and Eisenhardt, 2011; Ries, 2011; Gruber and Tal, 2013; Gans et al., 2019; Pillai et al., 2019; Shepherd and Gruber, 2020). The higher focus that characterizes more established firms helps them by improving the quality of the evidence that entrepreneurs collect, as well as their ability to interpret that evidence correctly. Designing a precise test to assess the value proposition is more difficult when the value proposition itself is still loosely defined. For instance, one should gather evidence about the extent to which different target customers find the idea appealing as well as the extent to which multiple sales channels fit the value proposition. Precise testing would require collecting evidence on each dimension holding all other conditions constant, resulting in a huge number of test combinations. Less precise tests, on the other hand, would make the interpretation of evidence from the test problematic, as there is more ambiguity about the relation between each individual choice and performance (Kauffman, 1989; Gell-Mann, 1994; Gans et al. 2019; Ott and Eisenhardt, 2020).

This is particularly relevant in an entrepreneurial setting where uncertainty resolution tends to be at least partially endogenous to firm action. Feedback made without or prior to committing to one particular strategic alternative is inherently "noisy" because it relies on assumptions that may not be realized in practice (McGrath & MacMillan, 1995; Bhide, 2000; Gruber, 2007; Gans et al. 2019). As emphasized by Gans et al. (2016, p.4) "*choosing between alternative strategic commitments requires knowledge that can only be gained through experimentation and learning, yet the process of learning and experimentation inevitably results in (at least some level) of commitment that forecloses other strategic options*". In addition, more established firms collect higher quality feedback as these entrepreneurs have already taken some actions towards defining a real market context to test their decision. This means that decision-makers obtain richer information compared to what can be obtained "in a lab" (Rosenberg, 1982; Rosenberg, 1994; Stern, 2005; Greenstein, 2012; Pillai et al. 2019).

Finally, entrepreneurs using a scientific approach to decision making are those who employ a systematic and critical assessment of the evidence, with the purpose of comparing the signals collected against an ideal threshold (Bennett & Chatterji, 2019). As entrepreneurs from more established firms have defined the sector in which they operate, they are more likely to identify thresholds more precisely. This is because the higher focus described above implies a better understanding of the context these entrepreneurs operate in, which facilitates the definition of a threshold. The definition of a clear threshold allows these entrepreneurs to more precisely assess the value of a particular choice based on test results.

Overall, the above arguments suggest that the positive effect of a scientific approach on performance is expected to be higher for more established firms due to the fact that focus and contextualization make the use of a scientific approach to decision making more effective and efficient. As an example of our logic, consider the case of Coach Delivery, an early-stage venture that aims to offer a fitness coaching service for busy individuals. But at an early stage of their journey, the founders did not have clarity on whether the service should be offered as a 'gym van' that could be driven to the customer's house or office, or as personal trainers visiting the customer's home, or through small fitness stations in neighborhoods with no gyms nearby. The founders kept all these options open. As a result, they struggled to develop a clear theory to evaluate the pros and cons of each choice, which delayed progress. This also led them to develop tests that were noisier as they were offering customers hypothetical versions of the products as opposed to real life versions. They also struggled to test the many different options through which they could have served target customers because of limited time and resources and because of the high cognitive load similar testing demands. In line with this logic, we expect that more established firms will benefit more from using the scientific approach compared to less established firms.

DATA AND METHODOLOGY

The RCT: Setting and Data Collection Process

To investigate the impact of a scientific approach to decision making on the performance of registered and unregistered firms, we conducted an RCT. Following best practices, we pre-registered the field experiment before the intervention took place (Duflo et al., 2020). We embedded the field experiment into a business support programme designed and run by the authors in London, UK. The program started in mid-February 2019 and ended in November 2019. We administered our treatment through a business support program, because similar interventions have been shown to affect outcomes for entrepreneurs (Anderson et al., 2018; Camuffo et al., 2020a).

We targeted entrepreneurial firms with less than 10 employees, as our empirical design requires that the subjects receiving the treatment are the firm key decision-makers. This condition is more accurately met in the context of micro-businesses, where all employees tend to be highly involved in the management of the firm. We recruited firms with an ad-hoc marketing campaign using online media (such as social media, blogs, and online communities) and offline channels (flyers), which produced about 500 applications. We screened out firms that reported having more than 10 employees. Our final sample included 274 entrepreneurial firms. We did not impose any restrictions in terms of industry, and firms admitted into the program operated in in a wide range of sectors, from software to retail.

Our setting gave us the opportunity to recruit into the programme both registered and unregistered firms, a feature that sets this programme apart from other studies where only registered (Guzman and Stern, 2016) or unregistered firms (Camuffo et al., 2020a; Camuffo et al., 2020b) participate. Registering a firm in the UK is a straightforward and inexpensive process, but it requires firm owners to clearly declare the nature of the business, put into place a separation between the owner's finances and the firm finances, and take on some accounting responsibilities.

