INSEAD The Business School for the World®

Working Paper

2021/40/EFE

When do Entrepreneurs Benefit from Acting Like Scientists? A Field Experiment in the UK

Elena Novelli
The Business School (formerly Cass), elena.novelli.1@city.ac.uk

Chiara Spina
INSEAD, chiara.spina@insead.edu

This version: July 27th 2021

Prior research suggests that firms in entrepreneurial settings benefit from a scientific approach to decision making that combines cognitive and evidence-based components. But to what extent and under what conditions is the scientific approach to decision-making associated with superior performance? To address this question, we conducted a field experiment with 261 UK entrepreneurs at different stages of business development, training half of them on a scientific approach to decision making. Our results show that firms make the most of scientific decision-making when they are at a more advanced stage of development, as they generate higher revenues and productivity. We elaborate on the mechanisms behind this result and the implications for future research.

Keywords: Entrepreneurial Strategy; Experimentation; Field Experiment; Innovation; Value Creation.

Electronic copy available at: http://ssrn.com/abstract=3894831

Author names are in alphabetical order.
We gratefully acknowledge financial support from the Department for Business, Energy & Industrial Strategy (BEIS) of the UK Government through the BEIS Business Basics Grant, and support from the Innovation Growth Lab. This project was also made possible by support from The Business School (Formerly Cass), Bocconi University, and Oxford University. We thank scholars who provided comments on previous versions of this manuscript, particularly Alfonso Gambardella, Myriam Mariani, Teppo Felin, Arnaldo Camuffo, Ethan Mollick, and attendees from presentations at Warwick, ESADE, University of Bologna, EPFL, the Wharton Technology Conference, the Strategic Management Society Entrepreneurship and Strategy Seminar Series.

1. INTRODUCTION

A fundamental question for research in strategy concerns the extent to which managerial approaches impact firm performance. This question is particularly relevant in entrepreneurial settings, where strategy makers face uncertainty in multiple domains, from technology (Folta, 1998; Gans and Stern, 2003; McGrath, 1997) to market preferences (Foss and Klein, 2012; Kirtley and O'Mahony, 2020; Sarasvathy, 2009) – and the resolution of uncertainty is often endogenous to action (Agarwal et al., 2007; Moeen et al., 2020; Ott and Eisenhardt, 2020). Recent research suggests two approaches can support decision making in these contexts: *cognitive*-based approaches, and *evidence*-based approaches. The former involve formulating a theory about the problem faced (Camuffo et al., 2020a; Csaszar and Laureiro-Martinez, 2018; Eisenhardt and Bingham, 2011; Felin et al., 2020a and b), the latter emphasize the systematic collection of evidence (Bloom et al., 2012; Ghosh et al., 2020; Ries, 2011) and its disciplined assessment (Kohavi and Thomke, 2017; Murray and Tripsas, 2004) to learn from the environment. Combining these insights, some scholars have identified synergies between these two approaches. For instance, Eisenhardt and Bingham (2017) provide qualitative evidence of the importance of combining "thinking *and* doing" to devise superior strategies. McDonald ad Eisenhardt (2020) show that entrepreneurs who combine cognition with evidence - such as using experimentation to test the key assumptions underlying a business model- accelerate their learning. Camuffo et al. (2020a) also outline the benefits of combining cognitive components (theory and hypothesis development) and experimental components (testing and evaluation) in decision-making. They refer to this approach as to "a scientific approach to decision-making", given its resemblance to the exploratory process followed by scientists.

Building on these premises, our study investigates *whether and to what extent a scientific approach to decision-making* – combining cognition and evidence – *is associated with superior performance.* Despite insights from prior work, little is known about the boundary conditions of this type of approach – or more generally, systematic approaches to decision making –, and the conditions that determine their effectiveness, as conceptual work in this area is still in its infancy. Second, despite interest among scholars and practitioners, empirical evidence on the use of systematic approaches to decision making is inherently challenging to collect as it requires monitoring the use of these approaches and performance within firms. The limited available evidence is based mostly on studies with firms at a relatively advanced stage of development (Bloom and VanReenen, 2010; Pillai et al., 2020; Yang et al, 2020). Far fewer studies have examined less established firms, as Kirtley and O'Mahony (2020) note, and it is difficult to generalize results from established firms to less developed businesses. The performance implications of systematic decision-making approaches for the latter tend to be ambiguous (Bruhn et al., 2018; Camuffo et al. 2020a and 2020b; Karlan et al., 2015), with few notable exceptions studying a focused set of practices and performance metrics (Koning et al., 2019). Hence, we lack a more general understanding of when systematic approaches result in superior performance.

In this paper we address this issue via a 9-month randomized control trial (RCT) with 261 UK entrepreneurial firms attending a strategy training program. Both treated and control firms underwent a training course and were exposed to elements of cognitive-based decision making (reasoning through strategy frameworks and tools) and evidence-based decision making (using data gathering and testing techniques) – for a total of 21 hours of training spread across 7 sessions. Entrepreneurs in the control group were free to use these tools and techniques intuitively, as typically happens in any business training course. Those in the treatment group, instead, were taught to apply these concepts and tools using a scientific approach that combined the cognitive and evidence-based components of decision making: they learned how to use strategy frameworks to formally develop a theory of the problems faced and predictions consistent with that theory, test those predictions and systematically evaluate the results.

Our sample addresses some of the empirical shortcomings of prior research in that it includes a heterogeneous set of firms at different levels of development, and it does so in an RCT context, thus offering the opportunity to test how different firms respond to our treatment. We found that firms in the treatment group at a more advanced stage of development outperformed the others. Even though they incurred higher costs, they achieved higher productivity – an effect that was not driven by greater experience, better ideas or more confidence. These results suggest that more established firms derive more benefit from a scientific approach to decision-making than less established ones. All treated firms, however, grew more than the control group in terms of employee number.

Our study makes three main contributions. First, it contributes to strategy research on managerial decision-making in showing that firms do not benefit equally from the use of a scientific approach, and that this is contingent on their stage of development. This result may also help understand the earlier mixed findings on the relationship between systematic decision-making and firm performance (Bloom and Van Reenen, 2010; Bruhn et al., 2018; Camuffo et al. 2020a; Karlan et al., 2015; Yang et al., 2020). Second, it contributes to research on entrepreneurial strategy. Scholarly – as well as practitioner-oriented work – advocates that experimentation is a valuable approach for early-stage entrepreneurial decision making (Kerr et al. 2014; Ries, 2011) – yet we find that less-established businesses do not benefit from these approaches as much as established firms. This is in line with the view that experimentation may be more fruitful for firms that have already made key choices (Agrawal et al., 2021; Gans et al., 2019; McDonald ad Eisenhardt, 2020) and consistent with preliminary empirical evidence from Pillai et al. (2020) focused exclusively on established firms. Our findings offer further evidence in this direction. Third, we advance the stream of research in strategy and economics that has shown that, under certain conditions, established businesses enjoy an advantage, particularly in entrepreneurial regimes (Agarwal and Audretsch, 2001; Geroski, 1995). Our paper contributes to this research by identifying a specific mechanism through which the level of business development supports firms in this context, i.e., by improving their ability to exploit specific approaches to decision making – in this case, one combining cognition and evidence – to support their learning (Agarwal and Gort, 2002, Gort and Klepper, 1982).

Beyond its academic contribution, our study offers insight to governments and institutions looking to foster economic growth through programs that support innovation. Initiatives that offer training with a view to stimulate growth and productivity often yield limited results (Lerner, 2009). This study suggests a possible explanation: only some firms benefit from training programs, at least within a limited time window. Awareness of which firms benefit from training programmes could be a starting point for a more efficient selection/admission process, and the provision of alternative forms of support for firms that benefit less from training programs.

2. THEORY

2.1 The effect of scientific decision-making on firm performance

Recent studies in strategy and entrepreneurship that provide insight on systematic decision-making approaches to entrepreneurial activities take the view that firm performance improves when entrepreneurs deliberately follow a structured process. This process could involve framing the problem, gathering information, or soliciting relevant feedback that will foster learning and mitigate the biases and bounded rationality problems that typically affect decision-making (Camuffo et al., 2020b; Cohen et al., 2019; Yu, 2020). This is also seen as a way to discipline entrepreneurs (Bennett and Chatterji, 2019; Chen et al., 2020; Parker, 2006).

