Short Messages Fall Short for Micro-Entrepreneurs: Experimental Evidence from Kenya

Muhammad Zia Mehmood*

October 31, 2023

Click here for the latest version.

Abstract

SMS-based business trainings are becoming a popular tool to remotely support micro-entrepreneurs in low-income settings due to their scalability and low costs. However, little evidence exists on the effectiveness of such trainings to improve business outcomes. In this study, I evaluate a field experiment in which access to an SMS-based training was randomized across 4,700 micro-entrepreneurs in Kenya. After three months, I find positive effects on knowledge and adoption of best practices. Younger entrepreneurs see stronger effects on sales, profits and business survival, driven by higher engagement with training content, more time spent on business, and getting larger loans. Contrary to predictions elicited from social scientists, I find that these positive effects disappear twelve months after the intervention, as all engagement with content ended within the first five months. Notwithstanding the low engagement and lack of longer-run effects, I find that micro-entrepreneurs are still willing to pay a small positive amount for additional SMS-based trainings, suggesting that they value access to the content. Findings from this study suggest that, despite the promise and wide-spread use, SMS-based trainings are unlikely to be effective for micro-entrepreneurs. Results highlight the importance of lack of engagement as a major challenge limiting the potential of remotely provided trainings.

JEL Codes: C93, L26, O12

Keywords: entrepreneurship, business training, randomized control trial

*University of California, Berkeley, mz_mehmood@berkeley.edu. I am grateful to Edward Miguel, Frederico Finan, Guo Xu, and Steve Tadelis for their support and advice over the course of this project. I also thank Stephanie Bonds, Ernesto Dal Bo, Muhammad Yasir Khan, Jedediah Silver, Osman Siddiqi and seminar participants at UC Berkeley Development and Business and Public Policy Seminars for helpful conversations, comments, and feedback. This fieldwork would not be possible without the field team at REMIT-Kenya, especially Carolyne Nekesa and Blastus Bwire. Jeff Ngugi provided excellent research assistance. I gratefully acknowledge funding from the International Growth Centre (IGC), Private Enterprise Development in Low-Income Countries (PEDL), the UC Berkeley Institute for Business Innovation, the UC Berkeley Center for African Studies, and SurveyCTO. The study was approved by the UC Berkeley Committee for Protection of Human Subjects and the Strathmore University Institutional Ethics Review Commitee and is registered at the AEA RCT Registry (AEARCTR-0007265).

1 Introduction

Employing 70% of the labor force world-wide and accounting for 40% of the GDP in emerging economies (ILO (2019); WorldBank (2021)), small businesses form the economic backbone of society in low-income countries across the globe. Moreover, they are also crucial vehicles for female empowerment as at least one third of them are owned by women (World Bank (2020)). Research aimed at exploring effective ways to address the challenges faced by small businesses is therefore key for poverty alleviation efforts.

Poor management practices is a major factor constraining firm productivity in low-income contexts (Bloom et al. (2010, 2013); Bloom and Van Reenen (2010); Bruhn, Karlan and Schoar (2010); McKenzie and Woodruff (2017)). Business management trainings aimed at encouraging adoption of best practices are a popular tool employed to address this challenge[1], and over $1 billion is spent annually to train 4-5 million entrepreneurs in low-income countries (McKenzie (2020)). However, most of these trainings are conventional in-person classroom-style trainings, which are expensive and hard to scale. Furthermore, most of them are conducted in or around large cities and often exclude entrepreneurs that are unable to take out time to participate in person, as well as those that are based in smaller cities and rural areas.

Phone-based trainings offer a potential solution to these challenges. In particular, SMS-based trainings are cheap, easy to scale, do not require in-person attendance or even internet access, and also allow targeted beneficiaries to move through the content at their own individual pace rather than having a single fixed pace for everyone. Due to this, SMS-based trainings are gaining popularity as a low-cost tool for information-based support across several low-income contexts.[2] However, despite the widespread use, there is little evidence on whether SMS-based trainings can be effective for improving outcomes, particularly for micro-entrepreneurs.

In this paper, I study the demand for and impact of SMS-based business trainings on business practices and outcomes for micro-entrepreneurs. To this end, I evaluate a field experiment with an embedded willingness to pay elicitation, whereby access to an SMS-based business training was randomized across 4,700 micro-entrepreneurs in Kenya. Data was collected by phone-based surveys conducted three months and twelve months after the intervention to estimate short and longer-run effects respectively. The main outcomes studied include knowledge and adoption of best practices, time spent on business and side jobs, labor employment decisions, credit outcomes, and business performance.

Kenya is an ideal setting for this study as Micro, Small, and Medium Enterprises (MSMEs) play a major role in the national economy; 7.4 million MSMEs engage over 90% of the active labor force in the country, and account for about a third of the GDP. Approximately 55% of these MSMEs are owned by women, and 98% are micro-enterprises[3]. The average education level for micro-entrepreneurs is approximately 11 years, yet adoption of basic best practices for

[1] The Start and Improve Your Business (SIYB) training program by the International Labor Organization has trained over 15 million entrepreneurs across the world (Mehtha (2017)), CEFE International has reached 13 million (Ramirez (2019)), International Finance Corporation's Business Edge training has reached over 100,000 entrepreneurs (*Business Edge : Status and Disposition* (2006)) etc.

[2] See Ulmann (2023); van Vark (2012); Haddad (2022); Hinrichsen and Ajadi (2020); *M-Shule SMS Learning & Training, Kenya | UIL* (2022), and work of TechnoServe (Regan-Sachs (2022)), and Arifu (*Arifu: WhatsApp Chatbot Provides Tips for Micro-Retailers* (N.d.)) etc.

[3] Less than 10 employees

business management is dismally low. Just under 80% of micro-entrepreneurs do not advertise any of their products in any way and almost 70% don't keep any type of business records - not even personal notes - to keep track of daily sales or expenses. Furthermore, less than 10% of micro-entrepreneurs account for prices of their competitors when setting prices for their own products and services. These statistics highlight a clear gap in management skills that could be constraining profitability, which can potentially be addressed through business management trainings, yet 90% of micro-entrepreneurs have never received any type of business training.[4]

The primary intervention in this study was aimed at addressing this gap through an SMS-based Business Education training course that used simply worded content to encourage micro-entrepreneurs to adopt business practices that have been shown to be highly correlated with profitability (Bloom and Van Reenen (2010)). This training was developed by my implementation partner - a local firm that specializes in creation and dissemination of digital content - in light of existing research on the importance of keeping training content simple in low-capacity contexts (Drexler, Fischer and Schoar (2014); Arráiz, Bhanot and Calero (2019)). Available in English as well as Swahili, the content covered practices including marketing, advertising, pricing, record-keeping and stock management, and was divided into bite-sized chunks spanning approximately 150 text messages. These messages were pushed to micro-entrepreneurs through an interactive chat-bot in a fixed sequence, with a limited number of reminders being sent to those who stopped engaging at any point.

The sample of micro-entrepreneurs used in the study was sourced from a list of contacts maintained by my implementation partner in collaboration with a local microfinance institution. This list was compiled by them through fieldwork aimed at identifying micro-entrepreneurs to target for their products. Out of the 4,700 individuals recruited from this list for the study, 2,820 micro-entrepreneurs were randomly selected into the Treatment group and provided access to this SMS training course, while the remaining 1,880 - the Control group - received placebo messages aimed at reminding them about their business without conveying any substantive information about best business management practices. 307 individuals were surveyed three months after the intervention, while 2,780 individuals were surveyed after another nine months to estimate short and longer-run effects on business outcomes, respectively.

In order to determine if the main findings from this study depart from priors held by social science experts, I also conducted a survey through the Social Science Predictions Platform (Mehmood (2023)). In this survey, I described the study to social science researchers and elicited their predictions about how key outcomes will be affected twelve months after the intervention. This exercise allows me to shed light on whether the observed results from this study are expected and obvious, or surprising and informative.

I measured demand for SMS-based trainings amongst micro-entrepreneurs by eliciting their willingness to pay for an additional SMS training using two incentive compatible methods; (I) Take-It-Or-Leave-It (TIOLI) offers, and (II) In-person willingness to pay elicitation using a modified version of the Becker, Degroot and Marschak (1964) (BDM) method. I sent the TIOLI offers to individuals in the treatment group[5] once they completed the first training or abandoned

[4] Statistics as of 2016, sourced from the country-wide *Micro, Small and Medium Enterprises Survey* (2016).

[5] And not the Control group to prevent contamination of the samples for estimation of the treatment effect of SMS trainings.

it, randomizing the price across three levels; (i) Free, (ii) KSH 5 (Half of the marginal cost of provision for the provider), and (iii) KSH 20 (Double the marginal cost). Comparing buying decisions across these price arms allows me to assess if there is any positive willingness to pay for SMS trainings, and if it varies systematically with the price. Second, immediately after the twelve-month follow-up, I randomly selected 103 Nairobi-based business owners across treatment and control groups to conduct an in-person elicitation using a modified version of the BDM method that uses a multiple-price list approach. In addition to offering an alternate measure of willingness to pay, this elicitation allows me to estimate the effect of the treatment on the demand for SMS trainings.

Three months after the intervention, I find that assignment to treatment increased knowledge and adoption of best practices by 0.20 and 0.33 standard deviations, respectively. I also find large positive, but statistically insignificant, effects on business performance in the overall sample, and significant positive effects for younger (below-median) micro-entrepreneurs on sales (109% increase), profits (38% increase), and business survival (11.6 percentage points increase). These positive effects for younger entrepreneurs are driven by higher engagement with the content, and larger effects on time spent on business, and loan amounts applied for and received.

However, these positive results dissipate in the longer run; twelve months after the intervention, I see no effects on knowledge and adoption of best practices, as well as business sales, profits and survival. Additionally, the positive effects on business outcomes observed for younger entrepreneurs after three months, also disappear after twelve months. The time-trend of engagement reveals that the lack of longer-run effects is likely driven by micro-entrepreneurs abandoning all interactions with the content within the first few months of the training deployment, and well before the twelve-month follow-up.

I therefore conclude that, despite their growing popularity, SMS-based trainings on their own are unlikely to be effective for micro-entrepreneurs. Comparing results with the predictions elicited from social science researchers reveals that social scientists overestimate the potential of SMS-based trainings, thus the findings from this study are contrary to priors, and informative.

Notwithstanding the low engagement and lack of longer run effects, I find that micro-entrepreneurs are still willing to pay a small amount for additional SMS-based business trainings, as measured using both willingness to pay elicitation methods, suggesting that entrepreneurs value access to the content.

This study contributes to three strands of literature. First, building on the literature connecting management practices and firm profitability (Bloom et al. (2010, 2013); Bloom and Van Reenen (2010); Bruhn, Karlan and Schoar (2010); McKenzie and Woodruff (2017); Bruhn, Karlan and Schoar (2018)), I contribute to the large body of evidence on the impact of business trainings on adoption of best practices and business outcomes. Most of the studies in this literature focus on conventional classroom-style trainings that are expensive and hard to scale, with older studies finding little to no effects on sales and profits (Cho and Honorati (2014); Blattman and Ralston (2015); McKenzie and Woodruff (2014)), and more recent work finding positive effects (McKenzie (2020); Chioda et al. (2021)). The evidence on remotely delivered business trainings is still thin and mixed; Davies et al. (2023) find positive short-run effects of Zoom-based trainings for micro-entrepreneurs in Mexico that dissipate within six months of the intervention and Estefan et al. (2023) find significant effects of a mobile app-based training with virtual one-on-one consulting meetings on business outcomes for micro-entrepreneurs in Guatemala. Cole, Joshi and Schoar (2021) find weekly pre-recorded Interactive Voice Response (IVR) messages to be ineffective for improving business outcomes for micro-entrepreneurs. To the best of my knowledge, this paper presents the first rigorous evaluation of an SMS-based business training for micro-entrepreneurs.

Second, this paper adds to an emerging literature on the potential of modifying training content based on insights from psychology to make it easier to internalize. Campos et al. (2017) evaluate a training intervention with psychology-based personal initiative-oriented content in Togo and observe positive effects on business outcomes. Drexler, Fischer and Schoar (2014) and Arráiz, Bhanot and Calero (2019) find encouraging returns from simplifying the training content and focusing on easy to internalize heuristics. The training content used in this study was inspired by these approaches, and this is the first study that tests the effectiveness of a fully automated remote delivery of such simplified content.

Third, I add to the limited evidence on demand for business trainings; Cole and Fernando (2020) estimate the willingness to pay for voice-based ICT advisory service amongst Indian farmers, while Maffioli, McKenzie and Ubfal (2020) estimate demand for conventional trainings amongst entrepreneurs in Jamaica. This study is the first to elicit willingness to pay for SMS-based business trainings. I find that micro-entrepreneurs are willing to pay positive amounts (greater than the marginal cost of provision locally) to get access to SMS-based business training content, suggesting that there might be some scope for a market-based delivery approach in this space.

The remainder of the paper is organized as follows: Section 2 describes the context of the study, Sections 3 outlines the research design, Section 4 discusses the data and timeline of the experiment, Section 5 presents the results, and Section 6 concludes.

2 Context

Home to over 47.6 million people, three-fourths of whom are under the age of 35, Kenya is the largest economy in Eastern and Central Africa (*Kenya Population and Housing Census* (2019)). Similar to other low-income countries, Micro, Small and Medium Enterprises (MSMEs) form the backbone of the economy in Kenya. According to statistics from the nation-wide *Micro, Small and Medium Enterprises Survey* (2016), 7.4 million MSMEs engage over 90% of the active labor force in the country, and contribute just above a third of the GDP. Approximately 55% of these MSMEs are owned by women, and 98% are micro enterprises.[6]

The average education level for micro-entrepreneurs is approximately 11 years, yet adoption of basic best practices for business management is dismally low. About 78.6% of micro-entrepreneurs do not advertise any of their products in any way and 69.8% don't keep any type of business records - not even personal notes to keep track of daily sales or expenses. Furthermore, less than 10% of micro-entrepreneurs account for prices of their competitors when setting prices for their own products and services.

[6] Less than 10 employees.

These statistics highlight a clear gap in management skills that could be constraining profitability, which can potentially be addressed through business management trainings. However, conventional business trainings are expensive and beyond the reach of most micro-entrepreneurs; the average micro enterprise in Kenya generates about USD 440 in a month (*Micro, Small and Medium Enterprises Survey* (2016)), while the average per trainee cost of business trainings in Kenya[7] can range from USD 125 to USD 900 (Mehtha (2017)). Due to this, most business training programs are funded externally and provided to micro-entrepreneurs free of cost. However, such programs are mostly implemented in or around large cities, and often exclude entrepreneurs that are unable to take out time from work and family to sit in on class-room style trainings spanning several hours to multiple days, as well as those that are based in smaller cities and rural areas. Indeed, 90% of micro-entrepreneurs surveyed in *Micro, Small and Medium Enterprises Survey* (2016) had never received any type of business training.