The program involving an initial formal training period of 7 sessions (21 hours in total) started in mid-February 2019 and finished in April 2019. We use the training period of this programme to administer the intervention and treat half of the entrepreneur with the scientific approach. The training exposed all participants to basic concepts, framework and tools in strategy. Specifically, the control group was exposed to basic concept of strategy (such as the Business Model Canvas or Balance Scorecards) and encouraged to make decisions based on testing and the collection of evidence. This is in line with the traditional approach to strategy formulation used by entrepreneurs, which tend to rely on trial-and-error techniques. The treatment group, instead, was also encouraged to apply the concepts with a scientific approach, elaborating a theory, formalizing that theory into hypotheses, testing them and assessing the test results systematically.

The training sessions were designed to be highly engaging and experiential – involving hands-on activities and feedback from the instructors. To achieve this goal, we assigned entrepreneurs in the treatment and control groups to smaller subgroups that were randomly matched with six experienced instructors, recruited and trained for this study. An important feature of the experimental design is that each instructor taught groups of entrepreneurs in the treatment and control groups, allowing to account for instructor-related differences in our regressions through fixed effects. All instructors received the training material from the research team and were carefully trained through multiple 'train-the-trainer' sessions, so that they would deliver the content of the program in line with our research design. We took several measures to ensure the internal validity of our results. We addressed contamination by teaching treated and control groups on different days of the week (Wednesday and Thursday) or different time slots of the same day (Saturday morning and Saturday afternoon), preventing them from meeting and discussing key elements of the treatment. We also kept communications about the program separate and discrete for the two groups.

We required all applicants to compile an extensive survey and to participate in a 30-minute call with a member of the data collection team which aimed at collecting baseline information on their business and their approach to decision making prior to the intervention. We used this information to randomize firms into one of the two arms of the experiment (treatment and control groups) using a statistical software (STATA). We also stratified the randomization process to ensure that registered and unregistered firms were balanced between treatment and control group. Following this process, 139 firms were assigned to the treatment group and 135 firms were assigned to the control group.

Data collection process

The intervention ran between February and April 2019, but we monitored firms' performance and decision making until the end of 2019. Despite this timeline is relatively short to observe an impact on firm performance, we were constrained to it due to funding availability. To keep participants engaged with our initiative after the end of the training, all entrepreneurs were invited to participate to exclusive monthly events covering topics of general interest, such as leadership and communication. The events served the purpose of keeping participants engaged but were delivered in the exact same manner to the treatment and control groups, which were kept separate to prevent contamination.

In addition to the pre-intervention survey and interview, we collected 8 data points through telephone interviews that focused on firm's decision making, and on key changes in the firm in terms of value proposition and performance. The first telephone interview post-intervention took place about eight weeks after the training program had begun. We then collected data once a month until November 2019. However, for firms that abandoned the program before the end, we only have data up to the period before they abandon. In conducting these calls, we followed an approach in line with Bloom and Van Reenen's (2010) and Camuffo et al.'s (2020b). The pre-defined protocol provided to the members of the data collection team included a mix of open-ended and closed-ended questions to guide the interview with entrepreneurs. In the case of the open-ended questions, we used an approach in line with qualitative interviews, by letting key themes about decision-making emerge from entrepreneurial narratives. We used closed-ended questions to ask entrepreneurs to self-report their performance.

During the post intervention data processing, it became evident that four participants provided implausible or incorrect data in their baseline survey responses. These observations were therefore dropped from the analyses. Also, nine participants refused to provide performance measures. In short, participants that provided data that turned out to be unreliable, or participants who were not willing to share data about their businesses, were excluded from the analysis. The final sample includes 261 firms. Table 1 compares the baseline characteristics of the treated and control groups for the final sample of 261 firms and show that the two groups remain balanced. It shows that treatment and control groups are not different in statistically meaningful ways when we remove these firms from the sample.

Add Table 1 about here

To check that the treatment produced the intended result, we measured the level of adoption of the scientific approach based on the content 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. In Table 2, we compare the level of scientific intensity of the treatment and control groups at the time of each interview. Results show that, while the difference between the two groups was not statistically significant at the baseline, the level of scientific intensity was significantly higher for treated firms in subsequent interviews, although it diminishes in size and significance over time.

Add Table 2 about here

Operationalization

Independent variables

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

Registration – This is a dummy variable taking a value of 1 for firms that are registered and 0 for those that are not registered.

Dependent variables

Revenue. During each telephone interview, the research assistants asked respondents the amount of revenue generated by each firm in the previous month in £. We create a cumulative measure by adding all the amounts of revenue generated up to each period.