Prior literature has emphasized two different types of structured processes that firms can employ when making decisions. A first stream of research emphasizes the benefits of a *cognitive-based approach* to decision making. This type of approach is centered on how the development of a theory (Felin and Zenger, 2009; Felin and Zenger, 2017; Zenger, 2015), simple rules (Bingham and Eisenhardt, 2011) or mental representations (Csaszar and Laureiro-Martinez, 2018; Gary and Wood, 2011) of business problems can drive business innovation, performance heterogeneity and superior strategy. A second stream of research emphasizes, instead, the importance of an *evidence-based approach* to decision making, relying on the systematic collection of evidence to guide subsequent action (Bingham and Eisenhardt, 2011; Leatherbee and Katila, 2020; McGrath, 2001). This approach focuses on developing predictions regarding the business and testing them - for instance via experimentation- to generate relevant feedback (Gans et al., 2019; McGrath, 1999; Murray and Tripsas, 2004; Ott and Eisenhardt, 2017; Pillai et al., 2020; Shepherd and Gruber, 2020). It also involves the systematic evaluation of the evidence that entrepreneurs gather (Bennett and Chatterji, 2019; Camuffo et al., 2020a; Chatterji et al., 2019; Cohen et al., 2019)[2].

More recently, some authors have advanced that cognitive and evidence-based approaches can be complementary and mutually reinforcing. Eisenhardt and Bingham (2017, p. 247) underline the importance of combining "*thinking and doing*" and of a holistic approach to decision making that involves both a cognitive understanding of the "*playing field*" and action/learning via experimentation. McDonald and Eisenhardt (2020) emphasize the benefits of testing assumptions underlying cognitive templates used by firms, such as business models. They suggest that combining cognition with evidence reduces the uncertainty faced by entrepreneurs regarding the most appropriate model to use and helps them ground models in realistic and relevant information, leading to quicker and faster learning. In the same spirit, Camuffo et al (2020a) emphasize how scientists' rigor in the discovery process, which *simultaneously* involves a *cognitive* component (i.e., theory development and the formulation

[2] Several useful toolkits aimed at supporting practitioners in experimenting have emerged in this area. They focus on different aspects of the experimentation process such as how to identify new business ideas (Gruber and Tal, 2017), how to strategize after identifying the initial business idea (Osterwalder and Pigneur, 2010), and how to experiment while searching for the right product-market fit (Ries, 2011).

of hypotheses) and an *evidence-based* component (i.e., testing and evaluation of evidence), can be successfully applied to entrepreneurial decision making. They call this the "scientific approach to decision-making" and we will use the same terminology in this paper.

Despite the relevance of these contributions, the study of the performance implications of an approach combining cognition and evidence and of its boundary conditions is limited. More in general, we still don't know much about the role in influencing firm performance of systematic approaches to decision making, an exemplar of which is the scientific approach. Research on systematic decision making processes is focused on firms at a relatively *advanced stage of development*. For example, Bloom and Van Reenen (2007) find that better management practices were associated with higher productivity, profitability and other performance measures, based on a sample of medium-sized manufacturing firms over 50 years old with more than 2,000 employees. A more recent study by Yang et al. (2020) find an association between the use of highly formalized, rigorous, deliberate processes by large firms and growth in employment. Other notable studies show that approaches to learning that rely on structure and codification are associated with superior performance in the context of acquisition integration based on samples of large and experienced acquirers (Heimericks, et al., 2012; Zollo and Winter, 2004).

When it comes to the performance implications of systematic approaches for *less-established firms*, Karlan et al. (2015) conducted an RCT in urban Ghana in which tailoring microenterprises received (i) advice from an international consulting firm, (ii) cash, (iii) both, (iv) neither. While all treatments led to changes in business practices and higher investments, they did not lead to higher profits, on average. Bruhn et al. (2018) conducted an RCT among 432 small and medium enterprises in Mexico, of which 150 were randomly chosen to receive the treatment – access to consulting services. They found a limited positive effect on some measures of performance, but it was not robust to all econometric specifications and assumptions regarding outliers. In conducting an RCT with very early-stage start-ups, Camuffo et al. (2021) studied a scientific approach to decision-making and found that treated entrepreneurs were more likely to pivot to alternative ideas and terminate their projects early, but the effect on firm performance showed a high degree of variability. Koning and colleagues (2020) investigated the use of experimentation on the performance of high technology start-ups. They find that A/B testing increased performance on specific metrics such as page views and new product features, but overall younger start-ups performed worse when using A/B testing than firms with more experienced managers.

The above evidence is informative, but it does not provide a clear picture of the boundary conditions of systematic approaches to decision-making. In particular, it is not clear whether different types of firms benefit equally from these approaches. We turn to this issue by studying the scientific approach to decision making as a specific type of systematic approach to decision making and by investigating the extent to which combining cognition and evidence benefits firms at different levels of development.

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

To illustrate how a scientific approach works, consider the following example related to an innovative firm producing and selling vegetarian food, that we will call Palette. If Palette's founder, Felicia, was acting like a scientific entrepreneur, she would start with a cognitive approach to the problem, elaborating a theory of how her company could create value for customers. For instance, Felicia's theory might be that vegetarian food will be increasingly popular because it represents a healthier, more sustainable choice and does not harm animal welfare compared to meat products; but that, despite these advantages, vegetarian food might not be appealing because it is often not tasty. In line with this reasoning, Felicia would conclude that value can be generated by finding innovative ways of cooking vegetarian food to make it tastier. Her theory might also posit that younger consumers could be the ideal target as they care more about sustainability and a healthier lifestyle and are willing to pay a premium for tasty vegetarian food. As a scientific entrepreneur, Felicia would then combine the cognitive approach described so far with an evidence-based approach, collecting data to test the theory developed. To do so, she would first derive testable hypotheses from the broad theory - that (1) her vegetarian food is as tasty as the non-vegetarian equivalent, and that, (2) conditional on the first hypothesis being supported, it is more likely to be preferred by younger customers. To put these hypotheses to the test, she would conduct a blind test of the first hypothesis. She could then sell vegetarian food via a pop-up stall where customers can sample food before purchase and observe who is more likely to purchase food after tasting it (whether younger or older consumers). Based on the results obtained, she could then use the findings to evaluate what to do next, e.g., whether to change the way the food is prepared or how to advertise the product.

In contrast, if Felicia was to act like a non-scientific entrepreneur, she would sell a product without a clear idea of the features valued by customers. In the absence of a theory, her decisions would be based on "what seems to work". She might sell different types of vegetarian food without a clear theory for selling them, and that vary in characteristics (i.e., produced with organic ingredients, gluten-free, etc) as she does not intend to test specific hypotheses. If she was to sell more food produced with organic ingredients, she would not know if it was because of the taste, the type of ingredients or some other feature. Any evidence from sales data would be unlikely to help in understanding what to do because of the causal ambiguity given by the 'test' design. Overall, in the absence of a clear assessment of what customers value, new products or services would be introduced randomly rather than within a clear frame of reference. As this example clarifies, a non-scientific entrepreneur may serendipitously perform well, but the lack of clear theory, hypotheses, testing and learning how value is created for customers makes the venture less likely to succeed in the long run.

2.3 A Scientific Approach to Decision Making for Different Types of Firms

We propose that one important characteristic determining the extent to which different firms can benefit from the use of a scientific approach to decision making is their *stage of business development*, defined as the extent to which the business is already operating and established as opposed to being less developed. Holding other conditions constant, we posit that two key characteristics distinguish firms with more developed businesses from others. First, they apply a decision making approach in a more *focused* way since the value proposition tends to be more clearly defined. This makes the application of the scientific approach more effective and efficient, irrespective of the quality of the underlying idea, as it improves the elaboration of theory, hypothesis/test design and evaluation of results, and hence the decisions taken. The second characteristic is higher *contextualization*. More established firms do not frame problems purely in hypothetical terms, but from the perspective of a company that is up and running – they assess the problem "in action" in a specific context, and learn from the real-life feedback gained via the scientific approach.