All these contextual features make Kenya a highly appropriate empirical setting to test the effectiveness and demand for SMS-based remote delivery of business trainings.

3 Research Design

In this section, I describe (i) the primary intervention in the study; the SMS-based business training, (ii) the randomization groups, and (iii) the elicitation of willingness to pay for SMS trainings amongst micro-entrepreneurs.

3.1 Intervention: SMS-based Business Training

The primary treatment consisted of an SMS-based Business Education training course, which was accessible through smartphones as well as feature-phones, and required no internet access. This course was developed by my primary implementing partner, a Kenyan education technology company that specializes in creation and dissemination of digital training content for audiences including small farmers and micro-entrepreneurs. For this project, I focus on their SMS-based business training course for micro-entrepreneurs. This course was developed in light of existing research on the importance of keeping training content simple in low-capacity contexts (Drexler, Fischer and Schoar (2014); Arráiz, Bhanot and Calero (2019)), and adapted to the local context through extensive qualitative piloting. Information about best practices was conveyed in an easy-to-internalize narrative format describing decision-making of hypothetical micro-entrepreneurs in different scenarios.

Available in English as well as Swahili (the two national languages of Kenya), the training course covered practices including marketing, advertising, pricing, record-keeping, and stock management. The content was divided into bite-sized chunks spanning over approximately 150 text messages, and was pushed to users through a chat-bot. The chat-bot was interactive, and users had to keep engaging with it by replying to its messages to keep receiving more content. All text messages sent to the chat-bot were completely free, and users were informed about this up front. Figure 1 in the Appendix shows what engagement with the content looked like for

[7] Taking the example of a well-known training implemented in Kenya and several other countries (*Start and Improve Your Business Programme (ENTERPRISES)* (N.d.))

users.[8]

The content was organized in a fixed sequence and users could go through the sequence at their own pace by only responding to the chat-bot when they wanted additional content. The entire training could be completed in four to six hours if one wanted to do it in one go. Users retained access to all content that they had engaged with up until any point, and could revisit it offline on their phones at will. Those who either did not start engaging with the training content, or started but subsequently abandoned engagement for at least a week, were sent an SMS reminder every week. The weekly reminders were halted if the user engaged at any time and would resume if engagement was abandoned for a week again. The reminders completely stopped after two consecutive months of no engagement.

This training is similar to other light-touch simplified content used for remotely supporting micro-entrepreneurs as well as small-scale agriculturists in low-income settings. Due to this, I expect results from this study to speak to the efficacy of this tool more generally instead of in the specific context of this experiment alone.

3.2 Randomization Groups

Stratified by gender, the primary sample of 4,701 micro-entrepreneurs who had agreed to participate in the study was randomized at the level of the individual into two groups: (I) Treatment, and (II) Control. The Treatment group of 2,820 micro-entrepreneurs (60% of the study sample) was offered access to the SMS-based business training described in the preceding section.[9] The Control group of 1,881 micro-entrepreneurs (40% of the study sample) received placebo messages designed to remind them about their business without providing any substantive information on best practices. Comparing outcomes across these two groups will allow for the evaluation of the effectiveness of SMS-based business trainings.

The Treatment group was further subdivided into three subgroups as part of the elicitation of willingness-to-pay for trainings; once the treatment individuals completed the training, or if they stopped engaging for at least two months straight, they were sent take-it-or-leave-it offers for the option to buy an additional SMS-based business training for a price, where the price was randomized across three levels. I present more details about this part of the design in Section 3.3.

3.3 Elicitation of Willingness-to-Pay

I elicited willingness to pay for SMS-based trainings using two methods: (I) Randomized Take-It-Or-Leave-It (TIOLI) offers in the treatment group, and (II) In-person elicitation of maximum willingness to pay adapting the method pioneered by Becker, Degroot and Marschak (1964) for a subset of the overall sample. Using two different methods with different samples allows for corroboration of observed trends across the exercises, and thus lends more credibility to findings.

[8] The entire content of the training cannot be provided due to commercial reasons

[9] The Treatment group was designed to be larger to accommodate outreach requirements from implementing partner.

3.3.1 Take it or Leave it offers

The 2,820 micro-entrepreneurs in the Treatment group that were offered the SMS-based training were later offered access to a second SMS-based business training at a randomly selected price. The offer was sent over SMS once the users completed the first training, or if they stopped engaging for at least two months straight. The elicitation was separately incentivised; individuals were promised additional airtime that was to be disbursed after they responded with their decision. If they chose to buy, the price of the training was deducted from the airtime value and the remaining airtime was disbursed. If they chose to not buy, the entire airtime was disbursed after they responded with their decision. The incentive was aimed at nudging people who chose not to buy to actually report their decision instead of just not responding to the invitation to choose, in order to get a better sense of willingness to pay.

Stratified by gender, the price in these TIOLI offers was randomized over three levels; (i) 704 individuals (25% of Treatment group) were offered a price of KSH 20, (ii) 697 individuals (25% of Treatment group) were offered a price of KSH 5, and (iii) 1,419 individuals (50% of Treatment group) were offered the second training for free.

The marginal cost of provision of the entire training incurred by the implementing partner was KSH 10 per person, thus the positive price levels in the TIOLI design represented double the marginal cost and half the marginal cost of provision, respectively. Observing buying decisions across these pricing arms allows for the evaluation of whether there was any positive willingness to pay for the trainings amongst entrepreneurs, and if it varies systematically with price.

3.3.2 Becker-DeGroot-Marschak Elicitation

Following the Endline Survey, I randomly select about 100 Nairobi-based business owners from my primary sample to conduct an in-person elicitation of willingness to pay for an additional SMS-based business training. Following Maffioli, McKenzie and Ubfal (2020), I used a modified version of the method proposed by Becker, Degroot and Marschak (1964), that uses a multiple-price list approach. The possible price level options were framed as resulting from a lottery for the amount of discount offered to respondents.

Respondents were asked if they would buy the SMS training at a sequence of prices starting with zero and increasing in increments of KSH 10, until the respondent switched their response from “Yes” to “No”. The respondents were then asked to quote their maximum willingness to pay between the price they rejected and the last price they accepted. After confirming if the respondent was sure about their response and that they would not be able to back out of their commitment to buy once the discount lottery was run, the enumerators ran the discount lottery and revealed the final price. The final incentive amount was disbursed via mobile money at the end of the interview, and, where applicable, an invitation to the additional training was sent to the respondents over SMS soon after.

Before the elicitation, respondents were provided a brief overview of the new SMS training content, and a detailed explanation about the elicitation method with hypothetical examples, highlighting that it was in the respondent’s interest to not commit to buying at a price that was lower or higher than their actual maximum willingness to pay for the SMS training.

To circumvent complications posed by the possibility of individuals reneging on commitment to buy at the price drawn through the lottery[10], respondents were informed up front that the payment for their potential purchase of the training would be taken out of the participation incentive amount committed to them before the start of the interview.

Unlike the TIOLI offers, the sample for this exercise included treatment as well as control individuals. This will allow me to estimate if there is any effect of treatment assignment on willingness to pay for SMS trainings.

4 Data and Timeline

There are three main sources of data for the project: (I) the back-end data from the SMS platform, (II) the Midline survey, and (III) the Endline Survey. In addition to these, I use two secondary sources: (i) the in-person BDM elicitation activity (as described in detail in Section 3.3.2, and (ii) an online elicitation of predictions for treatment effects from social science researchers. In this section, I offer more details about the main data sources and the predictions survey.

4.1 Main Data Sources

The implementing partner provided the back-end engagement data from the SMS training platform. This data contains information about how engagement levels of each entrepreneur changed over the course of the study period. It also contains the buying decisions of entrepreneurs from the TIOLI offers described in Section 3.3.1.

The second main data source is the Midline survey conducted three months after the intervention. Approximately 700 randomly selected leads from the primary sample were approached for the phone-based data collection activity, resulting in 307 completed surveys.[11] Response rates in the Treatment and Control groups were 45% and 42% respectively, with an overall response rate of 43.9%. In addition to demographic information, the Midline data consists of outcomes including measures of knowledge and adoption of best practices, time spent on business[12] and side jobs in the last 30 days, labor hours employed in business[13] in the last 30 days, loans applied for and received in the last 3 months, and business sales, profits and survival in the last 30 days.[14]

The third data source is the Endline survey conducted twelve months after the intervention. The full sample of 4,701 leads was approached for the phone-based data collection activity, resulting in 2,780 completed surveys. The response rate in the treatment, control and overall sample was the same at 59%. This is higher than the response rate in the Midline since more time was spent on calling back leads for which the respondent could not be reached in the first attempt. In addition to the outcomes measured in the Midline survey, the Endline data also consists of knowledge and adoption of more advanced business practices, and sales and profits from all businesses combined in the last 30 days, and time spent on business as well as labor

[10] As faced by Maffioli, McKenzie and Ubfal (2020) in their study.

[11] Those who had started engaging with content at the time were slightly over-sampled in the treatment group due to reporting requirements from implementing partner, but all analyses for this paper adjusts the weighting of observations to account for the sampling strategy

[12] For primary business as well as across all businesses

[13] For primary business as well as across all businesses

[14] Only for primary business.

hours employed in the last 7 days. Compared to the Midline, the Endline thus covered more outcomes for a larger sample.

4.2 Predictions for Treatment Effects

In order to determine whether the main findings from this study depart from priors held by social science experts, I conducted a survey through the Social Science Predictions Platform (Mehmood (2023)). In this survey, I described the study to social science researchers and elicited their predictions about how key outcomes will be affected twelve months after the SMS training intervention. More specifically, I ask them about their expectations for (i) the extensive margin engagement - i.e. what percentage of those offered the SMS training will start engaging with it, (ii) the intensive margin engagement - i.e. what will be the average percentage of training content that individuals offered the training will engage with, (iii) the effect of treatment assignment on knowledge about best practices, (iv) effect of treatment assignment on adoption of best practices, (v) the effect of treatment assignment on sales from primary business in the last 30 days, and (vi) the effect of treatment assignment on profits from primary business in the last 30 days.

In addition to improving interpretation of results by credibly highlighting whether the findings are unexpected and informative, comparing research findings with expert forecasts contributes to broader efforts aimed at improving accuracy of forecasts in the field, mitigating publication bias, and improving experimental designs in future work; see DellaVigna, Pope and Vivalt (2019) for a more detailed discussion of benefits.

4.3 Sample

The primary sample for the intervention came from a list of micro-entrepreneurs maintained by my primary implementation partner in collaboration with a local microfinance institution. This list was compiled through fieldwork they conducted all over Kenya with the aim of collecting contact information of micro-entrepreneurs to target their services to. Subjects were invited to participate in the study over SMS and offered an incentive of KSH 100. Those who accepted and signed on to the SMS platform were randomized into groups as detailed in Section 3.2. Figure 3 shows that an overwhelming majority of businesses in the sample either fall into the category of retail or services. Figure 2 shows that the entrepreneurs in the sample were very widely spread out geographically across Kenya, which bolsters the external validity of the findings from this sample.

No baseline survey could be conducted for the study due to timing and logistical constraints, and the only information available for each entrepreneur was their gender. I therefore draw on Midline and Endline data on covariates that are unlikely to change systematically across the randomization groups over the course of the study (e.g. years of education, age etc.), in addition to a limited set of retrospectively framed questions (e.g. did the respondent have a job in December 2021 etc.), for showing pre-intervention summary statistics, balance checks and heterogeneity analyses.

Table 9 in Appendix C.1 presents summary statistics for these pre-intervention covariates for the Midline and Endline samples. Almost half the micro-entrepreneurs in the study sample are women and approximately 45% are based in rural areas. The average micro-entrepreneur has just under 12 years of education, and is between 35 and 36 years old. Roughly 87% had an active business and 40% had an active loan at the time of the intervention deployment.

Table 10 shows that pre-intervention covariates are largely balanced across Treatment and Control groups, for Midline as well as Endline.

4.4 Timeline

Below, I detail the timeline of the experiment implementation and the main data collection activities.

Nov 2021 - Dec 2021	**Intervention:** Recruitment into Study and Intervention Deployment
March 2022	**Midline Survey:** Phone-based data collection on knowledge and adoption of best business practices, and business outcomes
Nov 2022 - Dec 2022	**Endline Survey:** Phone-based data collection on wider range of knowledge and adoption of best business practices, and business outcomes
Jan 2023	**BDM Elicitation:** In-person willingness to pay elicitation using the modified BDM method
Oct 2023 - Nov 2023	**Social Science Predictions Platform Survey:** Online elicitation of predictions for treatment effects from social science researchers

5 Results

This section reports the main results from the study. First, I report the main specifications used for all the analyses. Second, I present results from the Midline survey, detailing treatment effects on engagement, knowledge and adoption of best practices, business performance, and mechanisms. Third, I present results from the Endline survey in the same order. I then move on to comparisons of observed effects with predictions elicited from social scientists. Lastly, I shed light on results from the willing to pay elicitation exercises.

5.1 Specifications

I present results using two main specifications: the first uses OLS Intention-To-Treat (ITT) estimates of treatment assignment, the second uses LATE estimates where engagement in the training is instrumented by treatment assignment. Both estimation strategies control for gender, which is the stratifying variable. I discuss each specification below.

The first estimation strategy uses intention-to-treat (ITT) estimates of treatment group assignment on the outcomes of interest. The following equation represents the main specification:

$$Y_i = \beta_0 + \beta_1 T_i + X_j'\theta + \epsilon_i \tag{1}$$

where Y_i is the outcome of interest for individual i, T_i is the treatment indicator, X_i is a vector of controls including gender and pre-intervention covariates (if included), ϵ is the error term, and β_1 is the ITT estimate.

The second estimation strategy uses local average treatment effect (LATE) estimates of treatment on the outcomes of interest. The following equations represent the main specification:

$$Eng_i = \gamma_0 + \gamma_1 T_i + X_j'\psi + \eta_i \tag{2}$$

$$Y_i = \beta_0 + \beta_1 \hat{Eng_i} + X_j'\theta + \epsilon_i \tag{3}$$

where Y_i is the outcome of interest for inidividual i, Eng_i is a binary indicator for engagement in the training, T_i is the treatment indicator (instrument), X_i is a vector of controls including gender and pre-intervention covariates (if included), η and ϵ are error terms, and β_1 is the LATE estimate.