Innovation Revenue. During each telephone interview, the research assistants asked respondents the percentage of revenue generated from the sales of products or services that were new to the firm in the previous month. We then converted this percentage to the amount of revenue generated from innovation (based on the amount reported as revenue). One important aspect to consider when looking at this measure is that a product or service that can be called "new" in a period will be considered a "regular" product in one of the subsequent periods. For firms that generate higher revenue from innovation, *Innovation Revenue* will naturally decrease as soon as the new product or service is recognized as a regular product, which typically happens after two or three periods. We take the revenue from new products and services obtained by the entrepreneur in each period after the baseline. Our measure Innovation Revenue corresponds to the maximum value among them. This corresponds to the maximum amount of revenue from innovation obtained within our entire observation period after the baseline.

Costs. During each telephone interview, the research assistants asked respondents about the amount of total costs (including raw materials, cost of energy, services for business use, but excluding salaries for employees) incurred in the previous month in £. We create a cumulative measure by adding all the amount of costs incurred in up to each period.

Employees. During each telephone interview, the research assistants asked respondents the number of employees working at the firm, which allows us to measure if employees join or leave the firm. We measure this variable as the log of 1 plus the number of employees.

Value Added. We measure productivity as the difference between cumulative revenue and costs. This is a standard measure used to quantify the extent to which the company is adding value through the sales of products/services.

Revenue per Employee. This variable measures the productivity of a firm based on the amount of revenue produced per employee.

Table 3 provides descriptive statistics and pairwise correlation between variables.

Add Table 3 about here

RESULTS

Firm performance

We start by examining the impact of our intervention on firm performance, measured as revenue. Figure 1 (a, b, and c) provide a visual representation of our results. These figures show that treated firms tend to have higher revenues than control firms, an effect that becomes more relevant overtime. Figure 1b and Figure 1c represent the same relationship for registered firms and for unregistered firms, respectively. These sets of figures emphasize that the effect is present for registered firms, whereas there is virtually no difference in the average revenue of treated versus non treated unregistered firms.

To measure the size of this effect more accurately we perform a set of regression analyses. Table 4 reports the result of a regression analysis where we estimate the cumulative revenue of the firm as a function of the intervention and its interaction with the registration dummy. To control for unobserved heterogeneity, we include in the analysis firm fixed effects and time fixed effects. We cluster errors at the firm level. Model 1 reports the results when only the main effect of the intervention is included. While this effect is positive, it is not statistically significant at the conventional levels. Model 2 reports the results of the specification in which both the main effect of the intervention as well as its interaction with the registration dummy are included. The effect of the intervention is negative (B=-26,471.783, p=0.000), whereas the interaction is positive (B=50,575.465, p=0.003). In terms of economic significance, the results suggest that the revenue of treated firms that are registered tend to be about 24,000£ higher than other firms. This is a sizable result as it corresponds to about 39% of the average annual revenue for the firms in our sample at the baseline (£61,213.93). As a robustness check we also run a random-effect analysis, which reports results that are similar in terms of size and significance to those reported in Models 1 and 2.

Some of the firms participating to the program decided not to complete all interviews after the training was over. In the previous models, we assumed that the revenue of firms that left the program remained as when they left the program. We test the robustness of our results against this assumption by replicating the analysis and, for firms that left the program, including only the observations until they remained in the program. Results are reported in Models 3 and 4. We next checked the extent to which these results might have been driven by the presence of outliers in our sample, by replicating the analysis after winsorizing the dependent variable. Results are reported respectively in Models 5 and 6. Overall, these results support the intuition that the use of a scientific approach to managerial decision-making benefits more established firms.

Add Table 4 and Figure 1 about here

Innovation revenue

We then focus on the impact of the intervention on the revenue originated from innovative products or services. We suggested that a scientific approach to entrepreneurial decision making helps firms manage decisions under conditions of uncertainty that characterize the entrepreneurial setting. If so, the intervention should help firms not only improve their current value proposition, but it should also help them as they renew their value proposition. Results of this set of analyses are reported in Table 5. Results in Model 2 show that the effect of the intervention is not significant (B=-937.100, p=0.593), whereas the interaction is positive and statistically significant (B=3,747.947, p= 0.027). In terms of economic significance, the results indicate that the revenue of treated firms that are registered tend to be about £2,800 higher than other firms. In Models 3-6 we replicate the analysis by implementing the robustness checks described in the previous section. Results are robust to these checks and are visually represented in Figure 2.

Add Table 5 and Figure 2about here

Cost

Next, we investigate whether the effect that we observe is driven by treated registered firms investing more resources in the value proposition, and so, incurring higher costs. If this was the case, the firms would not be creating value, but merely transferring value to customers. Table 6 reports the results of the regression where the dependent variable is the cumulative cost and the independent variables are the intervention and the interaction between the intervention and the registration dummy. We include time and firm fixed effects and cluster the standard errors at the firm level. Results in Model 2 show that the effect of the intervention is negative and statistically significant (B=-13,356.017, p=0.049), whereas the interaction is positive and statistically significant (B=32,802.101, p= 0.017). Interestingly, this result indicates that registered firms that are treated tend to spend about £ 19,500 more than other firms. This result is further supported by the robustness checks presented in Models 3-6. The results are represented in Figure 3.