Focus and contextualization help firms make the most of a scientific approach in that they lead to (i) a better application of both the cognitive and evidence-based components as well as to (ii) a superior exploitation of the complementarities between the cognitive and evidence-based components that characterize it. More specifically, entrepreneurs that employ a scientific approach start with the use a theory or cognitive template to identify the key dimensions of the problem faced (Camuffo et al., 2020b; Felin et al., 2020b; McDonald and Eisenhardt, 2020). The sharper focus and contextualization characteristics of more advanced businesses leads to theories that are more nuanced, more accurate, and therefore more useful to guide subsequent action. This is consistent with organizational research that suggests that structure facilitates entrepreneurial decision making by showing what to pay attention to and the most promising course of action (Davis et al, 2009).

Increased focus also allows theory to be modularized – creating smaller, decomposable and addressable blocks to develop individual predictions or hypotheses (Felin and Zenger, 2016) with a lower level of causal ambiguity (Felin et al., 2020a). In settings of high uncertainty, this yields greater clarity regarding subsequent action as well as testing strategy (McDonald and Eisenhardt, 2020). Gathering evidence through rigorous tests, which can help distinguishing between good and bad projects (Bingham and Eisenhardt, 2011; Gans et al., 2019; Gruber et al., 2013; Murray and Tripsas, 2004; Thomke, 2003) is indeed another key component of a scientific approach to decision making. The higher focus that characterizes firms with more advanced businesses helps them improving the quality and the interpretation of the evidence they collected.

When the value proposition is loosely defined and choices are still open, gathering feedback will result in a large number of test permutations and high testing costs, as each dimension of the business (e.g., target customers, sales channels, etc) will have to be evaluated holding other conditions constant. The alternative would be to test only a few permutations, which would lead to greater ambiguity about the relation between individual choices and performance (Gans et al. 2019; Gell-Mann, 1994; Gruber, 2007; Kauffman, 1989; Ott and Eisenhardt, 2020). As emphasized by Gans et al. (2019, 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 developed businesses can test their ideas in a real context and derive richer information than that obtained "in a lab" (Greenstein, 2012; Pillai et al. 2020; Rosenberg, 1982; Stern, 2005) as well as greater clarity about the ideal threshold against which to assess the evidence collected thanks to a superior understanding of the core mechanisms supporting the value proposition (Bennett & Chatterji, 2019; Brea-Solis et al. 2015). This ensures that test results are objectively assessed, leading to a well-defined action plan or, alternatively, reconsideration of the theory.

The above arguments suggest that the effect of a scientific approach on performance should be positive but higher for firms with a more developed business due to their superior focus and contextualization, which improves the complementarity between its cognitive and evidence-based components. To illustrate the logic, we provide the example of Coach Guru, an early-stage venture with a vision to provide fitness coaching for busy individuals. In the early stages, the founders are unclear whether the service should be offered as a 'gym van' driven to the customer's house or office, or via personal trainers visiting the customer's home, or through small fitness units in neighborhoods with no gym. As a result, they struggle to develop a theory to evaluate the pros and cons of each option, which delays progress and leads to test results that are 'noisier' because tests are based on a hypothetical version of the products as opposed to a real-life version. They also have difficulty testing all the possible options on target customers because of limited time and resources, and the high cognitive load that such testing entails. In line with the logic illustrated with this example, we would expect more developed businesses to benefit more from the scientific approach than less developed firms, holding other conditions constant.

3. DATA AND METHODOLOGY

3.1 The RCT: Setting and Data Collection Process

To investigate the impact of a scientific approach to decision-making on firm performance, we conducted an RCT. Consistent with best practice, 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, from mid-February 2019 to November 2019. The treatment was administered through a training program, as 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 required that the subjects receiving the treatment were key decision-makers, a condition more accurately met in the context of micro-businesses, where all employees tend to be 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). Our final sample included 274 entrepreneurial firms. We did not impose any restrictions in terms of industry; firms admitted to the program operated in a wide range of sectors, from software to retail. Our setting enabled the recruitment of firms at different stages of business development, a feature that set the programme apart from other studies where only more established (Bruhn et al., 2018; Campos et al., 2018; Chatterji et al., 2019; Guzman and Stern, 2016) or less established firms participated (Camuffo et al., 2020a and b).

The program involved an initial formal training period of 7 sessions (21 hours in total), which started in mid-February 2019 and finished in April 2019. Participants were divided into a treatment and a control group, and the sessions were used to administer the intervention. The training in both groups exposed participants to elements of both cognitive-based decision making, such as strategy frameworks and tools (for instance, the Business Model Canvas or Balance Scorecard), and to evidence-based decision making (such as multiple data collection and testing techniques, including surveys, qualitative interviews and A/B testing to adapt to different entrepreneurial contexts). However, the control group was not explicitly encouraged to combine the two approaches, whereas the treatment group was encouraged to do so, employing a scientific approach to decision making. For instance, one of the training sessions in both the treatment and the control group was focused on the 'Business Model Canvas'. Both entrepreneurs in the treatment and control group were taught to apply the tool to their business and discuss it with their peers, but only those in the treatment group were explicitly taught to reflect on how the different elements of the business model connected to each other in a cohesive theory and were subsequently asked to explicitly formulate that theory and break it down into separate hypotheses. Later in the program, entrepreneurs in both groups were taught about the importance of making decisions based on the evidence collected, and were exposed to multiple evidence-gathering techniques (e.g., surveys, A/B testing, qualitative interviews). Entrepreneurs in the control group were free to apply those techniques based on their intuition, whereas entrepreneurs in the treatment group were explicitly encouraged to use these techniques to test the hypotheses developed in the previous sessions and reflect on how the evidence collected compared to their initial theory.

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 who were recruited and trained for this study. The experiment was designed such 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 underwent multiple 'train-the-trainer' sessions so that they would deliver the content of the program in line with our research design.

Several measures were taken 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 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 complete an extensive survey and 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 randomly assign firms to either the treatment or control groups) using a statistical software (STATA) - 139 firms were assigned to the treatment group and 135 firms to the control group.

Data collection and operationalization. The intervention ran between February and April 2019, but we monitored firms' performance and decision making until the end of 2019. Due to funding availability, we could only gather data over this relatively short time window - we take this aspect into consideration when discussing our results. 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 8 weeks after the training program had begun. We then collected data once a month until November 2019. In conducting these calls, we created a pre-defined protocol that included open and closed ended questions, an approach in line with Bloom and Van Reenen's (2010) and Camuffo et al.'s (2020b). We used open-ended questions to monitor entrepreneurs' decision-making process and let key themes emerge from narratives and closed-ended questions to elicit self-reported performance information.

The final sample included 261 firms, as we excluded data provided by four participants that gave inconsistent information about their business, and nine participants who were not willing to share data. Table 1 compares the baseline characteristics of the treated and control groups for the final sample of 261 firms. It shows that the two 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. 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 diminished in size and significance over time. Entrepreneurs completed their training between Interview 1 and Interview 2, indicating that the effect of the training was still visible months after it was completed.

Add Table 2 about here

Independent variables. Our main independent variable is *Intervention*, a dummy variable taking a value of 1 for firms in the treatment group after they were treated, and 0 for those in the control group. Intervention is equal to 0 for all firms at Interview 0 (baseline). Our second independent variable is *Degree of Business Development.* Our theory suggests that firms with more developed businesses will benefit more from the intervention. As a proxy for the level of business development we used the annual revenue of the company in the year before they started the program (in thousands of GBP). As a robustness check, we replicated all analyses using the number of firm employees at the baseline as an alternative measure.

Dependent variables. Revenue. During each telephone interview, our research assistants asked respondents about the amount of revenue generated by each firm in the previous month in pounds sterling. In our analysis, revenue was measured as the cumulative revenue generated up to each period.

