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# Is (Smart) Technology Really Making Us Dumber? Marketing Analytics Improves the Mental, Managerial and Financial Performance of Entrepreneurs

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# ABSTRACT

The literature in economics on the interplay between technology and human capital suggests that the adoption and usage of technology can potentially have a positive effect on the human capital of users – for example, by rearranging connections in their brains. On the other hand, due to issues such as analysis paralysis, confirmation bias, information overload and brain drain, other research has suggested a negative effect of technology. This paper sheds light on this tension by studying the impact of a particular Ed-Fintech solution (a marketing analytics technology) on the performance of emerging market firms and their entrepreneur-managers. We test the efficacy of this technology using a randomized controlled field experiment in which 550 Rwandan firms were assigned to one of three groups: Treatment (received a marketing analytics solution for nine months); Placebo (only received a smartphone and mobile internet access without any analytics); or Control (did not receive any intervention). We find novel evidence of changes at an individual entrepreneur level. First, *technology interaction* is initially low for treatment entrepreneurs, but by the third month an organic feedback loop sets in that raises daily usage rates to 90-95% as these managers become more reliant on data and analytics in their businesses. Second, as per objective ability and psychological tests, the Ed-Fintech solution has a positive causal impact on the *mental performance* of entrepreneurs (i.e., their aptitude improves in areas related to reasoning, memory, logic and calculations). In addition, greater interaction with the marketing analytics solution also leads to changes at an overall business level. One, the *managerial performance* of firms improves through spillovers from the online technology to offline business practices in accounting and product management. Two, we find a positive effect of Ed-Fintech (with marketing analytics) on the *financial performance* of firms as the treatment group increases monthly sales by 36.4% and monthly profits by 29.2% (on average). Taken together, these results offer new insights for stakeholders interested in enhancing productivity within businesses, increasing firm growth, or achieving greater financial inclusion.

**KEYWORDS:** Ed-Fintech, marketing analytics, manager-technology interaction, entrepreneur mental performance, small firm growth, entrepreneurship, emerging markets

# INTRODUCTION

The amount of data created worldwide has been increasing exponentially over the past decade with some estimates placing the total at 59 zettabytes as of 2020 (Statista 2020). Data without analytics, however, is of little value to business decision-makers aiming to improve performance and increase growth. It is therefore no surprise that top-tier consulting companies, analytics firms and business schools have been promoting the positive returns to greater usage of analytics technology (e.g., Bhandari, Singer and Scheer 2014; City et al. 2020; Loveman 2003; Ransbotham and Kiron 2018; Wind et al. 1989). And nowhere are data and analytics potentially more transformational than in emerging markets where hundreds of millions of entrepreneurs run small firms with little (if any) advanced business skills or technologies (La Porta and Shleifer 2014; McKenzie 2017, 2020). Indeed, given rising trends in smartphone affordability and mobile internet connectivity by billions of people (Bahia and Delaporte 2020; ITU 2018; Lund et al. 2021), policymakers and impact investors are touting Ed-Fintech solutions[1] – especially those leveraging analytics and smart technology – as a panacea for improving entrepreneur and firm outcomes globally.

Yet, despite this enthusiasm, there is little empirical evidence on the causal effects of such technology for stimulating changes at an individual entrepreneur level or at an overall business level. On the one hand, Ed-Fintech solutions could have *positive effects* on entrepreneurs and their firms. The literature in economics on the interplay between technology and human capital suggests that the adoption and usage of technology itself can potentially improve the human capital of users – for example, by rearranging connections in their brains (Bashir et al. 2021; Romer 1992). A handful of studies in marketing also imply a positive relationship may exist between analytics technology and business outcomes such as revenues (Germann et al. 2014), or customers and products (Berman and Israeli 2020). On the other hand, Ed-Fintech could lead to *negative effects*. Due to issues such as analysis paralysis, confirmation bias and information overload, other research suggests a negative impact of technology on human capital (Edmunds and Morris 2000; Peters and Waterman 1982;

[1]Ed-Fintech refers broadly to any technology that delivers educational and/or financial services through digital channels with the aim of improving human capital (e.g., skills training), managerial capital (e.g., business capabilities) or financial capital (e.g., money and its management). To maximize scalability and inclusivity, these services typically automate interaction (between users and technology) and increase access (remotely or virtually) by relying on smartphone-based mobile apps and online platforms.

Talbert 2017). Even the mere presence of ‘smart’ technology like a mobile phone can create brain drain for users by reducing attention and limiting cognitive resources (Ward, Duke, Gneezy and Bos 2020). In sum, the direction (and size) of the effect is ambiguous a priori: technology could help or hurt entrepreneurs and their firms.

We shed light on this tension by studying the impact of a particular Ed-Fintech solution (a marketing analytics technology) on the performance of emerging market firms and their entrepreneur-managers. The technology primarily involves daily or weekly entry of sales, product and customer data (inputs) along with basic analytics and metrics reported monthly (outputs). We test the efficacy of this technology using a randomized controlled field experiment in which 550 Rwandan entrepreneurs were assigned to one of three groups: (i) a Treatment group (n = 250) that received a marketing analytics solution for nine months from June 2019 to February 2020 (i.e., analytics app and platform, smartphone, mobile internet access, and monthly visits by a data analyst); (ii) a Placebo group (n = 50) that only received a technology for nine months (i.e., smartphone and mobile internet access without any analytics); and (iii) a Control group (n = 250) that did not receive any intervention. Firm and entrepreneur performance data was obtained for the entire sample (n = 550) through business site visits and audits conducted prior to the intervention starting (i.e., baseline in May 2019) and again nine months later (i.e., endline in February 2020).

This study provides new insights on how managers interact with technology, as well as the individual entrepreneur-level changes that result from this interaction. It also examines the overall business-level changes driven by greater technology use in small firms. In doing so, it addresses two novel research questions: (1) What is the main effect of Ed-Fintech on firm sales and profits? (2) What is the mechanism through which this effect occurs? Specifically, does greater manager-technology interaction affect (a) the mental performance of managers, and/or (b) the managerial performance of firms? From policymakers and impact investors to entrepreneurs and managers, answering these questions is important to stakeholders interested in increasing firm growth, enhancing productivity within businesses, or achieving greater financial inclusion.

At an individual entrepreneur level, two patterns of results emerge on: (i) a manager’s interaction with technology; and (ii) the impact of this technology on the manager. First, although adoption of the marketing analytics solution is 100%, *technology interaction* is initially low for entrepreneurs in the treatment group. These firm managers complete only 68% of the daily 'data entry' requirements during the first month and 83% in the second month. After an organic feedback loop sets in, however, these rates increase substantially with daily usage reaching 96% per entrepreneur (on average) and continuing in the 90-95% range for the entire intervention period. Treated entrepreneurs also report a greater reliance on data and analytics in their businesses over time (versus firms in the control or placebo groups). Thus, a manager's interaction with technology is enhanced by providing: runway to ramp-up usage (i.e., time for entering data and receiving the analytics feedback); and nudges to maintain high usage (e.g., automated system prompts, reminders from data analysts). In other words, a new technology must be utilized fully and frequently before an entrepreneur-manager understands the value it adds to her business.

Second, one of the study's central findings is that Ed-Fintech solution (namely, a marketing analytics technology) has a positive causal impact on the *mental performance* of entrepreneurs. Using objective ability and psychological measures, we obtain novel evidence that interaction with technology significantly improves an individual manager's aptitude in areas related to reasoning, memory, logic, and calculations. Compared to the control group, on average, entrepreneurs in the treatment group achieve 17.4% higher performance across a cognitive reflection test, a digit span test, a ravens test, and a financial numeracy test. The treated entrepreneurs also score 68.9% higher (on average) when reporting their orientation towards math and preference for data-based decision-making. Moreover, a global index representing mental performance (computed with all six measures) finds a 0.76 standard deviation improvement for entrepreneurs who received access to the marketing analytics solution – results that are significantly different for the treatment group in comparison to the control group and placebo group.

At an overall business level, two key results materialize: (i) spillovers to a firm's management practices; and (ii) the impact of technology on a firm's finances. Despite not encouraging any offline physical activities or record-keeping, the *managerial performance* of firms improved through spillovers from the Ed-Fintech solution to business practices. Adoption and usage of the marketing analytics solution led to a positive causal effect on Product Management effectiveness. At the endline, firms in the treatment group were implementing 3.16 (out of four) verifiable business practices related to changing product prices, improving or adding products, inspecting product quality, and monitoring levels of product inventory. This was significantly more than the average control firm (1.80 practices) and placebo firm (2.18 practices). In addition, the marketing analytics solution also resulted in greater Accounting Management effectiveness. All firms were audited at endline to verify if the following four business practices were conducted: separating business-from-personal finances, recording an income statement, keeping a budget, and regularly monitoring cash flow. On average, treatment firms were using 3.01 of the practices, whereas control firms were implementing 1.50 and placebo firms 1.82 of these accounting practices. These findings suggest that an online Ed-Fintech solution (focused on marketing analytics) can create positive spillovers that enhance a firm's managerial performance offline and in physical activities not directly linked to the digital technology.

Finally, given our study is conducted across hundreds of entrepreneurs and their firms, our experimental design allows for the first empirical test on the business impacts resulting from individual manager interaction with an Ed-Fintech solution. We find a positive and significant causal effect of marketing analytics on the *financial performance* of firms. On average, treatment group firms increase their monthly sales by 36.4% and monthly profits by 29.2% versus control firms – significant gains are also realized when compared to firms in the placebo group. This improvement represents 165 USD more sales each month for an average firm, which is equivalent to adding 43.7 purchases per month (roughly 2 per day) from newly acquired customers (based on an average basket size of 3.77 USD per visit at baseline). And for firms receiving the marketing analytics solution, these treatment effects translate into a 0.25 standard deviation increase when financial performance is measured using an index of all sales and profit measures. In addition, we examine underlying mechanisms to better understand how Ed-Fintech solution leads to increases in firm sales and profits. Our mediation analysis finds that entrepreneur 'mental performance' significantly mediates the effect of marketing analytics on the financial performance index. Said differently, 87.4% of the total effect on firm sales and profits is explained by this mediating relationship. The mediation effect is also significant when 'managerial performance' is included as an intervening variable. Overall, our analysis finds that marketing analytics has a statistically and economically significant impact on firm financial performance – with improvements in mental and managerial performance both representing mechanism channels through which this main effect occurs.

This paper aims to make contributions to the literature in marketing and economics, and more broadly to work on entrepreneurship and small firm growth. One, marketing research on technologies has largely examined online consumption contexts (e.g., websites, platforms) and the response of customers to digital stimuli (e.g., variation in ads, displays) with the objective of increasing their purchases. More generally, scholars in economics have argued that using technology in and of itself may positively alter human capital, however, there has not yet been a study isolating such human-technology effects in a firm setting. To the best of our knowledge, this is the first empirical paper that causally examines how managers interact with technology and in a business context where the aim is to improve human capital productivity. Two, this is, we believe, the first time that an 'Ed-Fintech solution' (focused on marketing analytics) has been studied in a field experiment with hundreds of firms. And the results link greater usage of Ed-Fintech to increased sales and profits. Thus, to the extent that it is a scalable and inclusive way to enhance firm performance, this intervention highlights the need to consider a role for analytics when developing new technology products or systems – as well as when designing business support services in emerging markets. Three, our paper contributes to the literature on small firm growth not only by validating the efficacy of a novel intervention, but also by identifying a new mechanism (entrepreneur mental performance) for explaining how such technology can drive greater sales and profits in business.

The paper proceeds as follows. First we review the relevant literature and develop hypotheses. We then describe the technology intervention and our research design. Next, we present analyses and results on individual impacts, followed by business impacts. Lastly, the paper concludes.

# LITERATURE AND HYPOTHESES

Scholars agree that human capital and technologies have a closely intertwined relationship as each affects the other (Bashir *et al.* 2021). Human capital is a key element in the successful implementation of any technology, for example, the use of micro-processors could help in economic growth but first the manpower needs to develop the necessary skills to use and maintain these devices (National Research Council US *et al.* 1992, Hanna 1991). At the same time, the implementation of technology can augment human capability. Some of the technologies linked to health, education or training can directly impact the cognitive capabilities and overall human capital. Examples include digital technologies for health and education service delivery in many South Asian countries, which are trying to reach the poor communities (Bashir *et al.* 2021). There are other data-driven technologies that influence the decision routines and hence the actions of users in all areas of their daily lives (Bashir *et al.* 2021). In the absence of data-backed insights, taking decisions could be sub-optimal and hence providing humans access to such analytics could lead to them making more informed decisions. The technology we designed, based on Ed-Fintech solution (marketing analytics technology), could be a great way to initiate firms into performing systematic computations on their own firm's data, which could generate meaningful insights for their business, thereby influencing their business decisions.

The humans using any technology invest effort to learn the codified information about the technology as well as the more tacit components related to it which become clear only after repeated use (Arrow 1971, Evenson & Westphal 1995). This learning and interaction with the technology could lead to a change in the aptitude or cognitive ability of the individual interacting with the technology. For example, a computer is a great piece of technology that can be used for various purposes, at the same time the human using the computer needs to store the commands related to the computer in their brain in order to effectively use it. Reading the software manual of the computer could be thought of as rearranging the connections of neurons in the brain of the human user, thereby making their human capital more valuable (Romer 1992). When interacting with our marketing analytics technology, this growth in human capital could manifest itself in higher analytical aptitude of the managers.

If the aggregate output is written as $Y = f(L, K, T, H)$, where L is labor, K is capital, T is technology and H is human capital, then based on the above discussion we hypothesize that H will indeed be a function of T. The technology (T) can affect H by changing the aptitude of the humans interacting with the technology and by modifying the decisions made by them. Our study helps in identifying the effects of technology interaction on both the decisions as well as the aptitude of the managers interacting with the technology.

Further, our analytics-based technology could be relevant for firms in both developing as well as developed countries. Mckenzie & Woodruff 2015 show that more than half of the firms surveyed in their study, do not keep basic records such as daily sales of products or use those records to analyze the increase/decrease in their product sales. Their sample is representative of enterprises in low- and middle-income countries (such as Sri Lanka, Chile, Kenya, Mexico etc.). In the absence of any studies which provide us with an idea of the status of analytics usage by small firms in developing countries, this paper gives us a sense of the status of data recording which could be considered as a precursor to analytics adoption. It is important to note that these firms do not use a formal technology for data recording and analytics. This information poverty of the developing countries manifests in several forms : poor information to support managerial decision-making and planning without facts (Hanna 1991). In addition, the studies listed above do not evaluate the impact of analytics usage on firms. As data recording itself is not widespread in most small firms, we can imagine the primitive state of analytics used by small firms in low-income countries.

This is not specific to low-income countries, as SMEs in more developed countries also face similar challenges. Hill & Scott 2004 conducted a qualitative study with 11 small firms in Ireland and show that even though these firms record basic sales and customer information, they did not connect the disparate business data they collected and did not analyze the data in any meaningful way. Sadok & Lesca 2009 conduct a similar study with 20 SMEs in France, and they find that there is no formal process for data acquisition or storage. While some enterprise members collected field data, it was mostly memorized in the mind of individuals who collected it and remained in an abstract form. Given the state of data collection, it was not possible for the data to be used in any analytics for decision-making. These examples provide us some insights into the crude way in which data is used in many small firms even in countries with more evolved economies. As a result, we believe our study, which exogenously shifts the use of marketing analytics for some firms to study its causal impact on the firm, will be relevant for all the managers or entrepreneurs who are a part of such firms, and still in the early stages of analytics adoption.

**Ed-Fintech and Mental Performance**

To the best of our knowledge, within the marketing literature, there is no existing paper that studies the impact of exposure to marketing analytics or any other Ed-Fintech solution adoption on the aptitude of the managers who use it. But, due to the unique data-set that we generate in our study, we can test for this interaction of the individual manager with the analytics technology. Our sample primarily consists of firms with single decision makers who are provided with access to marketing analytics tools. The experiment has exogenous adoption of the Ed-Fintech solution by individual entrepreneurs, as a result we can study the changes at a psychological level for these entrepreneurs who are exposed to the Ed-Fintech solution. It is important to note that, in the absence of an experiment it would be difficult to test if Ed-Fintech usage leads to a change in individual's aptitude due to the intrinsic reverse causality in this context.

The rest of the literature in the broader economics area is also quite scanty, and we don't see any study evaluating the impact of a technology such as analytics on an individual manager's performance. We find some tangentially related studies on education, where there is evidence of teaching school curriculum leading to students becoming better in math. Dillon et al. (2017) show that pre-schoolers receiving math training through interactive games leads to them having higher symbolic math skills. Banerjee et al. (2007) show remedial education and computer-assisted learning program can improve math and language scores of the students. While improvement in math skills of students is not the same as a change in aptitude of a manager, this does signal that usage of analytics could have a positive effect on improving aptitude of managers.

Behavioral studies report that low numeracy could lead to biased decision-making - susceptible to moods and context factors (Reyna *et al.* 2009). Studies show that individuals with better numeracy end up choosing normatively better options (Pachur & Galesic 2013). Paulos 1988 shows that low ability to deal with probabilities and small likelihoods of large outcomes, results in misinformed personal decisions and government policies, as well as an increased reliance on pseudo-science. Most of the literature in this area comes from psychology, and it does point to the importance of aptitude in the day-to-day decision-making by individuals. We feel this should be of benefit in a commercial setting too, for running day-to-day business operations in a more effective manner. This brings us to our first hypothesis.

**Hypothesis 1** *Usage of Ed-Fintech (with marketing analytics) improves an entrepreneur's mental performance (in areas related to reasoning, memory, logic, and calculations).*

**Ed-Fintech and Managerial Performance**

We study the actions of the entrepreneurs in our sample, in order to uncover the impact of technology on business decision-making of the managers. One of the more obvious changes that might happen to firms as a result of the adoption of marketing analytics is that they might start adopting better business practices. The response of the manager as a result of being exposed to the outputs from the marketing analytics tool is a key aspect, which could determine the effectiveness of Ed-Fintech (marketing analytics solution) adoption. To the best of our knowledge, there isn't any existing literature that evaluates these changes in actions or decisions at the manager level as a result of exposure to marketing analytics. We study managerial actions directly related to technology i.e. Marketing based and indirectly related to the technology i.e. financial recording and accounting based.

Berman & Israeli 2021 show that as a result of analytics exposure, firms integrate better customer prospecting technologies to their websites which in turn help in attracting more paid visitors to their websites. Bajari *et al.* 2019 state that by using analytics for demand forecasting, Amazon.com is able to link its purchase ordering system to the forecasting system that helps in efficient inventory management minimizing cases of stock-outs or over-stocks. While further adoption of related technologies might be an obvious consequence of the adoption of analytics, we feel that it could also lead to changes in day-to-day marketing and non-marketing decisions of the entrepreneurs too. Marketing analytics might provide helpful insights to the managers which nudges them to adopt better practices across finance, operations etc. Thus, our next hypothesis is outlined below.