Add Table 6 and Figure 3 about here

Number of Employees

Following the same logic, we are interested in understanding whether the effect that we observe is driven by treated registered firms hiring a higher number of employees. We therefore investigate whether our intervention and its interaction with the dummy registration have an impact on the number of employees in a set of regression analyses that we report in Table 7. Results in Model 1 show that the intervention has a positive effect on firm size as measured by the logarithm of 1 plus the number of employees (B=0.092, p=0.073). To the extent that the size of the firm can be interpreted as an early measure of firm performance, this result might suggest that all firms benefit from the treatment. Results in Model 2 show that the interaction between the intervention and the dummy for registration is not statistically significant at the conventional levels suggesting that registered treated firms do not hire more employees than other firms. Results from the robustness checks presented are in line with this finding. We also graphically represent the results in Figure 4.

Add Table 7 and Figure 4 about here

Productivity – Value Added

Previous results suggest that the performance of treated and registered firms increases more than the extent to which cost increases, indicating that these firms create value. We test this intuition directly with a regression in which we estimate the value added (calculated as revenue minus cost) as a function of the intervention and the interaction between intervention and registration dummy, including firm and time fixed effects and clustering the standard errors at the firm level. Results, reported in Table 8, support our prediction and show that the intervention has a negative effect on the dependent variable (B=-13,115.766, p=0.016), whereas the interaction term has a positive effect on the dependent variable (B=17,773.363, p=0.018). Overall, treated and registered firms generate about £4700 more than other firms. Results are represented graphically in Figure 5.

Add Table 8 and Figure 5 about here

Productivity – Revenue over Employees

For firms that already had employees when they started the program, we replicate the analyses presented above on a different measure of productivity, revenue over employees. Results, reported in Table 9, are consistent with those presented in the previous tables. Specifically, looking at Model 2, the main effect of the intervention is negative (B=-11,082.997, p=0.008) whereas the interaction term is positive (B=16,241.638, p=0.005). This implies that, on average, treated and registered firms tend to have a labor productivity that is about £5200 higher than other firms. These results are represented graphically in Figure 6.

Add Table 9 and Figure 6 about here

Our results have shown that treated registered firms generate higher revenue and higher revenue from innovation. These firms also incur higher costs. However, we also find that the productivity of these firms is higher. These patterns suggest that registered firms benefit from the use of a scientific decision-making approach.

DISCUSSION AND CONCLUSIONS

This study reports the results of a field experiment with 261 entrepreneurial firms in the UK taking part to a training program. We use the program to teach a scientific approach to decision-making to half of the participants, while keeping the other half in a control condition. Our sample includes entrepreneurial firms, some of which are registered and some of which are not registered. We find that entrepreneurs from registered firms trained to use a scientific approach generate higher revenue and higher innovation revenue. While these firms incur in higher costs, they are more productive both in terms of value added as well as in terms of revenue per employee.

To further investigate the mechanisms underlining these results, we analyzed if treated firms that are registered exert more effort and if this is why they achieve better results. To do so, we examined whether treated registered firms work longer hours. Results in Table 10 show that being registered and treated does not have an impact on the number of hours worked or the number of hours devoted to innovation.

Add Table 10 about here

Taken together, these results contribute to strategy research on the use of more systematic and deliberate approaches to managerial decision making. They show that the use of a more scientific approach to decision making does not benefit firms equally. Registered firms make the most out of these approaches, whereas unregistered firms do not seem to benefit from it within the time window of our study. This is a relevant result if we consider that prior research focusing on the benefit of systematic approaches to managerial decision making on firm performance has mostly focused on established firms (Bloom and van Reenen, 2007, Yang et al, 2020; Zollo and Winter, 2004). Most importantly, these results emphasize the existence of a possible bias in previous studies focusing on larger firms. We suggest that those results should be interpreted with caution in the light of these findings.

This paper also contributes to research on strategic entrepreneurship that advocates for the importance of testing and purposeful experimentation for firm performance (Thomke, 2003; Murray & Tripsas, 2004; Bingham & Eisenhardt, 2011; Gruber & Tal, 2013; Shepherd & Gruber, 2020). In line with these studies, our results support the view that evidence-based approaches are useful and lead to superior performance. However, the key finding is that the more established firms are the ones that really benefit from the use of systematic approaches to decision making. This stands in stark contrast with a literature primarily oriented to practitioners that emphasized, instead, the relevance of the feedback and evidence that very early-stage entrepreneurs can successfully gather. The Lean Start-up movement, for instance, advances the idea that experimentation, customer feedback and iterative design are superior choices compared to planning, top-down innovation and upfront design investments (Blank, 2013; Ries, 2011). The underlying assumption of these studies is that being as nimble and as flexible as possible will help entrepreneurs adjust more easily in a context characterized by high uncertainty, delaying important choices and substantial investments until they reach a stage where they have enough evidence to commit to a course of action. As a result, a key tenet of this philosophy has been ‘build fast and fail fast’, using minimum viable products to obtain feedback on early-stage ideas. This study’s results warn about the fact that the benefits that these entrepreneurs can obtain from the use of evidence-based approaches to decision-making might be limited. Our results highlight instead that it is rather firms with a more established value proposition that can benefit more from evidence-based approaches.