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

Value Added. We measure productivity as the difference between cumulative revenue and costs, a standard measure used to quantify the extent to which the company adds value through the sales of products/services. Table 3 provides descriptive statistics and pairwise correlation between variables.

Add Table 3 about here

Methodology. We assess the impact of the intervention for firms at different levels of business development on firm performance by employing a difference-in-difference estimation strategy. We use data at the firm-interview level and estimate firm performance as a function of *(i)* the intervention and *(ii)* the interaction between the intervention and the level of business development. For each firm we use two observations, i.e., the observation at the baseline interview (pre-treatment) and at the final interview (post-treatment). This resulted in a total of 522 observations. For firms that did not complete all interview rounds, we assume that their performance remained at the level corresponding to the last interview round completed. To control for unobserved heterogeneity, we include firm fixed effects and time fixed effects in all the analyses. We cluster errors at the firm level. Specifically, we fit the following model:

$$Performance_{it} = \alpha_i + \beta I_{it} + \gamma I_{it} BD_i + \delta_t + \epsilon_{it}$$

where *i* indexes the firm and *t* is the time, α_i are firm fixed effects, I_{it} is the intervention dummy, BD_i is the business development level of the firm *i* at the baseline, δ_t are time effects, and ϵ_{it} is the error term.

4. RESULTS

4.1 Firm performance

We start by examining the impact of our intervention on firm performance, measured as revenue. Table 4 reports the result of a regression analysis where we estimate the cumulative revenue of each firm. Model 1 includes only the intervention dummy, whereas Model 2 includes the intervention dummy and its interaction with the level of business development. 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 conventional levels (B=10,794.349, p=0.451). Model 2 reports the results of the specification in which both the main effect of the intervention as well as its interaction with the level of development of the firm before the program. The effect of the intervention is negative (B=-34,129.286, p=0.000), whereas the interaction is positive (B=908.018, p=0.000). In terms of economic significance, over the observed period, the intervention had a positive impact on revenue of about £21,000 for firms that had a level of business development equal to the sample average (60,5) prior to joining the program. This is a sizable result as it corresponds to an increase of about 34% with respect to the average annual revenue at the baseline (£60,510). Because our variable *Degree of Business Development* is time invariant (it is measured at the baseline), its main effect is not estimated in our fixed effect model. As a robustness check, we also conduct a random-effect analysis, which is reported in Models 3 and 4 with results that are similar in terms of size and significance to those reported in Model 2.

Add Table 4 about here

Alternative mechanisms. In Models from 1 to 4 we use annual revenue before entering the program as a proxy for the level of business development. We then ask: To what extent is the positive effect that we observe for treated firms with higher revenue driven by other mechanisms that might also be associated with higher revenue? We consider three possible alternative mechanisms. First, research has extensively emphasized the importance of prior experience for firm survival (Agarwal and Shah, 2014; Klepper and Sleeper, 2005), and performance (Agarwal et al., 2016; Azoulay et al., 2020; Gruber et al., 2013; Shah et al., 2019). However, it is not clear if experience enables or constrains the adoption of a scientific approach to decision-making. Second, it is possible that entrepreneurs with higher quality business ideas are those that generate more revenue (Cusolito et al., 2020; Scott et al., 2015) and also benefit more from the treatment. Third, one could argue that the effect observed is driven by the confidence of the entrepreneurs in the project (Bennett and Chatterji, 2019; Chen et al., 2018; Hayward et al., 2010). To address these alternative explanations we replicate the analyses but introduce the interactions between the intervention and (a) prior work experience of the team at baseline (measured as the average number of years of experience of the entrepreneurial team) in Model 5; (b) the value of the entrepreneurial idea at the baseline (measured as the estimated value of the project, ranging from 0 to 100) in Model 6; and (c) the level of confidence of the entrepreneur at the baseline (measured as the agreement on a 1-5 scale with statements related to confidence) in Model 7. Results reported in Table 5 show that none of these interactions had a positive and statistically significant impact on our dependent variable, suggesting that the effect observed was driven by the level of development of the business and the resources available as opposed to other factors such as experience, quality of ideas or confidence.

Outliers. We checked if these results might have been driven by the presence of outliers in our sample by replicating the analysis after winsorizing the dependent variable at the 99th percentile. Results were consistent in terms of size as well as significance with those reported in Table 4 – for brevity's sake we do not report these results in the manuscript, but they are available upon request.

Alternative measures. As a further robustness check we replicated our analysis using the monthly revenue at the baseline and the number of employees at the baseline as alternative measures of business development. As alternative measures of prior experience we used the average number of years of industry, managerial and entrepreneurial experience of the team. Results were consistent with those presented in Table 4: the intervention had a positive and statistically significant effect on the revenue of firms with a higher number of employees or higher monthly revenue, but not for firm firms with greater experience.

4.2 Cost

Next, we investigated whether the effect on revenue was driven by treated firms at a later stage of development investing more resources in their business, thus incurring higher costs. If this was the case, these firms would not be creating value but merely transferring value to customers. Table 5 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 our measure of business development. Results from Model 2 show that the effect of the intervention is negative and statistically significant (B -23,706.244, p=0.000), whereas the interaction is positive and significant (B=697.739, p= 0.000). This indicates that for firms that a level of business development equal to the sample average (60.5) before joining the program, the intervention had a positive impact on their cost of about £18,000. We conducted the same robustness checks described in the previous section to check for the impact of outliers and alternative measures and all results of these additional analyses consistently supported the results presented above. These results are not reported for the brevity's sake but are available upon request.

Add Table 5 about here

4.3 Value Added

Previous results suggest that the performance of treated firms with higher revenue increases more than cost increases, indicating that these firms create value. We tested 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 the business development level. Results reported in Table 6 support our prediction and show that the intervention has a negative effect on the dependent variable (B=-10,423.042, p=0.018), whereas the interaction term has a positive effect on the dependent variable (B= 210.279, p=0.000). Overall, the intervention had a positive impact on their value added of about £2,300 for firms that had a level of business development equal to the sample average (60,5) prior to joining the program. This result is robust to the sensitivity analyses described in the previous sections.

Add Table 6 about here

4.4 Radical and not radical pivot

We find that entrepreneurs whose business is at a later stage of development and who have been trained to use a scientific approach generate higher revenue. While they also incur higher costs, they are more productive in terms of value added. We also find that entrepreneurs with more prior experience, higher quality ideas or more confidence do not benefit more from the treatment than others. The question, then, is what makes firms at a more advanced stage of development (as measured by higher revenue or a higher number of employees) benefit to a larger extent from the use of a scientific approach to decision making?

Our theoretical explanation points to their increased focus and contextualization, which enable them to apply the scientific approach in a more nuanced and precise way. In comparison, less developed firms enjoy smaller returns on investment because their efforts to apply the approach are spread over a much wider decision space and are more prone to exploration rather than exploitation. In seeking evidence of this mechanism, we examined whether more developed firms had a more focused approach by looking at the changes they made to their business (i.e., if they pivot and to what extent). If indeed they are more focused in applying the approach, we should find that they explore new opportunities less, and hence do not change their value proposition or key target market. We therefore estimate the number of pivots (i.e., changes to key elements of the business idea), the number of radical pivots (i.e., changes to the value proposition or customer segments, following Camuffo et al., 2020a) and the number of non-radical pivots (i.e., changes to business idea in areas other than value proposition or customer segments) performed by the firm within the observation period.

Results in Table 7 (Model 1), imply that a one standard deviation increase in the annual revenue before entering the program is associated with about 5% more pivoting for treated firms. However, Models 4 and 6 show that this effect is not driven by more developed treated businesses engaging in a higher number of radical pivots: the interaction between *Intervention* and the *Degree of Business Development* has a non significant impact on the number of radical pivots (B=-0.000, p=0.930). Instead, the interaction between *Intervention* and the *Degree of Business Development* has a positive and statistically significant impact on the number of non radical pivots (B=0.001, p=0.008), suggesting that more developed treated businesses engage in a higher number of non-radical pivots. In particular a one standard deviation increase in the Degree of Business Development (corresponding to 171.293) corresponds to about a 4% increase in the dependent variable for treated firms. This supports our theoretical intuition that treated firms with more developed businesses employ the scientific approach to focus and scale their business proposition by changing components of the business to enhance their key value proposition to customers (higher number of non-radical pivots and costs) as opposed to engaging in broader exploration of new value propositions or markets (no impact on the number of radical pivots).