**Hypothesis 2** *Usage of Ed-Fintech (with marketing analytics) improves a firm's managerial performance through spillovers from the technology to business practices (in accounting and product management).*

**Ed-Fintech and Financial Performance**

While analytics and data science are gaining widespread popularity in organizations, there is not much academic literature that provides robust empirical evidence of the impact it has on firms. There are quite a few case studies that show the successful implementation of marketing analytics tools at some organizations, leads to a positive impact on the firm. Wixom *et al.* 2013 show how GUESS?, Inc., a clothing and retail company, used business analytics in order to identify the right product placement in stores. Bajari *et al.* 2019, study the impact of more data on the demand forecasting system for Amazon and find more data improves demand forecasts over time, though with diminishing marginal utility. Davenport *et al.* 2007 even present a case study that highlights how at times using marketing analytics may end up revealing so much about the customers that it might lead to a violation of customer trust. Even though we cannot use these studies to claim robust evidence of a positive impact of analytics on firm performance, these studies are useful to further develop our understanding of the use of analytics in organizations. Nair *et al.* 2017 use a randomized trial at a single firm, to show an increase in the theoretical spending of consumers as a result of the firm using an improved customer targeting tool. While the study isolates a causal impact of a sophisticated targeting technology on the firm, they are unable to provide insights on the individual interaction of a manager with a complete system of analytics technology.

Moving on from the single firm case study based approach, Germann *et al.* 2013, use data from a survey run with 212 senior executives of Fortune 1000 firms, to study the impact of the use of marketing analytics on the performance of the firms. They complement the performance data from the survey response with firm-wise actual income and asset information. Their study finds that marketing analytics is positively associated with firm revenue. Further they also highlight several moderating factors such as support from the top management team, analytical skills of employees and capturing of appropriate data, which are essential to ensure the effectiveness of marketing analytics. The paper however does not consider the impact of the self-selection bias of the Fortune 1000 firms that chose to adopt marketing analytics, on the performance metric of the firms. One could argue the presence of several unobservable variables that could be causing an effect on firm performance. The authors acknowledge this gap and only claim a correlation between firm performance and marketing analytics without commenting on causality. Further, this study also does not provide insights on the interaction of the individual managers with the analytics technology. Another study conducted along similar lines is by Brynjolfsson *et al.* 2011, which provides evidence of a positive connection between data-driven decision-making and firm productivity, using data from 179 large publicly traded firms. While they do use an instrument variable approach to take care of reverse causality and potential endogeneity, they still are unable to find a causal relationship between firm profits and use of data-driven decision-making, even though the impact on sales seems to be significant.

In intent, the closest paper to our study is Berman & Israeli 2021, although the nature of the intervention, the context and the identification strategy are all quite different. They use a quasi experiment that identifies the effect of analytics on firms utilizing staggered adoption of analytics and panel data. They also show mechanism evidence i.e., actions taken by the online retailers across advertising, pricing and adoption of other technologies. However, similar to the other papers listed earlier, their study too, doesn't look at the impact of marketing analytics on an individual manager and the change in the manager's performance due to interaction with the technology, rather it studies its impact on the firm level only. Next, their dependent variable is firm revenue, but the impact on overall benefit to the firm as a result of adopting analytics, in terms of firm profitability, can't be concluded from their study. Since one of the key identification techniques they use is staggered adoption of the analytics technology, there could be some self-selection issues, even though the authors present various results using matching as well as use of instrument variables to show robustness. Our field experiment, involving hundreds of firms in which the technology intervention is at the level of the individual manager running the business, provides us a clean causal way to analyze the impact of marketing analytics at an individual manager level. Thus, we are able to provide insights on the changes in actions as well as aptitude of the individual manager as a result of marketing analytics adoption. We also study the impact of the analytics intervention on firm profitability along with firm sales, thereby allowing us to conduct a cost benefit analysis of analytics adoption.

The literature also provides some evidence on possible negative effects of adoption of analytics by firms. Research shows that for corporate decisions in an uncertain environment, both intuition as well as analysis are used, with intuition overpowering analysis in most cases (Huang & Pearce 2015). Due to the limited availability of time, managers worry that marketing analytics would slow them down in return for marginal or no improvement in performance (Harari 1996). Researchers have also made a case for intuition, interpersonal interaction and judgmental decision-making, stating that unlike scientists, managers do not always have the time for ordered rational analysis (Simon 1987, Barnard 1936). Some other concerns include abstraction from reality and analysis paralysis (Peters and Waterman 1982). In the absence of a study that provides a return on investment assessment for the adoption of analytics, or conclusively shows a positive causal impact on the sales and profits of firms, it could be possible that the adoption of analytics leads to a negative impact or no impact on the firm's performance. Based on these studies and the above discussion, we make our final hypotheses.

**Hypothesis 3** *Usage of Ed-Fintech (with marketing analytics) increases a firm's financial performance (in sales and profits).*

**Hypothesis 4** *The main effect of Ed-Fintech on financial performance is mediated by two mechanism channels: the improved mental performance (of entrepreneurs); and the improved managerial performance (of firms).*

Through our field experiment, we test for all these four hypotheses by providing initial causal evidence of what happens to firms when they get exposed to a marketing analytics solution that nudges them to shift to a data and analytics-based approach for their business.

# TECHNOLOGY INTERVENTION

The intervention ran for nine months. Our main objective was to introduce marketing analytics into firms that have been unexposed to the use of data or analytics in the past. Thus we needed a manipulation that could help these small Rwandan firms in – i) capturing the business data which would act as the input for marketing analytics, ii) performing the basic analytics and presenting simple tables and data visuals that could be insightful for the business and iii) understanding the analytics output that gets generated as an end product of this manipulation. For this purpose, we designed a "Market Manager" mobile phone application (app) which would enable the firms to both record the information and perform the analytics on the recorded data which could then be presented to the firms for use. The app enhances the firm owner's ability to access, track and take action on marketing analytics. It was important to ensure that the application is user-friendly and easy to understand, especially since the majority of firm-owners had not gone to college and many of them had never used a smartphone before. The exposure to a marketing analytics solution for the firms in our sample provided the firms in our sample with relatively simple statistics and visual representation of their business data.

We provided an Android smartphone with a fast and stable internet connection to the treatment and placebo entrepreneurs. On each of the smartphones provided to the treatment firms, the Market Manager application was installed and the entrepreneur was made to log in using a unique ID and password. The entrepreneur used the mobile application for both data entry and to look at the analytics results which the app generated each month based on the data that was entered by them. We also hired a team of 18 data analysts and an on-ground research manager to oversee the team of data analysts (and conduct surprise visits to keep a check on the data analysts). Each data analyst was in-charge of managing about 15 treatment firms. The job of the data analysts was two-fold. First, they helped the entrepreneur in understanding the data entry process in the app both at the daily and weekly levels. Second, they helped the entrepreneurs interpret the analytics output of the application by linking it to the data that they had entered into the application. Critically, however, these analysts provided *no* consulting or inputs into how the owners could use the data for decision-making. See Appendix Figure A1 for a schematic of the intervention set-up. As mentioned earlier, most of the entrepreneurs in our sample were not technologically savvy and many of them were using a smartphone for the first time, the initial support of the data analysts was required to ensure data entry compliance by the firm owner.

For the first two months of the intervention (July to August 2019), the data analysts visited the entrepreneurs on a weekly basis to familiarize them with the smartphone, the application use, what each data entry question in the app meant and most importantly, how they could enter data into the app. After two months, the data analysts visited each treatment entrepreneur on a monthly basis to explain the analytics output from the application. These monthly visits continued till January 2020. Overall, the feedback that we collected from the treatment group at the end of the experiment shows that the firms found the marketing analytics solution useful. On a scale of 1 to 7 (1 corresponds to ”Strongly Disagree” and 7 to ”Strongly Agree”), on average, the entrepreneurs rated their satisfaction with the intervention as 6.28. On whether this Ed-Fintech tool represented a good value for their time, they provided an average rating of 5.55. About 76% of the entrepreneurs were willing to pay for the intervention if it had not been offered for free.

The app focused on four key aspects of the business for recording data as well as conducting analytics – daily sales, products, customers and marketing activities. Below we describe in detail each of these. The reason we focused on these topics which covered revenue, product margin analysis, customer segment analysis, promotions and customer relationship, was that these form a key part of the syllabus of the core marketing course at most business schools. We looked at the syllabus for the introductory marketing core course at the top 10 B-schools as per Financial Times rankings and these topics formed a part of each of their curriculum. These topics, embedded in our analytics app, are central to Marketing and are considered the basic tools that managers can equip themselves with in order to improve the decisions they make regarding any business.

**Market Manager Application: Data Entry (Inputs)**

The entrepreneurs were expected to enter four sets of data into the app periodically. First, the daily sales amount of the products they sold (in Rwandan Francs) was to be entered by the entrepreneur each day after they closed their shop. Next, at a bi-weekly frequency, the products, marketing activities and customer data were entered. The first and third weeks of the month were dedicated to the entry of product and marketing activity information and the second and fourth weeks were dedicated to capturing customer information. The product data captured included sales, price and cost for each of the top three selling products for the firms. The marketing activity data captured included the number of times the firm had changed the price of some product in the past week to promote sales, the number of times promotional activities were undertaken by the firms (e.g. flyers, discount coupons, surprise gifts etc.), and the number of times the firms’ owners interacted with their customers (to understand their needs, to build a closer relationship with their customers, to enquire about customer satisfaction and to enquire about customer appetite for a new or improved product). The customer data was captured for loyal, irregular and new customer segments and for each segment it included the number of customers, basket size of purchase, business clients and the number of customers from outside their neighborhood. Some snapshots of the app and the data recording process can be seen in Appendix Figure A2.

**Market Manager Application: Analytics Reports (Outputs)**

Each month, based on the data captured for the month, the application generated a standard set of predefined analytics which included simple statistics and visualization of the data entered. The output was available to the entrepreneurs in the mobile phone app. In addition, every month, the data analysts delivered a hard copy of the same analytics report that was available in the app to the firm owner (about 35 pages in total). The data analyst then sat with the entrepreneur and explained how each table and graph in the report was developed. For these entrepreneurs who were not used to looking at any data related to their business, the analytics could be overwhelming to understand on their own and hence the data analysts provided them with explanations.

The analytics output had four sections to it, which mapped well to the data entry sections. The first part was the sales section which presented a summary of the daily, weekly and monthly sales trends along with the average sales numbers across all customers. The month-on-month sales graphs were presented to help the entrepreneurs get a picture of their firm performance and how it increased or decreased across time. The second section of the report was on products (top 3 selling products of the entrepreneur). For each of the top three products, it provided the over time (weekly, monthly) volume sold, average margin, sales value, and profit value. The pie chart and bar chart of the volume sold, and profits earned for each of the products could help the entrepreneur clearly view which product sells more in quantity and which helps them generate more profits. The third section of the report was on customers (loyal, irregular and new customer segments). This part presented over time (weekly, monthly) customer-segment-wise average basket size per customer visit, customer count and amount of sales. Here too the data visualization in terms of pie charts and bar charts, could help the entrepreneur compare the customer segment-wise performance, e.g., it enabled the firm-owner to view which segments were driving maximum revenue and by how much. Finally, the marketing activities section of the report presented the time trend across weeks, of the marketing activities (promotions, price changes, customer contacts for post-purchase satisfaction etc.) undertaken by the firm. Appendix Figure A3 shows the images of some of the output screens from the app that have the analytics results, Appendix Figure A4 shows snapshots of the analytics output in the report which was used to print out the hard-copy. Each entrepreneur in the treatment group received 7 analytics reports in total at end of each month from July 2019 to January 2020.

**Actions Based on the Analytics**

The mobile application as well as the analytics report supplied to the entrepreneurs as a hard copy provided a standardized list of generic actions owners could take in each section. All owners could access this list which was not customized in any way. For example, the sales section provided a list that included the question "What can you do to increase the number of units sold?" with actions such as lowering prices. The list was pre-coded into the app even before the launch of the intervention and did not change over time. Indeed some actions would have been inappropriate in the context of a specific firm. The list was included to make it comparable to dashboards available on similar commercial software.

To reiterate, and importantly, none of the data analysts provided any information or advice to the entrepreneurs on how to use the analytics output in their business. The data analysts were trained to specifically provide the entrepreneurs an understanding of how the data entry and analytics in the application work. In fact, they were specifically told not to provide any additional advice to the entrepreneurs on how to use the analytics results.

# RESEARCH DESIGN

To empirically identify the impact of the Ed-Fintech solution (with marketing analytics) on firm performance would be difficult using observational data. This is due to – (1) difficulty in getting data for marketing analytics adoption, i.e. when firms start to record, aggregate and analyze data from their business for the first time. It may not be possible to identify firms moving from a clean slate where there is no analytics use, to a scenario where they start using data and analytics for their business. In most cases, the firms for which data are publicly available are already exposed to analytics in some form and may be using it to arrive at decisions related to their businesses.

Hence, they will not be suitable candidates for analysis. (2) Even if we are able to identify such a data-set of firms beginning to adopt marketing analytics, we would still have endogeneity concerns, since firms with certain internal characteristics or external situations may be more likely to opt for analytics use. If these internal or external variables are also correlated with firm performance, it would lead to incorrect causal interpretations of the impact of the marketing analytics solution on firm sales or profits. (3) We may also face the problem of reverse causality, wherein changes in firm performance may influence the analytics adoption decision of the firms rather than vice-versa. Given these identification concerns, running a randomized controlled field experiment addresses these issues and provides us with clean causal inferences of the impact of the Ed-Fintech solution (with marketing analytics) on firm sales and profits.

**Empirical Context: Rwanda**

The choice of Rwanda for this study was made since we could easily identify small firms which were completely unexposed to any form of data analytics and hence, as discussed earlier, this provided us with an opportunity to measure the impact of Ed-Fintech solution (with marketing analytics) on these firms. We could exogenously shift the exposure to marketing analytics for a random subset of the firms and measure the changes, if any, amongst the firms. Further, in recent years, Rwanda has had a strong government push towards a technology revolution to make it the next Silicon Valley. The government has built initiatives to expand internet connectivity as well as access to technology with the goal of transforming their society into a highly digitized country. This push came in handy to us, from a logistics standpoint, as internet connectivity was stable for our recruited sample. Further, the government's zeal for improving small business performance helped us to get the necessary permissions from the government for running the study.

**Recruitment and Sample**

We obtained our sample of entrepreneurs through door-to-door recruitment of firms. We hired an on-ground team of 20 research assistants who canvassed the streets of Kigali, Muhanga and Musanze to recruit firms for our study. They approached a total of about 15,000 firm owners of which 3,140 completed the recruitment survey. Then, we used a Growth Index to identify the top 1,500 firms that were growth-oriented and hence most suitable to be a part of this study. The Growth

Index was calculated using the data collected in the recruitment survey and is a sum of 10 key components evaluated on a total of 100 possible points. These 10 components covered metrics that helped us assess the firm's and entrepreneur's characteristics[2]. Using the Growth Index for selecting our sample ensures that we include firms that are operational, will be willing to participate and adopt our intervention and have a proper physical structure (which increases the possibility of being able to locate these firms a few months after launching the intervention). We excluded the firms which were at subsistence levels, unwilling to participate in our intervention and without a fixed physical structure.

### Baseline Data Collection

We reached out to these 1,500 shortlisted firms and were able to find 954 firms during the baseline, that agreed to be a part of the project. However, we experienced technical delays in the application development and ran another baseline about 3 years later when we were finally ready to launch the intervention[3]. The detailed timeline for the project is presented in Appendix Figure A5. This final baseline (which is what we are using in this paper) consisted of 550 firms, the remaining firms from the previous baseline were either not found or refused to be a part of the study. The baseline survey contained questions on the business and entrepreneur background and business performance. The firms in our sample on average had 0.5 full-time employees, an asset value of 2,640 USD, last month's sales of 707 USD and last month's profits of 113 USD. About 45% of the entrepreneurs in our sample were female; average age was 37 years and only 13.5% of the entrepreneurs had attended a prior business education or training program. The firm owners were not highly educated either and more than 87% of them never went to college. Due to these characteristics of the sample, we ensured that the manipulation we introduce to increase the analytics exposure of the firms was simple and easy to understand. We will describe this in more detail in the subsequent sections.

[2]The 10 components are - firm endowments (which is the start-up capital) if the firm has an established business location, number of paid employees of the business, business effectiveness (e.g. record keeping, separate finances), experimentation (new activities or innovations), entrepreneur education (traditional schooling and business training), previous work experience of the entrepreneur (salaried job or a job at a larger/corporate environment), entrepreneur's exposure (if the entrepreneur has visited or lived in other countries), external research (considering others' perspectives) and finally enumerator's evaluation (i.e. enumerator assessment of the entrepreneur)

[3]We ran one more baseline with 1044 firms, approximately a year after completing the first baseline. We tried to contact the top 2000 firms as per our original recruitment survey, so as to be able to get a large enough sample size, of which we were able to find 1044 firms who agreed to be a part of the study. This baseline was conducted in anticipation of launching the intervention, however we experienced a major bottleneck in the application development which resulted in further delays.

**Randomization and Balance Checks**

After we conducted the baseline survey (May - June 2019) for the 550 firms in our sample, we randomized them into the three experimental groups – Treatment, Placebo and Control. Group 1 was the treatment (n=250) which received the Ed-Fintech (with marketing analytics) intervention (smartphone and app), Group 2 was the placebo (n=50) which received just the smartphone with the internet connection and Group 3 was control (n=250) which received no experimental manipulation. The Placebo group was incorporated into the experiment so we could rule out alternative explanations linked to exposure to the internet or smartphone use.

We conducted balance checks at the beginning of the intervention to test the randomization. These are reported in Appendix Table A1. The data from the baseline survey was used for conducting the balance checks on the sample. We used 39 variables in total, which include firm performance variables, business characteristics and entrepreneur characteristics. The firm performance variables include the sales and profits of the firm. The business characteristics include the number of employees (full-time and part-time), assets (total value, tangible assets, working capital), number of business partners, products (number of products, product margins) and customers (number of regular and new customers, basket size of purchase). Finally, the entrepreneur characteristics include education, age, prior ownership of a business and orientation towards the use of data. As can be seen from Appendix Table A1, the sample is balanced when tested across these variables at the baseline.

**Endline Data Collection**

Post randomization, we started the Ed-Fintech (with marketing analytics) intervention in July 2019 which continued for seven months up to January 2020. Finally, seven months after having started the intervention, we conducted the endline survey from February to March 2020, which concluded right before the country-wide lock-down due to COVID-19 began in Rwanda (Detailed timeline in Figure A5). The endline survey included most of the variables measured at the baseline such as entrepreneur and business characteristics. The focus of the endline survey was also to collect data on the mechanism which included marketing activities, spill-over activities to the finance and operations functions of the firm and the entrepreneur level ability.

We also repeated the balance checks at the endline for the firms that could be tracked post attrition (n=527) and again the sample was balanced (results presented in Appendix - Table B1). This makes us confident that the randomization worked well and that attrition did not cause the sample to become unbalanced. However, in the results section of the paper, we conduct robustness checks, by running LASSO regressions for the main effects as well as the mechanisms by including all the variables on which we conducted the balance checks as covariates.

**Attrition and Survival Checks**

As mentioned earlier, we were able to conduct the endline survey for 527 of the 550 firms in our sample, thus experiencing attrition of 23 firms that we were unable to contact or locate. These attrition numbers are quite low and non-systematic between the experimental groups. The same can be seen in Appendix Table A2. Of these 527 firms, 33 firms shut down due to various reasons. Table A2 shows that firm survival is about 4.3% higher for the treatment group as compared to the control. The results that we report in the later sections are all ITT (Intention to Treat) effects. But, we also report the main effects conditional on survival and the results are robust.