Recent research in strategy and entrepreneurship on the role of commitment in decision making provides a possible explanation for these results (Gans et al., 2019; Gans et al., 2020; Pillai et al., 2019). This work builds on the idea that commitment to some initial choices plays a central role in determining the quality of the subsequent decision-making process (Ghemawat and Levinthal, 2008). Commitment refers to the extent to which the decision maker makes some early decisions that “*constrain subsequent behaviour*” (Ghemawat, 1991, p.10). In stark contrast with the precepts of the Lean Start-up movement, these studies advance the idea that feedback obtained on “*early strategies*” (Gans et al., 2019, p.744) obtained by entrepreneurs without any commitment may have an inducement effect, leading to broadening the search rather than to focusing and exploiting one trajectory. As Gans et al. (2019) put it: “*When an entrepreneur begins the initial exploration of a strategic alternative and receives a positive signal, that indicates not only the potential of that alternative, but also the favorability of the distribution over which search is being undertaken*” (p.744). These studies suggest that feedback made without or prior to committing to one particular strategic alternative is inherently “noisy” because it relies on assumptions that may not be realized in practice (McGrath & MacMillan, 1995; Bhide, 2000; Gruber, 2007; Gans et al. 2019). Instead, experimentation performed within the context of higher commitment leads obtain "rich" information (Rosenberg, 1982; Rosenberg, 1994; Stern, 2005; Greenstein, 2012; Pillai et al. 2019), which is particularly relevant in entrepreneurial settings where uncertainty resolution depends on actions taken by the entrepreneur. Our results show that registered firms – most likely characterized by a higher level of commitment – make the most out of a systematic approach to managerial decision making. This provides a possible preliminary test of the ideas around the role of commitment, suggesting that the investigation of the role of this aspect in entrepreneurial decision making might be a fruitful path forward.

In making these considerations, we acknowledge some limitations of this study, which also point to opportunities for future research. Firstly, due to funding constraints, we are only able to observe firms for a relatively short period. This implies that, while we observe that registered firms benefit significantly more from the use of a scientific approach to decision making, we cannot exclude that less established firms might also benefit from it in the long run. It would be very useful for future research to replicate this study over a longer time span to examine whether the difference between registered and unregistered firms disappears over time and if both group of firms benefit from the use of the approach. Secondly, we focus on firms with less than 10 employees. This is an advantage of the design of the study in that it allowed us to ensure that the treatment was administered to the individuals directly involved in the firm's decision making. However, a drawback of this choice is that it does not allow us to understand whether the treatment would produce the same effect with larger firms. We see this as an opportunity for future research.

Finally, these results provide important policy insights. Encouraging entrepreneurship has been one of the major goals of policy makers as a way to spur economic growth (Bennett and Chatterji, 2019; Decker et al., 2014; Lerner, 2009). Bennett and Chatterji (2019) conduct a national representative survey on the pre-entry activities conducted by potential entrepreneurs in the US. They find that fewer than half of those who considered starting a business take the lowest cost steps, such as searching the Internet for potential competitors or speaking with a friend. They speculate that this might be due to the psychological costs associated with learning the true promise of an idea and conclude that a way to increase the quality and quantity of entrepreneurial ventures would be to lower the cost of experimentation at the very beginning of the entrepreneurial process. Our results show that an intervention intended to encourage systematic experimentation to support decision-making was helpful but for more established rather than for less established firms, at least within the observed time window. These results therefore stress that more work should be devoted to identifying the ideal time window for programs targeted to these types of firms or, more in general, their most effective design choices. Given the importance of this topic for the economy, we consider this a very promising path for future research.