Heterogeneity analysis is based on ITT estimates (as in Equation 1) from the relevant subsamples (e.g. results using respondents of median age and above, and those using respondents of below median age etc.), with the difference in treatment effects across subsamples estimated using the following equation:

$$Y_i = \beta_0 + \beta_1 T_i * M_i + \beta_2 T_i + \beta_3 M_i + X_j'\theta + N_j'\zeta + \epsilon_i \tag{4}$$

where Y_i is the outcome of interest for individual i, T_i is the treatment indicator, M_i is the binary covariate of interest for heterogeneity analysis, X_i is a vector of other controls including gender and other pre-intervention covariates (if included), N_i is a vector of interactions of gender and other included pre-intervention covariates with M_i, ϵ is the error term, and β_1 is the estimated difference in treatment effects across the subsamples.

As per my registered pre-analysis plan, I explore heterogeneity of treatment effects along four dimensions: (i) gender, (ii) age, (iii) rural/urban, and (iv) education. I report the comprehensive set of heterogeneity results in the online appendix.

5.2 Midline

In this section, I examine effects on key outcomes for the Midline sample, measured three months after the intervention deployment.

5.2.1 Engagement at Midline

First, I examine the treatment effect on engagement with the training content. I construct four different measures of engagement (Table 1). Column 1 shows the effect of treatment assignment on extensive margin engagement - that is, a binary indicator for whether or not the individual started engaging with the content. Column 2 shows the effect on whether or not the individual engaged with at least 25% of the training content. Column 3 shows the treatment effect on intensive margin engagement conditional on starting to engage. Finally, Column 4 shows the treatment effect on unconditional intensive-margin engagement, i.e. the percentage of training content that the individual engaged with, including those who never engaged as zeros. No controls are added to these regressions.

Table 1 shows the results on engagement at Midline; I find that roughly 30% of the treatment group engaged with the training. Overall, only 8.4% of treatment individuals completed at least one-fourth of the training, (Table 1 Column 2). Conditional on starting to engage, average percentage of training content completed was 23.4% (Table 1, Column 3), and the unconditional average percentage training content completed was 7% (Table 1, Column 4). Taken together, these results suggest that engagement levels three months after the intervention were generally low; most treatment group individuals did not start engaging, and those that did only covered a quarter of the training content on average. Heterogeneity results by age (above or below median age) show that younger entrepreneurs engaged significantly more with the content (Table 11).

5.2.2 Knowledge and Adoption at Midline

Next, I examine whether engaging with the content affects knowledge and adoption of best business practices. Table 2 shows the OLS (Columns 1 and 3) and 2SLS (Columns 2, and 4) estimates on means effect indices of knowledge and adoption of best practices, respectively. Coefficients show effects in terms of control group standard deviations. The endogenous variable in Columns (2) and (4) is whether or not the individual engaged with training content. Results show that the training led to a 0.198 SD increase in knowledge of best business practices, which was statistically significant at the 10% level (Table 2 Column 1). Conditional on engaging with any of the content (Table 2 Column 2) there is a 0.67 SD effect, which is also significant at the 10% level.

Turning to adoption, I see a large and statistically significant effect of treatment assignment on adoption of best business practices. The OLS regression indicates that assignment to the treatment increases adoption of best business practices by 0.332 Standard Deviations, with the effect being statistically significant at the 5% level (Table 2). The LATE estimate is also statistically significant, with an effect of 1.115 SDs. I find that this large and statistically significant increase in the adoption index is driven by an increase in advertising (putting up business posters); Table 12 shows that treatment individuals are 8.4 percentage points more likely to put up posters (over a control mean of 3.8%). Conditional on covering the module on advertising, the effect size is 81.2 percentage points (Column 6).

5.2.3 Midline Sales, Profits, and Business Survival

Finally, I examine business sales, profits and survival at Midline in order to test whether the gain in adoption of best business practices led to meaningful improvements in business outcomes three months after the intervention. Table 3 shows the intent-to-treat and local average treatment effect estimates of SMS trainings on primary business sales and profits from last 30 days, and business survival. Coefficients in columns (1) thought (4) represent effects in terms of Kenyan Shillings, while those in columns (5) and (6) represent probability of the individual having an active business.

The effect of assignment to treatment was positive for sales (KSH 5,721) and profits (KSH 1,680.6) in the last 30 days, as well as business survival (4.14 percentage point higher survival) in the overall sample, however these effects are not statistically significant.

I do find larger and statistically significant impacts of trainings on business performance for below-median age micro-entrepreneurs. Table 14 shows that observable pre-intervention covariates are balanced across treatment and control, for younger as well as older entrepreneurs, which shows that the treatment and control groups in each of these age groups are comparable. Table 13 shows the treatment effects; I find that for younger entrepreneurs, the training increased sales by KSH 35,607 (a 109% increase), which is statistically significant at the 5% level. Profits increased by 38% but this increase in borderline insignificant at the 10% level with a p-value of 0.115. Finally, younger entrepreneurs in the treatment group saw a positive and statistically significant increase in business survival of 11.6 percentage points. Business sales and business survival are statistically significantly different across above- and below-median-aged entrepreneurs.

5.2.4 Midline Mechanisms

Results thus far show that the treatment induced some engagement with the content, particularly for younger entrepreneurs, and improved knowledge and adoption of best business practices. Sales, profits, and business survival increase overall, but only statistically significant so for younger (below-median-age) micro-entrepreneurs. I examine three mechanisms to better understand these effects: (1) time spent on business, (2) labor employed in business, and (3) credit outcomes.

Results show that the treatment led business owners to work an additional 28.88 hours on their primary business in the last 30 days - an increase of 16 percent from the control mean of 178.6 hours (Table 4). Table 15 shows a similar increase when I consider time spent on all businesses combined to account for cases where the entrepreneur had more than one business. To determine whether this was a result of reallocation of time away from leisure or other income generating activities, I also look at the effect of treatment assignment on time spent on side jobs; Table 16 shows a small negative effect on time spent on side jobs that is not statistically significant, so I conclude that it is indeed leisure time that is being reallocated to the business.

Table 4 further shows that treatment assignment did not have an impact on labor hours employed, loan amount applied for, nor loan amount received; The coefficients are small and not statistically significant.

Table 17 examines time spent on business by age, and finds a statistically significant difference for younger individuals. The training led below median-age individuals to spend 67 more hours on their primary business and 70.9 more hours on all of their businesses in the last 30 days, and the differences between above and below median age households is statistically significantly different at the 5% level. There is no statistically significant difference in labor hours employed by age, but I find that younger entrepreneurs also applied to and received significantly larger loans (Table 18).

Taken together, these results suggest that the increased engagement, time spent on business, and loan amount applied for and received may explain the improvement in business performance experienced by younger micro-entrepreneurs.

5.2.5 Midline Summary of Results

To summarize the Midline results, I find that the treatment group engaged with the training content but engagement levels were low. Despite this, the treatment micro-entrepreneurs saw significant improvements in knowledge and adoption of best practices, and large positive but statistically insignificant effects on business sales, profits and survival. Furthermore, I find that younger entrepreneurs see large statistically significant increases in business performance, driven by higher engagement, more time spent on business, and applying for and receiving larger loans.

5.3 Endline

Paralleling the Midline analysis, I turn to the Endline data collected twelve months after the launch of the intervention in order to examine the longer run effects of the training on knowledge and adoption of best business practices, and business sales, profits, and survival. The Endline survey targeted the full study sample and measured a wider set of outcomes compared to the Midline. This section shows effects on Endline outcomes covered in the Midline as well as those that were not covered in the Midline.

Since the Midline sample was considerably smaller than the Endline sample, there can be a concern that the samples for the two rounds of data collection are systematically different and thus a comparison of treatment effects across Midline and Endline doesn't show how effects changed over time, but rather effects at different time periods for different samples. I address this concern by showing that, within the Endline, the sample matched with the Midline[15] is very similar to the sample that is not matched with the Midline, on observable pre-intervention covariates (Table 20), as well as control group outcomes (Table 21). Furthermore, I run the Endline regressions using just the sample matched with the Midline to check robustness in all my analyses and I find no meaningful difference in results.

5.3.1 Endline Engagement

First, I examine engagement with the content at Endline, measured twelve months after the launch of the training. Column 1 of Table 5 shows the effect of treatment assignment on extensive margin engagement, Column 2 shows the effect on whether or not the individual engaged with at least 25% of the training content, Column 3 shows the effect on intensive margin engagement conditional on starting to engage, and Column 4 shows the effect on the unconditional intensive margin engagement.

I find that 28% of the treatment group engaged with the training after twelve months of the training, with 8.2% covering at least 25% of the training content (Table 5 Column 2). Conditional on starting to engage, the average engagement was 23.3% (Table 5, Column 3), and the unconditional average engagement was 6.5% (including those who never engaged as zeros) (Table 5, Column 4).

These results are more or less the same as the results at Midline, indicating that there was little if any engagement beyond the first three months of the intervention.

5.3.2 Endline Knowledge and Adoption

At Endline, in addition to testing knowledge and adoption of basic business practices (same as Midline), I also test knowledge and adoption of more advanced business practices which were not explicitly covered by the training content. Table 6 shows the intent-to-treat and local average treatment effect estimates of SMS trainings on means effect indices of basic and advanced knowledge and adoption. Results show that there are no significant improvement in knowledge

[15] Out of 307 entrepreneurs surveyed in the Midline, 227 were surveyed again in the Endline.

or adoption of best business practices - both for basic as well as advanced practices. Running the same analysis but with the Midline matched sample shows the same result of no effects for basic as well as advanced practices (Table 23).

5.3.3 Endline Sales, Profits, and Business Survival

Table 7 shows that the training had no effect on sales and profits from primary business in the last 30 days, as well as on business survival. While the coefficient signs are negative, the magnitudes are very small and the p-values are very large. Table 24 shows the results from running the same regressions with the Midline sample; I find the same takeaway of no significant effect of SMS trainings on business performance.

In the Endline, I measure business performance not just for the primary business, but also for all businesses combined, to account for any reallocation across businesses for those who have more than one. Table 25 shows that including other businesses into the equation does not change the results, and Table 26 confirms that the story stays the same when I restrict the analysis to the Midline-matched sample.

In the Midline, younger entrepreneurs saw significant effects on primary business performance, so I check for heterogeneity by age in the Endline as well, but find no effects for younger entrepreneurs (Table 24), and this result also does not change when I restrict the analysis to the Midline-matched sample (Table 28). I also check for effects on business performance across younger and older entrepreneurs aggregating sales and profits across all businesses, but I see the same result in the full Endline sample (Table 29), as well as the Midline-matched samples (Table 30)

5.3.4 Endline Mechanisms

I examine the same potential mechanisms at Endline as I did at Midline. Table 6 indicates that there was a negative and statistically significant decrease in hours worked on primary business for treatment individuals, but the magnitude is small compared to positive effects observed at Midline (9.7 hours less in the last 30 days), with this negative effect primarily driven by rural entrepreneurs. Table 31 shows that the negative effect goes away when I restrict the analysis to the Midline-matched sample. Tables 32 and 33 show that the negative effect on hours worked on primary business is also not robust to aggregating time spent across all businesses, and when focusing on the Midline-matched sample for this analysis too. Taken together, these results show that there was no treatment effect on time spent on business twelve months after the intervention. Moreover, Tables 34 and 35 show that there is no significant effect on time spent on side jobs either.

Tables 38, 39, 38, and 39 furthermore show that younger entrepreneurs no longer spend more time on business, whether I look at the last 30 days (as in the Midline), or the last 7 days.

Tables 40, 41, 42, and 43 show that there are no effects of treatment assignment on labor hours employed as well.

Lastly, I observe that the positive treatment effects for younger entrepreneurs on loan amounts applied for and received also disappear (Tables 44 and 45).

Taken together, these results show that there was no meaningful improvement in any of the intermediate business outcomes twelve months after the launch of the training.

5.3.5 Endline Summary

In summary, all positive effects observed at Midline were short-lived, and within twelve months of the intervention, there was no difference across treatment and control individuals in terms of any outcome of interest.

These lack of effects could potentially be explained by the fact that engagement levels looked very similar at Midline and Endline, suggesting that there wasn't much engagement beyond the three month follow-up. This is largely confirmed when I look at how engagement levels changed over time. Figure 4 shows the survival curve of engagement of all approximately 30% of the treatment group that started engaging with the content during the course of the study. The figure reveals that all interactions with the SMS training platform ended within the first few months of the intervention, and well before the Endline. Despite the two month long reminder protocol described in Section 3, almost no one in the treatment group interacted with the SMS chat-bot after June 2022.

5.4 Predictions vs Observations

Are the main results I observe expected and obvious, or are they surprising and informative? Hindsight bias makes it hard to objectively answer this question once the results are revealed. I circumvent this problem by eliciting predictions for the Endline treatment effects from social science researchers without informing them about my findings, as detailed in Section 4.2. In this section, I present comparisons of predicted and observed treatment effects to argue that the findings in this study are indeed surprising and informative.

The predictions survey received 70 responses. About 89% listed Economics as one of their main disciplines, and 7.7% listed Political Science. Other social science disciplines represented, but in significantly smaller numbers, included Psychology and Sociology.

Figure 5 illustrates how the predicted extensive and intensive margin engagement compares with observed levels. Respondents predicted that, at the Endline, about 50% of the treatment group will have started engaging with the training content, and the average micro-entrepreneur in the treatment group will have covered approximately 40% of the training content. The actual engagement levels observed are much lower; only about 30% of the treatment group had started engaging by Midline, and the extensive margin engagement stood at the same level by the Endline. Additionally, the average micro-entrepreneur in the treatment group only covered approximately 7% of the training content by Midline, and this unconditional intensive margin engagement level stayed largely the same by the Endline.

Figure 6 shows respondent expectations for the effect of assignment to treatment on knowledge and adoption of best practices in terms of control group standard deviations. Respondents predicted that knowledge and adoption will increase by approximately 0.3 and 0.2 standard deviations respectively at the Endline. While I observe 0.2 and .33 standard deviations increases in knowledge and adoption at Midline, respectively, these positive effects disappear by the Endline. Hence, I find that respondents also overestimated the effect of treatment assignment on knowledge and adoption of best practices twelve months after the intervention.

Figure 7 shows a similar story for effects on sales and profits. Respondents predicted a 13% and 12% increase in sales and profits in the Endline, respectively. While observed effects in Midline are of similar magnitudes as the predictions, albeit statistically insignificant, the observed effects are close to zero for the Endline. I therefore find that respondents also overestimated the effect of treatment assignment on sales and profits twelve months after the intervention.