**Empirical Specification for Analysis**

The empirical specification we follow is an ANCOVA to measure the ITT (Intention to Treat) effects of being offered the treatment and the placebo. We define the exact specification below for firm ‘i’ in the Endline follow-up survey:

$$Y_i = \beta_0 + \beta_1 Treatment_i + \beta_2 Placebo_i + x_i'\theta + \gamma Y_{i,t=0} + \varepsilon_i \tag{1}$$

Here $Y_i$ is the given outcome variable measured post-treatment, $Y_{i,t=0}$ is its baseline value and $\varepsilon_i$ is the error term. $\beta_1$ (and $\beta_2$) will then provide the intent-to-treat effects, which are the effects of being assigned to the treatment (or placebo) relative to being a firm in the control. Since random assignment is at the individual firm level, robust (Eicker-Huber-White) standard errors are used. Even though our sample is balanced, as a part of the robustness checks, we use the double-lasso method of Belloni *et al.* 2014 to select the covariates to include as control, using the list of variables that are used in the balance checks. These controls should also help in correcting for any non-random attrition related to these baseline variables, even though the attrition does not seem to be systematic. We focus on intention-to-treat effects for the most part of the analysis as it provides an unbiased estimate of the impact of the treatment on firm performance (e.g., sales, profits). These ITT results represent the cleanest identification of treatment effects given they rely on an exogenous source of variation (randomization into experimental groups).

We first report the impact of Ed-Fintech (with marketing analytics) on the performance of the entrepreneur by showing evidence of the entrepreneurs' interaction with the analytics technology and the impact on their mental performance as a result of the technology use. Then we present evidence on the firms' managerial performance that led to changes in the product-related and accounting-related business practices. Finally, we show the results for firm performance measures of sales and profits. All the regressions, unless otherwise noted, report the intention to treat effects and thus include all firms including non-survivors (except for the attrited firms).

## ANALYSIS AND RESULTS: INDIVIDUAL ENTREPRENEUR CHANGES

### Manager-Technology Interaction

We begin by looking at the results of entrepreneurs' interaction with the Ed-Fintech application. We find that during the initial months of the intervention, the entrepreneurs' interaction with the application was around 68% which is quite low (as shown in Figure A6). But the firms experienced a ramp-up period in compliance with data entry for the initial two months of the launch of the intervention. Though the compliance to data entry was low during July 2019, it grew with time and from September 2019, we experienced high data entry compliance rates of more than 90 % which continued till January 2020. The high data entry rate shows that the entrepreneurs were not missing out on capturing the daily and weekly data entry schedules. The monthly report provided to the firms helped in setting up this positive feedback loop as entrepreneurs realized the benefit of the marketing analytics reports which further helped in boosting their data entry compliance.

We also check for entrepreneurs' compliance with the use of marketing analytics output and the reports in their business. We present results of manipulation checks to test if the treatment entrepreneurs utilized the analytics results provided to them in the mobile application and the reports. We measured some metrics that are directly linked to the analytics topics presented to the entrepreneurs each month in the report in order to check if the entrepreneurs were following those topics closely and were getting accustomed to using the analytics results. We find that the treatment firms proved to be significantly higher in the use of overall data analytics, sales analytics, customer-segment information and product-related insights (Table A3), which were the exact subjects on which the analytics results were provided. This shows that the treatment firms were paying attention to the topics in the analytics report, just as we intended.

Lastly, to assess how the entrepreneurs felt after interacting with the analytics application as a part of this intervention, we collected feedback from the treatment group at the end of the experiment. It shows that the firms found the marketing analytics solution very useful. On a scale of 1 to 7 (1 corresponds to ”Strongly Disagree” and 7 to ”Strongly Agree”), on average, the entrepreneurs rated their satisfaction with the intervention as 6.28. On whether the analytics solution represented a good value for their time, they provided an average rating of 5.55. Ex-post, about 76% of the entrepreneurs were willing to pay for the Ed-Fintech tool if it had not been offered for free.

These results suggest that managers might experience a ramp-up period when a new technology like an Ed-Fintech (with marketing analytics) solution is introduced to their business. But the managers must keep utilizing the technology fully and frequently for them to realize the benefits it can add to their business.

**Impact of Ed-Fintech on Mental Performance**

Hypothesis 1 proposes that one of the key mechanisms through which marketing Analytics impacts the sales and profits of the firms could be by enhancing the mental performance of the firms. To test this mechanism, we study the difference in reasoning, logical ability, memory and numerical ability between treatment and control entrepreneurs. We use a combination of six psychological tests in order to measure the ability of the entrepreneurs to work with numerical problem solving and logical reasoning. The Cognitive Reflection Test, Digit Span Test, Raven’s Test and Numerical Aptitude Test are strictly objective in nature; entrepreneurs were presented with a set of problems with a correct answer, and they had exactly 60 seconds to solve each problem. The Mental Math

Calculation and Numerical Orientation Tests are self-report tests, where the entrepreneurs are asked about their ability and preference towards the use of numbers, data and graphs. Figure 1 presents the graphs of the entrepreneur performance on each of these six tests, across the three experimental groups. Looking at these graphs, it seems the Treatment entrepreneurs are having better mental performance than the other groups which is encouraging. Table 1 shows the regression results for the tests that we conducted to measure the entrepreneur's numerical reasoning and logical ability as well as their preference for use of data and analytics. We see that on each of those tests the Treatment group firms perform significantly better than the control and the placebo firms. The overall analytics ability index is also significantly higher for the Treatment group, which shows support for hypothesis 1; adoption of the marketing analytics tool makes the entrepreneurs more numerically able.

Even though we had imposed a strict time limit on the entrepreneurs to answer each of the questions in the objective tests, we also test for the difference in interview duration across the experimental groups as a part of our robustness checks (See Appendix Table A4). But we did not find the interview duration to be significantly different across the groups, which assures us that the results that we show in this section are not caused due to a difference in the attention towards the survey across the experimental groups. We also wish to highlight the unique nature of our evidence regarding entrepreneurs' improvement in ability at a mental level as a result of interventions aimed at improving firm sales or performance.

## ANALYSIS AND RESULTS: OVERALL BUSINESS CHANGES

### Impact of Ed-Fintech on Managerial Performance

Next, we test Hypothesis 2, to see if there are any spillovers of the marketing analytics technology on managerial performance. We test for the differences in the adoption of Product-related and Accounting-related management practices across firms.

Figure 1: Model-Free Evidence for Entrepreneur's Analytics Ability

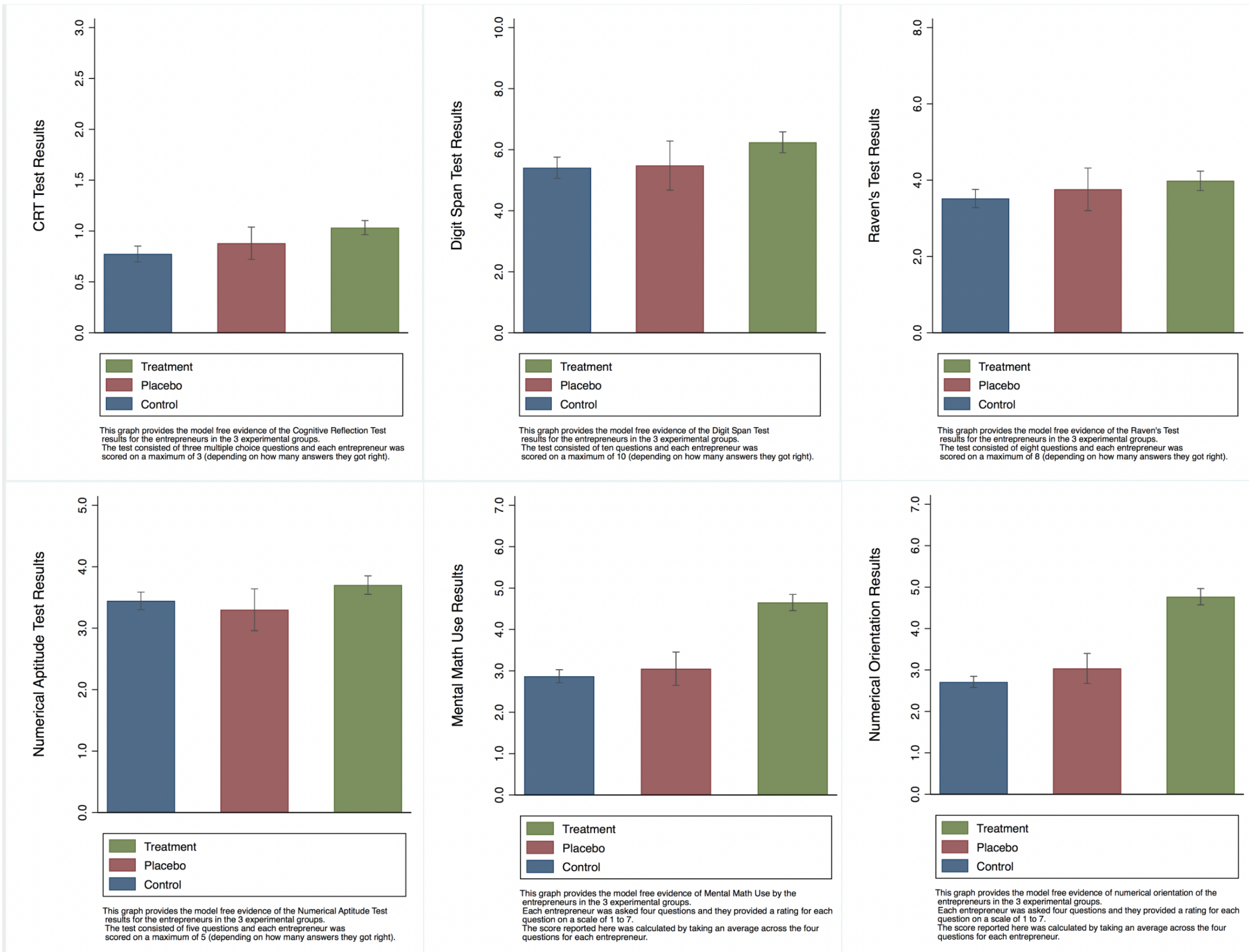


Table 1: Impact of Marketing Analytics on Entrepreneurs' Analytical Ability

| | (1)<br>CRT | (2)<br>Digit Span Test | (3)<br>Raven's Test | (4)<br>Numerical Aptitude | (5)<br>Mental Math Uses | (6)<br>Numerical Orientation | (7)<br>Analytical Ability Index |
|---|---|---|---|---|---|---|---|
| Treatment | 0.260*** | 0.829*** | 0.464*** | 0.258** | 1.782*** | 2.057*** | 0.763*** |
| | (0.0531) | (0.247) | (0.177) | (0.105) | (0.129) | (0.121) | (0.0611) |
| Placebo | 0.106 | 0.0700 | 0.241 | -0.144 | 0.181 | 0.324* | 0.108 |
| | (0.0879) | (0.435) | (0.301) | (0.183) | (0.215) | (0.192) | (0.0923) |
| Mean of DV: Control | 0.774 | 5.410 | 3.519 | 3.444 | 2.869 | 2.711 | 0 |
| SD of DV: Control | 0.614 | 2.716 | 1.878 | 1.121 | 1.254 | 1.053 | 0.595 |
| Effect Size in SD: Treatment | 0.423 | 0.305 | 0.247 | 0.230 | 1.422 | 1.952 | 1.284 |
| Effect Size in %: Treatment | 33.53 | 15.33 | 13.20 | 7.497 | 62.11 | 75.85 | |
| Effect Size in SD: Placebo | 0.172 | 0.0258 | 0.128 | -0.128 | 0.144 | 0.307 | 0.182 |
| Effect Size in %: Placebo | 13.69 | 1.293 | 6.854 | -4.168 | 6.300 | 11.94 | |
| Obs. | 527 | 527 | 527 | 527 | 527 | 527 | 527 |
| $\beta\_treat = \beta\_placebo$ | 0.0744 | 0.0804 | 0.463 | 0.0303 | 2.17e-12 | 3.12e-16 | 2.99e-11 |

Notes: This table summarizes analysis for the effect of marketing analytics on entrepreneurs' analytical ability (from baseline to endline). The results in each column represent the intention-to-treat effects (ITT) of the randomly assigned intervention to a treatment group entrepreneur. Column (1) presents a measure for the Cognitive Reasoning Test score (it is measured on a scale of 0 to 3). Column (2) presents a measure for Digit Span Test score (it is on a scale of 0 - 10). Column (3) presents a measure for the Raven's Test score (it is on a scale of 0 - 8). Column (4) presents a measure of the Numerical Aptitude Score (it is on a scale of 0 - 5). Column (5) presents a measure of the Mental Math Use (it is self-reported on a scale of 1 to 7). Column (6) presents a measure of Numerical Orientation (it is self-reported on a scale of 1 to 7). Column (7) presents an index measure for Entrepreneurs' Analytical Ability. Each of the six analytical measures were standardized and then the average of these values was computed to construct the overall 'analytical ability' index. All regressions include firms that failed as at endline (non-operational with zero monthly sales or profits) as we were able to run these tests with the owners of firms that were shut-down too. Robust standard errors are in parentheses. P-values are highlighted as: $p < 0.1$ $p < 0.05^{**}$ $p < 0.01^{***}$

First we look at the model-free evidence in Figure 2. The graphs suggest that the treatment group seems higher in the adoption of best practices in business across products-related and accounting-related activities. Next, we look at the regression results. Table 2 shows that marketing analytics impacts the product-focused activities that the firms adopt, such as changes in prices of products, improvement/addition of products, inspecting the products for their quality etc. The overall product management activities index is also significantly higher for the treatment group as compared to the control and the placebo.

While our marketing analytics intervention had a direct impact on product management practices of the firms, we also looked at the impact on the accounting practices. Table 2 shows the impact of marketing analytics on accounting or record-keeping practices of the firms. We see that the treatment firms start recording and creating documents based on financial data such as - creating an income statement, creating a future budget and monitoring the cash flow of the business. Figure 3 shows some of the data and records that the treatment firms started maintaining to aid them in their business.

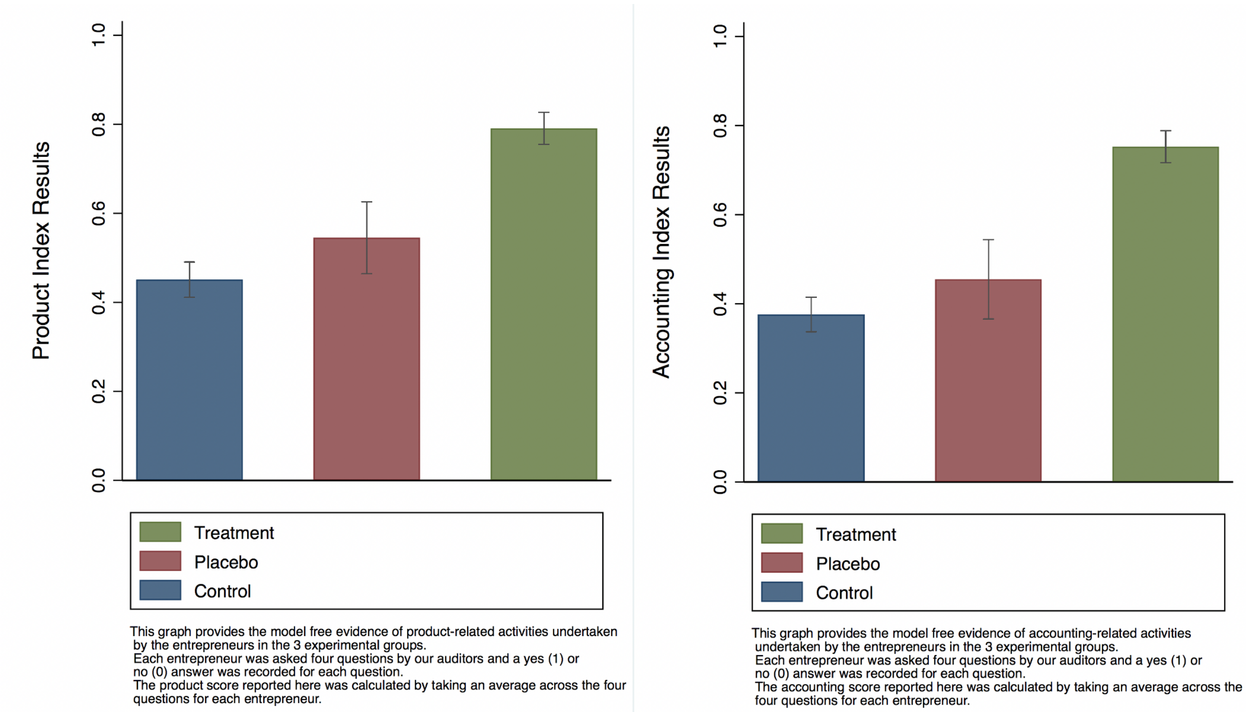
As a robustness check, we test the impact of the marketing analytics tool on business activities such as production and process improvements. These activities are seemingly unrelated to the exposure to marketing analytics and hence we do not expect them to be influenced by the analytics tool adoption. Appendix Table B2 shows the impact of Marketing Analytics on these activities. We do not find any significant impact on these operational activities, as predicted. Hence, again we show that hypothesis 2 also holds as we conclude that the adoption and use of the Ed-Fintech tools (with marketing analytics) led the firms to improve their product and accounting management practices.

**Impact of Ed-Fintech on Financial Performance**

We first present some model-free evidence by plotting the graphs of the monthly sales and profits of the firms. Looking at Figure 4 (Additional evidence from Figures A7 and A8 in Appendix), it seems that the treatment is doing much better than the control and placebo groups.

It can be seen from the figures that the sales and profits for the pre-intervention period were not

Figure 2: Model-Free Evidence for Business Actions




very different between the treatment and control groups, but post the intervention, we see an improvement in the treatment group's performance relative to the control. Next, we present the regression outcomes (note that the values for sales and profits are presented in 1000 RWFs). The results for the main effects on sales and profits are presented in Table 3.

It shows the mean effect on the two measures of performance – average monthly sales and average monthly profits. The average monthly sales is the average of the last month's sales (for Jan 2020) and the typical month's sales (for the months of Oct-Dec 2019) of the firm. Similarly, the average monthly profits is the average of the last month's profits (for Jan 2020) and typical month's profits (for the months of Oct-Dec 2019).