Add Table 7 about here

4.5 Size growth

We observed that firms with more developed businesses make the most out of the scientific approach in the time window of this study, whereas less established firms do not benefit from using it. This raises an important question: What happens in the longer term? Do treated but less developed businesses eventually achieve the level of business development where they enjoy positive results from the application of the scientific approach? The ideal way to answer this question would be to monitor these firms for a longer time window, but funding constraints prevented us from doing so. As an alternative, we investigated the impact of the treatment on firms' growth, measured as the log of one plus the number of firms' employees. Prior studies indicate that firm growth can be interpreted as an early measure of firm performance (Delmar et al., 2003; Yang et al., 2020). Our results are reported in Table 8 and show that the intervention has on average a positive effect on firm size (B=0.116, p=0.020) for all firms. In terms of economic significance, being treated is associated with an increase of about 12% in the size of the firm. This result supports the possibility that all firms benefit from the treatment in the longer term.

Add Table 8 about here

5. DISCUSSION AND CONCLUSIONS

This study reports the results of a field experiment with 261 entrepreneurial firms in the UK, using a training program to teach treated firms a scientific approach to decision-making, defined as an approach to decision making that combines cognitive-based and evidence-based components. We treated half of the participants, keeping the other half in a control condition. Our sample was unique in that it included different types of firms at various levels of business development. We found that more developed businesses benefitted more from exposure to a scientific approach to decision-making in terms of revenue and value added, but all treated firms grew in terms of size.

Our study contributes to research in strategy and entrepreneurship in multiple ways. First, our results provide insight on the performance implications of the use of a scientific approach to decision making, and, more broadly, on the use of decision-making approaches that combine cognitive-based and evidenced-based components. We show that the use of a scientific approach does not benefit entrepreneurs equally. Those with a more developed business get the most out of this approach; less developed businesses do not seem to benefit from this approach in terms of revenue or value added within the time window of our study. This is of particular relevance given that prior research focusing on the benefit of systematic approaches to managerial decision making has mostly focused on established firms (Bloom and van Reenen, 2007; Yang et al, 2020; Zollo and Winter, 2004). Most importantly, our results emphasize the existence of a possible bias in previous studies focusing on larger firms and suggest that their findings should be applied with caution to less developed businesses. We show, however, that all treated firms grow in terms of employee number. To the extent that employee growth can be interpreted as an early measure of performance, these results suggest the possibility that all firms benefit from the approach in the longer term. Nevertheless, they emphasize that one should expect the benefits of a scientific approach to decision making to unfold differently for firms at different levels of business development.

Our paper also contributes to research on strategic entrepreneurship that advocates for the importance of testing and purposeful experimentation for firm performance (Bingham and Eisenhardt, 2011; Gruber and Tal, 2017; Murray and Tripsas, 2004; Shepherd and Gruber, 2020; Thomke, 2003). In line with these studies, our results support the view that testing and experimentation can be useful. However, the finding that established firms benefit more from the use of a scientific approach to decision making stands in stark contrast with literature that emphasizes that very early-stage entrepreneurs can successfully gather feedback through experimentation. The Lean Start-up movement, in particular, 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. Indeed, a key tenet of this philosophy is ‘Build fast and fail fast', using minimum viable products to obtain feedback on early-stage ideas. Our results suggest, instead, that it is rather firms with a more established value proposition that benefit more from approaches based on experimentation and testing.

Our findings are in line with recent strategy research on the role of commitment in decision making (Gans et al., 2019; Gans et al., 2020; Gruber and Tal, 2017; McDonald and Eisenhardt, 2020; Pillai et al., 2020). This work builds on the idea that commitment to some initial choices – i.e., the extent to which the decision maker makes some early decisions that "*constrain subsequent behaviour*" (Ghemawat, 1991, p.10) - plays a central role in determining the quality of the subsequent decision-making process (Ghemawat and Levinthal, 2008). It advances the idea that feedback obtained by entrepreneurs on "*early strategies*" (Gans et al., 2019, p.744), 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). Also, 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 (Bhide, 2000; Gans et al. 2019; Gruber, 2007; McGrath et al., 1995). Instead, experimentation performed within the context of higher commitment leads to "rich" information (Greenstein, 2012; Rosenberg, 1982; Stern, 2005; Pillai et al. 2020). Our results – which show that more developed businesses, often characterized by a higher level of commitment, make the most of the scientific approach to managerial decision making – provide preliminary evidence in support of a positive role of commitment in entrepreneurial decision-making, and suggest that further investigation is warranted.

Finally, our results contribute to the strategy and economics literature on the relationship between firm level development and its performance (Agarwal and Audretsch, 2001; Agarwal and Gort, 2002). Research in this area has emphasized that learning "about (the firm) itself" (Agarwal and Gort, 2002, p.185) is associated with superior performance (Agarwal and Audretsch, 2001; Agarwal and Gort, 2002; Gort and Klepper, 1982). These studies highlight that size is a good proxy for a firm's learning about itself (Agarwal and Gort, 2002). Our paper shows that larger firms, in terms of either revenue or employees, benefit more from scientific decision making. In doing so, it advances the intriguing possibility of a virtuous learning cycle, with firms that have greater knowledge of their value proposition and competences enjoying a superior position in using approaches that foster additional learning. Interestingly, our results show an effect despite the relatively limited variance of our sample in terms of size– suggesting that it has a powerful effect even for firms of small size. In this way our study emphasizes an additional mechanism through which size affects performance that should be explored further by future research.

In making these considerations, we also acknowledge the limitations of this study which point to opportunities for future research. First, our study is focused on firms with less than 10 employees. This is an advantage in that it allowed us to ensure that the treatment was administered to the individuals directly involved in the firm's decision making. However, 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. Second, future research could replicate our analyses in a longer time window to confirm that less-established firms (not only more established ones) can benefit from the approach in the long run.

A final contribution is to offer insights to policymakers. Encouraging entrepreneurship has been a major means to spur economic growth (Bennett and Chatterji, 2019; Decker et al., 2014; Lerner, 2009). Bennett and Chatterji (2019)'s nationally representative survey on the pre-entry activities conducted by potential entrepreneurs in the US found 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, a phenomenon they attribute to the psychological costs associated with learning the true promise of an idea. They conclude that one 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 is helpful - for more established firms - at least within the observed time window. They underline the need for further work to be devoted to identifying the ideal time window for programs targeted to these types of firms, as well as the most effective design choices. Given the importance of this topic for the economy, we consider this a promising path for future research.

REFERENCES

Agarwal, R., & Audretsch, D.B. (2001). Does entry size matter? The impact of the life cycle and technology on firm survival. *The Journal of Industrial Economics*, *49*(1)—21-43.

Agarwal, R., Audretsch, D., & Sarkar, M. B. (2007). The process of creative construction: knowledge spillovers, entrepreneurship, and economic growth. *Strategic Entrepreneurship Journal*, *1*(3-4)—263 -286.

Agarwal, R., Campbell, B. A., Franco, A. M., & Ganco, M. (2016). What do I take with me? The mediating effect of spin-out team size and tenure on the founder–firm performance relationship. *Academy of Management Journal*, *59*(3)—1060-1087.

Agarwal, R., & Gort, M. (2002). Firm and product life cycles and firm survival. *American Economic Review*, *92*(2)—184-190.

Agarwal, R., & Shah, S. K. (2014). Knowledge sources of entrepreneurship: Firm formation by academic, user and employee innovators. *Research policy*, *43*(7)—1109-1133.

Agrawal, A., Gans, J. S., & Stern, S. (2021). Enabling entrepreneurial choice. *Management Science*.