In light of these results, I conclude that social science researchers overestimate the potential of SMS-based trainings to improve outcomes for micro-entrepreneurs, and the findings from this study are thus contrary to priors. Updating these priors is important as investment of resources into such remote information-based support programs by policy makers and practitioners are often informed by beliefs about impacts held by social scientists.

5.5 Willingness to Pay

About 415 individuals responded to the TIOLI invitations described in Section 3.3.1, with 272 choosing to buy the additional training, 111 choosing not to buy, and 32 invalid responses that the system could not categorize. I use a conservative acceptance rate by grouping the last category with those who explicitly chose to not buy.

Figure 11 shows the (inverse) demand curve constructed using buying decisions amongst the TIOLI sample. I observe that 70% of individuals choose to accept the offer when the training is offered for free. When the price is half the marginal cost per user for the full training faced by the provider (KSH 5), acceptance rate falls slightly to 67.8%. From the price being half the marginal cost to double the marginal cost, there is a significant reduction in the acceptance rate, but even at KSH 20, 47% of individuals are willing to buy the training.

The sample for the willingness to pay elicitation using the modified BDM method described in Section 3.3.2 differs from the TIOLI sample in four different ways, (i) it spans across treatment and control groups[16], (ii) it only covers respondents based in Nairobi[17], (iii) it only covers micro-entrepreneurs with an active business[18], and (iv) it only covers 103 respondents[19].

Figure 12 shows the (inverse) demand curve constructed using the maximum willingness to pay elicited using the BDM method. I find that the entire sample is willing to buy the SMS training when it is free. Approximately 35% of the sample is willing to pay KSH 100, which is ten times the marginal cost. The average maximum willingness to pay in the sample is KSH 50, and the distribution shows bunching of responses at KSH 0 (9%), KSH 20 (10%), KSH 50 (27%), and KSH 100 (24%).[20]

Both methods of elicitation, therefore, show that micro-entrepreneurs are willing to pay a small amount to get access to SMS-trainings.

Since about 70% of the treatment group did not start engaging with the content and no one in the control group had been exposed to it either, the willingness to pay in the TIOLI as well

[16] This was to allow for estimation of the effect of treatment assignment on willingness to pay.

[17] This was for logistical convenience - the full study sample contains micro-entrepreneurs spread across all 47 counties of Kenya.

[18] This was for logistical convenience - it was easier and safer for enumerators to approach business owners since they had a place of work that the enumerator could get to. Almost 90% of the micro-entrepreneurs in the sample had an active business so this particular restriction did not meaningfully restrict the sample.

[19] This was due to financial constraints

[20] This is not surprising in light of literature on round-number bias (Lynn, Flynn and Helion (2013)).

as BDM elicitation could be driven by those with less or no engagement with the content. If this was the case, I would see a clear negative relationship between exposure to training content and willingness to pay. I test for this by (i) comparing engagement levels in the TIOLI sample across those who bought the training and those who did not, and (ii) estimating the effect of training on willingness to pay elicited through the BDM. However, I do not find evidence for a negative relationship between exposure to content and willingness to pay for SMS-based trainings. Table 46 shows that extensive and intensive margin engagement levels are not lower amongst those who rejected the invitation to buy an additional SMS-based training in the TIOLI sample - in fact, engagement levels are slightly higher for those who chose to buy, albeit the difference is not statistically significant. Furthermore, I do not find a negative treatment effect on willingness to pay in the BDM sample either; in fact, similar to the findings from the TIOLI sample, I observe a small positive effect of treatment assignment on willingness to pay that is not statistically significant (Table 47. I therefore conclude that the willingness to pay results are actually driven by those who had more exposure to the SMS-training.

The observed positive willingness to pay could also be due to reciprocity (Gouldner (1960)); respondents might have felt the need to give back for being part of the study by agreeing to buy the additional training. This might be a concern for the BDM sample since it involved enumerators meeting respondents in person to conduct the elicitation. It is unlikely that reciprocity affected responses to TIOLI offers since that elicitation was done over SMS and was completely automated, and yet I still observe positive willingness to pay.

The observed willingness to pay could also just be because a certain type of people would say yes to anything. However, I argue that this is also unlikely since I find that willingness to pay systematically decreases with price level; the demand curves are downward sloping.

I therefore conclude that the decision to buy the SMS-trainings is a reflection of micro-entrepreneurs' intrinsic valuation of having access to the trainings.

Qualitative interviews with a small subset of individuals in the treatment group reveal that the reason micro-entrepreneurs did not engage with the content even though they were willing to pay for access to more trainings was that they were "busy during the day with customers" and then "forgot to engage after getting free". This suggests that engagement levels may not perfectly reflect actual demand for the content, and might point towards a behavioral explanation driving these decisions (in line with Della Vigna and Malmendier (2006); Bai et al. (2021); de Oliveira (2023)). I leave a deeper dive into possible behavioral drivers to in this context future work.

6 Conclusion and Policy Implications

This paper assesses the demand for and potential of SMS-based business trainings to improve business outcomes for micro-entrepreneurs via a field experiment in Kenya with an embedded willingness to pay elicitation. About 4,700 micro-entrepreneurs recruited over SMS were randomized into a Treatment and a Control group; the 2,820 entrepreneurs in the Treatment group were provided access to SMS-based training content, while the remaining 1,880 were sent placebo messages aimed at reminding them about their business.

Three months after the intervention, I find positive effects on knowledge and adoption of best practices, particularly for advertising, and large positive but statistically insignificant effects on business sales, profits and survival. I further find significant positive effects on business performance for younger entrepreneurs, driven by higher engagement with the training content, and larger increases in time spent on business, and amount of credit applied for and received.

However, these positive results dissipate in the longer run; twelve months after the intervention, I see no effects on knowledge and adoption of best practices, as well as business sales, profits and survival. Additionally, the positive effects on business outcomes observed for younger entrepreneurs after three months also disappear within twelve months.

The time-trend of engagement reveals that the lack of longer-run effects is likely driven by micro-entrepreneurs abandoning all interactions with the content within the first few months of the intervention. Additionally, notwithstanding the low engagement and lack of longer-run effects, I find that micro-entrepreneurs are willing to pay a small amount for an additional SMS-based training, suggesting that they value access to the content.

I therefore conclude that, despite their growing popularity, SMS-based trainings on their own are unlikely to be effective for micro-entrepreneurs. Comparing results with elicited priors of social science researchers reveals that social scientists overestimate the potential of SMS-based trainings, thus the findings from this study are surprising and informative.

The takeaways from this study raise another interesting question that is key to unlocking the full potential of digital technologies to impact remote learning; why was engagement low? There can be two possible non-mutually exclusive components to blame for this - (i) the content, and/or (ii) the content delivery. If entrepreneurs believe that the content is not worth engaging with, they are unlikely to invest any time engaging with it. It is unlikely that this was the case in this study as 70% of the treatment group never started engaging with the content, and so did not even see what was in the training. For those who did start engaging, they were still willing to pay a positive, albeit small, amount to get access to another SMS-training (across both elicitation methods, willingness to pay was positively correlated with exposure to the training). Nevertheless, better content is an important research direction, with a growing body of evidence on the benefits of simplifying the message (Drexler, Fischer and Schoar (2014); Arráiz, Bhanot and Calero (2019)), adding psychology-based personal initiative oriented content (Campos et al. (2017)), and also customizing the content in light of the needs of the recipients (Fabregas et al. (2022)), and further research in this direction can help move the needle more on addressing the challenge of low engagement in remotely provided trainings.

The other reason for low engagement can be the nature of the content delivery. This component perhaps speaks to why, despite having access to basic as well as advanced knowledge about countless subjects through the internet[21], we still have to attend school and other classroom-type environments for acquiring knowledge and skills beyond foundational language and mathematics. Further research in this direction, possibly guided by insights from psychology and behavioral economics (as reflected in the likes of Della Vigna and Malmendier (2006); Bai et al. (2021); de Oliveira (2023)) can add to our understanding of what makes people engage or not engage with remotely provided content, which can greatly help unlock the full potential of digital technologies for remote learning.

[21] Through resources including Youtube, Khan Academy, Udemy, Coursera, Lynda, Skillshare, Udacity etc.

References

Arifu: WhatsApp Chatbot Provides Tips for Micro-Retailers. N.d. https://strivecommunity.org/programs/arifu.

Arráiz, Irani, Syon Bhanot and Carla Calero. 2019. Less Is More: Experimental Evidence on Heuristics-Based Business Training in Ecuador. Technical report IDB Invest.

Bai, Liang, Benjamin Handel, Edward Miguel and Gautam Rao. 2021. "Self-control and demand for preventive health: Evidence from hypertension in India." *Review of Economics and Statistics* 103(5):835–856.

Becker, Gordon M., Morris H. Degroot and Jacob Marschak. 1964. "Measuring Utility by a Single-Response Sequential Method." *Behavioral Science* 9(3):226–232.

Blattman, Christopher and Laura Ralston. 2015. "Generating Employment in Poor and Fragile States: Evidence from Labor Market and Entrepreneurship Programs.".

Bloom, Nicholas, Aprajit Mahajan, David McKenzie and John Roberts. 2010. "Why Do Firms in Developing Countries Have Low Productivity?" *American Economic Review* 100(2):619–623.

Bloom, Nicholas, Benn Eifert, Aprajit Mahajan, David McKenzie and John Roberts. 2013. "Does Management Matter? Evidence from India." *The Quarterly Journal of Economics* 128(1):1–51.

Bloom, Nicholas and John Van Reenen. 2010. "Why Do Management Practices Differ across Firms and Countries?" *Journal of Economic Perspectives* 24(1):203–224.

Bruhn, Miriam, Dean Karlan and Antoinette Schoar. 2010. "What Capital Is Missing in Developing Countries?" *American Economic Review* 100(2):629–633.

Bruhn, Miriam, Dean Karlan and Antoinette Schoar. 2018. "The Impact of Consulting Services on Small and Medium Enterprises: Evidence from a Randomized Trial in Mexico." *Journal of Political Economy* 126(2):635–687.

Business Edge : Status and Disposition. 2006. Technical Report 4 World Bank Group Washington, DC: .

Campos, Francisco, Michael Frese, Markus Goldstein, Leonardo Iacovone, Hillary C. Johnson, David McKenzie and Mona Mensmann. 2017. "Teaching Personal Initiative Beats Traditional Training in Boosting Small Business in West Africa." *Science* 357(6357):1287–1290.

Chioda, Laura, David Contreras-Loya, Paul Gertler and Dana Carney. 2021. "Making Entrepreneurs: Returns to Training Youth in Hard Versus Soft Business Skills.".

Cho, Yoonyoung and Maddalena Honorati. 2014. "Entrepreneurship Programs in Developing Countries: A Meta Regression Analysis." *Labour Economics* 28(C):110–130.

Cole, Shawn Allen and A. Fernando. 2020. 'Mobile'Izing Agricultural Advice: Technology Adoption, Diffusion, and Sustainability. SSRN Scholarly Paper ID 2179008 Social Science Research Network Rochester, NY: .

Cole, Shawn Allen, Mukta Joshi and Antoinette Schoar. 2021. "Heuristics on Call: The Impact of Mobile Phone Based Business Management Advice.".

Davies, Elwyn, Peter Deffebach, Leonardo Iacovone and David Mckenzie. 2023. *Training Microentrepreneurs over Zoom: Experimental Evidence from Mexico*. Policy Research Working Papers The World Bank.

de Oliveira, Priscila. 2023. "Why Businesses Fail: Underadoption of Improved Practices by Brazilian Micro-Enterprises.".

Della Vigna, Stefano and Ulrike Malmendier. 2006. "Paying not to go to the gym." *American Economic Review* 96(3):694–719.

DellaVigna, Stefano, Devin Pope and Eva Vivalt. 2019. "Predict Science to Improve Science." *Science* 366(6464):428–429.

Drexler, Alejandro, Greg Fischer and Antoinette Schoar. 2014. "Keeping It Simple: Financial Literacy and Rules of Thumb." *American Economic Journal: Applied Economics* 6(2):1–31.

Estefan, Alejandro, Martina Improta, Romina Ordoñez and Paul Winters. 2023. "Digital Training for Micro-Entrepreneurs: Experimental Evidence from Guatemala." *The World Bank Economic Review* p. lhad029.

Fabregas, Raissa, Michael Kremer, Matthew Lowes, Robert On and Giulia Zane. 2022. "Digital Information Provision and Behavior Change: Lessons from Six RCTs in East Africa.".

Gouldner, Alvin W. 1960. "The Norm of Reciprocity: A Preliminary Statement." *American Sociological Review* 25(2):161–178.

Haddad, Josette. 2022. "Training Tanzanian Farmers Through Text Messaging.".

Hinrichsen, Simone and Samuel Ajadi. 2020. "Using Technology to Fight COVID-19: A Spotlight on SMS-based Education Start-up, Eneza Education.".

ILO. 2019. Small Matters. Technical report International Labour Office Geneva: .

Kenya Population and Housing Census. 2019. https://www.knbs.or.ke/?p=5621.

Lynn, Michael, Sean Masaki Flynn and Chelsea Helion. 2013. "Do Consumers Prefer Round Prices? Evidence from Pay-What-You-Want Decisions and Self-Pumped Gasoline Purchases." *Journal of Economic Psychology* 36:96–102.

Maffioli, Alessandro, David McKenzie and Diego Ubfal. 2020. *Estimating the Demand for Business Training : Evidence from Jamaica*. Policy Research Working Papers The World Bank.

McKenzie, David. 2020. "Small Business Training to Improve Management Practices in Developing Countries: Reassessing the Evidence for "Training Doesn't Work"." *Policy Research Working Paper* p. 40.

McKenzie, David and Christopher Woodruff. 2014. “What Are We Learning from Business Training and Entrepreneurship Evaluations around the Developing World?” *World Bank Research Observer* 29(1):48–82.

McKenzie, David and Christopher Woodruff. 2017. “Business Practices in Small Firms in Developing Countries.” *Management Science* 63(9):2967–2981.

Mehmood, Muhammad Zia. 2023. “Predicting effects of an SMS-based business management training.” https://socialscienceprediction.org/.

Mehtha, Susanne van Lieshout-Pranati. 2017. THE NEXT 15 MILLION Start and Improve Your Business Global Tracer Study 2011-15. Publication International Labour Organization.

Micro, Small and Medium Enterprises Survey. 2016. http://www.knbs.or.ke/?p=572.

M-Shule SMS Learning & Training, Kenya | UIL. 2022. https://uil.unesco.org/case-study/effective-practices-database-litbase-0/m-shule-sms-learning-training-kenya.