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TABLES

Table 1. Balance checks

	Treatment		Control		Difference	
	mean	sd	mean	sd	b	p
Business age (years)	2.48	3.22	3.28	5.17	0.8	(0.14)
Number of employees	2.14	1.95	2.31	2.14	0.18	(0.49)
Percentage of female	0.42	0.42	0.5	0.44	0.08	(0.15)
Average age	35.77	8.56	36.37	9.2	0.6	(0.59)
Average working hours	31.55	18.57	29.61	17.18	-1.94	(0.39)
Percentage economics	0.15	0.29	0.15	0.29	0	(0.94)
Percentage STEM	0.3	0.39	0.36	0.43	0.06	(0.26)
Average education level	2.67	0.81	2.58	0.79	-0.1	(0.34)
Confidence	3.41	0.7	3.34	0.76	-0.07	(0.44)
Probability to change	45.85	28.18	42.12	26.99	-3.72	(0.28)
Probability to change customers	38.18	26.16	40.55	26.26	2.38	(0.47)
Probability to expand	68.25	27.4	66.59	28.12	-1.67	(0.63)
Annual turnover (£)	50616.11	145448.79	71977.35	195899.81	21361.24	(0.32)
Monthly turnover (£)	5113.83	17734.76	6099.5	24490.47	985.67	(0.71)
Hours devoted to innovation	46.05	33.35	40.02	32.68	-6.04	(0.14)
Hours devoted to innovation (monthly)	39.46	34.16	36.84	34.59	-2.62	(0.54)
Average value of idea	66.73	17.05	66.62	20.22	-0.11	(0.96)
Range of value of idea	39.26	22.03	38	21.94	-1.26	(0.65)
Average industry experience (years)	6.75	6.47	7.7	7.56	0.95	(0.28)
Average work experience (years)	13.02	7.98	13.53	8.59	0.51	(0.62)
Average entrepreneurial experience (years)	3.85	3.49	4.64	5.95	0.79	(0.20)
Average managerial experience (years)	5.96	5.29	6.22	6.16	0.26	(0.73)
Observations	133		128		261	

Table 2. Scientific intensity

	Treatment		Control		Difference	
Scientific intensity	Mean	SD	Mean	SD	b	p
Interview 0	2.56	1.23	2.35	1.29	-0.2	(0.20)
Interview 1	2.93	1.07	2.69	1.18	-0.25*	(0.08)
Interview 2	2.98	1.01	2.73	1.04	-0.25*	(0.05)
Interview 3	3.01	0.98	2.76	1.01	-0.24**	(0.05)
Interview 4	2.95	0.93	2.73	1.02	-0.22*	(0.06)
Interview 5	2.94	0.95	2.75	1.02	-0.19	(0.12)
Interview 6	2.95	0.93	2.76	0.99	-0.19	(0.12)
Interview 7	2.97	0.94	2.78	0.99	-0.18	(0.13)
Interview 8	2.97	0.95	2.83	0.99	-0.14	(0.24)
Scientific intensity	133		128			261

Table 3 Descriptive statistics and pairwise correlations

		Obs	Mean	SD	Min	Max	1	2	3	4	5	6	7	8
1	Intervention	522	0.2547893	0.4361607	0	1	1							
2	Registration	522	0.7547893	0.4306247	0	1	-0.0244	1						
3	Revenue	522	22895.08	94031.59	0	1465192	0.1376	0.1202	1					
4	Innovation Revenue	522	2494.565	14493.46	0	200000	0.0749	0.0938	0.6354	1				
5	Cost	522	16150.32	66436.72	0	1092902	0.1653	0.0966	0.9308	0.5866	1			
6	Number of Employees	522	1.911877	2.350296	0	15	0.0482	0.2005	0.2842	0.1777	0.2608	1		
7	Value Added	522	6744.759	40324.13	-161040	390900	0.0486	0.1212	0.7983	0.5151	0.523	0.233	1	
8	Labour Productivity	332	9890.06	28694.41	0	366298	0.2019	0.1125	0.8498	0.536	0.7907	0.0308	0.6809	1

Table 4. Revenue

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Intervention	10,794.349	-26,471.783***	9,305.151	-29,772.419***	-1,657.040	-26,181.119***
	(0.451)	(0.000)	(0.525)	(0.000)	(0.845)	(0.000)
Intervention x Registered		50,575.465***		51,983.170***		33,282.679***
		(0.003)		(0.002)		(0.000)
Constant	5,553.100	5,553.100	5,553.100	5,553.100	5,553.100***	5,553.100***
	(0.126)	(0.123)	(0.122)	(0.119)	(0.009)	(0.009)
Observations	522	522	522	522	522	522
R-squared	0.083	0.100	0.113	0.131	0.145	0.165
Number of id	261	261	261	261	261	261
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered Errors	Firm	Firm	Firm	Firm	Firm	Firm

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

Table 5. Innovation Revenue

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Intervention	3,698.746*	937.100	3,902.520	928.348	1,957.450	-0.400
	(0.086)	(0.593)	(0.108)	(0.692)	(0.160)	(1.000)
Intervention x Registered		3,747.947**		3,956.410**		2,657.082**
		(0.027)		(0.042)		(0.044)
Constant	2,101.452***	2,101.452***	2,101.452***	2,101.452***	1,543.616***	1,543.616***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	522	522	522	522	522	522
R-squared	0.016	0.020	0.082	0.087	0.018	0.024
Number of id	261	261	261	261	261	261
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered Errors	Firm	Firm	Firm	Firm	Firm	Firm

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

Table 6. Cost

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Intervention	10,813.952	-13,356.017**	9,265.986	-16,656.798**	3,341.670	-11,280.915*
	(0.321)	(0.049)	(0.408)	(0.022)	(0.565)	(0.064)
Intervention x Registered		32,802.101**		34,483.937**		19,844.938***
		(0.017)		(0.010)		(0.004)
Constant	2,084.272	2,084.272	2,084.272	2,084.272	2,084.272	2,084.272
	(0.449)	(0.447)	(0.445)	(0.441)	(0.152)	(0.149)
Observations	522	522	522	522	522	522
R-squared	0.095	0.107	0.126	0.139	0.186	0.201
Number of id	261	261	261	261	261	261
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered Errors	Firm	Firm	Firm	Firm	Firm	Firm