We also create an overall index – Sales Profit Index, which is an average of the standardized IHS (inverse hyperbolic sine) transforms of the sales and profit measures of performance listed above. This index helps us in avoiding multiple hypothesis testing and captures all the relevant

Table 2: Impact of Marketing Analytics on Business Activities

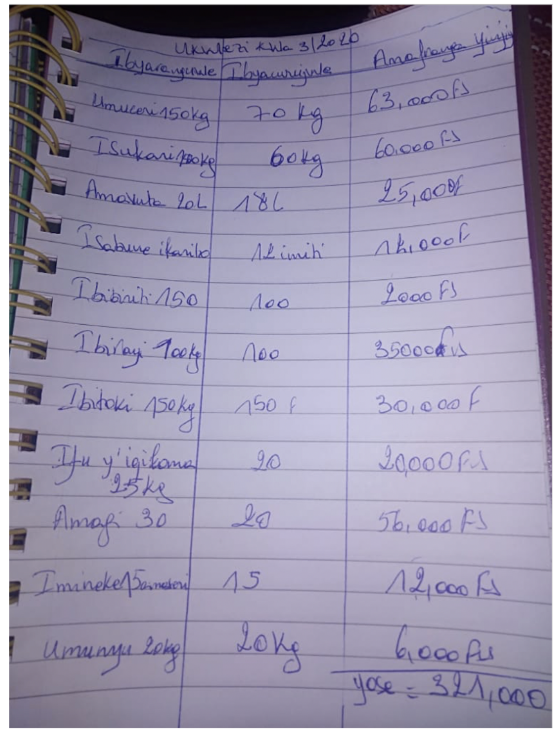
| | Product Related | | | | Accounting Related | | | | Overall |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| | Change Prices | Improve/Add Products | Inspect Products | Monitor Product Inventory | Separate Business Finances | Create Income Statement | Create Future Budget | Monitor Cash Flow | Analytical Activity Index |
| Treatment | 0.489*** | 0.492*** | 0.238*** | 0.141*** | 0.376*** | 0.421*** | 0.433*** | 0.276*** | 0.359*** |
| | (0.0399) | (0.0396) | (0.0367) | (0.0404) | (0.0417) | (0.0398) | (0.0414) | (0.0357) | (0.0235) |
| Placebo | 0.163** | 0.168** | 0.00310 | 0.0431 | 0.0983 | 0.129* | 0.0533 | 0.0356 | 0.0866** |
| | (0.0766) | (0.0727) | (0.0739) | (0.0719) | (0.0777) | (0.0678) | (0.0744) | (0.0731) | (0.0411) |
| Mean of DV: Control | 0.297 | 0.192 | 0.657 | 0.657 | 0.402 | 0.151 | 0.307 | 0.644 | 0.413 |
| SD of DV: Control | 0.458 | 0.395 | 0.476 | 0.476 | 0.491 | 0.358 | 0.462 | 0.480 | 0.270 |
| Effect Size in SD: Treatment | 1.067 | 1.246 | 0.500 | 0.297 | 0.765 | 1.176 | 0.937 | 0.575 | 1.329 |
| Effect Size in %: Treatment | 164.5 | 255.8 | 36.24 | 21.53 | 93.52 | 279.8 | 141.1 | 42.81 | 86.74 |
| Effect Size in SD: Placebo | 0.356 | 0.424 | 0.00651 | 0.0906 | 0.200 | 0.361 | 0.115 | 0.0743 | 0.321 |
| Effect Size in %: Placebo | 54.85 | 87.04 | 0.471 | 6.561 | 24.48 | 85.89 | 17.37 | 5.532 | 20.96 |
| Obs. | 527 | 527 | 527 | 527 | 527 | 525 | 526 | 527 | 527 |
| $\beta\_treat = \beta\_placebo$ | 0.0000194 | 0.0000155 | 0.000858 | 0.161 | 0.000284 | 0.0000500 | 0.000000386 | 0.000490 | 4.33e-11 |

Notes: This table summarizes analysis for the effect of marketing analytics on activities that the business performs (from baseline to endline). The results in each column represent the intention-to-treat effects (ITT) of the randomly assigned intervention to a treatment group entrepreneur. These results are based on a Yes/No response on each of these activities, as recorded by the auditors in-person review of each of the firms in our sample. Column (1) presents a measure for changing the prices of products/services to increase total sales. Column (2) presents a measure for introducing new products/services, or improving your existing products/services, to provide more benefits to customers. Column (3) presents a measure for inspection of products to ensure they are of the highest quality. Column (4) presents a measure of monitoring stocks of supplies to prevent stock overflow or stock-outs. Column (5) presents a measure of keeping business finances separate from personal finances. Column (6) presents a measure of creating an income statement to track all the money that comes 'in' (sales) and goes 'out' (purchases, expenditures) from the business. Column (7) presents a measure for creating a budget that states how much is expected in sales and costs for a future period (e.g. next month). Column (8) presents a measure for tracking how much cash is available in the business to ensure there is enough money for daily operations to continue. Column (9) presents an index for the analytical activities performed by the business. This overall index is calculated by taking an average of each of the eight business measures. All regressions include firms that failed as at endline (non-operational with zero monthly sales or profits, and their business activity response is considered to be 'no'. All regression exclude the firms that attrited during the Endline survey round. Robust standard errors are in parentheses. P-values are highlighted as: $p < 0.1$ $p < 0.05^{**}$ $p < 0.01^{***}$

Figure 3: Examples of financial records maintained by firms

Daily product-wise revenue and cost information being noted for all sales

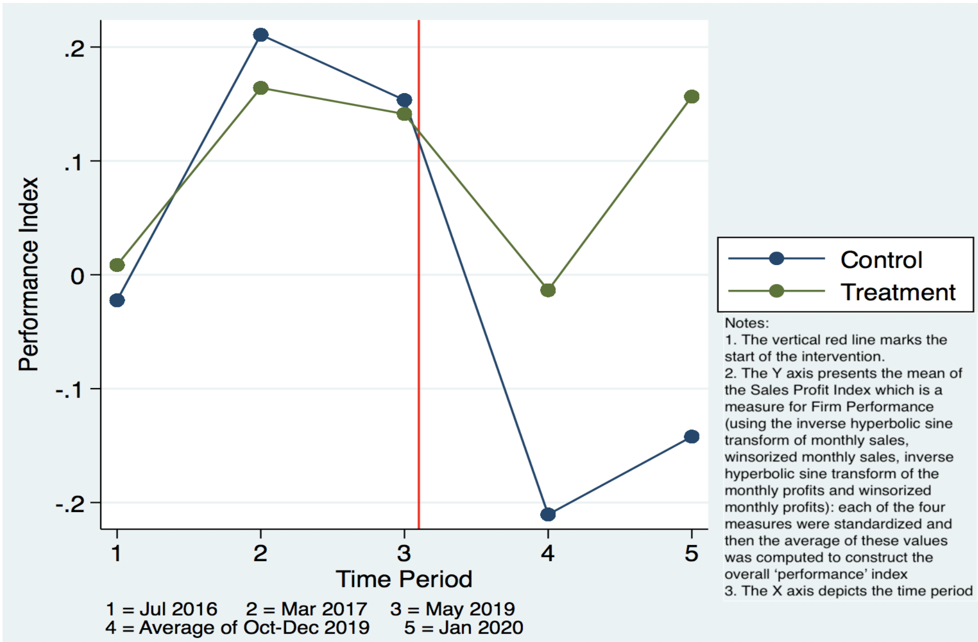
Stock for all products being noted and tracked



performance measures into a single metric (McKenzie 2017). Table 3 suggests that all of the sales as well as profits metrics are significant for the treatment firms but not the Placebo firms. The same is true for the overall Sales Profit Index as well. Looking at the last month's sales and profits, we see that the marketing analytics tool led to about 45 % improvement in sales and 36 % improvement in profits for the treatment firms. Since the placebo group does not seem to show any significant change in sales or profits, we can safely rule out alternative explanations such as the effects of the treatment group being driven by the exposure to a smartphone or the access to the internet.

***Robustness Checks:*** Also, looking at Figure 5, we see that the effects on performance are all across the distribution of the firms and are not being driven by a few outliers. This is encouraging to see since this means the intervention had an impact across different firm sizes. Lastly, we run

Figure 4: Model-free evidence of main effects - Performance Index




a set of robustness checks. We ran the same main effects analysis for survived firms only and the results continue to hold (See Appendix Table B3). This shows the effects are not just being driven by the extensive margin of improved chances of survival, but the intensive margin of actual firm performance is also improving for the treatment group.

We ran LASSO regressions for the main effects by including the baseline entrepreneur and business characteristics (Appendix Table B4). We also include another regression with all the entrepreneur and business characteristics as covariates as another robustness check and the treatment effects still hold in all these cases (Appendix Table B5). Finally, we also run the same main effects regression only on those firms which maintained records of their sales or profits at the baseline i.e., before the start of our intervention (Appendix Table B6). A smaller subset of our sample (only 104 firms) recorded their sales or profits at the baseline. We see that the direction of our results still holds post conditioning on baseline sales/profits recording, even though we lose out on the power of our experiment.

Note that we did not observe any increase in the time spent on the business by the treatment entrepreneurs. In Appendix Table B7 we see that the percentage of days in a month for which the shop is open did not change for the treatment firms across time.

We also compare the monthly sales data from the endline survey to the sales data as reported by the treatment entrepreneurs in the analytics app. We see that the correlation between the two is 97.44%. We see that the endline survey reported last month's sales tracks very well with the sales reported in the analytics application for the same period by the treatment entrepreneurs (Appendix Table B8).

We also provide additional evidence to support the main effects that we pick up, by looking at the product and customer-related outcomes (Appendix Table B9) of the firms. The product-related outcomes show that the treatment group sells more of their (top 3) products and ends up generating significantly higher revenue and profits from them too, as compared to the control group. The customer outcomes show that the amount of goods being purchased by customers from the treatment firms is increasing as are the referrals provided to other potential customers by the existing customers. These product and customer outcomes help us justify the increase in profits and sales of the firms that we capture in the main effects.

We present additional evidence of the robustness of the main effects by performing attrition bounding analysis (Appendix Table B10) and calculating the local average treatment effects (Appendix Table B11). We see that our treatment effects continue to hold in all scenarios of the attrition bounding analysis. Further, we see that the LATE (local average treatment effect) is higher than the ITT effect which proves that our treatment is working as we had expected.

Lastly, we see that the control firms are not experiencing statistically different sales if there is a competing treatment firm nearby (Appendix Table B12). This provides evidence that the treatment firms are not performing better at the expense of control firms of our sample. Overall, this analysis presents evidence in favor of hypothesis 3.

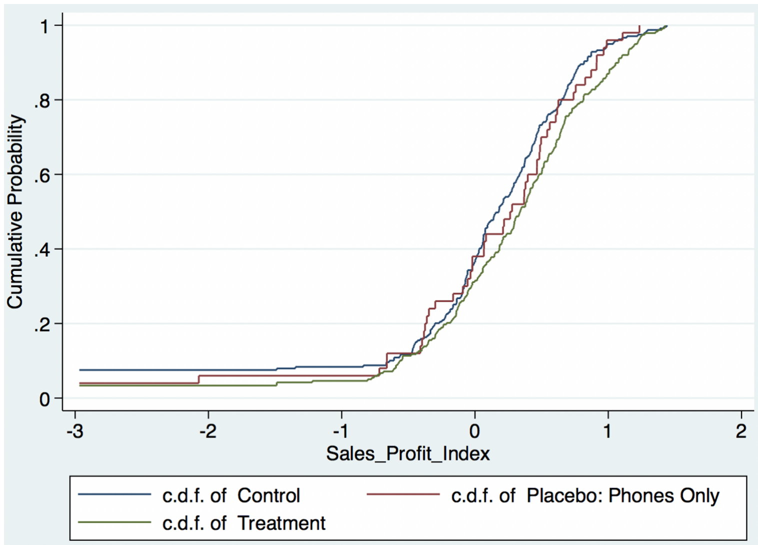
***Mechanism Analysis:*** Having established a significant increase in the main effect outcomes of the treatment firms, we now shift our focus to understanding the possible mechanisms that might be

Table 3: Impact of Marketing Analytics on Firm Sales and Profits

| | DV: Monthly Sales | | DV: Monthly Profits | | Overall |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | Average | IHS | Average | IHS | Performance Index |
| Treatment | 165.3*** | 0.795*** | 24.98*** | 0.621** | 0.250*** |
| | (58.60) | (0.293) | (7.939) | (0.263) | (0.0703) |
| Placebo | -35.20 | 0.255 | 11.88 | 0.475 | 0.0823 |
| | (81.65) | (0.499) | (12.03) | (0.398) | (0.0965) |
| Mean of DV: Control | 454.9 | 12.28 | 85.60 | 10.94 | 0 |
| SD of DV: Control | 706.5 | 3.633 | 79.29 | 3.217 | 0.814 |
| Effect Size in SD: Treatment | 0.234 | 0.219 | 0.315 | 0.193 | 0.307 |
| Effect Size in %: Treatment | 36.35 | 79.5 | 29.18 | 62.1 | |
| Effect Size in SD: Placebo | -0.0498 | 0.0703 | 0.150 | 0.148 | 0.101 |
| Effect Size in %: Placebo | -7.739 | 25.5 | 13.88 | 47.5 | |
| Obs. | 527 | 527 | 527 | 527 | 527 |
| $\beta\_treat = \beta\_placebo$ | 0.0193 | 0.257 | 0.304 | 0.698 | 0.0859 |

Notes: This table summarizes analysis for the main effect of marketing analytics on firm performance outcomes (from baseline to endline). The results in each column represent the intention-to-treat effects (ITT) of the randomly assigned intervention to a treatment group entrepreneur. Column (1) presents a winsorized measure for Average Monthly Sales (it refers to the average sales for the last full calendar month for the firm, which for our sample was January 2020) and the sales for a typical month (average for the months Oct 2019 to Dec 2020) : estimates after winsorizing each 1% on both tails. Column (2) presents an IHS transformed measure for Average Monthly Sales: estimates after transforming the average monthly sales with the inverse hyperbolic sine function. Column (3) presents a winsorized measure for Average Monthly Profits (it refers to the average profits for the last full calendar month for the firm, which for our sample was January 2020) and the profits for a typical month (average for the months Oct 2019 to Dec 2020) : estimates after winsorizing each 1% on both tails. Column (4) presents an IHS transformed measure for Average Monthly Profits: estimates after transforming the average monthly profits using the inverse hyperbolic sine function. Column (5) presents an index measure for Firm Performance (IHS last month's sales; IHS typical sales monthly; IHS last month's profits; IHS typical profits monthly): each of the four measures were standardized and then the average of these values was computed to construct the overall 'performance' index. Column (6) presents an index measure for Firm Performance (using IHS average sales monthly; IHS average profits monthly): each of the two measures were standardized and then the average of these values was computed to construct the overall 'performance' index. All regressions include firms that failed as at endline (non-operational with zero monthly sales or profits). Any firm growth values in levels (sales; profits) are listed as Rwandan Francs (RWF) in 1000s. The regressions also include: the baseline value of the dependent variable. The IHS results are robust to the scaling of the profits/sales numbers. Robust standard errors are in parentheses. P-values are highlighted as: $p < 0.1$ $p < 0.05^{**}$ $p < 0.01^{***}$

Figure 5: CDF of the Overall Performance Index




leading to these changes in sales and profits for the firms. We test if the mechanisms that we captured above are indeed mediating the main effect on firm sales and profits that we had shown earlier. We run the mediation analysis for numerical ability and management practices as constructs independently mediating the sales profit index of the firms. We find that for numerical ability, the average causal mediation effect (ACME) significantly mediates the main effect and explains 87.35% of the total effect (Appendix Table B13). Similarly, for management practices, we find the ACME to be very significant (Appendix Table B14). Within the assumptions of sequential unconfoundedness, these mediation tests support hypothesis 4 and provide further evidence that marketing analytics led to improvement in firms' performance through the mechanisms of improvement in numerical ability of the entrepreneurs and adoption of better business practices by the firms.

# CONCLUSION

Analytics technology has been gaining a lot of popularity, yet despite its prevalence there is a dearth of empirical evidence on the causal effects of such technology for stimulating changes at the entrepreneur level or the firm level.

We conduct a randomized controlled field experiment with 550 Rwandan entrepreneurs to identify the impact of an Ed-Fintech solution (with marketing analytics) on the entrepreneur-manager utilizing the tool and the overall business performance. The analysis results in four key findings. First, the interaction of the managers with the analytics tool had an initial ramp-up period of three months, due to which the application usage was low to begin with but owing to a positive feedback loop later usage rates increased to 90-95 %. Second, we find novel evidence of improvement in the mental performance (logical reasoning, memory and numerical calculations) of the entrepreneur-manager interacting with the technology. Third, at the firm level we see a spillover effect of technology usage which causes an improvement in the managerial performance of the firms across product-related and accounting-related practices. Finally, we show that the treatment firms increase monthly sales by 36.4 % and monthly profits by 29.2 % over the period of the study. This effect on financial performance of the firm is shown to be mediated by the mechanism channels of mental performance at the entrepreneur level and managerial performance at the firm level.

**Implications for Practice**

The results of this study have implications for multiple stakeholders. First, our findings should encourage *executives and managers* to incorporate elements of 'marketing analytics' into their future Ed-Fintech apps and platforms (whether intended for users internally or externally). They may also wish to consider designing these solutions in ways that facilitate full and frequent technology interaction by users (e.g., internal workers and managers; or external customers and entrepreneurs). Doing so can lead to improvements in their mental, managerial and financial performance.

Second, given the potential business and individual benefits, the study's results are also relevant to *entrepreneurs* running small and growing firms. A cost-benefit-analysis of our intervention shows that entrepreneurs can increase monthly profits by roughly $35 per month, while the total cost of the marketing analytics solution is about $25 per month (i.e., when not subsidized by our project). Thus, on average, entrepreneurs could obtain a net gain of $10 per month if they adopted such a technology on their own. In the future, as time and budget allow, entrepreneurs can assess investments in other business technologies that may improve their productivity and performance.

Third, our findings are relevant to *policymakers and impact investors* aiming to support small firms and promote financial inclusion, particularly in developing economies. The majority of firms in these contexts lack access to more advanced skills, technologies, and funding. While Ed-Fintech is not a one-size-fits-all solution, these types of digital technologies offer the promise of greater scalability and inclusivity. Moreover, as this study demonstrates, they also hold tremendous performance-enhancing potential. Ed-Fintech solutions should therefore be part of any policy-maker's toolkit in their battle to improve the human, managerial and financial capital of entrepreneurs operating in lower socio-economic markets.

**Use of marketing analytics in the aftermath of COVID-19**

On 14 March 2020 Rwanda recorded its first case of COVID-19. About a week later, the government declared its first country-wide lockdown to contain the spread of COVID-19, becoming the first country in Africa to declare a lockdown. Borders were closed, as was inter-city travel, and all non-essential businesses were shut-down while essential businesses (medicines, groceries etc.) were allowed to open under restrictions, for about a month. Then, by mid-January 2021 the country saw a renewed surge in COVID cases, thus leading to another lockdown for about 40 days, where businesses were completely shut-down (as was inter-city travel) except for essential businesses which were allowed to open with strict restrictions. The businesses started opening again from 1st March 2021, post this second lock-down. In March 2021, we conducted a follow-up qualitative survey with a set of randomly selected 14 treatment firms from our sample to check for the use of marketing analytics by the firms and to see if the treatment firms are still sticking to the learnings they received during the experiment. We had not kept in touch with these firms for about a year (since our Endline survey concluded in March 2020). As can be seen from Appendix Figure B1, 13 of the 14 entrepreneurs that we surveyed kept some sort of data record for their business. In addition, 11 of the 14 entrepreneurs analyzed the data they recorded and used it to make business decisions. Finally, 9 of the 14 entrepreneurs claimed that the use of data analytics helped them through the COVID-related disruption caused to their business. Some of the benefits from the use of data analytics reported by these 9 firms, that helped develop resilience in their business to COVID-related shocks, have been described in Appendix Figure B1.

While this evidence is descriptive in nature, it does suggest the role technology and specifically Ed-Fintech tools can play in building resilience in firms, to adverse shocks, and could have important implications for not just marketing researchers but also entrepreneurs/managers and policy-makers.

**Limitations and Future Research**

Although our study provides useful insights for practice, this research is not without its limitations. One caveat with interpreting our results is that we do not have data beyond nine months of the intervention and, thus, we can not comment on the long-run persistence of the sales effects. Relatedly, this study might have limits to its generalizability to other contexts. We implemented this study in a single emerging market with a carefully screened sample of growth-oriented entrepreneurs running small businesses. The magnitude of our main effects may not carry over to other contexts. Thus, researchers can add knowledge by launching new 'Ed-Fintech' experiments in a different country (e.g., a more advanced market) and with a novel unit-of-analysis (e.g., medium-sized/larger businesses or startups under incubation).

Finally, we only measure the impact of marketing analytics on the mental, managerial and financial performance at one point in time (at the endline) and so we could miss some strategic changes that happened earlier (e.g., just after the baseline or a few months before the endline). Thus, despite rigorously verifying the occurrence of these performance changes at the entrepreneur and the firm level, our measures may not fully capture the causal chain if firms were first improving on mental performance and then as a result of that improving on managerial & financial performance.