Ramirez, Cristina. 2019. CEFE GLOBAL IMPACT STUDY 2019. Technical report CEFE International.

Regan-Sachs, Rebecca. 2022. “No Smartphone? No Problem: 3 Keys to Training Unconnected Farmers %.” https://www.technoserve.org/blog/3-keys-to-training-unconnected-farmers/.

Start and Improve Your Business Programme (ENTERPRISES). N.d. https://www.ilo.org/empent/areas/start-and-improve-your-business/lang–en/index.htm.

Ulmann, Selina. 2023. “Improving Organic Farming Practices in Africa with SMS, IVR, App-Based Training.” https://www.rural21.com/english/a-closer-look-at/detail/article/improving-organic-farming-practices-in-africa-with-sms-ivr-app-based-training.html.

van Vark, Caspar. 2012. “Empowering Farmers through SMS.” *The Guardian* .

World Bank, Gender Data Portal. 2020. “Entrepreneurship.” https://genderdata.worldbank.org/topics/entrepreneurship.

WorldBank. 2021. “World Bank SME Finance.” https://www.worldbank.org/en/topic/smefinance.

A Main Tables

A.1 Midline

Table 1: Midline: Engagement

	(1) Engaged	(2) Covered ≥ 25%	(3) % Covered (cond.)	(4) % Covered (uncond.)
Training	0.298***	0.0844***	0.234***	0.0698***
	(0.0306)	(0.0150)	(0.0229)	(0.00988)
Control Mean	0	0	0	0
Observations	307	307	229	307

Notes: This table shows the output from OLS regressions of four measures of engagement on treatment assignment at Midline, with no controls added. Column (1) shows effect of treatment assignment on extensive margin engagement - i.e. whether or not the individual started engaging with content. Column (2) shows the effect on whether or not the individual engaged with at least 25% of the training content. Column (3) shows the effect on percentage of training content that the individual engaged with conditional on starting to engage. The observations used for this regression exclude the 78 individuals in the treatment group who had not started engaging with the content, thus the number of observations is 307 - 78 = 229. Column (4) shows the unconditional effect on percentage of training content that the individual engaged with. Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 2: Midline: Knowledge and Adoption of Best Practices

	Knowledge		**Adoption**	
	OLS	IV	OLS	IV
Training	.198*		.332**	
	(.118)		(.155)	
Engaged		.673*		1.115**
		(.404)		(.535)
Female	.0402	.00138	-.175	-.243
	(.117)	(.123)	(.183)	(.208)
P-value	.0953	.0957	.0330	.0371
Control Mean	0	0	0	0
Observations	307	307	297	297

Notes: This table shows the intent-to-treat and local average treatment effect estimates of SMS trainings on means effect indices of knowledge and adoption of best practices at Midline. Coefficients represent effects in terms of control group standard deviations. Columns (1) and (3) show output from OLS regressions, and columns (2) and (4) show output from 2SLS regressions where the endogenous variable is whether or not the individual engaged with training content. Robust standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 3: Midline: Sales, Profits and Survival

	Sales		**Profits**		**Survival**	
	OLS	IV	OLS	IV	OLS	IV
Training	5721.0		1680.6		.0414	
	(10814.3)		(1601.9)		(.0326)	
Engaged		19112.7		5407.1		.141
		(35918.8)		(5134.1)		(.111)
Female	-34684.4***	-35888.4***	-7567.2***	-7926.3***	-.0350	-.0431
	(11785.7)	(12228.7)	(1674.6)	(1837.3)	(.0299)	(.0311)
P-value	.597	.595	.295	.292	.204	.207
Control Mean	47581.2	47581.2	10886.9	10886.9	.908	.908
Observations	290	290	294	294	307	307

Notes: This table shows the intent-to-treat and local average treatment effect estimates of SMS trainings on primary business sales and profits from last 30 days, and business survival at Midline. Coefficients in columns (1) thought (4) represent effects in terms of Kenyan Shillings, while those in columns (5) and (6) represent probability of individual having an active business. Columns (1), (3) and (5) show output from OLS regressions, and columns (2), (4) and (6) show output from 2SLS regressions where the endogenous variable is whether or not the individual engaged with training content. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Midline: Intermediate Outcomes

	Hrs. worked		**Lab. Hrs. employed**		**Loan Applied**		**Loan Received**	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Training	28.88*		4.933		-365.6		987.1	
	(16.52)		(29.64)		(7629.7)		(5570.2)	
Engaged		108.4*		16.74		-1240.6		3349.5
		(63.22)		(100.0)		(25767.3)		(18792.9)
Female	-5.896	-12.26	-81.69***	-82.66***	-14817.1**	-14745.6**	-11173.2**	-11366.5**
	(16.94)	(18.25)	(26.02)	(25.56)	(6344.6)	(6715.8)	(5249.0)	(5669.1)
P-value	.0817	.0864	.868	.867	.962	.962	.859	.859
Control Mean	178.6	178.6	122.6	122.6	13818.3	13818.3	10104.6	10104.6
Observations	269	269	307	307	307	307	307	307

Notes: This table shows the intent-to-treat and local average treatment effect estimates of SMS trainings on hours worked and labor hours employed in the primary business in the last 30 days, and loan amounts applied for and received (in Kenyan Shillings) in the last 3 months at Midline. Columns (1), (3), (5), and (7) show output from OLS regressions, and columns (2), (4), (6), and (8) show output from 2SLS regressions where the endogenous variable is whether or not the individual engaged with training content. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.2 Endline

Table 5: Endline: Engagement

	(1) Engaged	(2) Covered ≥ 25%	(3) % Covered (cond.)	(4) % Covered (uncond.)
Training	0.280***	0.0821***	0.233***	0.0651***
	(0.0110)	(0.00672)	(0.0115)	(0.00411)
Control Mean	0	0	0	0
Observations	2780	2780	1578	2780

Notes: This table shows the output from OLS regressions of four measures of engagement on treatment assignment at Endline, with no controls added. Column (1) shows effect of treatment assignment on extensive margin engagement - i.e. whether or not the individual started engaging with content. Column (2) shows the effect on whether or not the individual engaged with at least 25% of the training content. Column (3) shows the effect on percentage of training content that the individual engaged with conditional on starting to engage. Column (4) shows the unconditional effect on percentage of training content that the individual engaged with. Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 6: Endline: Knowledge and Adoption of Best Practices

	Basic Knowledge		**Basic Adoption**		**Advanced Knowledge**		**Advanced Adoption**	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Training	.0248		-.0638		-.0355		-.0223	
	(.0384)		(.0399)		(.0387)		(.0410)	
Engaged		.0887		-.222		-.127		-.0777
		(.137)		(.139)		(.138)		(.143)
Female	.0127	.0113	-.287***	-.284***	-.0833**	-.0814**	-.0491	-.0479
	(.0376)	(.0376)	(.0390)	(.0391)	(.0382)	(.0383)	(.0405)	(.0405)
P-value	.518	.518	.110	.110	.359	.359	.586	.586
Control Mean	0	0	0	0	0	0	0	0
Observations	2780	2780	2563	2563	2780	2780	2563	2563

Notes: This table shows the intent-to-treat and local average treatment effect estimates of SMS trainings on means effect indices of basic and advanced knowledge and adoption of best practices at Endline. Basic knowledge and basic adoption indices are similar to the knowledge and adoption indices analysed for the Midline, while the advanced knowledge and adoption indices are based on best practices are a bit more advanced and not necessarily directly mentioned in the SMS-trainings. Coefficients represent effects in terms of control group standard deviations. Columns (1), (3), (5), and (7) show output from OLS regressions, and columns (2), (4), (6), and (8) show output from 2SLS regressions where the endogenous variable is whether or not the individual engaged with training content. Robust standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 7: Endline: Sales, Profits and Survival

	Sales		**Profits**		**Survival**	
	OLS	IV	OLS	IV	OLS	IV
Training	-2206.5		-220.6		-.0159	
	(3534.1)		(1009.0)		(.0112)	
Engaged		-7891.3		-789.6		-.0568
		(12640.7)		(3610.8)		(.0400)
Female	-34537.5***	-34415.8***	-9444.3***	-9432.7***	.00903	.00990
	(3380.7)	(3389.6)	(982.3)	(982.6)	(.0111)	(.0111)
P-value	.532	.532	.827	.827	.154	.155
Control Mean	59356.0	59356.0	19453.4	19453.4	.915	.915
Observations	2772	2772	2770	2770	2779	2779

Notes: This table shows the intent-to-treat and local average treatment effect estimates of SMS trainings on primary business sales and profits from last 30 days, and business survival at Endline. Coefficients in columns (1) thought (4) represent effects in terms of Kenyan Shillings, while those in columns (5) and (6) represent probability of individual having an active business. Columns (1), (3) and (5) show output from OLS regressions, and columns (2), (4) and (6) show output from 2SLS regressions where the endogenous variable is whether or not the individual engaged with training content. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

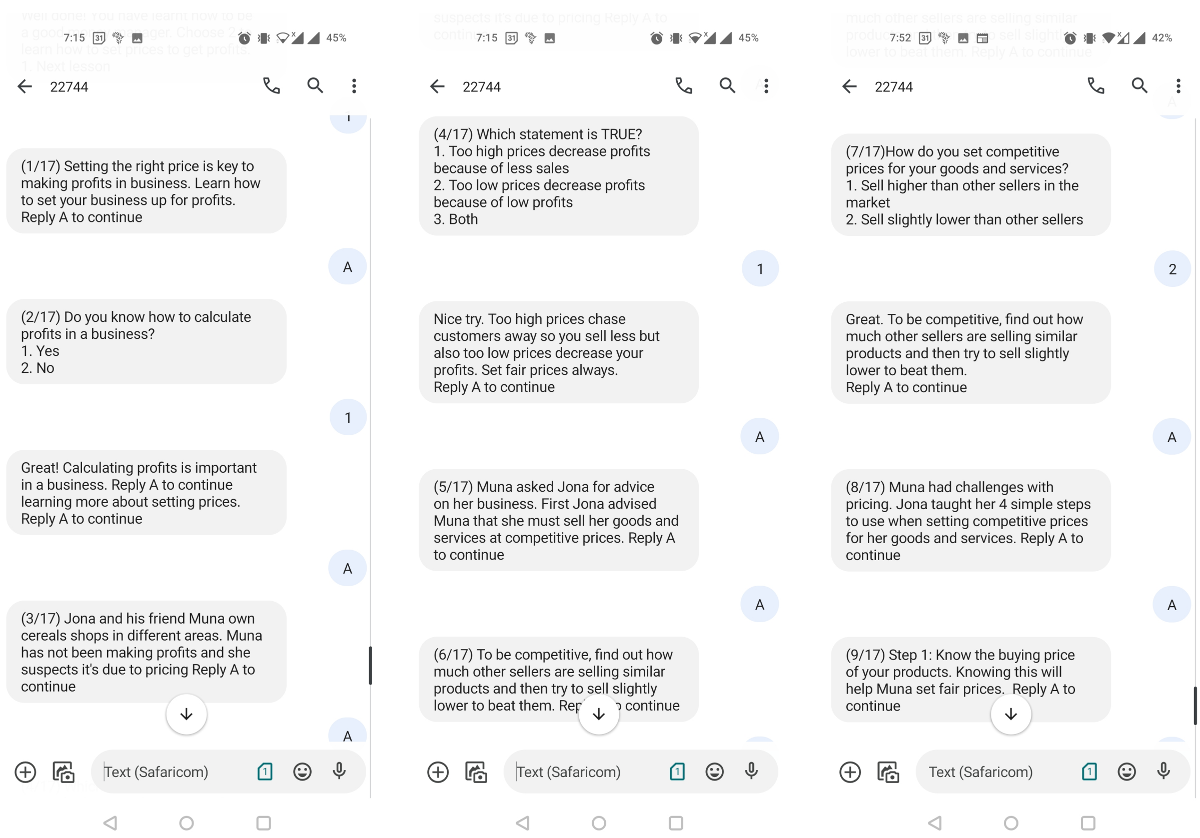
Table 8: Endline: Intermediate Outcomes

	Hrs. worked		**Lab. Hrs. employed**		**Loan Applied**		**Loan Received**	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Training	-9.702**		-2.085		-667.9		-397.2	
	(4.459)		(6.554)		(2321.2)		(2071.2)	
Engaged		-34.67**		-7.438		-2384.6		-1418.2
		(15.99)		(23.38)		(8282.3)		(7390.0)
Female	-2.011	-1.466	-68.08***	-67.97***	-7467.3***	-7431.5***	-5751.0***	-5729.7***
	(4.343)	(4.364)	(6.368)	(6.415)	(2220.8)	(2217.8)	(1977.4)	(1973.8)
P-value	.0296	.0302	.750	.750	.774	.773	.848	.848
Control Mean	215.6	215.6	91.26	91.26	20392.3	20392.3	16813.0	16813.0
Observations	2777	2777	2778	2778	2780	2780	2780	2780

Notes: This table shows the intent-to-treat and local average treatment effect estimates of SMS trainings on hours worked and labor hours employed in the primary business in the last 30 days, and loan amounts applied for and received (in Kenyan Shillings) in the last 3 months at Endline. Columns (1), (3), (5), and (7) show output from OLS regressions, and columns (2), (4), (6), and (8) show output from 2SLS regressions where the endogenous variable is whether or not the individual engaged with training content. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