Anderson, S. J., Chandy, R., & Zia, B. (2018). Pathways to profits: The impact of marketing vs. finance skills on business performance. *Management Science*, *64*(12)—5559-5583.

Azoulay, P., Jones, B. F., Kim, J. D., & Miranda, J. (2020). Age and high-growth entrepreneurship. *American Economic Review: Insights*, *2*(1)—65-82.

Bennett, V., & Chatterji, A. (2019). The entrepreneurial process: Evidence from a nationally representative survey. *Strategic Management Journal*.

Bhidé, A. (2010). The judgment deficit. *Harvard Business Review*, *88*(9)—44-53.

Bingham, C., & Eisenhardt, K. (2011). Rational heuristics: the 'simple rules' that strategists learn from process experience. *Strategic Management Journal*, *32*(13)—1437-1464.

Blank, S. (2013). Why the lean startup changes everything, *Harvard Business Review*. https://hbr.org/2013/05/why-the-lean-start-upchanges-everything

Bloom, N., Sadun, R., & Van Reenen, J. (2012). The organization of firms across countries. *The Quarterly Journal of Economics*, *127*(4) —1663-1705.

Bloom, N., & Van Reenen, J. (2007). Measuring and explaining management practices across firms and countries. *The Quarterly Journal of Economics*, *122*(4) —1351-1408.

Bloom, N., & Van Reenen, J. (2010). Why do management practices differ across firms and countries? *Journal of Economic Perspectives*, *24*(1) —203-24.

Brea-Solís, H., Casadesus-Masanell, R., & Grifell-Tatjé, E. (2015). Business model evaluation: Quantifying Walmart's sources of advantage. *Strategic Entrepreneurship Journal*, *9*(1), pp.12-33.

Bruhn, M., Karlan, D., & Schoar, A. (2018). The impact of consulting services on small and medium enterprises: Evidence from a randomized trial in Mexico. *Journal of Political Economy*, *126*(2)—635-687.

Campos, F., Frese, M., Goldstein, M., Iacovone, L., Johnson, H. C., McKenzie, D., & Mensmann, M. (2018). Is personal initiative training a substitute or complement to the existing human capital of women? Results from a randomized trial in Togo. In *AEA Papers and Proceedings* (Vol. 108, pp. 256-61).

Camuffo, A., Cordova, A., Gambardella, A., & Spina, C. (2020). A scientific approach to entrepreneurial decision making: Evidence from a randomized control trial. *Management Science*, *66*(2) —564-586.

Camuffo, A, Gambardella, A, Messinese, D, Novelli, E, Paolucci, E., & Spina, C. (2021). A scientific approach to innovation management: evidence from four field experiments. Camuffo, A., Gambardella, A., & Spina, C. (2020). Small changes with big impact: experimental evidence of a scientific approach to the decision-making of entrepreneurial firms.

London, Centre for Economic Policy Research. DP15972

Chatterji, A., Delecourt, S., Hasan, S., & Koning, R. (2019). When does advice impact startup performance?. *Strategic Management Journal*, *40*(3)—331-356.

Chen, J. S., Elfenbein, D. W., & Posen, H. E. (2020). The problems and promise of entrepreneurial partnerships: Decision making, overconfidence, and learning in founding teams. *Academy of Management Review*, *(Forthcoming)*.

Cohen, S. L., Bingham, C. B., & Hallen, B. L. (2019). The role of accelerator designs in mitigating bounded rationality in new ventures. *Administrative Science Quarterly*, *64*(4) —810-854.

Csaszar, F., & Laureiro-Martínez, D. (2018). Individual and organizational antecedents of strategic foresight: A representational approach. *Strategy Science*, *3*(3) —513-532.

Cusolito, A. P., Dautović, E., & McKenzie, D. J. (2020). Can government intervention make firms more investment-ready? A randomized experiment in the Western Balkans.

Davis, J. P., Eisenhardt, K. M., & Bingham, C. B. (2009). Optimal structure, market dynamism, and the strategy of simple rules. *Administrative Science Quarterly*, *54*(3) —413-452.

Decker, R., Haltiwanger, J., Jarmin, R., & Miranda, J. (2014). The role of entrepreneurship in US job creation and economic dynamism. *Journal of Economic Perspectives*, *28*(3)—3-24.

Delmar, F., Davidsson, P., & Gartner, W. B. (2003). Arriving at the high-growth firm. *Journal of Business Venturing*, *18*(2) —189-216.

Duflo, E., Banerjee, A., Finkelstein, A., Katz, L. F., Olken, B. A., & Sautmann, A. (2020). In praise of moderation: Suggestions for the scope and use of pre-analysis plans for RCTs in economics (No. w26993). National Bureau of Economic Research.

Eisenhardt, K.M., & Bingham, C.B. (2017). Superior strategy in entrepreneurial settings: Thinking, doing, and the logic of opportunity. *Strategy Science*, *2*(4)—246-257.

Felin, T., Gambardella, A., Stern, S., & Zenger, T. (2020a). Lean startup and the business model: Experimentation revisited. *Long Range Planning*, *53*(4).

Felin, T., Kauffman, S., & Zenger, T. (2020b). Microfoundations of resources: a theory. *Available at SSRN*.

Felin, T., & Zenger, T. (2009). Entrepreneurs as theorists: on the origins of collective beliefs and novel strategies. *Strategic Entrepreneurship Journal*, 3(2) —127-146.

Felin, T., & Zenger, T. (2016). CROSSROADS—Strategy, problems, and a theory for the Firm. *Organization Science*.

Felin, T., & Zenger, T. (2017). The theory-based view: Economic actors as theorists. *SSRN Electronic Journal*.

Folta, T. (1998). Governance and uncertainty: the trade-off between administrative control and commitment. *Strategic Management Journal*, *19*(11)—1007-1028.

Foss, N., & Klein, P. (2012). *Organizing Entrepreneurial Judgment*. Cambridge: Cambridge University Press.

Furr, N., & Dyer, J. (2014). *The Innovator's Method: Bringing the Lean Start-Up Into Your Organization*. Harvard Business Review Press.

Gans, J., & Stern, S. (2003). The product market and the market for “ideas”: commercialization strategies for technology entrepreneurs. *Research Policy*, *32*(2) —333-350.

Gans, J., & Stern, S. (2017). Endogenous Appropriability. *SSRN Electronic Journal*.

Gans, J., Stern, S., & Wu, J. (2019). Foundations of entrepreneurial strategy. *Strategic Management Journal*, *40*(5)—736-756

Gary, M.S., & Wood, R.E. (2011). Mental models, decision rules, and performance heterogeneity. *Strategic Management Journal*, *32*(6)—569-594.

Gell-Mann, M. (1994). *The quark and the jaguar: Adventures in the simple and the complex*. New York, NY: W.H. Freeman.

Geroski, P.A. (1995). What do we know about entry? *International Journal of Industrial Organization*, *13*(4)—421-440.

Ghemawat, P. (1991). *Commitment*. Riverside: Free Press.

Ghemawat, P., & Levinthal, D. (2008). Choice interactions and business strategy. *Management Science*, *54*(9)— 1638-1651.

Ghosh, S., Thomke, S., & Pourkhalkhali, H. (2020). The effects of hierarchy on learning and performance in business experimentation. In *Academy of Management Proceedings* (Vol. 2020, No. 1, p. 20500). Briarcliff Manor, NY 10510: Academy of Management.

Gort, M., & Klepper, S. (1982). Time paths in the diffusion of product innovations. *The Economic Journal*, *92*(367) —630-653.

Greenstein, S. (2012). Economic experiments and the development of Wi-Fi. In *History and strategy*. Emerald Group Publishing Limited.

Gruber, M. (2007). Uncovering the value of planning in new venture creation: A process and contingency perspective. *Journal of Business Venturing*, *22*(6) —782-807.

Gruber, M., MacMillan, I. C., & Thompson, J. D. (2013). Escaping the prior knowledge corridor: What shapes the number and variety of market opportunities identified before market entry of technology start-ups?. *Organization Science*, *24*(1) —280-300.