We trust that the results from this study may offer glimpses, which could serve as the basis for further research, about the impact of technologies such as marketing analytics and Ed-FinTech on managers and firms far beyond the context we study here.

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# Appendix

Table A1: Balance Checks with the sample at Baseline

| **Variable** | (1)<br>**Control (N=250)**<br>Mean<br>[SE] | (2)<br>**Placebo (N=50)**<br>Mean<br>[SE] | (3)<br>**Treatment (N=250)**<br>Mean<br>[SE] | (4)<br>**Total (N=550)**<br>Mean<br>[SE] | (5)<br>**F-test**<br>Joint<br>orthogonality |
|---|---|---|---|---|---|
| Capital with which Business was started (RWFs) | 3.87e+05<br>[37852.098] | 3.27e+05<br>[47560.813] | 4.74e+05<br>[54532.307] | 4.21e+05<br>[30572.814] | 1.384 |
| Paid full-time employees working at the business | 0.584<br>[0.128] | 0.340<br>[0.109] | 0.428<br>[0.064] | 0.491<br>[0.066] | 0.900 |
| Number of Business Partners | 0.088<br>[0.021] | 0.260<br>[0.075] | 0.084<br>[0.020] | 0.102<br>[0.015] | 5.633*** |
| Total value of Assets of the Business (RWFs) | 2.71e+06<br>[3.72e+05] | 1.68e+06<br>[4.20e+05] | 2.52e+06<br>[3.77e+05] | 2.53e+06<br>[2.44e+05] | 0.681 |
| Number of different products sold at the shop | 3.464<br>[0.190] | 3.020<br>[0.385] | 3.696<br>[0.203] | 3.529<br>[0.131] | 1.109 |
| Number of loyal customers | 30.760<br>[8.273] | 24.160<br>[4.400] | 19.804<br>[1.455] | 25.180<br>[3.841] | 0.928 |
| Number of new customers | 47.092<br>[12.662] | 29.300<br>[5.056] | 28.268<br>[1.925] | 36.918<br>[5.847] | 1.264 |
| Basket-size of a loyal customer per visit (RWFs) | 4023.362<br>[533.720] | 3602.447<br>[855.380] | 5557.940<br>[850.896] | 4683.076<br>[463.966] | 1.519 |
| Basket-size of a new customer per visit (RWFs) | 3362.571<br>[702.357] | 6567.708<br>[4149.033] | 3128.327<br>[422.540] | 3539.566<br>[522.487] | 1.662 |
| Last month sales (30 days, RWFs) | 7.08e+05<br>[63890.066] | 6.68e+05<br>[1.65e+05] | 7.62e+05<br>[89309.109] | 7.29e+05<br>[52045.251] | 0.193 |
| Last month profits (30 days, RWFs) | 1.28e+05<br>[7019.585] | 1.27e+05<br>[16961.824] | 1.38e+05<br>[14074.110] | 1.32e+05<br>[7305.860] | 0.238 |
| Rely on “gut-feeling” instead of “data analytics” | 2.876<br>[0.079] | 3.040<br>[0.187] | 2.988<br>[0.081] | 2.942<br>[0.054] | 0.652 |
| Organizing customers into segments | 4.008<br>[0.054] | 3.840<br>[0.108] | 4.048<br>[0.053] | 4.011<br>[0.036] | 1.293 |
| Calculating profit margins | 4.384<br>[0.044] | 4.440<br>[0.091] | 4.500<br>[0.039] | 4.442<br>[0.028] | 1.967 |
| Age of entrepreneur | 36.955<br>[0.533] | 35.304<br>[0.999] | 37.341<br>[0.622] | 36.980<br>[0.383] | 1.071 |

*The value displayed for F-tests are the F-statistics. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.*

Figure A1: Intervention Set-up

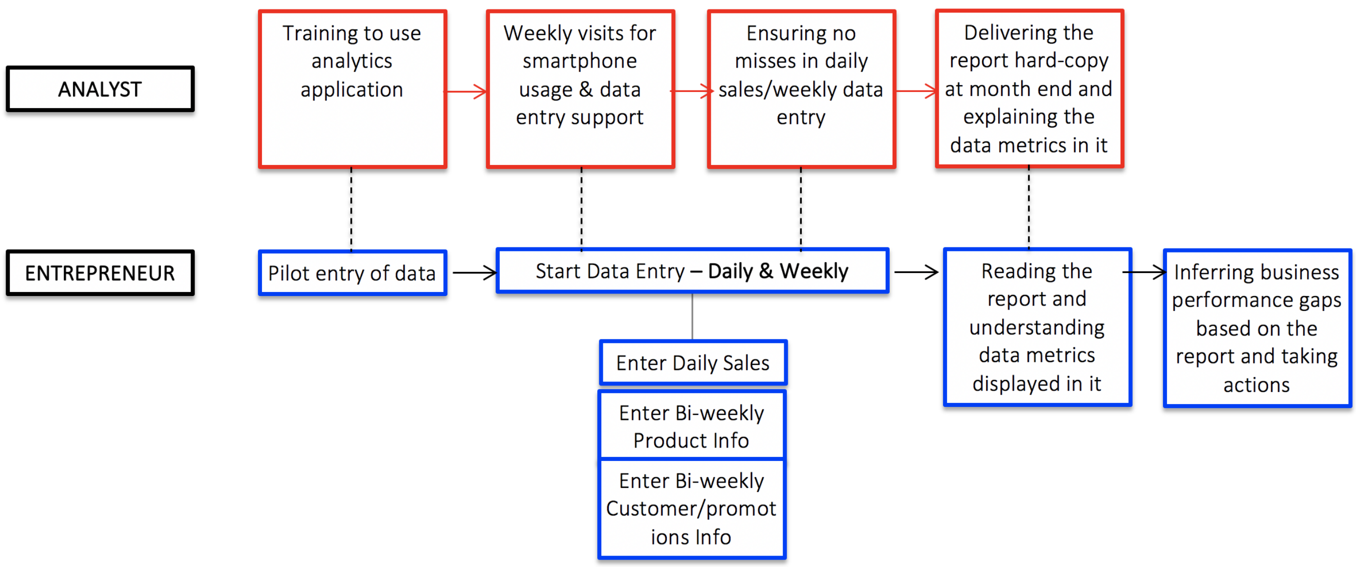


Table A2: Sample Attrition and Survival Checks

| | (1) Attrition | (2) Survival |
|---|---|---|
| Treatment | 0.00400 | 0.0400* |
| | (0.0188) | (0.0212) |
| Placebo | -0.0440*** | 0.0200 |
| | (0.0130) | (0.0378) |
| Mean of DV: Control | 0.044 | 0.920 |
| SD of DV: Control | 0.205 | 0.271 |
| Effect Size in SD: Treatment | 0.019 | 0.147 |
| Effect Size in %: Treatment | 9.09 | 4.34 |
| Effect Size in SD: Placebo | -0.214 | 0.073 |
| Effect Size in %: Placebo | -100 | 2.17 |
| Obs. | 550 | 550 |
| $\beta\_treat = \beta\_placebo$ | 0.000 | 0.577 |

Notes: This table presents the Attrition and Survival checks for our sample of firms. Column (1) presents the Attition measure (it is 1 if the firm has attrited and 0 if not). Column (2) presents the survival measure which is 1 if firm is operating and 0 if it has shut-down (attrited firms are excluded from the survival checks). Robust standard errors are in parentheses. P-values are highlighted as: $p < 0.1$ $p < 0.05^{**}$ $p < 0.01^{***}$

Figure A2: Snapshots from the app depicting the data entry process

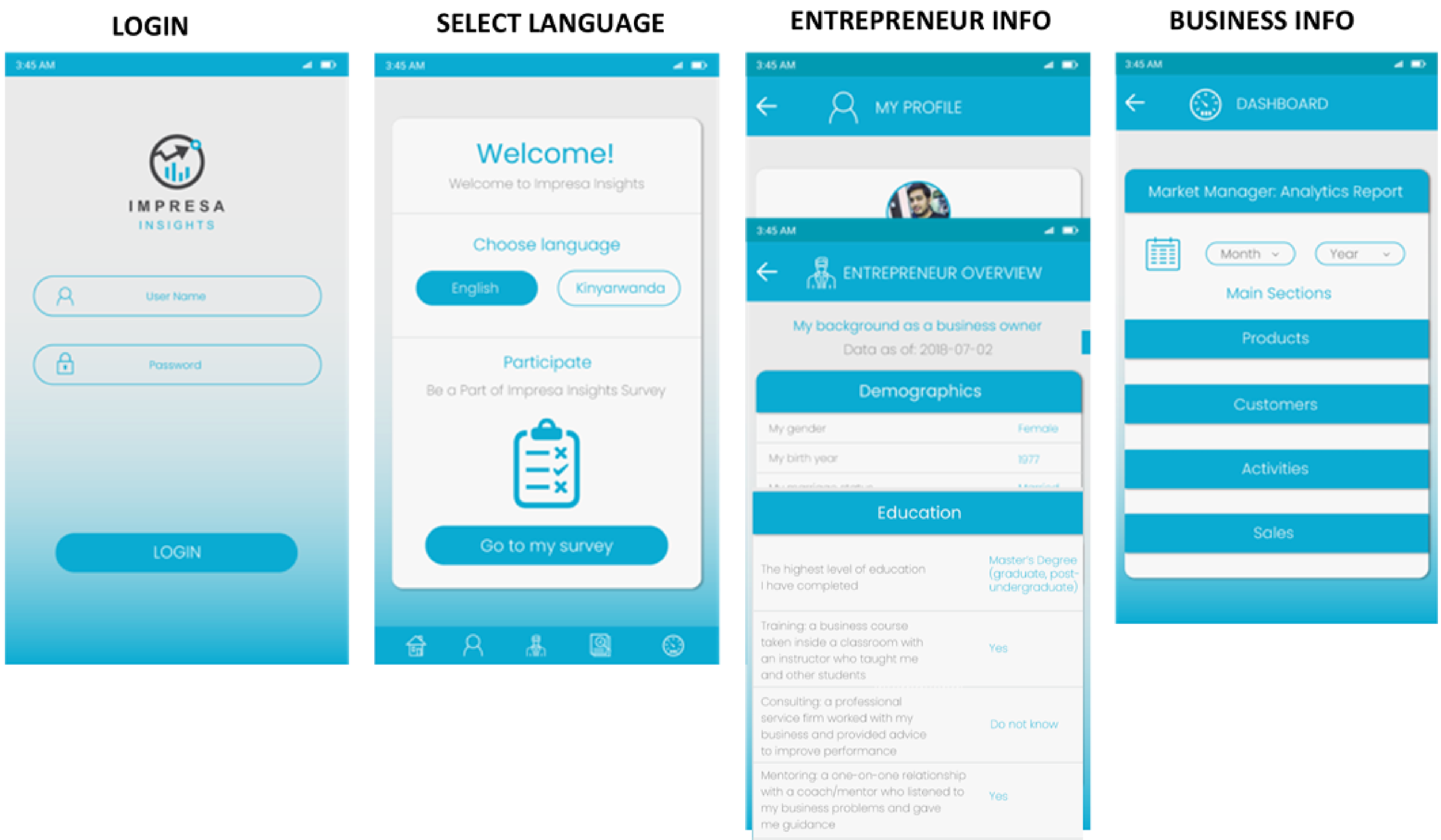


Figure A3: Snapshots from the app depicting the analytics output accessible to the entrepreneur

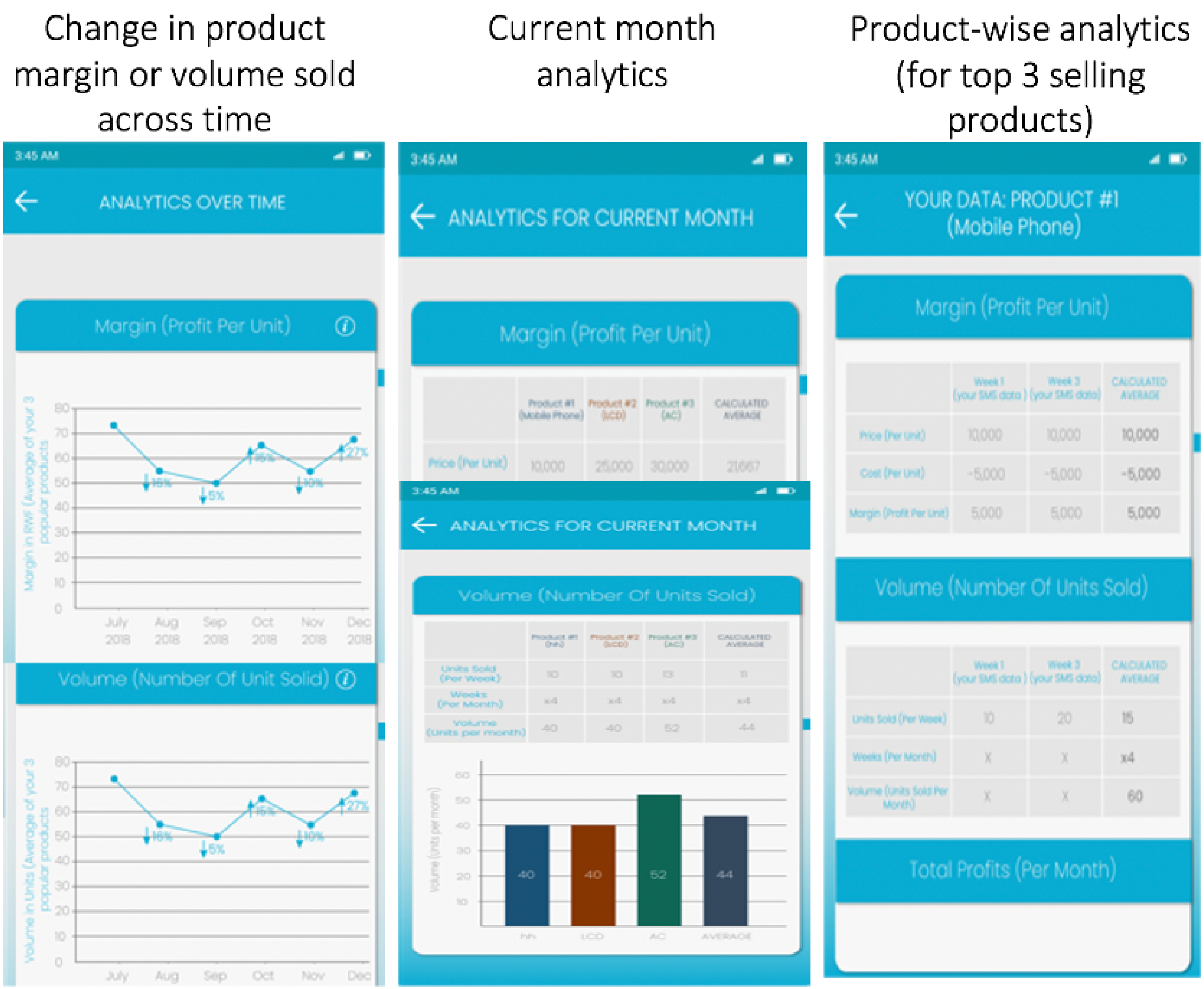
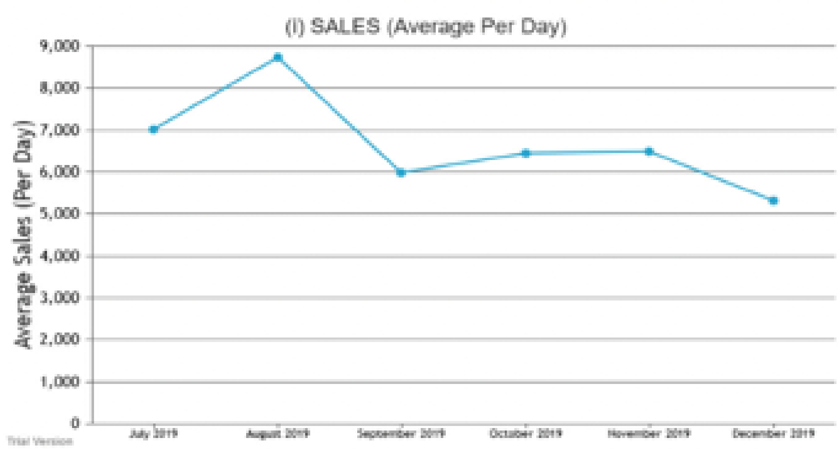


Figure A4: Snapshots from the report depicting the analytics output accessible to the entrepreneur

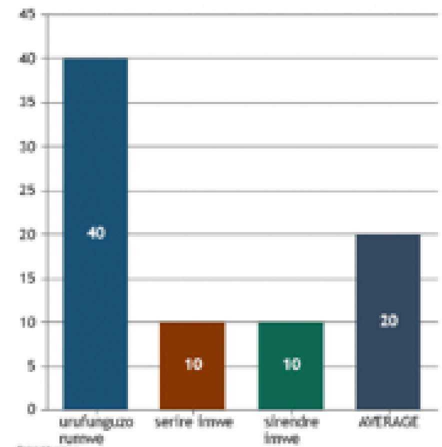
## Sales Related Information – Overall and week-wise

### MONTHLY SALES (Total Per Month)

| Steps to Calculate | Estimated Values |
|---|---|
| DAYS OPEN (based on question replies) | 23 |
| MONTHLY SALES SUB-TOTAL (actual sales entered) | 122,300 |
| **AVERAGE SALES PER DAY** | **5,317** |
| MISSING RESPONSES | 0 |
| IMPUTED DAILY SALES | 0 |
| **MONTHLY SALES TOTAL** | **122,300** |