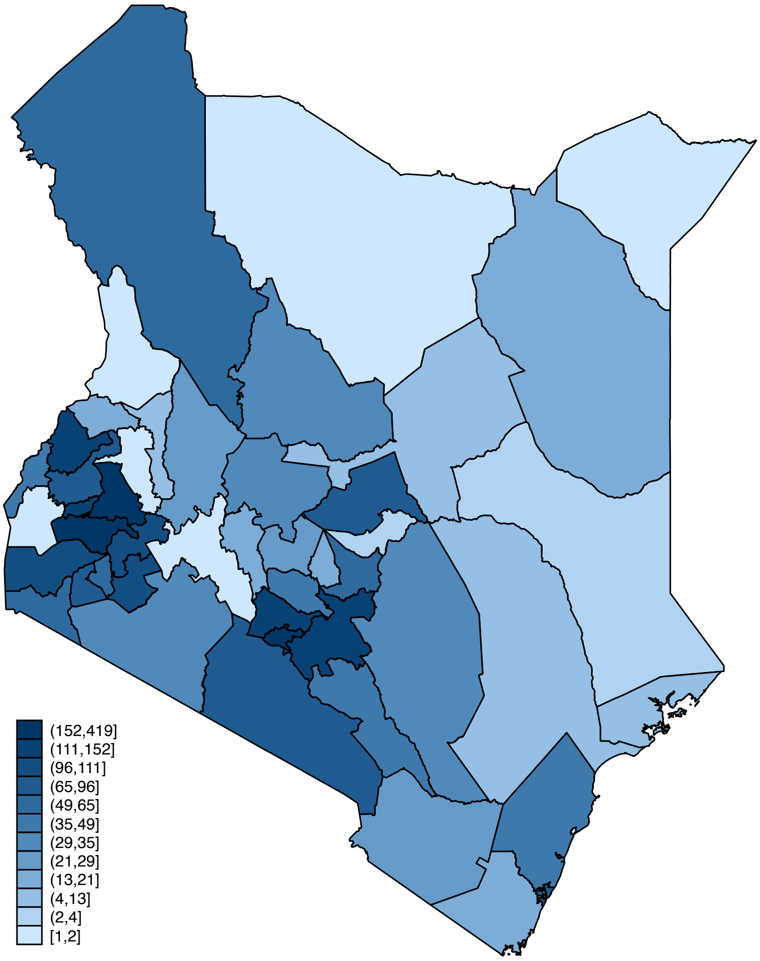
B Figures

Figure 1: SMS Business Training Content



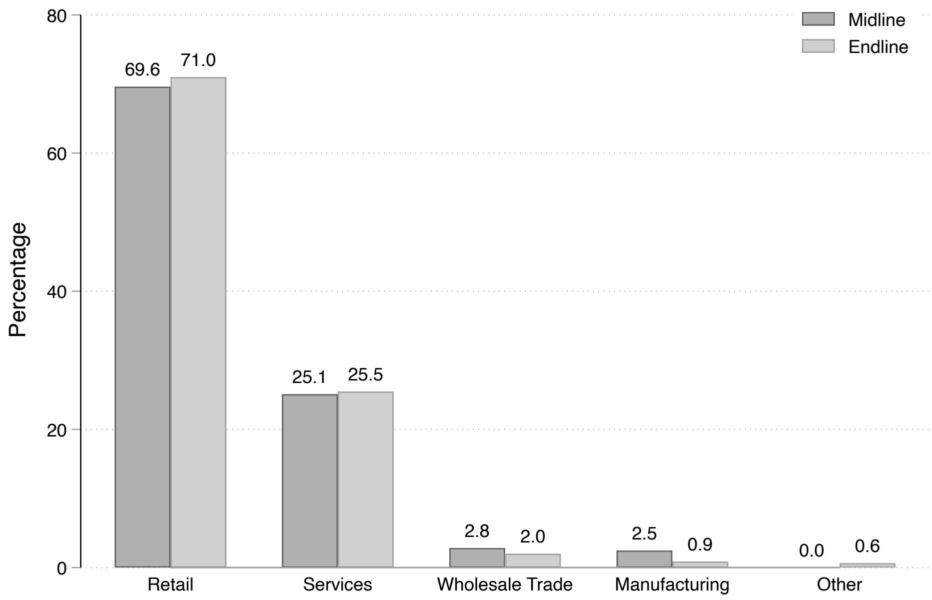
Notes: This figure shows screenshots of interactions with the SMS-based chatbot as it pushes out content to users. In this context, most micro-entrepreneurs set prices just based on their buying costs, without accounting for prices of their competitors, so the content pushes them to change their pricing strategy.

Figure 2: Geographical Spread of Study Sample



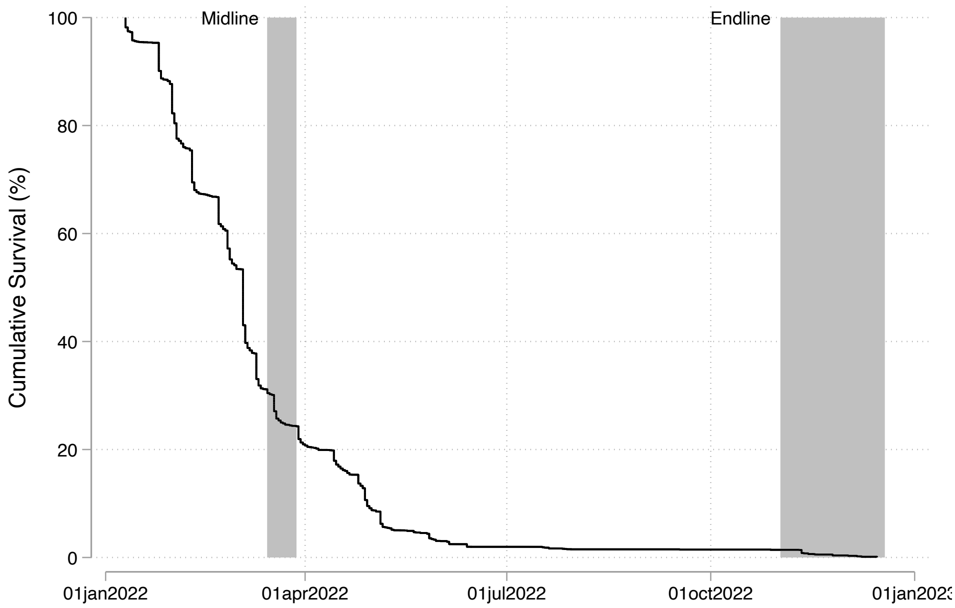
Notes: This figure shows the geographical distribution of micro-entrepreneurs in the study sample. The figure legend in the bottom-left assigns color-coding to number of micro-entrepreneurs based in each of the 47 counties of Kenya.

Figure 3: Nature of Businesses



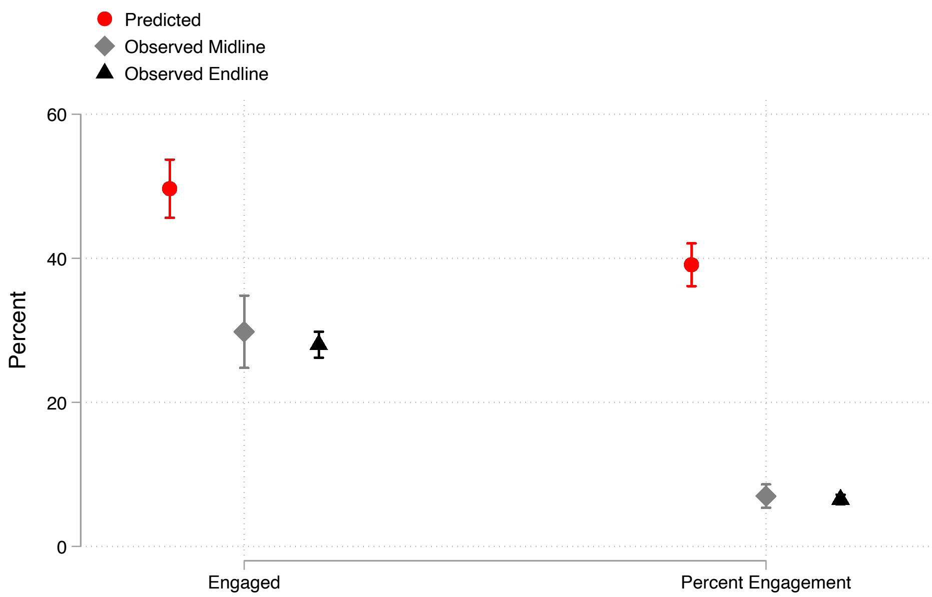
Notes: This figure shows the composition of the study samples across Midline and Endline in terms of nature of business of micro-entrepreneurs.

Figure 4: Engagement Survival Curve



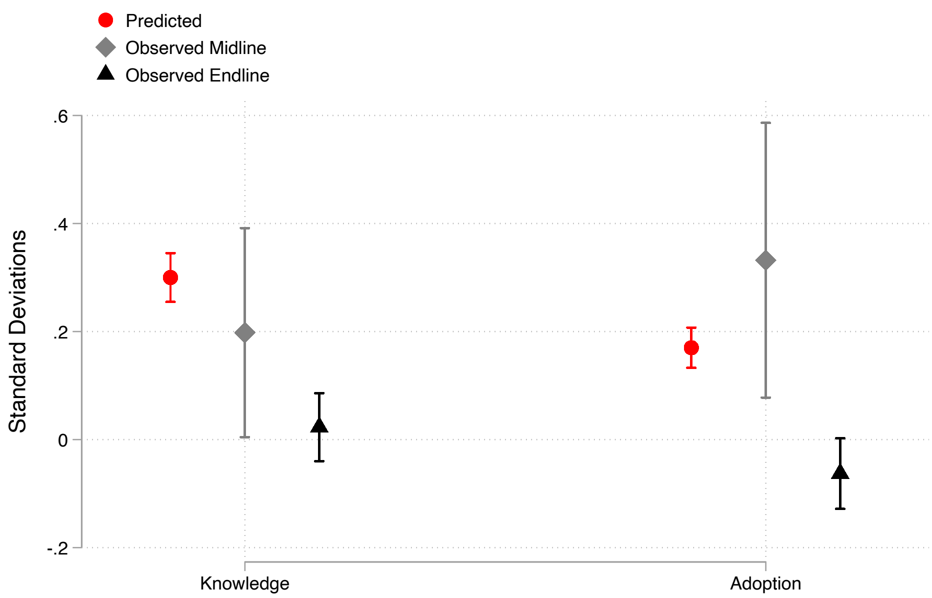
Notes: This figure illustrates how interactions with the SMS platform were distributed throughout the study period. The plot shows reverse cumulative engagement over time; for example, it shows that 80% of all the interactions with the chat-bot throughout the course of the study, had ended by 4/1/2022. The shaded areas represent the time-spans during which the Midline and Endline surveys were being conducted.

Figure 5: Predictions vs. Observations - Engagement



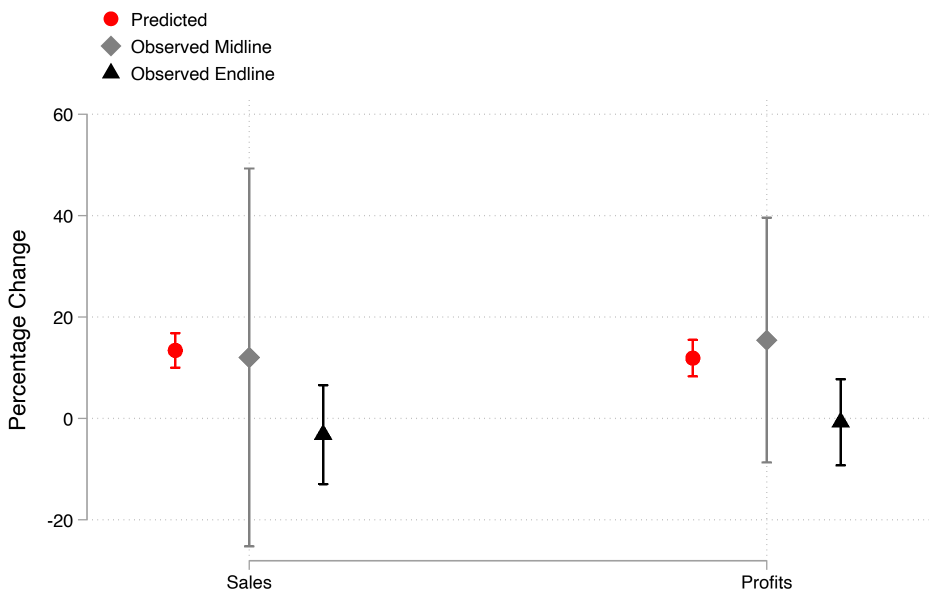
Notes: This figure shows how predicted treatment effects on extensive and intensive margin engagement for the Endline compare with observed Midline and Endline effects. Effects are in terms of percentage points. Error bars represent 90% confidence intervals.

Figure 6: Predictions vs. Observations - Knowledge and Adoption



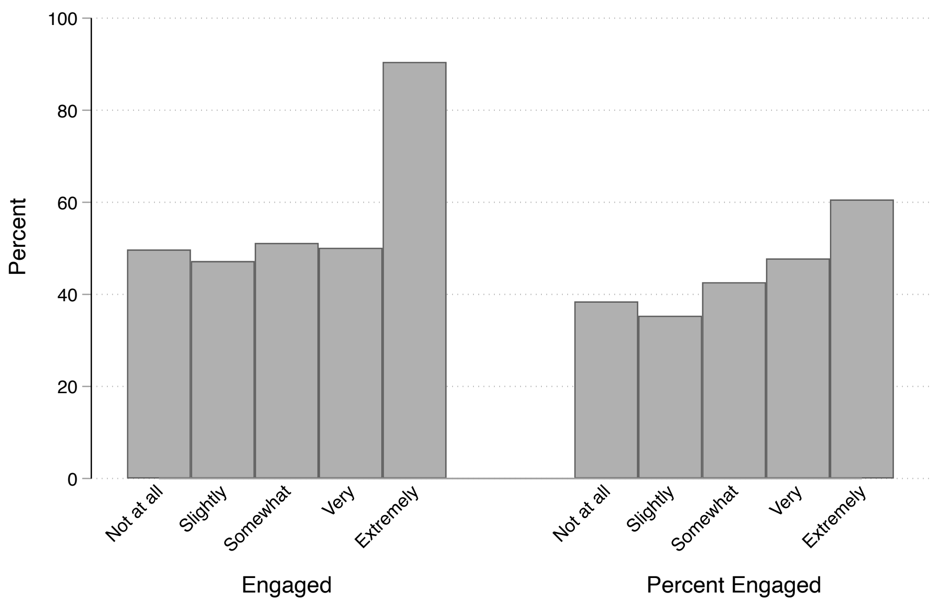
Notes: This figure shows how predicted treatment effects on knowledge and adoption of best practices for the Endline compare with observed Midline and Endline effects. Effects are in terms of control group standard deviations. Error bars represent 90% confidence intervals.