Gruber, M., & Tal, S. (2017). *Where to play*. FT Publishing International.

Guzman, J., & Stern, S. (2016). The state of American entrepreneurship: New estimates of the quantity and quality of entrepreneurship for 15 US states, 1988-2014 (No. w22095). Cambridge: National Bureau of Economic Research.

Hayward, M. L., Forster, W. R., Sarasvathy, S. D., & Fredrickson, B. L. (2010). Beyond hubris: How highly confident entrepreneurs rebound to venture again. *Journal of Business Venturing*, *25*(6) —569-578.

Heimeriks, K. H., Schijven, M., & Gates, S. (2012). Manifestations of higher-order routines: The underlying mechanisms of deliberate learning in the context of postacquisition integration. *Academy of Management Journal*, *55*(3) —703-726.

Karlan, D., Knight, R., & Udry, C. (2015). Consulting and capital experiments with microenterprise tailors in Ghana. *Journal of Economic Behavior & Organization*, *118*, pp.281-302.

Kauffman, S. (1989). Adaptation on rugged fitness landscapes. In E. Stein (Ed.), *Lectures in the science of complexity,* (pp. 517–618). Reading, MA: Addison-Wesley.

Kerr, W., Nanda, R., & Rhodes-Kropf, M., 2014. Entrepreneurship as experimentation. *Journal of Economic Perspectives*, *28*(3) —25-48.

Kirtley, J., & O'Mahony, S. (2020). What is a pivot? Explaining when and how entrepreneurial firms decide to make strategic change and pivot. *Strategic Management Journal*.

Klepper, S., & Sleeper, S. (2005). Entry by spinoffs. *Management Science*, *51*(8) —1291-1306.

Kohavi, R., & Thomke, S. (2017). The surprising power of online experiments. *Harvard Business Review*, *95*(5) —74-82.

Koning, R., Hasan, S., & Chatterji, A. (2019). *Experimentation and startup performance: Evidence from A/B testing* (No. w26278). National Bureau of Economic Research.

Leatherbee, M., & Katila, R. (2020). The lean startup method: Early-stage teams and hypothesis-based probing of business ideas. *Strategic Entrepreneurship Journal*, *14*(4) —570-593.

Lerner, J. (2009). *Boulevard of broken dreams: why public efforts to boost entrepreneurship and venture capital have failed--and what to do about it*. Princeton University Press.

McDonald, R.M., & Eisenhardt, K.M. (2020). Parallel play: Startups, nascent markets, and effective business-model design. *Administrative Science Quarterly*, 65(2) —483-523.

McGrath, R., (1997). A real options logic for initiating technology positioning investments. *Academy of Management Review*, *22*(4) —974-996.

McGrath, R. (1999). Falling forward: Real options reasoning and entrepreneurial failure. *The Academy of Management Review*, *24*(1) —13.

McGrath, R. (2001). Exploratory learning, innovative capacity, and managerial oversight. *Academy of Management Journal*, *44*(1) —118-131.

McGrath, R., Macmillan, I., & Venkataraman, S. (1995). Defining and developing competence: A strategic process paradigm. *Strategic Management Journal*, *16*(4) —251-275.

Moeen, M., Agarwal, R., & Shah, S. K. (2020). Building industries by building knowledge: Uncertainty reduction over industry milestones. *Strategy Science, 5*(3), 218-244.

Murray, F., & Tripsas, M. (2004). The exploratory processes of entrepreneurial firms: The role of purposeful experimentation. Advances in Strategic Management, *21*—45-75.

Osterwalder, A., Pigneur, Y., & Clark, T. (2010). *Business Model Generation*. Hoboken, New Jersey: John Wiley & Sons.

Ott, T., & Eisenhardt, K. (2020). Decision weaving: Forming novel, complex strategy in entrepreneurial settings. *Strategic Management Journal*, *41*(12) —2275-2314.

Parker, S. C. (2006). Learning about the unknown: How fast do entrepreneurs adjust their beliefs?. *Journal of Business Venturing*, *21*(1) —1-26.

Pillai, S. D., Goldfarb, B., & Kirsch, D. A. (2020). The origins of firm strategy: Learning by economic experimentation and strategic pivots in the early automobile industry. *Strategic Management Journal*, *41*(3) —369-399.

Ries, E. (2011). The Lean Startup: How today's entrepreneurs use continuous innovation to create radically successful businesses. New York: Crown Publishing Group.

Rosenberg, N. (1982). *Inside The Black Box*.

Sarasvathy, S. D. (2009). *Effectuation: Elements of entrepreneurial expertise*. Edward Elgar Publishing.

Scott, E. L., Shu, P., & Lubynsky, R. M. (2015). Are better ideas more likely to succeed?: An empirical analysis of startup evaluation (No. 16-013). *Harvard Business School.*

Shah, S. K., Agarwal, R., & Echambadi, R. (2019). Jewels in the crown: Exploring the motivations and team building processes of employee entrepreneurs. *Strategic Management Journal*, *40*(9), 1417-1452.

Shepherd, D., & Gruber, M. (2020). The lean startup framework: closing the academic–practitioner divide. *Entrepreneurship Theory and Practice*.

Stern, S. (2005). *Economic experiments: The role of entrepreneurship in economic prosperity. In understanding entrepreneurship: A research and policy report*. Ewing Marion Kauffman Foundation, 16–20. Available at SSRN: https://ssrn.com/abstract=1262370

Thomke, S. (2003). *Experimentation Matters*. Boston, Mass.: Harvard Business School Press.

Yang, M. J., Christensen, M., Bloom, N., Sadun, R., & Rivkin, J. (2020). How do ceos make strategy? (No. w27952). National Bureau of Economic Research.

Yu, S. (2020). How do accelerators impact the performance of high-technology ventures?. *Management Science*, *66*(2) —530-552.

Zenger, T. (2015). New ways to compete: Build a theory, then a strategy. *Harvard Business Review*.

Zollo, M., & Singh, H. (2004). Deliberate learning in corporate acquisitions: post-acquisition strategies and integration capability in US bank mergers. *Strategic Management Journal*, *25*(13) —1233-1256.

TABLES

Table 1. Balance checks

		Treatment		Control		Difference	
Variable	Definition	mean	sd	mean	sd	b	p
Business Age	Age of the business (years)	2.48	3.22	3.28	5.17	0.8	(0.14)
Team size	Number of team members	2.14	1.95	2.31	2.14	0.18	(0.49)
Gender (Female)	Proportion of women in the team	0.42	0.42	0.5	0.44	0.08	(0.15)
Age	Age (team average)	35.77	8.56	36.37	9.2	0.6	(0.59)
Hours - Total Weekly	Weekly hours dedicated to the company (team average)	31.55	18.57	29.61	17.18	-1.94	(0.39)
Background-Economics	Team members with Economics backgrounds (%)	0.15	0.29	0.15	0.29	0	(0.94)
Background - STEM	Team members with a STEM (Science Technology Engineering Mathematics) backgrounds (%)	0.3	0.39	0.36	0.43	0.06	(0.26)
Education	Highest educational level attained by team members (5= PhD, 4=MBA, 3=MSc, 2=BA, 1=high school, 0=otherwise; team average)	2.67	0.81	2.58	0.79	-0.1	(0.34)
Confidence	Agreement on a 1-5 scale with the following statements (team average): "We are confident in our entrepreneurial skills", "We are sure we are deploying the best strategy for our business", "We are confident in our ability to manage our business", "We master the competences necessary for our venture", "We are sure there is no better business model for our idea"	3.41	0.7	3.34	0.76	-0.07	(0.44)
Probability Pivot Idea	Probability of making a radical change to the business	45.85	28.18	42.12	26.99	-3.72	(0.28)
Probability Pivot Problem	Probability of changing the problem and customer segment	38.18	26.16	40.55	26.26	2.38	(0.47)
Probability Expansion	Probability of expanding the business outside of the current industry or market	68.25	27.4	66.59	28.12	-1.67	(0.63)
Turnover Annual	Annual turnover (2018) £	50616.11	145448.79	71977.35	195899.81	21361.24	(0.32)
Turnover Monthly	Monthly turnover (January 2019) £	5113.83	17734.76	6099.5	24490.47	985.67	(0.71)
Hours - % Innovation yearly	Working hours dedicated to the design of new products or services in the last year (2018, %)	46.05	33.35	40.02	32.68	-6.04	(0.14)
Hours - % Innovation monthly	Working hours dedicated to the design of new products or services in the last month (January 2019, %)	39.46	34.16	36.84	34.59	-2.62	(0.54)
Idea Value - Mean	Estimated value of the project (mean, 0 to 100)	66.73	17.05	66.62	20.22	-0.11	(0.96)
Idea Value - Range	Estimated value of the project (range, 0 to 100)	39.26	22.03	38	21.94	-1.26	(0.65)
Experience - Industry	Number of years of experience in industry (Team Average)	6.75	6.47	7.7	7.56	0.95	(0.28)
Experience - Work	Number of years of work experience (Team Average)	13.02	7.98	13.53	8.59	0.51	(0.62)
Experience - Entrepreneurial	Number of years of entrepreneurial experience (team average)	3.85	3.49	4.64	5.95	0.79	(0.20)
Experience - Managerial	Number of years of managerial experience (team average)	5.96	5.29	6.22	6.16	0.26	(0.73)
		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)
Observations	133		128			261