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

Table 7. Employees

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Intervention	0.092*	0.175*	0.087*	0.170*	0.089*	0.175*
	(0.073)	(0.054)	(0.087)	(0.055)	(0.077)	(0.054)
Intervention x Registered		-0.113		-0.111		-0.116
		(0.232)		(0.224)		(0.212)
Constant	0.807***	0.807***	0.807***	0.807***	0.807***	0.807***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	522	522	522	522	522	522
R-squared	0.016	0.023	0.063	0.070	0.016	0.024
Number of id	261	261	261	261	261	261
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered Errors	Firm	Firm	Firm	Firm	Firm	Firm

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

Table 8. Value Added

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Intervention	-19.603	-13,115.766**	39.166	-13,115.621**	-4,149.385	-13,115.766**
	(0.997)	(0.016)	(0.994)	(0.022)	(0.300)	(0.016)
Intervention x Registered		17,773.363**		17,499.233**		12,168.659**
		(0.018)		(0.019)		(0.035)
Constant	3,468.828**	3,468.828***	3,468.828**	3,468.828***	3,190.793***	3,190.793***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.002)	(0.001)
Observations	522	522	522	522	522	522
R-squared	0.022	0.039	0.037	0.053	0.023	0.037
Number of id	261	261	261	261	261	261
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered Errors	Firm	Firm	Firm	Firm	Firm	Firm

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

Table 9. Revenue per employees

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Intervention	2,519.375	-11,082.997***	699.595	-11,798.571**	320.680	-9,618.680***
	(0.658)	(0.008)	(0.901)	(0.015)	(0.928)	(0.005)
Intervention x Registered		16,241.638***		14,690.579**		11,867.892***
		(0.005)		(0.011)		(0.001)
Constant	2,354.234*	2,436.923*	2,354.567*	2,416.208*	2,385.403***	2,445.824***
	(0.085)	(0.068)	(0.071)	(0.060)	(0.004)	(0.003)
Observations	329	329	329	329	329	329
R-squared	0.164	0.177	0.249	0.259	0.266	0.282
Number of id	178	178	178	178	178	178
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered Errors	Firm	Firm	Firm	Firm	Firm	Firm

Robust pval in parentheses *** p<0.01, ** p<0.05, * p<0.1. The dependent variable could be calculated only on firms with at least one employee therefore the number of observations is lower than in the other tables.

Table 10. Number of hours worked

	(1)	(2)	(3)	(4)
	Number of Hours Worked	Number of Hours Worked	Number of Hours Worked for Innovation	Number of Hours Worked for Innovation
VARIABLES	(Log 1+)	(Log 1+)	(Log 1+)	(Log 1+)
Intervention	-0.152	-0.543**	-0.453	-1.136
	-0.258	-0.036	-0.344	-0.146
Intervention x Registered		0.531**		0.926
		-0.041		-0.259
Constant	3.247***	3.248***	5.387***	5.389***
	0	0	0	0
Observations	512	512	512	512
R-squared	0.048	0.071	0.057	0.062
Number of firms	260	260	260	260
Time FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Clustered Errors	Firm	Firm	Firm	Firm