Figure 7: Predictions vs. Observations - Sales and Profits



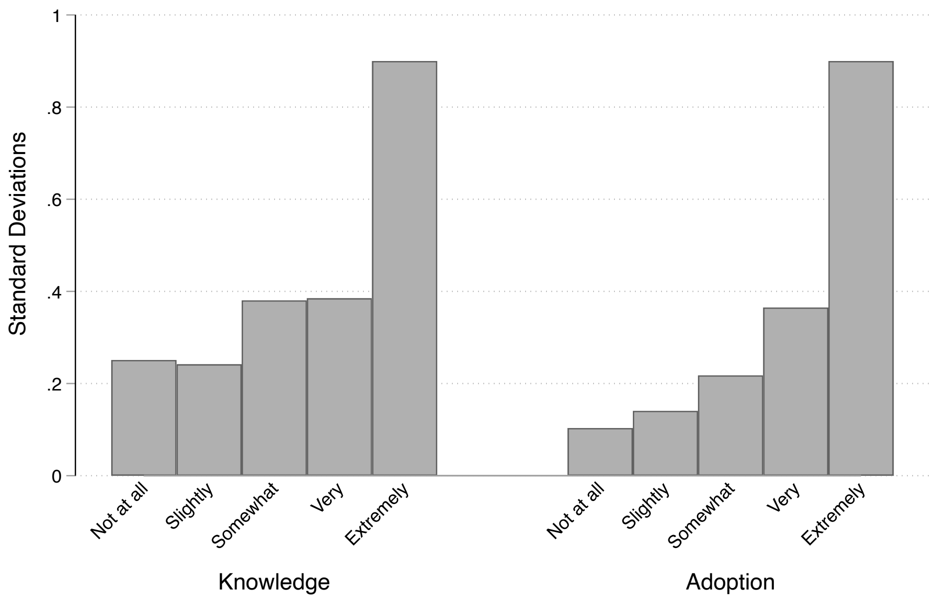
Notes: This figure shows how predicted treatment effects on business sales and profits in the last 30 days for the Endline compare with observed Midline and Endline effects. Effects are in terms of percentage changes. Error bars represent 90% confidence intervals.

Figure 8: Predictions by Confidence - Engagement



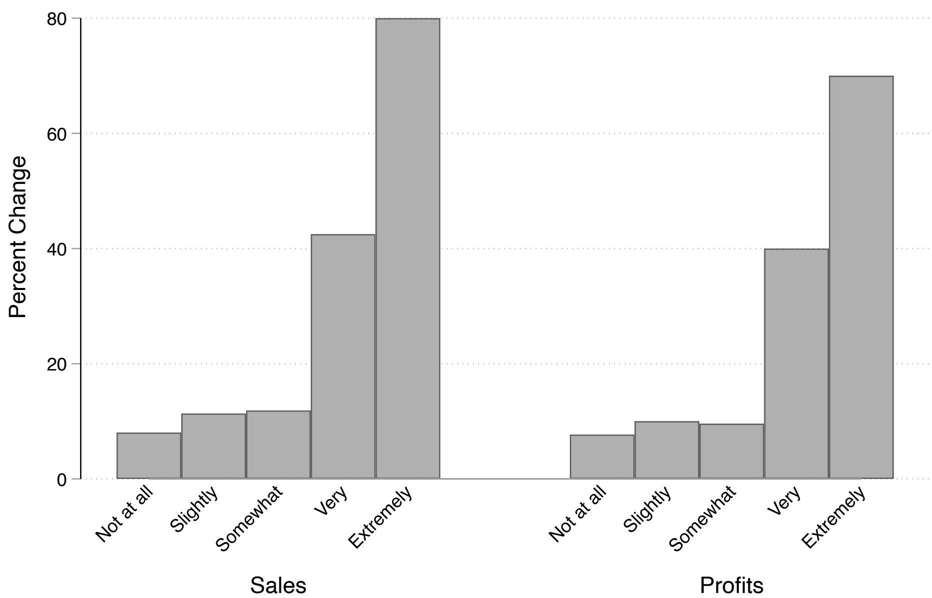
Notes: This figure shows predicted Endline effects on extensive and intensive margin engagement by level of confidence in predictions expressed by respondents. Predictions are in terms of percentage points.

Figure 9: Predictions by Confidence - Knowledge and Adoption



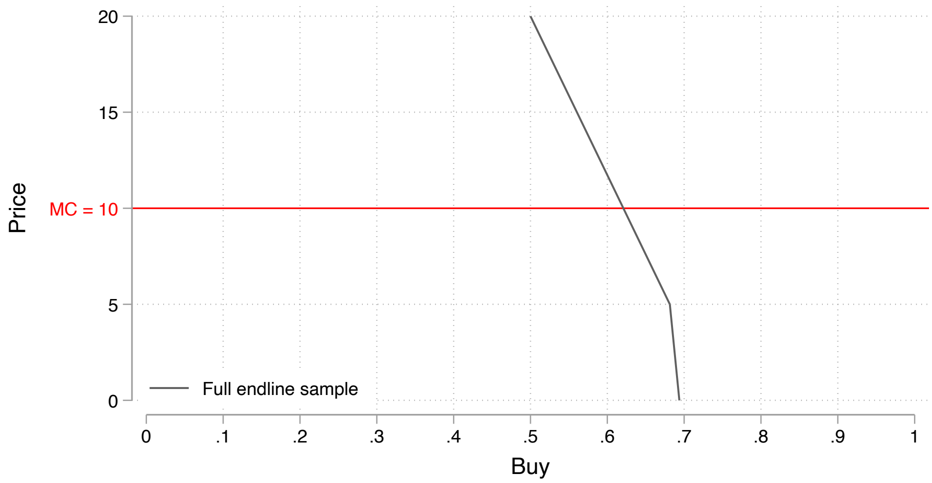
Notes: This figure shows predicted Endline effects on knowledge and adoption of best practices by level of confidence in predictions expressed by respondents.Predictions are in terms of control group standard deviations.

Figure 10: Predictions by Confidence - Sales and Profits



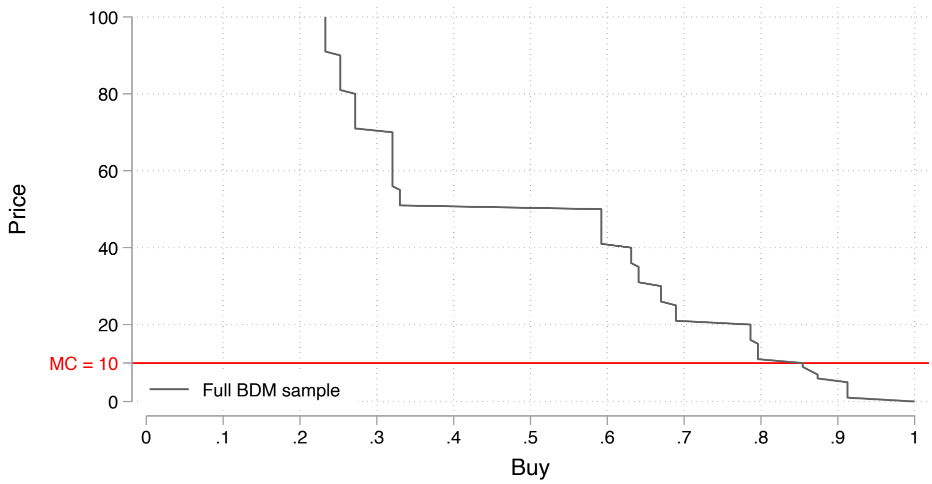
Notes: This figure shows predicted Endline effects on business sales and profits in the last 30 days by level of confidence in predictions expressed by respondents. Predictions are in terms of percentage changes.

Figure 11: Willingness to Pay - TIOLI Offers



Notes: This figure shows the (inverse) demand curve based on buying decisions from randomized take-it-or-leave-it offers sent to treatment individuals. The horizontal red line represents the per person marginal cost faced by provider for delivering the entire training.

Figure 12: Willingness to Pay - BDM



Notes: This figure shows the (inverse) demand curve based on the maximum willingness to pay elicited using the in-person elicitation using the modified BDM method. The horizontal red line represents the per person marginal cost faced by provider for delivering the entire training.

C Additional Tables

C.1 Summary Statistics and Balance Across Treatment and Control

Table 9: Summary Statistics

	Midline			Endline		
Variable	Mean	SD	Obs.	Mean	SD	Obs.
Female	0.50	0.50	307	0.47	0.50	2,780
Rural	0.44	0.50	307	0.46	0.50	2,780
Years of education	11.81	2.52	307	11.88	2.70	2,779
Age	35.80	9.73	306	35.30	9.15	2,779
Num of adults in household	2.58	1.50	306	2.63	1.34	2,776
Num of children in household	2.16	1.70	306	2.16	1.49	2,776
Job before intervention	0.25	0.44	307	0.17	0.38	2,780
Business before intervention	0.89	0.31	307	0.85	0.36	2,780
Loan before intervention	0.41	0.49	307	0.38	0.49	2,779

Notes: This table shows the mean, standard deviation, and number of observations for pre-intervention covariates for Midline and Endline.

Table 10: Balance Table

	Midline				Endline			
Variable	Full	Treatment	Control	Diff	Full	Treatment	Control	Diff
Female	0.50	0.53	0.44	0.08	0.47	0.46	0.48	-0.02
	(0.50)	(0.50)	(0.50)	(0.06)	(0.50)	(0.50)	(0.50)	(0.02)
Rural	0.44	0.47	0.38	0.09	0.46	0.46	0.46	-0.00
	(0.50)	(0.50)	(0.49)	(0.06)	(0.50)	(0.50)	(0.50)	(0.02)
Years of education	11.81	11.73	11.97	-0.25	11.88	11.84	11.95	-0.11
	(2.52)	(2.48)	(2.60)	(0.30)	(2.70)	(2.73)	(2.65)	(0.10)
Age	35.80	36.52	34.50	2.02*	35.30	35.00	35.75	-0.75**
	(9.73)	(10.19)	(8.73)	(1.16)	(9.16)	(9.03)	(9.33)	(0.35)
Num of adults in household	2.58	2.68	2.39	0.29	2.63	2.62	2.65	-0.03
	(1.50)	(1.66)	(1.11)	(0.18)	(1.34)	(1.34)	(1.34)	(0.05)
Num of children in household	2.16	2.16	2.17	-0.01	2.16	2.14	2.20	-0.07
	(1.70)	(1.75)	(1.61)	(0.20)	(1.49)	(1.50)	(1.49)	(0.06)
Job before intervention	0.25	0.25	0.27	-0.02	0.17	0.18	0.17	0.00
	(0.44)	(0.43)	(0.44)	(0.05)	(0.38)	(0.38)	(0.38)	(0.01)
Business before intervention	0.89	0.89	0.88	0.01	0.85	0.84	0.86	-0.02*
	(0.31)	(0.31)	(0.33)	(0.04)	(0.36)	(0.37)	(0.35)	(0.01)
Loan before intervention	0.41	0.42	0.40	0.02	0.38	0.39	0.37	0.01
	(0.49)	(0.49)	(0.49)	(0.06)	(0.49)	(0.49)	(0.48)	(0.02)
F-test p-value ($\beta_{diff} = 0$)				0.24				0.18
Observations	307	198	109	307	2,779	1,668	1,111	2,779

Notes: This table shows the balance of pre-intervention covariates across treatment and control groups for Midline and Endline samples. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.2 Midline

Table 11: Midline: Engagement by Age

	Full		**Age >= 34**		**Age < 34**		**Diff**	
	Engaged	% Engaged	Engaged	% Engaged	Engaged	% Engaged	Engaged	% Engaged
Training	0.298***	0.0698***	0.235***	0.0555***	0.375***	0.0896***		
	(0.0306)	(0.00988)	(0.0356)	(0.0116)	(0.0542)	(0.0181)		
Train x Age ≥ 34							-0.141**	-0.0341
							(0.0649)	(0.0215)
P-value	0	0	0	0	0	0	0.0310	0.114
Control Mean	0	0	0	0	0	0	0	0
Observations	307	307	160	160	146	146	306	306

Notes: This table shows the effect of treatment assignment on extensive and intensive margin engagement at Midline for the full sample (Columns 1 and 2, respectively), the sample with median and above age (Columns 3 and 4, respectively), the sample with below median age (Columns 5 and 6, respectively), and the difference in treatment effects across median and above, and below median age samples (Columns 7 and 8, respectively). Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 12: Midline: Knowledge and Adoption of Advertising

	Knowledge			**Adoption**		
	OLS	IV	IV	OLS	IV	IV
Training	.0913			.0839**		
	(.0633)			(.0344)		
Engaged		.310			.282**	
		(.216)			(.120)	
Covered advertising			.875			.812**
			(.614)			(.360)
Female	.0579	.0401	.0193	-.123***	-.140***	-.155***
	(.0696)	(.0726)	(.0786)	(.0430)	(.0493)	(.0562)
P-value	.150	.151	.154	.0154	.0183	.0241
Control Mean	.385	.385	.385	.0380	.0380	.0380
Observations	307	307	307	297	297	297

Notes: This table shows the intent-to-treat and local average treatment effect estimates of SMS trainings on knowledge and adoption of advertising at Midline. The dependent variable in the first three columns is a binary variable that indicates whether the individual responded correctly to the question testing knolwedge of advertising, while in the last three columns it is a binary variable that indicates whether the individual advertised any of their products in the last three months. Columns (1) and (4) show output from OLS regressions, Columns (2) and (5) show output from a 2SLS regressions where the endogenous variable is whether or not the individual engaged with training content, and Columns (3) and (6) show output from 2SLS regressions where the endogenous variable is whether or not the individual engaged with the part of the training content that covered advertising. Robust standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 13: Midline: Primary Business Performance by Age

	Full			**Age >= 34**			**Age < 34**			**Diff**		
	Sales	Profits	Survival	Sales	Profits	Survival	Sales	Profits	Survival	Sales	Profits	Survival
Training	5721.0	1680.6	0.0414	-23403.5	-450.1	-0.0289	35607.9**	3993.1	0.116**			
	(10814.3)	(1601.9)	(0.0326)	(16185.3)	(2031.0)	(0.0388)	(14825.0)	(2517.4)	(0.0482)			
Train x Age $\geq$ 34										-59011.5***	-4443.2	-0.145**
										(21949.1)	(3234.3)	(0.0619)
P-value	0.597	0.295	0.204	0.150	0.825	0.458	0.0180	0.115	0.0180	0.00800	0.171	0.0200
Control Mean	47581.2	10886.9	0.908	64450	11349.4	0.962	32586.7	10482.1	0.860	47581.2	10886.9	0.908
Observations	290	294	307	152	151	160	138	143	146	290	294	306

Notes: This table shows the effect of treatment assignment on primary business sales in the last 30 days, primary business profits in the last 30 days, and business survival at Midline for the full sample (Columns 1, 2 and 3, respectively), the sample with median and above age (Columns 4, 5, and 6, respectively), the sample with below median age (Columns 7, 8, and 9, respectively), and the difference in treatment effects across median and above, and below median age samples (Columns 10, 11, and 12, respectively). Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 14: Midline: Balance Across Treatment and Control by Age