## Product, Customer and Activity Based Analytics



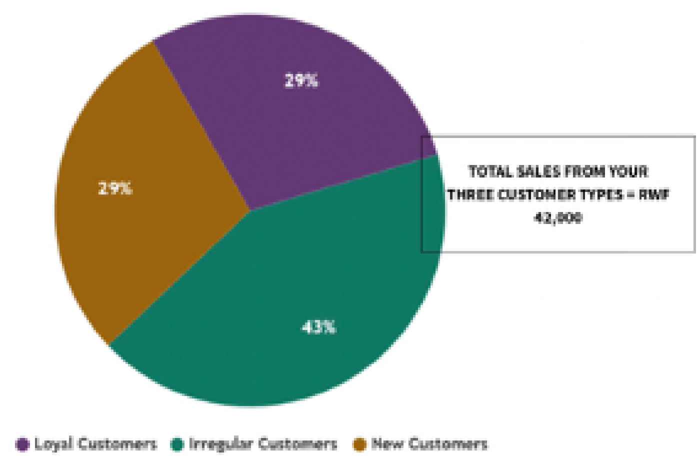



Figure A5: Experimental Timeline

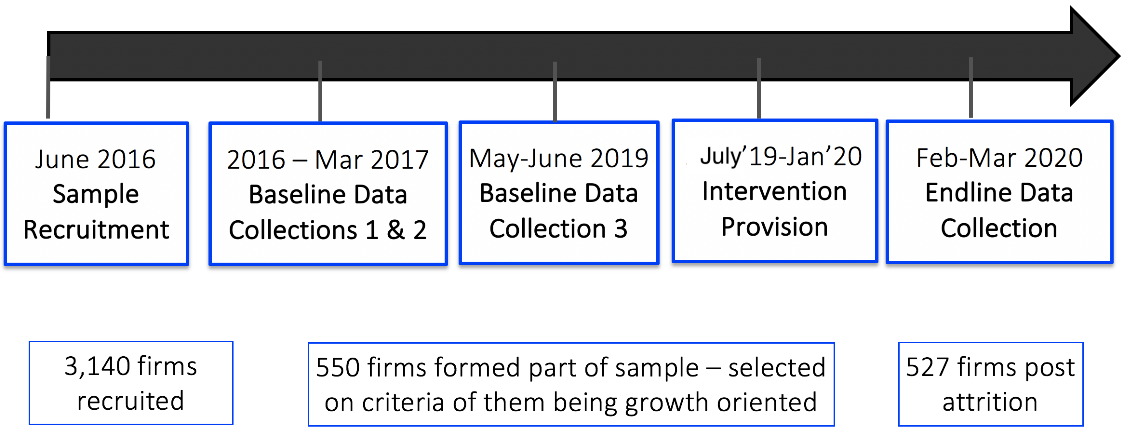
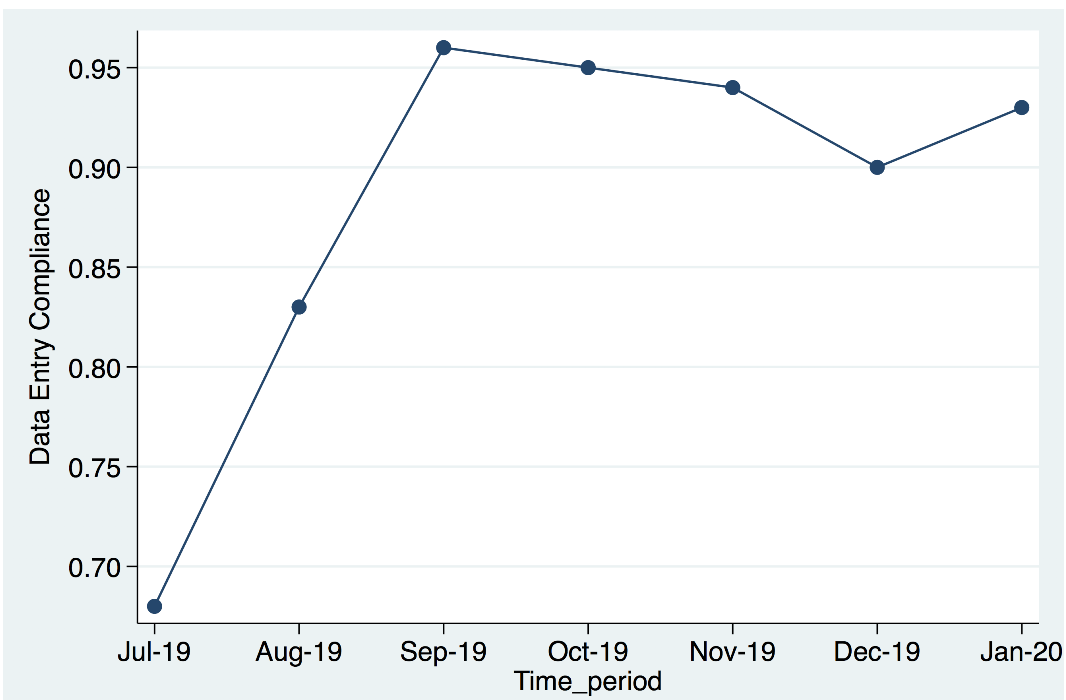



Figure A6: Data Entry Compliance by the entrepreneurs




This graph plots the average monthly compliance of the entrepreneurs to daily data entry on the Marketing Analytics App

Table A3: Intervention Checks on the use of Analytics Report

| | (1) Data Analytics | (2) Customer Analytics | (3) Product Analytics | (4) Sales Analytics |
|---|---|---|---|---|
| Treatment | 2.216*** | 2.575*** | 2.436*** | 2.412*** |
| | (0.107) | (0.101) | (0.109) | (0.0847) |
| Placebo | 0.316 | 0.396** | 0.413* | 0.247 |
| | (0.218) | (0.199) | (0.223) | (0.150) |
| Mean of DV: Control | 3.420 | 2.852 | 3.403 | 2.797 |
| SD of DV: Control | 1.290 | 1.069 | 1.349 | 0.867 |
| Effect Size in SD: Treatment | 1.718 | 2.409 | 1.806 | 2.782 |
| Effect Size in %: Treatment | 64.80 | 90.29 | 71.60 | 86.21 |
| Effect Size in SD: Placebo | 0.245 | 0.371 | 0.307 | 0.284 |
| Effect Size in %: Placebo | 9.237 | 13.89 | 12.15 | 8.812 |
| Obs. | 527 | 527 | 527 | 527 |
| $\beta\_treat = \beta\_placebo$ | 6.01e-18 | 7.34e-25 | 1.74e-19 | 9.94e-39 |

Notes: This table summarizes the manipulation checks for our marketing analytics intervention on the firms. The analytics report that was presented to the entrepreneurs on a monthly level included each of these sections on customers, products and sales of the firm, hence these results aim to check if the treatment firms have indeed paid attention to these report, as we had intended as a part of our marketing analytics intervention. The results in each column represent the intention-to-treat effects (ITT) of the randomly assigned intervention to a treatment group entrepreneur. Column (1) presents a measure of whether the firms have started paying attention to overall data analytics. Column (2) presents a measure of whether the firms have started paying attention specifically to customer analytics. Column (3) presents a measure of whether the firms have started paying attention specifically to product analytics. Column (4) presents a measure of whether the firms have started paying attention specifically to sales analytics. All regressions include firms that failed as at endline (non-operational with zero monthly sales or profits). Robust standard errors are in parentheses. P-values are highlighted as: $p < 0.1$ $p < 0.05^{**}$ $p < 0.01^{***}$

Table A4: Difference in Interview Duration across Experimental Groups

| | (1)<br>Interview Duration Analysis |
|---|---|
| Treatment | 0.118 |
| | (0.178) |
| Placebo | 0.413 |
| | (0.346) |
| Mean of DV: Control | 2.512 |
| SD of DV: Control | 1.773 |
| Effect Size in SD: Treatment | 0.0665 |
| Effect Size in %: Treatment | 4.695 |
| Effect Size in SD: Placebo | 0.233 |
| Effect Size in %: Placebo | 16.46 |
| Obs. | 527 |
| $\beta\_treat = \beta\_placebo$ | 0.404 |

Notes: This table summarizes analysis for the interview duration for the Endline Survey. Column (1) presents the winsorized measure for time taken from the start to the end of the Endline survey : estimates after winsorizing each 1% on both tails. Robust standard errors are in parentheses. P-values are highlighted as: $p < 0.1$ $p < 0.05^{**}$ $p < 0.01^{***}$

Figure A7: Model-free evidence of main effects - monthly sales

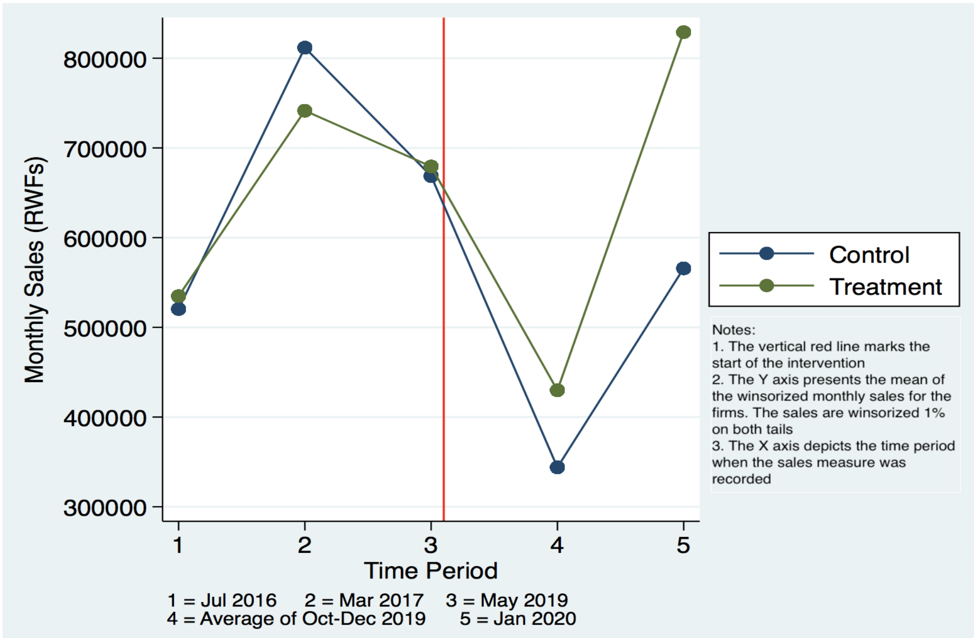
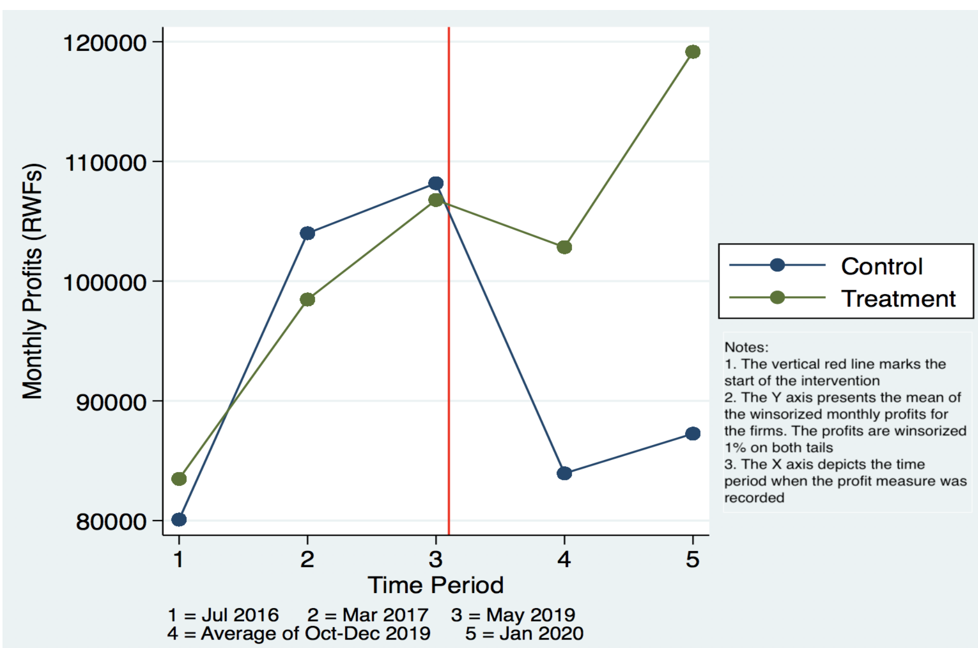



Figure A8: Model-free evidence of main effects - monthly profits



# Web Appendix B: Robustness to Alternative Mechanisms

Table B1: Balance Checks with the sample at Endline

| **Variable** | (1)<br>**Control (N=239)**<br>Mean<br>[SE] | (2)<br>**Placebo (N=50)**<br>Mean<br>[SE] | (3)<br>**Treatment (N=238)**<br>Mean<br>[SE] | (4)<br>**Total (N=527)**<br>Mean<br>[SE] | (5)<br>**F-test**<br>Joint<br>orthogonality |
|---|---|---|---|---|---|
| Capital with which Business was started (RWFs) | 3.81e+05<br>[37919.976] | 3.27e+05<br>[47560.813] | 4.75e+05<br>[56545.972] | 4.19e+05<br>[31250.368] | 1.480 |
| Paid full-time employees working at the business | 0.590<br>[0.134] | 0.340<br>[0.109] | 0.437<br>[0.067] | 0.497<br>[0.069] | 0.838 |
| Number of Business Partners | 0.092<br>[0.022] | 0.260<br>[0.075] | 0.071<br>[0.017] | 0.099<br>[0.015] | 6.796*** |
| Total value of Assets of the Business (RWFs) | 2.78e+06<br>[3.87e+05] | 1.68e+06<br>[4.20e+05] | 2.50e+06<br>[3.95e+05] | 2.55e+06<br>[2.53e+05] | 0.750 |
| Number of different products sold at the shop | 3.464<br>[0.195] | 3.020<br>[0.385] | 3.634<br>[0.207] | 3.499<br>[0.134] | 0.854 |
| Number of loyal customers | 31.494<br>[8.650] | 24.160<br>[4.400] | 19.496<br>[1.461] | 25.380<br>[4.003] | 1.022 |
| Number of new customers | 48.230<br>[13.241] | 29.300<br>[5.056] | 28.487<br>[1.984] | 37.518<br>[6.098] | 1.283 |
| Basket-size of a loyal customer per visit (RWFs) | 3927.568<br>[541.035] | 3602.447<br>[855.380] | 5454.054<br>[868.076] | 4586.629<br>[470.340] | 1.425 |
| Basket-size of a new customer per visit (RWFs) | 3229.915<br>[717.556] | 6567.708<br>[4149.033] | 3108.581<br>[436.671] | 3483.439<br>[539.432] | 1.676 |
| Last month sales (30 days, RWFs) | 7.04e+05<br>[65675.656] | 6.68e+05<br>[1.65e+05] | 7.29e+05<br>[85010.302] | 7.12e+05<br>[50959.931] | 0.067 |
| Last month profits (30 days, RWFs) | 1.27e+05<br>[7162.005] | 1.27e+05<br>[16961.824] | 1.29e+05<br>[10559.747] | 1.28e+05<br>[5979.965] | 0.011 |
| Rely on ?gut-feeling? instead of ?data analytics? | 2.895<br>[0.080] | 3.040<br>[0.187] | 2.983<br>[0.083] | 2.949<br>[0.055] | 0.428 |
| Organizing customers into segments | 4.004<br>[0.056] | 3.840<br>[0.108] | 4.050<br>[0.054] | 4.009<br>[0.037] | 1.300 |
| Calculating profit margins | 4.372<br>[0.046] | 4.440<br>[0.091] | 4.492<br>[0.039] | 4.433<br>[0.029] | 1.971 |
| Age of entrepreneur | 36.915<br>[0.538] | 35.304<br>[0.999] | 37.609<br>[0.644] | 37.076<br>[0.392] | 1.429 |

*The value displayed for F-tests are the F-statistics. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.*

Table B2: Impact of Marketing Analytics on Other Activities of the Business

| | (1) Machine Maintenance | (2) Process Efficiency | (3) Competition Research | (4) Receipts or Invoices | (5) Other Activities Index |
|---|---|---|---|---|---|
| Treatment | -0.00840 | 0.0221 | 0.0189 | 0.000141 | 0.00850 |
| Placebo | 0.0659 | 0.0722 | 0.0463 | -0.0135 | 0.0430 |
| Mean of DV: Control | 0.294 | 0.268 | 0.494 | 0.0335 | 0.272 |
| SD of DV: Control | 0.457 | 0.444 | 0.501 | 0.180 | 0.247 |
| Effect Size in SD: Treatment | -0.0184 | 0.0499 | 0.0377 | 0.000780 | 0.0343 |
| Effect Size in %: Treatment | -2.857 | 8.265 | 3.824 | 0.420 | 3.124 |
| Effect Size in SD: Placebo | 0.144 | 0.163 | 0.0924 | -0.0747 | 0.174 |
| Effect Size in %: Placebo | 22.40 | 26.97 | 9.373 | -40.25 | 15.82 |
| $\beta\_treat = \beta\_placebo$ | 0.317 | 0.495 | 0.725 | 0.555 | 0.398 |

Notes: This table summarizes analysis for the effect of marketing analytics on activities that the business performs (from baseline to endline). The results in each column represent the intention-to-treat effects (ITT) of the randomly assigned intervention to a treatment group entrepreneur. These results are based on a Yes/No response on each of these activities, as recorded by the auditors in-person review of each of the firms in our sample. Column (1) presents a measure for conducting preventative maintenance on the machines, equipments or tools used by the business. Column (2) presents a measure for replacing any processes, procedures, techniques or methods used in the business with new approaches that are more efficient. Column (3) presents a measure for conducting market research on competition and suppliers. Column (4) presents a measure of provision of receipts or invoices to customers once they have made a purchase. Column (5) presents an index for these 'other' activities performed by the business. This overall index is calculated by taking an average of each of the four business measures. All regressions include firms that failed as at endline (non-operational with zero monthly sales or profits, and their business activity response is considered to be 'no'. All regression exclude the firms that attrited during the Endline survey round. Robust standard errors are in parentheses. P-values are highlighted as: $p < 0.1$ $p < 0.05^{**}$ $p < 0.01^{***}$

Table B3: Impact of Marketing Analytics on Firm Sales and Profits for firms surviving till Endline

| | DV: Sales | | | | DV: Profits | | | | Overall |
|---|---|---|---|---|---|---|---|---|---|
| | (1) Last Month | (2) IHS Last Month | (3) Typical | (4) IHS Typical | (5) Last Month | (6) IHS Last Month | (7) Typical | (8) IHS Typical | (9) Performance Index |
| Treatment | 268.5** | 0.326*** | 78.07*** | 0.211*** | 30.34*** | 0.231*** | 17.00** | 0.151** | 0.262*** |
| | (106.7) | (0.0795) | (26.49) | (0.0696) | (9.124) | (0.0728) | (7.520) | (0.0731) | (0.0730) |
| Placebo | -131.5 | 0.0692 | -7.013 | 0.0598 | 15.04 | 0.113 | 4.774 | -0.0390 | 0.0555 |
| | (164.7) | (0.122) | (49.88) | (0.115) | (13.44) | (0.119) | (11.96) | (0.133) | (0.122) |
| Mean of DV: Control | 629.6 | 13.35 | 374.0 | 13.17 | 95.23 | 11.84 | 91.04 | 11.80 | 0 |
| SD of DV: Control | 1329.6 | 1.037 | 305.2 | 0.886 | 83.33 | 0.800 | 75.98 | 0.814 | 0.907 |
| Effect Size in SD: Treatment | 0.202 | 0.314 | 0.256 | 0.238 | 0.364 | 0.288 | 0.224 | 0.185 | 0.289 |
| Effect Size in %: Treatment | 42.65 | 32.6 | 20.88 | 21.1 | 31.86 | 23.1 | 18.68 | 15.1 | |
| Effect Size in SD: Placebo | -0.0989 | 0.0667 | -0.0230 | 0.0675 | 0.180 | 0.141 | 0.0628 | -0.0479 | 0.0612 |
| Effect Size in %: Placebo | -20.89 | 6.92 | -1.875 | 5.98 | 15.79 | 11.3 | 5.244 | -3.9 | |
| Obs. | 494 | 494 | 494 | 494 | 494 | 494 | 494 | 494 | 494 |
| $\beta\_treat = \beta\_placebo$ | 0.0160 | 0.0389 | 0.0923 | 0.191 | 0.290 | 0.328 | 0.324 | 0.159 | 0.0965 |