Table 3 Descriptive statistics and pairwise correlations

		Obs	Mean	SD	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12
1	Intervention	522	0.255	0.436	0	1	1.000											
2	Degree of Business Development	522	60.510	171.293	0	1500	-0.038	1.000										
3	Prior Experience	522	13.244	8.174	0	40	-0.018	0.010	1.000									
4	Idea Quality	522	66.730	18.502	1	100	0.003	0.143	-0.066	1.000								
5	Confidence	522	3.378	0.723	1	5	0.028	0.117	-0.115	0.300	1.000							
6	Revenue	522	22,895.080	94,031.590	0	1,465,192	0.138	0.525	0.036	0.144	0.050	1.000						
7	Cost	522	16,150.320	66,436.720	0	1,092,902	0.165	0.427	0.037	0.144	0.059	0.931	1.000					
8	Value Added	522	6,744.759	40,324.130	-161,040	390,900	0.049	0.520	0.024	0.099	0.020	0.798	0.523	1.000				
9	Number of Pivots	522	2.013	4.063	0	25	0.245	-0.022	0.064	0.019	-0.008	0.217	0.206	0.166	1.000			
10	Number of Radical Pivots	522	0.588	1.290	0	8	0.225	-0.070	0.057	-0.005	-0.006	0.080	0.079	0.057	0.852	1.000		
11	Number of Not Radical Pivots	522	1.425	3.040	0	18	0.232	0.001	0.061	0.027	-0.008	0.256	0.242	0.198	0.975	0.715	1.000	
12	Number of employees	522	1.912	2.350	0	15	0.048	0.326	-0.068	0.161	0.119	0.284	0.261	0.233	0.006	-0.041	0.025	1.000

Table 4. Revenue

VARIABLES	(1) Revenue OLS Panel	(2) Revenue OLS Panel	(3) Revenue OLS Panel	(4) Revenue OLS Panel	(5) Revenue OLS Panel	(6) Revenue OLS Panel	(7) Revenue OLS Panel	(8) Revenue OLS Panel
Intervention	10,794.349	-34,129.286	16,237.837	-31,448.843	5,763.948	-92,706.926	-51,296.819	-24,239.100
	(0.451)	(0.000)	(0.246)	(0.000)	(0.729)	(0.161)	(0.414)	(0.509)
Intervention X Degree of Business Development		908.018		888.133				907.427
		(0.000)		(0.000)				(0.000)
Degree of Business Development			289.551	130.203				
			(0.002)	(0.000)				
Intervention X Prior Experience					387.249			-463.902
					(0.645)			(0.417)
Intervention X Idea Quality						1,548.706		256.346
						(0.164)		(0.412)
Intervention X Confidence							18,197.720	-6,144.902
							(0.377)	(0.415)
Constant	5,553.100	5,553.100	- 11,967.709	-2,325.538	5,553.100	5,553.100	5,553.100	5,553.100
	(0.126)	(0.011)	(0.043)	(0.089)	(0.126)	(0.122)	(0.125)	(0.011)
Observations	522	522	522	522	522	522	522	522
R-squared	0.083	0.668			0.084	0.106	0.089	0.669
Number of id	261	261	261	261	261	261	261	261
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	-	-	Yes	Yes	Yes	Yes
Clustered Errors	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm

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

Table 5. Cost

	(1)	(2)	(3)	(4)
	Cost	Cost	Cost	Cost
VARIABLES	OLS Panel	OLS Panel	OLS Panel	OLS Panel
Intervention	10,813.952	-23,706.244	13,333.822	-22,706.009
	(0.321)	(0.000)	(0.202)	(0.000)
Intervention X Degree of Business Development		697.739		673.679
		(0.000)		(0.000)
Degree of Business Development			166.825	45.967
			(0.029)	(0.043)
Constant	2,084.272	2,084.272	-8,010.380	-697.231
	(0.449)	(0.201)	(0.092)	(0.540)
Observations	522	522	522	522
R-squared	0.095	0.684		
Number of id	261	261	261	261
Time FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	-	-
Clustered Errors	Firm	Firm	Firm	Firm

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

Table 6. Value Added

VARIABLES	(1) Value Added OLS Panel	(2) Value Added OLS Panel	(3) Value Added OLS Panel	(4) Value Added OLS Panel
Intervention	-19.603	-10,423.042	2,304.968	-9,055.530
	(0.997)	(0.018)	(0.678)	(0.041)
Intervention X Degree of Business Development		210.279		212.592
		(0.000)		(0.000)
Degree of Business Development			122.668	84.530
			(0.001)	(0.026)
Constant	3,468.828	3,468.828	-3,953.848	-1,646.126
	(0.010)	(0.003)	(0.022)	(0.281)
Observations	522	522	522	522
R-squared	0.022	0.265		
Number of id	261	261	261	261
Time FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	-	-
Clustered Errors	Firm	Firm	Firm	Firm

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

Table 7. Focus

VARIABLES	(1) (Log 1+) #Pivot OLS Cross Section	(2) (Log 1+) #Pivot OLS Cross Section	(3) (Log 1+) # Radical Pivot OLS Cross Section	(4) (Log 1+) # Radical Pivot OLS Cross Section	(5) (Log 1+) #Not Radical Pivot OLS Cross Section	(6) (Log 1+) #Not Radical Pivot OLS Cross Section
Intervention	-0.042	-0.119	-0.039	-0.037	-0.056	-0.136
	(0.725)	(0.341)	(0.624)	(0.660)	(0.608)	(0.226)
Intervention X Degree of Business Development		0.001		-0.000		0.001
		(0.030)		(0.930)		(0.008)
Degree of Business Development	-0.001	-0.001	-0.001	-0.001	-0.000	-0.001
	(0.115)	(0.000)	(0.001)	(0.005)	(0.336)	(0.001)
Constant	0.937	0.980	0.485	0.484	0.749	0.794
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	261	261	261	261	261	261
R-squared	0.038	0.050	0.032	0.032	0.039	0.055
Mentor dummies	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. Employees

VARIABLES	(1) (Log 1+) # Employees OLS Panel	(2) (Log 1+) # Employees OLS Panel	(3) (Log 1+) # Employees OLS Panel	(4) (Log 1+) # Employees OLS Panel
Intervention	0.116	0.105	0.117	0.102
	(0.020)	(0.043)	(0.018)	(0.048)
Intervention X Degree of Business Development		0.000		0.000
		(0.024)		(0.062)
Degree of Business Development			0.001	0.001
			(0.000)	(0.000)
Constant	0.802	0.802	0.721	0.724
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	522	522	522	522
R-squared	0.022	0.026		
Number of id	261	261	261	261
Time FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	-	-
Clustered Errors	Firm	Firm	Firm	Firm

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