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

FIGURES

Figure 1. Revenue

a. All firms	b. Registered	c. Unregistered

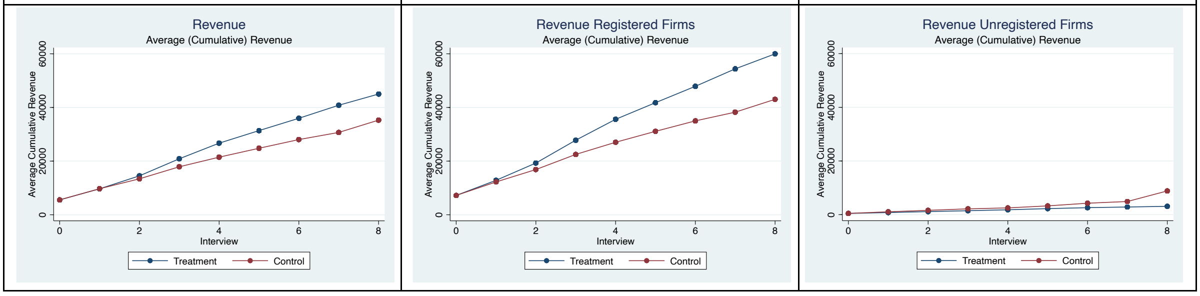


Figure 2. Innovation Revenue

a. All firms	b. Registered	c. Unregistered

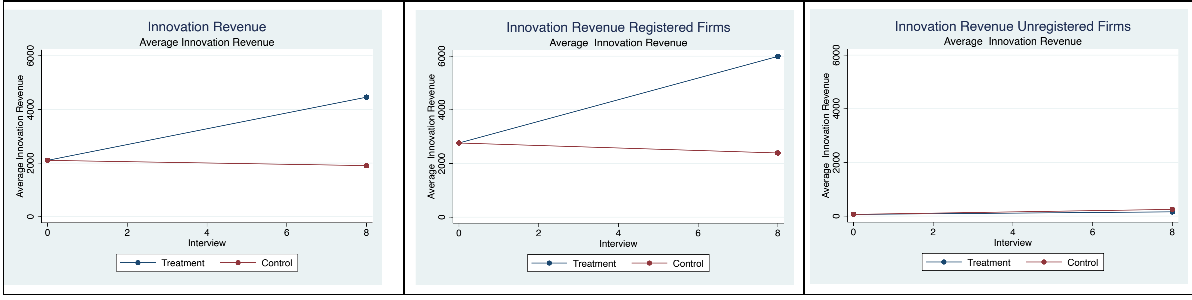


Figure 3. Cost

a. All firms	b. Registered	c. Unregistered

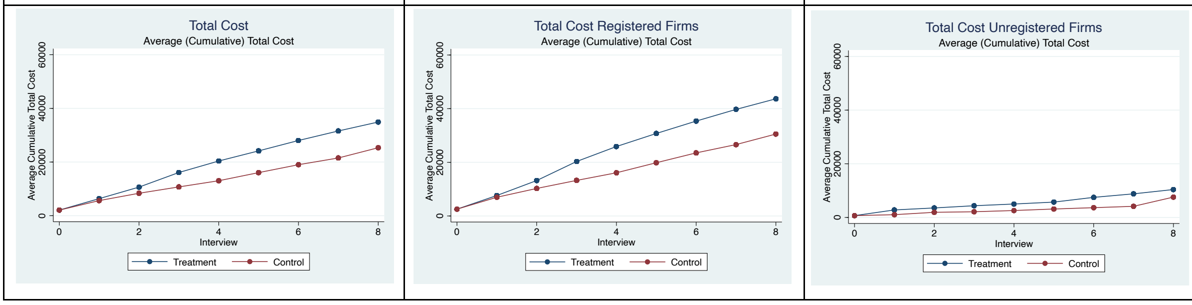


Figure 4. Employees

a. All firms	b. Registered	c. Unregistered

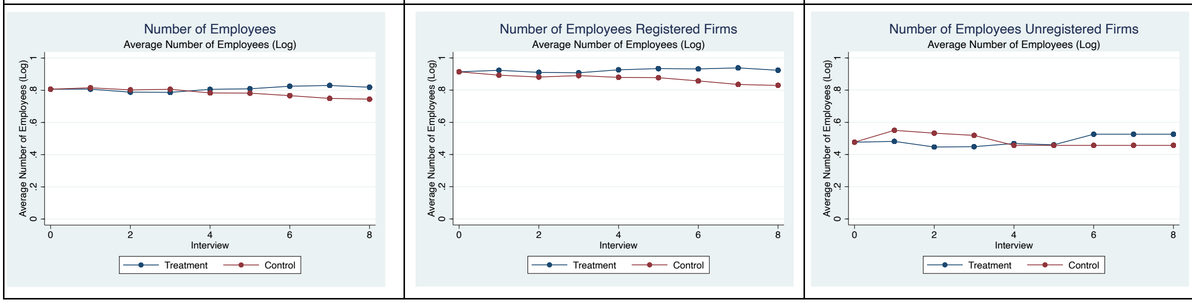


Figure 5. Value added

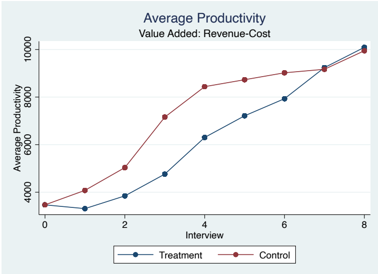
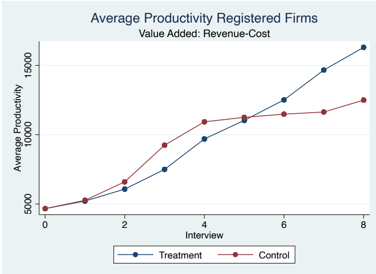
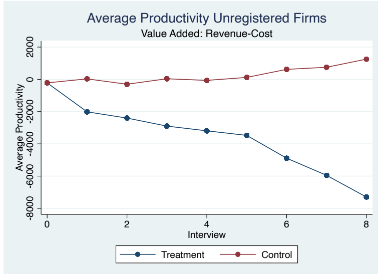
a. All firms	b. Registered	c. Unregistered
		

Figure 6. Revenue per employee

a. All firms	b. Registered	c. Unregistered