Notes: This table summarizes analysis for the main effect of marketing analytics on firm performance outcomes (from baseline to endline). The results in each column represent the effects of the randomly assigned intervention to a treatment group entrepreneur conditional on the firms being operation at the time the Endline Survey was run. Column (1) presents a winsorized measure for Monthly Sales (it refers to the sales for the last full calendar month for the firm, which for our sample was January 2020): estimates after winsorizing each 1% on both tails. Column (2) presents an IHS transformed measure for Monthly Sales: estimates after transforming each with the inverse hyperbolic sine function. Column (3) presents a winsorized measure for Typical Sales (average for the months Nov 2019 to Jan 2020): estimates after winsorizing each 1% on both tails. Column (4) presents an IHS transformed measure for Typical Sales: estimates after transforming each with the inverse hyperbolic sine function. Column (5) presents a winsorized measure for Monthly Profits (it refers to the profits for the last full calendar month for the firm, which for our sample was January 2020): winsorized 1% on both tails. Column (6) presents an IHS transformed measure for Monthly Profits: total monthly profits transformed with the inverse hyperbolic sine function. Column (7) presents a winsorized measure for Typical Profits (average for the months Nov 2019 to Jan 2020): estimates after winsorizing each 1% on both tails. Column (8) presents an IHS transformed measure for Typical Profits: estimates transformed with the inverse hyperbolic sine function. Column (9) presents an index measure for Firm Performance (IHS sales monthly; IHS sales yearly; IHS profits monthly; IHS profits yearly): each of the four measures were standardized and then the average of these values was computed to construct the overall 'performance' index. All regressions exclude firms that failed as at endline (non-operational with zero monthly sales or profits). Any firm growth values in levels (sales; profits) are listed as Rwandan Francs (RWF) in 1000s. The regressions also include: the baseline value of the dependent variable. The IHS results are robust to the scaling of the profits/sales numbers. Robust standard errors are in parentheses. P-values are highlighted as: $p < 0.1$ $p < 0.05^{**}$ $p < 0.01^{***}$

Table B4: Impact of Marketing Analytics on Firm Sales and Profits - LASSO Regressions

| | DV: Sales | | | | DV: Profits | | | | Overall |
|---|---|---|---|---|---|---|---|---|---|
| | (1) Last Month | (2) IHS Last Month | (3) Typical | (4) IHS Typical | (5) Last Month | (6) IHS Last Month | (7) Typical | (8) IHS Typical | (9) Performance Index |
| Treatment | 277.3*** | 0.821*** | 87.86*** | 0.718** | 34.83*** | 0.647** | 21.27*** | 0.566** | 0.197** |
| | (95.99) | (0.310) | (25.54) | (0.285) | (8.146) | (0.277) | (6.788) | (0.257) | (0.0781) |
| Placebo | -38.71 | 0.379 | 13.75 | 0.267 | 17.05 | 0.377 | 9.003 | 0.404 | 0.103 |
| | (162.9) | (0.525) | (43.35) | (0.483) | (13.85) | (0.468) | (11.54) | (0.435) | (0.132) |
| Mean of DV: Control | 565.8 | 12.23 | 343.9 | 12.17 | 87.26 | 10.85 | 83.94 | 10.91 | -8.02e-09 |
| SD of DV: Control | 1203.5 | 3.833 | 308.9 | 3.584 | 84.02 | 3.374 | 76.66 | 3.216 | 0.982 |
| Effect Size in SD: Treatment | 0.230 | 0.214 | 0.284 | 0.200 | 0.415 | 0.192 | 0.277 | 0.176 | 0.200 |
| Effect Size in %: Treatment | 49.02 | 82.1 | 25.55 | 71.8 | 39.91 | 64.7 | 25.34 | 56.6 | |
| Effect Size in SD: Placebo | -0.0322 | 0.0990 | 0.0445 | 0.0746 | 0.203 | 0.112 | 0.117 | 0.126 | 0.105 |
| Effect Size in %: Placebo | -6.843 | 37.9 | 3.997 | 26.7 | 19.54 | 37.7 | 10.73 | 40.4 | |
| Obs. | 527 | 527 | 527 | 527 | 527 | 527 | 527 | 527 | 527 |
| $\beta\_treat = \beta\_placebo$ | 0.0524 | 0.400 | 0.0875 | 0.351 | 0.199 | 0.564 | 0.288 | 0.709 | 0.479 |

Notes: This table summarizes analysis for the main effect of marketing analytics on firm performance outcomes (from baseline to endline). The results in each column represent the intention-to-treat effects (ITT) of the randomly assigned intervention to a treatment group entrepreneur. Column (1) presents a winsorized measure for Monthly Sales (it refers to the sales for the last full calendar month for the firm, which for our sample was January 2020): estimates after winsorizing each 1% on both tails. Column (2) presents an IHS transformed measure for Monthly Sales: estimates after transforming each with the inverse hyperbolic sine function. Column (3) presents a winsorized measure for Typical Sales (average for the months Nov 2019 to Jan 2020): estimates after winsorizing each 1% on both tails. Column (4) presents an IHS transformed measure for Typical Sales: estimates after transforming each with the inverse hyperbolic sine function. Column (5) presents a winsorized measure for Monthly Profits (it refers to the profits for the last full calendar month for the firm, which for our sample was January 2020): winsorized 1% on both tails. Column (6) presents an IHS transformed measure for Monthly Profits: total monthly profits transformed with the inverse hyperbolic sine function. Column (7) presents a winsorized measure for Typical Profits (average for the months Nov 2019 to Jan 2020): estimates after winsorizing each 1% on both tails. Column (8) presents an IHS transformed measure for Typical Profits: estimates transformed with the inverse hyperbolic sine function. Column (9) presents an index measure for Firm Performance (IHS sales monthly; IHS sales yearly; IHS profits monthly; IHS profits yearly): each of the four measures were standardized and then the average of these values was computed to construct the overall 'performance' index. All regressions include firms that failed as at endline (non-operational with zero monthly sales or profits). Any firm growth values in levels (sales; profits) are listed as Rwandan Francs (RWF) in 1000s. The LASSO regressions include the baseline value of the dependent variable and: twenty controls for entrepreneur characteristics at baseline (these include - employee mindset, use of data Vs intuition, education, prior business ownership, prior training/consulting/mentorship in business, entrepreneur's age); and nineteen controls for business characteristics at baseline (provision of goods Vs services, start-up capital, number of employees, asset value, number of products offered, margin of products, number of customers - new vs loyal, basket size of customers - new vs loyal, firm's sales and profits at baseline). The IHS results are robust to the scaling of the profits/sales numbers. Robust standard errors are in parentheses. P-values are highlighted as: $p < 0.1$ $p < 0.05^{**}$ $p < 0.01^{***}$

Table B5: Robustness Checks for Main Effects - Including Controls

| | DV: Sales | | | | DV: Profits | | | | Overall |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| | Last Month | IHS Last Month | Typical | IHS Typical | Last Month | IHS Last Month | Typical | IHS Typical | Performance Index |
| Treatment | 261.7** | 0.841** | 92.38*** | 0.756** | 34.25*** | 0.673** | 20.83*** | 0.583** | 0.203** |
| | (105.4) | (0.346) | (25.98) | (0.320) | (8.076) | (0.304) | (6.886) | (0.287) | (0.0878) |
| Placebo | -26.69 | 0.258 | 14.79 | 0.114 | 17.86 | 0.263 | 7.458 | 0.248 | 0.0640 |
| | (123.2) | (0.579) | (39.39) | (0.558) | (11.86) | (0.522) | (10.60) | (0.455) | (0.146) |
| Mean of DV: Control | 565.8 | 12.23 | 343.9 | 12.17 | 87.26 | 10.85 | 83.94 | 10.91 | -8.02e-09 |
| SD of DV: Control | 1203.5 | 3.833 | 308.9 | 3.584 | 84.02 | 3.374 | 76.66 | 3.216 | 0.982 |
| Effect Size in SD: Treatment | 0.217 | 0.219 | 0.299 | 0.211 | 0.408 | 0.200 | 0.272 | 0.181 | 0.207 |
| Effect Size in %: Treatment | 46.25 | 84.1 | 26.86 | 75.6 | 39.25 | 67.3 | 24.81 | 58.3 | |
| Effect Size in SD: Placebo | -0.0222 | 0.0673 | 0.0479 | 0.0318 | 0.213 | 0.0778 | 0.0973 | 0.0770 | 0.0651 |
| Effect Size in %: Placebo | -4.717 | 25.8 | 4.300 | 11.4 | 20.47 | 26.3 | 8.884 | 24.8 | |
| Obs. | 527 | 527 | 527 | 527 | 527 | 527 | 527 | 527 | 527 |
| $\beta\_treat = \beta\_placebo$ | 0.0182 | 0.318 | 0.0494 | 0.251 | 0.189 | 0.439 | 0.220 | 0.457 | 0.340 |

Notes: This table summarizes analysis for the main effect of marketing analytics on firm performance outcomes (from baseline to endline). The results in each column represent the intention-to-treat effects (ITT) of the randomly assigned intervention to a treatment group entrepreneur, while including covariates on entrepreneur and business characteristics. Column (1) presents a winsorized measure for Monthly Sales (it refers to the sales for the last full calendar month for the firm, which for our sample was January 2020): estimates after winsorizing each 1% on both tails. Column (2) presents an IHS transformed measure for Monthly Sales: estimates after transforming each with the inverse hyperbolic sine function. Column (3) presents a winsorized measure for Typical Sales (average for the months Nov 2019 to Jan 2020): estimates after winsorizing each 1% on both tails. Column (4) presents an IHS transformed measure for Typical Sales: estimates after transforming each with the inverse hyperbolic sine function. Column (5) presents a winsorized measure for Monthly Profits (it refers to the profits for the last full calendar month for the firm, which for our sample was January 2020): winsorized 1% on both tails. Column (6) presents an IHS transformed measure for Monthly Profits: total monthly profits transformed with the inverse hyperbolic sine function. Column (7) presents a winsorized measure for Typical Profits (average for the months Nov 2019 to Jan 2020): estimates after winsorizing each 1% on both tails. Column (8) presents an IHS transformed measure for Typical Profits: estimates transformed with the inverse hyperbolic sine function. Column (9) presents an index measure for Firm Performance (IHS sales monthly; IHS sales yearly; IHS profits monthly; IHS profits yearly): each of the four measures were standardized and then the average of these values was computed to construct the overall 'performance' index. All regressions include firms that failed as at endline (non-operational with zero monthly sales or profits). Any firm growth values in levels (sales; profits) are listed as Rwandan Francs (RWF) in 1000s. The regressions include: the baseline value of the dependent variable. In addition, we also include twenty controls for entrepreneur characteristics at baseline (these include - employee mindset, use of data Vs intuition, education, prior business ownership, prior training/consulting/mentorship in business, entrepreneur's age); and nineteen controls for business characteristics at baseline (provision of goods Vs services, start-up capital, number of employees, asset value, number of products offered, margin of products, number of customers - new vs loyal, basket size of customers - new vs loyal, firm's sales and profits at baseline) The IHS results are robust to the scaling of the profits/sales numbers. Robust standard errors are in parentheses. P-values are highlighted as: $p < 0.1$ $p < 0.05^{**}$ $p < 0.01^{***}$

Table B6: Impact of Marketing Analytics on Firm Sales and Profits Conditional on Recording of Data at Baseline

| | DV: Sales | | | | DV: Profits | | | | Overall |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| | Last Month | IHS Last Month | Typical | IHS Typical | Last Month | IHS Last Month | Typical | IHS Typical | Performance Index |
| Treatment | 253.8 | 1.303* | 101.9* | 0.780 | 56.88*** | 1.214* | 38.68** | 0.886 | 0.306 |
| | (183.8) | (0.715) | (60.96) | (0.654) | (21.47) | (0.675) | (17.75) | (0.628) | (0.188) |
| Mean of DV: Control | 657.6 | 12.09 | 388.5 | 12.22 | 101.2 | 10.75 | 96.09 | 10.94 | -0.0110 |
| SD of DV: Control | 1377.0 | 4.291 | 336.2 | 3.809 | 98.28 | 3.801 | 85.80 | 3.433 | 1.062 |
| Effect Size in SD: Treatment | 0.184 | 0.304 | 0.303 | 0.205 | 0.579 | 0.319 | 0.451 | 0.258 | 0.289 |
| Effect Size in %: Treatment | 38.59 | 10.78 | 26.23 | 6.382 | 56.20 | 11.29 | 40.25 | 8.093 | -2786.5 |
| Obs. | 104 | 104 | 104 | 104 | 104 | 104 | 104 | 104 | 104 |

Notes: This table summarizes analysis for the main effect of marketing analytics on firm performance outcomes (from baseline to endline) for those firms that recorded their sales and profits at the baseline. Of the total 104 firms which recorded data at baseline, 56 are treatment firms and 48 are control firms. The results in each column represent the intention-to-treat effects (ITT) of the randomly assigned intervention to a treatment group entrepreneur, conditional on maintaining sales and profits records at baseline (before the start of the intervention). Column (1) presents a winsorized measure for Monthly Sales (it refers to the sales for the last full calendar month for the firm, which for our sample was January 2020): estimates after winsorizing each 1% on both tails. Column (2) presents an IHS transformed measure for Monthly Sales: estimates after transforming each with the inverse hyperbolic sine function. Column (3) presents a winsorized measure for Typical Sales (average for the months Nov 2019 to Jan 2020): estimates after winsorizing each 1% on both tails. Column (4) presents an IHS transformed measure for Typical Sales: estimates after transforming each with the inverse hyperbolic sine function. Column (5) presents a winsorized measure for Monthly Profits (it refers to the profits for the last full calendar month for the firm, which for our sample was January 2020): winsorized 1% on both tails. Column (6) presents an IHS transformed measure for Monthly Profits: total monthly profits transformed with the inverse hyperbolic sine function. Column (7) presents a winsorized measure for Typical Profits (average for the months Nov 2019 to Jan 2020): estimates after winsorizing each 1% on both tails. Column (8) presents an IHS transformed measure for Typical Profits: estimates transformed with the inverse hyperbolic sine function. Column (9) presents an index measure for Firm Performance (IHS sales monthly; IHS sales yearly; IHS profits monthly; IHS profits yearly): each of the four measures were standardized and then the average of these values was computed to construct the overall 'performance' index. All regressions include firms that failed as at endline (non-operational with zero monthly sales or profits). Any firm growth values in levels (sales; profits) are listed as Rwandan Francs (RWF) in 1000s. The regressions also include: the baseline value of the dependent variable. The IHS results are robust to the scaling of the profits/sales numbers. Robust standard errors are in parentheses. P-values are highlighted as: $p < 0.1$ $p < 0.05^{**}$ $p < 0.01^{***}$

Table B7: Change in Business Time

| | (1) Percent_Days_Open |
|---|---|
| Month_num | -0.0000184 |
| | (0.00260) |
| Obs. | 1428 |

Notes: This table summarizes, change in percentage of days for which the treatment entrepreneur's shop was open across-months (July to Dec 2019). We use a panel data of month on month percentage of days for which each of the 238 treatment shops (post attrition) was open to doing business. The regression includes firm level fixed effects and standard errors are clustered at firm level. P-values are highlighted as: $p < 0.1$ p $<0.05^{**}$ $p < 0.01^{***}$

Table B8: Correlation between sales submitted in the App and reported in the Endline Survey

| | (1) Endline Survey Sales |
|---|---|
| App Sales | $1.004^{***}$ |
| | (0.0538) |
| Obs. | 225 |
| $\beta\_AppSales = 1$ | 0.935 |
| $Constant = 0$ | 0.890 |

Notes: This table summarizes analysis for the comparison between the last month sales reported in the Endline Survey and the Analytics Application. The treatment entrepreneurs entered daily sales in the analytics application which was added for the last month (Jan 2020) in order to calculate the sales for the full month (as per the application). The analysis is conducted for 225 of the 238 treatment entrepreneurs, as the remaining did not enter data in the analytics application for the month of interest. Robust standard errors are in parentheses. P-values are highlighted as: $p < 0.1$ p $<0.05^{**}$ $p < 0.01^{***}$

Table B9: Robustness Checks for Main Effects - Additional Evidence

| | (1) Product Sales Metric | (2) IHS Product Sales Metric | (3) Product Profits Metric | (4) IHS Product Profits Metric | (5) Customer Purchase | (6) IHS Customer Purchase | (7) Referrals | (8) IHS Referrals |
|---|---|---|---|---|---|---|---|---|
| Treatment | 52.55 | 0.546* | 3.617 | 0.499* | 112.0** | 0.775** | 0.268 | 0.203** |
| | (37.99) | (0.286) | (5.630) | (0.255) | (55.47) | (0.304) | (0.871) | (0.101) |
| Placebo | -5.374 | 0.242 | 1.217 | 0.381 | 118.3 | 0.495 | 0.0702 | 0.0592 |
| | (35.83) | (0.488) | (7.410) | (0.435) | (114.1) | (0.524) | (1.741) | (0.173) |
| Mean of DV: Control | 150.3 | 11.05 | 32.64 | 9.627 | 277.5 | 11.47 | 5.548 | 1.709 |
| SD of DV: Control | 349.6 | 3.492 | 58.29 | 3.120 | 494.8 | 3.690 | 10.40 | 1.151 |
| Effect Size in SD: Treatment | 0.150 | 0.156 | 0.0620 | 0.160 | 0.226 | 0.210 | 0.0258 | 0.176 |
| Effect Size in %: Treatment | 34.98 | 4.947 | 11.08 | 5.187 | 40.35 | 6.756 | 4.829 | 11.85 |
| Effect Size in SD: Placebo | -0.0154 | 0.0694 | 0.0209 | 0.122 | 0.239 | 0.134 | 0.00675 | 0.0514 |
| Effect Size in %: Placebo | -3.577 | 2.193 | 3.728 | 3.954 | 42.63 | 4.317 | 1.265 | 3.464 |
| Obs. | 527 | 527 | 527 | 527 | 527 | 527 | 527 | 527 |
| $\beta\_treat = \beta\_placebo$ | 0.161 | 0.515 | 0.753 | 0.775 | 0.958 | 0.579 | 0.907 | 0.402 |

Notes: This table summarizes additional evidence for the main effect of marketing analytics on firm performance outcomes (from baseline to endline) by analyzing the product and customer related outcome variables. The results in each column represent the intention-to-treat effects (ITT) of the randomly assigned intervention to a treatment group entrepreneur. Column (1) presents a winsorized measure for Product Sales (it refers to the sum-product of the prices and volumes of the top 3 selling products of the business for the last full week for the firm): estimates after winsorizing each 1% on both tails. Column (2) presents an IHS transformed measure for Product Sales: estimates after transforming each with the inverse hyperbolic sine function. Column (3) presents a winsorized measure for Product Profit (it refers to the sum-product of the margins and volumes of the top 3 selling products of the business for the last full week for the firm): estimates after winsorizing each 1% on both tails. Column (4) presents an IHS transformed measure for Product Profit: estimates after transforming each with the inverse hyperbolic sine function. Column (5) presents a winsorized measure for Customer Purchase (it refers to the product of the total number of customers and their average basket size per visit, for the last full calendar month for the firm which for our sample was January 2020): winsorized 1% on both tails. Column (6) presents an IHS transformed measure for Customer Purchase: estimates transformed with the inverse hyperbolic sine function. Column (7) presents a winsorized measure for Customer Referrals (average for the number of customers who have recommended the firm or its products to potential customers): estimates after winsorizing each 1% on both tails. Column (8) presents an IHS transformed measure for Customer Referrals: estimates transformed with the inverse hyperbolic sine function. All regressions include firms that failed as at endline (non-operational with zero monthly sales or profits). Any firm growth values in levels (sales; profits) are listed as Rwandan Francs (RWF) in 1000s. Robust standard errors are in parentheses. P-values are highlighted as: $p < 0.1$ $p < 0.05^{**}$ $p < 0.01^{***}$

Table B10: Robustness Checks for Main Effects - Attrition Bounding

| | DV: Sales | | | | DV: Profits | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) Sales Growth Bound 1 | (2) Sales Growth Bound 2 | (3) Sales Growth Bound 3 | (4) Sales Growth Bound 4 | (5) Profits Growth Bound 1 | (6) Profits Growth Bound 2 | (7) Profits Growth Bound 3 | (8) Profits Growth Bound 4 |
| Treatment | 228.4** | 247.5** | 261.9*** | 249.6** | 28.96*** | 31.98*** | 37.25*** | 35.59*** |
| | (100.1) | (96.26) | (96.73) | (96.93) | (8.898) | (9.019) | (10.21) | (10.27) |
| Placebo | -57.65 | -82.54 | -81.81 | -93.83 | 20.73 | 17.44 | 18.38 | 16.78 |
| | (131.9) | (143.6) | (147.2) | (147.9) | (13.51) | (12.85) | (12.96) | (13.00) |
| Mean of DV: Control | 540.9 | 568.4 | 568.4 | 580.5 | 83.42 | 88.23 | 88.23 | 89.86 |
| SD of DV: Control | 1182.4 | 1185.7 | 1185.7 | 1197.2 | 84.08 | 85.31 | 85.31 | 88.37 |
| Effect Size in SD: Treatment | 0.193 | 0.209 | 0.221 | 0.209 | 0.344 | 0.375 | 0.437 | 0.403 |
| Effect Size in %: Treatment | 42.23 | 43.54 | 46.08 | 43.00 | 34.71 | 36.24 | 42.23 | 39.61 |
| Effect Size in SD: Placebo | -0.0488 | -0.0696 | -0.0690 | -0.0784 | 0.247 | 0.204 | 0.215 | 0.190 |
| Effect Size in %: Placebo | -10.66 | -14.52 | -14.39 | -16.16 | 24.84 | 19.76 | 20.84 | 18.68 |
| Obs. | 550 | 550 | 550 | 550 | 550 | 550 | 550 | 550 |
| $\beta\_treat = \beta\_placebo$ | 0.0426 | 0.0293 | 0.0269 | 0.0276 | 0.569 | 0.294 | 0.185 | 0.187 |

Notes: This table summarizes robustness analysis for the main effect of marketing analytics on firm performance outcomes (from baseline to endline). We show treatment effects under different assumptions on attrition. Column (1) assigns all attriters a sales growth of zero. Column (2) assigns all attriters the average sales growth of the control group. Column (3) assigns all control attiters the sales growth rate of the control group and all treatment attriters a sales growth of zero. Column (4) assigns all control attriters the average sales growth of the treatment groups and all treatment attriters a sales growth of zero. Column (5) assigns all attriters a profit growth of zero. Column (6) assigns all attriters the average profit growth of the control group. Column (7) assigns all control attiters the profit growth rate of the control group and all treatment attriters a profit growth of zero. Column (8) assigns all control attriters the average profit growth of the treatment groups and all treatment attriters a profit growth of zero. All regressions include firms that failed as at endline (non-operational with zero monthly sales or profits). Any firm growth values in levels (sales; profits) are listed as Rwandan Francs (RWF) in 1000s. The regressions also include: the baseline value of the dependent variable. Robust standard errors are in parentheses. P-values are highlighted as: $p < 0.1$ $p < 0.05^{**}$ $p < 0.01^{***}$

Table B11: Robustness Checks for Main Effects - Local Average Treatment Effect

| | DV: Sales | | DV: Profits | | Overall |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | Last Month | Typical | Last Month | Typical | Performance Index |
| Treatment | 353.8*** | 112.1*** | 40.74*** | 25.22*** | 0.354*** |
| | (105.4) | (27.35) | (9.465) | (7.642) | (0.0651) |
| Mean of DV: Control | 565.8 | 343.9 | 87.26 | 83.94 | 0 |
| SD of DV: Control | 1203.5 | 308.9 | 84.02 | 76.66 | 0.982 |
| Effect Size in SD: Treatment | 0.294 | 0.363 | 0.485 | 0.329 | 0.360 |
| Effect Size in %: Treatment | 62.54 | 32.60 | 46.69 | 30.04 | |
| Obs. | 439 | 439 | 439 | 439 | 439 |

Notes: This table summarizes analysis for the main effect of marketing analytics on firm performance outcomes (from baseline to endline). The results in each column represent the local average treatment effects (LATE) of the randomly assigned intervention to a treatment group entrepreneur, computed via 2SLS, with treatment adoption (defined as signing-up on the analytics app) and compliance (defined as entering data for at least one week for each intervention month between July - Dec 2019) instrumented by the random treatment assignment. Column (1) presents a winsorized measure for Monthly Sales (it refers to the sales for the last full calendar month for the firm, which for our sample was January 2020): estimates after winsorizing each 1% on both tails. Column (2) presents a winsorized measure for Typical Sales (average for the months Nov 2019 to Jan 2020): estimates after winsorizing each 1% on both tails. Column (3) presents a winsorized measure for Monthly Profits (it refers to the profits for the last full calendar month for the firm, which for our sample was January 2020): winsorized 1% on both tails Column (4) presents a winsorized measure for Typical Profits (average for the months Nov 2019 to Jan 2020): estimates after winsorizing each 1% on both tails. Column (5) presents an index measure for Firm Performance (sales monthly; sales yearly; profits monthly; profits yearly): the IHS transforms of each of the four measures were standardized and then the average of these values was computed to construct the overall 'performance' index. All regressions include firms that failed as at endline (non-operational with zero monthly sales or profits). Any firm growth values in levels (sales; profits) are listed as Rwandan Francs (RWF) in 1000s. The regressions also include: the baseline value of the dependent variable. Robust standard errors are in parentheses. P-values are highlighted as: $p < 0.1$ $p < 0.05^{**}$ $p < 0.01^{***}$

Table B12: Robustness Checks for Main Effects - Impact on Control Firms if There is Competing Treatment Firm Nearby

| | DV: Monthly Sales | | DV: Monthly Profits | | Overall | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Average | IHS | Average | IHS | Performance Index | Average Performance Index |
| Close Treatment Competitor | 84.78 | 0.273 | 13.10 | 0.227 | 0.0913 | 0.0682 |
| | (65.61) | (0.615) | (10.18) | (0.578) | (0.174) | (0.174) |
| Mean of DV: Control | 330.6 | 11.95 | 70.76 | 10.66 | -0.104 | -0.0887 |
| SD of DV: Control | 303.1 | 3.880 | 56.95 | 3.442 | 1.065 | 1.066 |
| Effect Size in SD: Competitor | 0.280 | 0.0704 | 0.230 | 0.0659 | 0.0858 | 0.0640 |
| Effect Size in %: Competitor | 25.64 | 2.287 | 18.51 | 2.128 | -87.44 | -76.98 |
| Obs. | 239 | 239 | 239 | 239 | 239 | 239 |

Notes: This table summarizes analysis for the spillover effect on the control firms of having a treatment firm nearby. The regression is run on the sample of control firms, and provide effect on the control firm of having at least one treatment firm nearby (within 1 km of Haversine distance from the focal firm) which belongs to the same sector (pre coded industry variable) as the focal firm. Column (1) presents a winsorized measure for Average Monthly Sales (it refers to the average sales for the last full calendar month for the firm, which for our sample was January 2020) and the sales for a typical month (average for the months Oct 2019 to Dec 2020) : estimates after winsorizing each 1% on both tails. Column (2) presents an IHS transformed measure for Average Monthly Sales: estimates after transforming the average monthly sales with the inverse hyperbolic sine function. Column (3) presents a winsorized measure for Average Monthly Profits (it refers to the average profits for the last full calendar month for the firm, which for our sample was January 2020) and the profits for a typical month (average for the months Oct 2019 to Dec 2020) : estimates after winsorizing each 1% on both tails. Column (4) presents an IHS transformed measure for Average Monthly Profits: estimates after transforming the average monthly profits using the inverse hyperbolic sine function. Column (5) presents an index measure for Firm Performance (IHS last month's sales; IHS typical sales monthly; IHS last month's profits; IHS typical profits monthly): each of the four measures were standardized and then the average of these values was computed to construct the overall 'performance' index. Column (6) presents an index measure for Firm Performance (using IHS average sales monthly; IHS average profits monthly): each of the two measures were standardized and then the average of these values was computed to construct the overall 'performance' index. All regressions include firms that failed as at endline (non-operational with zero monthly sales or profits). Any firm growth values in levels (sales; profits) are listed as Rwandan Francs (RWF) in 1000s. The regressions also include: the baseline value of the dependent variable. Robust standard errors are in parentheses. P-values are highlighted as: $p < 0.1$ $p < 0.05^{**}$ $p < 0.01^{***}$

Table B13: Mediation Analysis - Analytical Ability of the Entrepreneur

| | Estimate | p-value |
|---|---|---|
| ACME | 0.1578 | 2e-16*** |
| ADE | 0.0229 | 0.814 |
| Total Effect | 0.1807 | 0.008*** |
| Proportion Mediated | 0.8735 | 0.008*** |

*Non parametric bootstrap confidence intervals with the Percentile Method*
*ACME = Average Causal Mediation Effect and ADE = Average Direct Effect*
*Sample size = 527, simulations = 1000*
*P-values are highlighted as:* $p < 0.1$ $p < 0.05^{**}$ $p < 0.01^{***}$

Table B14: Mediation Analysis - Analytical Activity of the Entrepreneur

| | Estimate | p-value |
|---|---|---|
| ACME | 0.6597 | 2e-16*** |
| ADE | -0.4709 | 2e-16*** |
| Total Effect | 0.1889 | 0.008*** |
| Proportion Mediated | 3.493 | 0.008*** |

*Non parametric bootstrap confidence intervals with the Percentile Method*
*ACME = Average Causal Mediation Effect and ADE = Average Direct Effect*
*Sample size = 527, simulations = 1000*
*P-values are highlighted as: $p < 0.1$ $p < 0.05^{**}$ $p < 0.01^{***}$*

Figure B1: Post COVID-19, Qualitative Survey

| Firm | Data Recording | Data Analytics | Role of Data Analytics during COVID-19 related shocks |
|---|---|---|---|
| General Merchandise Store (Retail Trade) | I keep a record of the number of units sold per product and of my competitors' prices. I have it all written in a notebook that I maintain. I also record the profit I make per month, people who owe me money and how much. In addition I keep a separate record of how much I received on mobile money everyday at the end of the day. | At the end of each week, I review the data that I have collected for my business and analyze it to make projections about customer purchase patterns. It also hels me to know when to add new products or increase my stock. I can also see how a product is being bought, and understand if customers are liking it or not, accordingly I can choose to replace it with a new product or a similar product from a different brand. For example, I have noticed that my consumers make a lot of purchases through mobile payments on Friday, just before going for the weekend so I ensure I have adequate stock for Fridays. I also noticed that at the beginning of the school year or when schools re-open after vacations, I get a lot of consumers seeking school-related products so, I stock-up accordingly with things that students need especially boarding-school students. | Yes most definitely data analytics helped me get through the lockdowns, I was able to ensure that I reach my monthly target of sales by doing home delivery, and I was able to pay for the rent because I knew how much to sell to keep operating my business. |
| Music and Video Entertainment (Services) | Yes, I maintain an excel sheet with the daily sales (number of units) and also the cost of the internet that I buy to be able to download movies or videos that I sell at my store. | Yes I do analyze the data I maintain in the excel sheet. In fact it was by analyzing this data that I realized I was not making much money through movie rentals because I had to invest a lot in downloading them. So now, I have completely shifted my business to music rental only. I also have seen from my sales and product data that people now prefer more Rwandan songs, so I am no longer spending time and data downloading other songs. Further, as a result of COVID lockdowns, young people are not going to school and I noticed an icrease in young customers at my store. I am now catering to their tastes better by creating lists of songs that the youth enjoy. | No it did not help my business during COVID shocks |

| Firm | Data Recording | Data Analytics | Role of Data Analytics during COVID-19 related shocks |
|---|---|---|---|
| Garment Styling and Alterations (Services) | I record the sales revenue, number of clothes like dresses, shirts etc that I style, and my monthly profit. I have a book in which I put in all my orders and sales on a daily basis. I also record the advance that people pay, the number of orders and their deadlines. | I periodically look through my recorded sales and order data. That way, I have been able to check which of my loyal customers have not been ordering from me, and I call them to ensure that I retain them. Based on the total number of orders that I have, I can purchase more fabric, and also know if I can give some orders to my colleagues and pay them (if I am facing too many urgent orders). I had also started to target customers who had weddings, and that way I was able to make a lot of money. But now due to COVID, since wedding ceremonies are not allowed to be held, that sale has stopped. | No, the lockdown was so unpredictable that it was extremely difficult to pre-empt anything even based on the information I have about my business. |
| Kitchen Supplies Store (Retail Trade) | I record stock data for each of my products, weekly sales data, prices of the product and the addresses of my loyal customers. Every Saturday I record this data on a fresh sheet of paper. The customer order data is recorded for my - loyal, irregular and new customers, along with product information, on a weekly basis. | I have to analyse the orders that have been made and their volume, to understand how much I need to purchase as raw material stock. According to my sales data, I know what to stock in good quantity. Analyzing the number of units ordered for each product, helps me understand what people like more, and this helps me in ensuring that I always have those products at my shop. For example, customers have started ordering fruits (especially citric fruits) a lot of because of COVID, and I have ensured that every weekend I have enough stock of lemons, lime, oranges etc. | Yes, I had a full list of my loyal customers and the last time that they had purchased from my store, along with the products they generally purchase. So, I continued to focus on my loyal customers by actively calling them, taking orders from them and ensuring timely delivery to their houses. |
| Charcoal shop (Retail trade) | I keep a dedicated notebook. In which I write down the daily sales revenue of my shop, number of units sold, monthly profits, number of pending orders and loyal customers information. In the same bookI also note down all the expenses that I have (including loading and offloading costs), man power etc. | Analyzing the sales data has proved to be of a great help for me. Due to the decrease in the prices of gas the sale of charcoal has taken a hit, and hence I have suspended some casual workers who used to helped me in the past. But because I knew that my sales are going to reduce, and my new projected margins and sales were not able to cover the costs of the casuals, I had to let them go. | Yes analytics did help me, because I had a record of my loyal customers and could find them in their homes, and deliver to them my product. |

| Firm | Data Recording | Data Analytics | Role of Data Analytics during COVID-19 related shocks |
| --- | --- | --- | --- |
| Hair Styling Salon (Services) | I just record the number of clients that visited my shop per day. | I haven't been using the data lately as there is not much I can do with it in my business. | Yes analytics did help me a lot. Actually I maintained a record of my loyal customers along with their contact information and preferences. So during lockdown, I was able to schedule their appointments over the phone and cater to them through home-visits. That kept my sales a little bit stable. |
| Shoe Repairing Shop (Services) | I don't do any data recording at all now. I had to give up on the physical space of my shop due to loss of business during the COVID lockdowns. I am sitting in the street now to run my services, and cannot find time for any data work. | I don't work with any business data as it is very difficult to that in my current business situation. | No it did not. |
| Restaurant (Services) | I have a business book that I have dedicated for recording sales data, stock data, expenses and customers' contact. I have also started monthly subscription service for my customers and record the same along with when to expect money from each of my subscription customer. | I review my data almost on a daily basis. By comparing the prices of my stock with the prices charged by other similar stores in the market, I know how much I can charge my customers. The same information also gives me a picture of how much projected profit I can make. Total sales per unit data tells me which products I can invest in more. It also tells me what types of products different customer segments like, accordingly I customize the food plate for breakfast or for lunch that I offer. | No, I only worked with the hospitals to provide them with tiffins during the lockdown. |
| Garment Shop (Retail Trade) | I have a book that I use to record all my sales, number of orders received, the advance payment I have received and how much people owe me (credit). I also periodically account for the payments I receive through Mobile money, cash and money in the bank to see my total sales. | I set monthly sales targets for my business and analyzing the recorded data help me to know if I have been able to reach my sales goal or how much was I short. I can accordingly reach out to some of the clients who haven't been showing up and see if they can come to the shop, to ensure I reach my sales goal. This also helps me to know if my sales will be enough to keep the helpers who help me to cut the fabrics, to iron the clothes etc, or if I will have to plan to do these tasks myself for that month. The projections of sales also help me order adequate fabrics. | Yes data analytics helped me as I had a list of my loyal customers, and I have been contacting them and providing home based services. |

| Firm | Data Recording | Data Analytics | Role of Data Analytics during COVID-19 related shocks |
|---|---|---|---|
| Electronics Repair Shop (Services) | I record daily sales and daily expenses in a notebook. This helps me calculate the business profit on a daily basis. I periodically also. Record some key stock information. | I just analyze my profit on a daily basis. Apart from that, there are some spare parts that I have to always ensure I have at all times. I keep monitoring there stock level information and always avoid to have zero stocks on those items. | Yes the data helped me a lot. As I already knew my monthly sales estimations, in the second week of the lockdown and curfew, I had already understood that I won't be able to pay the rent and the electricity for my shop. So, I decided to leave the shop and operate from my home. |
| Automobile Repair Shop (Services) | I just maintain a list of products I stock, along with their prices, but we don't change that very often. | I don't really invest much time analyzing the data, because I don't record much of it anyway. | No, I don’t think so. |
| Garments Shop (Retail Trade) | I record the new stock purchases and their sales. Everyday I keep track of any new customers that come to my store, for them I record what s/he pays and what products they purchased. I do this only for my new clients who come to my shop for the first time. I also record business expenses like rent and electricity. I use an app in my phone to record all this information (it is a different app, not the one which was provided to us as a part of the project). | I check my weekly sales to see if I need to increase the price of my products for the rest of the month in order to get to my monthly profit target. Almost everyday, I also check on how the month has been so far and what the new sale mean is for me. Depending on how the current sales are, I come to know if I will need new stocks before the end of the month and I order accordingly. | Yes, during the pandemic, I have only focused on the most popular products, and that is all that I have sold. This helped me to sell my whole stock quickly and buy new ones. This has also helped me in doing home-deliveries because I knew the contact information as well as product-prefeences of my loyal customers. I called them and they purchased all the stock I had. |

| Firm | Data Recording | Data Analytics | Role of Data Analytics during COVID-19 related shocks |
|---|---|---|---|
| Grocery Store (Retail Trade) | I capture daily sales data in my business book. This also includes what I have sold, its quantity, type of product, and the cost of purchase to my business. I also record the phone numbers and other information of any new customer that comes to my shop. I do that so that I can call them as a reminder to come back and visit/purchase from my shop. | I can't do anything in my business without anakyzing the data beforehand. I firstly check the status of my business using the recorded data. Everyday, I go through my daily sales and do an audit to see if I didn't lose any money. When I am thinking of giving people credit or when I am thinking of introducing a new product in my store, I go through the same numbers and consider that data. | Yes, a lot, because some of our products can be damaged when they are not purchased directly, or they just get expired. Having in mind the average of my monthly or weekly sales was very helpful to minimize that loss. I also knew my loyal customers and the quantity they generally like to purcahse. So, everytime that I purchased new stock, I considered that. |
| Dairy Products and Hot Beverages Store (Retail Trade) | I have been keeping a close tab on my daily sales data ever since the project began, I am still continuing to do it as it has helped me a lot. I record sales data for every customer who purchases something at my shop. I also take note of my monthly expenses like rent, raw-materials and employee payments. | I make a projection of sales for each day based on my past sales numbers. This helps me in knowing how much I should purchase as stock, and minimizes over-stocking or under-stocking as I purchase the products according to my data-based estimate of how much the consumption is going to be for the day. During sunny periods people I have noticed that people don't drink hot milk or tea. So I have started to provide juice as well at my shop, and I accordingly reduce the number of casual workers for those days as we don't have to prepare tea. | Yes, during the COVID lockdown, using analytics I had identified my loyal customers and I knew what they buy everytime from my store. After the lockdown, I have invested a lot in those people and asked them what they would like to get on reduced price because most of them didn't have a lot of money. I have managed to retain them until now and they form a bigger percentage of my sales today, |