	Age ≥ 34				Age < 34			
Variable	Full	Treatment	Control	Diff	Full	Treatment	Control	Diff
Female	0.59	0.64	0.50	0.14*	0.39	0.39	0.39	0.01
	(0.49)	(0.48)	(0.50)	(0.08)	(0.49)	(0.49)	(0.49)	(0.08)
Rural	0.46	0.50	0.38	0.12	0.41	0.44	0.37	0.07
	(0.50)	(0.50)	(0.49)	(0.08)	(0.49)	(0.50)	(0.49)	(0.08)
Years of education	10.85	10.72	11.12	-0.39	12.86	12.92	12.75	0.17
	(2.62)	(2.57)	(2.73)	(0.44)	(1.93)	(1.73)	(2.23)	(0.33)
Num of adults in household	2.78	2.92	2.50	0.42	2.36	2.39	2.30	0.10
	(1.59)	(1.77)	(1.08)	(0.27)	(1.36)	(1.48)	(1.15)	(0.23)
Num of children in household	2.50	2.45	2.60	-0.14	1.79	1.80	1.77	0.03
	(1.67)	(1.65)	(1.71)	(0.28)	(1.66)	(1.81)	(1.41)	(0.28)
Job before intervention	0.19	0.19	0.21	-0.03	0.32	0.31	0.32	-0.00
	(0.40)	(0.39)	(0.41)	(0.07)	(0.47)	(0.47)	(0.47)	(0.08)
Business before intervention	0.92	0.91	0.94	-0.03	0.86	0.88	0.82	0.05
	(0.27)	(0.29)	(0.24)	(0.05)	(0.35)	(0.33)	(0.38)	(0.06)
Loan before intervention	0.46	0.49	0.40	0.09	0.36	0.33	0.40	-0.08
	(0.50)	(0.50)	(0.50)	(0.08)	(0.48)	(0.47)	(0.49)	(0.08)
Observations	160	108	52	160	146	89	57	146

Notes: This table shows the balance of pre-intervention covariates across treatment and control groups at Midline for the sample with median and above age, and the sample with below median age. Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 15: Midline: Hours Spent Across All Businesses

	Hrs. worked	
	OLS	IV
Training	31.46*	
	(17.74)	
Engaged		116.9*
		(66.91)
Female	-10.73	-17.15
	(17.72)	(18.82)
P-value	.0774	.0807
Control Mean	198.5	198.5
Observations	267	267

Notes: This table shows the intent-to-treat and local average treatment effect estimates of SMS trainings on time spent across all businesses in the last 30 days at Midline. Coefficients represent effects in terms of hours worked. Column (1) shows output from an OLS regression, and Column (2) shows output from a 2SLS regression where the endogenous variable is whether or not the individual engaged with training content. Robust standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 16: Midline: Side Jobs

	Job		**Job Hours**	
	OLS	IV	OLS	IV
Training	-.0295		-5.951	
	(.0533)		(10.27)	
Engaged		-.102		-20.72
		(.184)		(35.75)
Female	-.0786	-.0722	-22.81**	-21.45*
	(.0557)	(.0582)	(10.15)	(11.52)
P-value	.580	.580	.563	.562
Control Mean	.236	.236	35.06	35.06
Observations	296	296	291	291

Notes: This table shows the intent-to-treat and local average treatment effect estimates of SMS trainings on employment in and time spent on side jobs in the last 30 days at Midline. Coefficients in Columns (1) and (2) represent effects in terms of probability of having a side job, while those in Columns (3) and (4) represent effects in terms of hours worked. Columns (1) and (3) show output from OLS regressions, while Columns (2) and (4) show output from 2SLS regressions where the endogenous variable is whether or not the individual engaged with training content. Robust standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 17: Midline: Time Spent on Business by Age

	Full		**Age $>=$ 34**		**Age $<$ 34**		**Diff**	
	Primary	All	Primary	All	Primary	All	Primary	All
Training	28.88*	31.46*	-14.94	-14.55	67.23***	70.90***		
	(16.52)	(17.74)	(23.74)	(24.50)	(22.06)	(24.69)		
Train x Age $\geq$ 34							-82.17**	-85.46**
							(32.41)	(34.78)
P-value	0.0817	0.0774	0.530	0.553	0.00300	0.00500	0.0120	0.0150
Control Mean	178.6	198.5	214.8	238.6	148.0	164	178.6	198.5
Observations	269	267	139	139	129	127	268	266

Notes: This table shows the effect of treatment assignment on hours spent working on primary business and across all businesses in the last 30 days at Midline for the full sample (Columns (1), and (2), respectively), the sample with median and above age (Columns (3), and (4), respectively), the sample with below median age (Columns (5), and (6), respectively), and the difference in treatment effects across median and above, and below median age samples (Columns (7), and (8), respectively). Robust standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 18: Midline: Labor Hours Employed in Last 30 days

	HH Labor Hrs. - Primary		**Outside Labor Hrs. - Primary**		**HH Labor Hrs. - All**		**Outside Labor Hrs. - All**	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Training	2.496		-3.282		-8.693		-7.263	
	(12.03)		(27.48)		(14.53)		(33.37)	
Engaged		8.430		-11.33		-29.50		-25.06
		(40.42)		(94.36)		(49.21)		(114.6)
Female	-37.96***	-38.40***	-40.06*	-39.36*	-50.76***	-49.06***	-50.49	-48.95
	(11.80)	(12.54)	(23.91)	(23.09)	(14.11)	(15.09)	(31.73)	(30.13)
P-value	.836	.835	.905	.904	.550	.549	.828	.827
Control Mean	42.50	42.50	83.03	83.03	64.19	64.19	107.3	107.3
Observations	302	302	297	297	307	307	297	297

Notes: This table shows the intent-to-treat and local average treatment effect estimates of SMS trainings on household and outside labor employed in primary business and across all businesses in the last 30 days at Midline. Coefficients across all Columns represent effects in terms of labor hours employed. Columns (1), (3), (5), and (7) show output from OLS regressions, while Columns (2), (4), (6), and (8) show output from 2SLS regressions where the endogenous variable is whether or not the individual engaged with training content. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 19: Midline: Loan Amount Applied for and Received by Age

	Full		**Age >= 34**		**Age < 34**		**Diff**	
	Applied	Received	Applied	Received	Applied	Received	Applied	Received
Training	-365.6	987.1	-15646.6	-9935.4	15236.9*	12081.4*		
	(7629.7)	(5570.2)	(13477.2)	(9249.4)	(8471.6)	(7082.0)		
Train x Age ≥ 34							-30883.5*	-22016.8*
							(15921.5)	(11650.4)
P-value	0.962	0.859	0.247	0.284	0.0740	0.0900	0.0530	0.0600
Control Mean	13818.3	10104.6	23442.3	16980.8	5038.6	3831.6	13818.3	10104.6
Observations	307	307	160	160	146	146	306	306

Notes: This table shows the effect of treatment assignment on loan amount applied for and received in Kenyan Shillings in the last 3 months at Midline for the full sample (Columns (1), and (2), respectively), the sample with median and above age (Columns (3), and (4), respectively), the sample with below median age (Columns (5), and (6), respectively), and the difference in treatment effects across median and above, and below median age samples (Columns (7), and (8), respectively). Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.3 Endline Vs Midline Samples

Table 20: Endline VS Midline Samples: covariates

Variable	Matched with Midline	Unmatched with Midline	Diff
Female	0.48	0.47	0.02
	(0.50)	(0.50)	(0.03)
Years of education	11.91	11.88	0.03
	(2.40)	(2.73)	(0.19)
Age	36.26	35.22	1.04
	(9.00)	(9.17)	(0.63)
Rural	0.46	0.46	-0.00
	(0.50)	(0.50)	(0.03)
Num of adults in household	2.55	2.63	-0.08
	(1.25)	(1.35)	(0.09)
Num of children in household	2.11	2.17	-0.06
	(1.42)	(1.50)	(0.10)
Job before intervention	0.15	0.18	-0.03
	(0.36)	(0.38)	(0.03)
Business before intervention	0.85	0.85	-0.00
	(0.36)	(0.36)	(0.02)
Loan before intervention	0.39	0.38	0.01
	(0.49)	(0.49)	(0.03)
F-test p-value ($\beta_{diff} = 0$)			0.96
Observations	227	2,553	2,780

Notes: This table shows comparison of pre-intervention covariates across the Endline sample matched with the Midline, and the Endline sample not matched with the Midline. Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 21: Endline VS Midline Samples: Control Outcomes

Variable	Matched with Midline	Unmatched with Midline	Diff
Basic Knowledge	0.74	0.73	0.01
	(0.16)	(0.18)	(0.02)
Advanced Knowledge	0.77	0.79	-0.02
	(0.18)	(0.18)	(0.02)
Overall Knowledge	0.75	0.76	-0.01
	(0.14)	(0.14)	(0.02)
Basic Adoption	0.64	0.70	-0.06**
	(0.22)	(0.21)	(0.02)
Advanced Adoption	0.67	0.67	-0.00
	(0.26)	(0.22)	(0.03)
Overall Adoption	0.66	0.69	-0.03
	(0.17)	(0.18)	(0.02)
Owns Business	0.92	0.92	0.00
	(0.28)	(0.28)	(0.03)
Num of Businesses Owned	0.98	1.01	-0.03
	(0.38)	(0.44)	(0.05)
Business Registered	0.51	0.46	0.05
	(0.50)	(0.50)	(0.06)
Num of Businesses Registered	0.55	0.50	0.05
	(0.57)	(0.55)	(0.07)
7-day Sales from Primary Business	15454.17	15780.95	-326.79
	(21356.77)	(23449.46)	(2644.42)
30-day Sales from Primary Business	62773.81	59075.36	3698.45
	(93706.85)	(90622.07)	(10312.33)
7-day Sales from All Businesses	15993.45	16975.15	-981.70
	(21397.30)	(25210.13)	(2831.15)
30-day Sales from All Businesses	64934.52	64413.61	520.91
	(93808.84)	(102112.05)	(11521.62)
7-day Profits from Primary Business	4725.00	4793.07	-68.07
	(5138.23)	(6190.39)	(694.35)
30-day Profits from Primary Business	18878.57	19500.64	-622.07
	(19334.51)	(25710.48)	(2870.13)
7-day Profits from All Businesses	4908.93	5221.90	-312.97
	(5180.22)	(6997.48)	(780.62)
30-day Profits from All Businesses	19560.71	21215.50	-1654.78
	(19391.96)	(29073.36)	(3230.30)
Applied for a Loan	0.52	0.47	0.06
	(0.50)	(0.50)	(0.06)
Loan Amount Applied	20970.24	20345.08	625.16
	(39903.22)	(61354.25)	(6810.69)
Loan Amount Received	17396.90	16765.28	631.63
	(32061.82)	(55158.15)	(6102.47)
Loan Application Success Rate	0.91	0.88	0.03
	(0.29)	(0.33)	(0.05)
Loan Payment Missed/Late	0.53	0.56	-0.03
	(0.51)	(0.50)	(0.12)
F-test p-value ($\beta_{diff} = 0$)			0.998
Observations	84	1,027	1,111

Notes: This table shows comparison of control group outcomes across the Endline sample matched with the Midline, and the Endline sample not matched with the Midline. Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

C.4 Endline

Table 22: Endline: Engagement by Age

	Full		**Age $>=$ 34**		**Age $<$ 34**		**Diff**	
	Engaged	% Engaged	Engaged	% Engaged	Engaged	% Engaged	Engaged	% Engaged
Training	0.280***	0.0651***	0.281***	0.0605***	0.279***	0.0700***		
	(0.0110)	(0.00411)	(0.0157)	(0.00549)	(0.0155)	(0.00616)		
Train x Age ≥ 34							0.00194	-0.00945
							(0.0220)	(0.00825)
P-value	0	0	0	0	0	0	0.930	0.252
Control Mean	0	0	0	0	0	0	0	0
Observations	2780	2780	1426	1426	1353	1353	2779	2779

Notes: This table shows the effect of treatment assignment on extensive and intensive margin engagement at Endline for the full sample (Columns 1 and 2, respectively), the sample with median and above age (Columns 3 and 4, respectively), the sample with below median age (Columns 5 and 6, respectively), and the difference in treatment effects across median and above, and below median age samples (Columns 7 and 8, respectively). Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 23: Endline: Knowledge and Adoption of Best Practices Using Midline Sample

	Basic Knowledge		**Basic Adoption**		**Advanced Knowledge**		**Advanced Adoption**	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Training	-.0393		.159		-.132		-.0128	
	(.143)		(.139)		(.171)		(.137)	
Engaged		-.103		.404		-.347		-.0333
		(.376)		(.356)		(.453)		(.353)
Female	.0523	.0607	-.114	-.150	-.153	-.125	.161	.164
	(.154)	(.155)	(.139)	(.147)	(.213)	(.215)	(.129)	(.141)
P-value	.785	.783	.256	.257	.442	.444	.926	.925
Control Mean	0	0	0	0	0	0	0	0
Observations	227	227	217	217	227	227	216	216

Notes: This table shows the intent-to-treat and local average treatment effect estimates of SMS trainings on means effect indices of basic and advanced knowledge and adoption of best practices at Endline, using the sample matched with Midline only. Basic knowledge and basic adoption indices are similar to the knowledge and adoption indices analysed for the Midline, while the advanced knowledge and adoption indices are based on best practices are a bit more advanced and not necessarily directly mentioned in the SMS-trainings. Coefficients represent effects in terms of control group standard deviations. Columns (1), (3), (5), and (7) show output from OLS regressions, and columns (2), (4), (6), and (8) show output from 2SLS regressions where the endogenous variable is whether or not the individual engaged with training content. Robust standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 24: Endline: Primary Business Sales, Profits and Survival Using Midline Sample

	Sales		**Profits**		**Survival**	
	OLS	IV	OLS	IV	OLS	IV
Training	-17305.1		-182.8		.00879	
	(11060.5)		(3005.2)		(.0407)	
Engaged		-45882.8		-484.7		.0232
		(29928.4)		(7915.2)		(.107)
Female	-36873.9***	-32984.0***	-10376.6***	-10335.5***	-.0380	-.0399
	(8353.9)	(9411.3)	(3298.1)	(3571.9)	(.0455)	(.0445)
P-value	.119	.125	.952	.951	.829	.828
Control Mean	62773.8	62773.8	18878.6	18878.6	.917	.917
Observations	226	226	226	226	227	227

Notes: This table shows the intent-to-treat and local average treatment effect estimates of SMS trainings on primary business sales and profits from last 30 days, and business survival at Endline, using the sample matched with Midline only. Coefficients in columns (1) through (4) represent effects in terms of Kenyan Shillings, while those in columns (5) and (6) represent probability of individual having an active business. Columns (1), (3) and (5) show output from OLS regressions, and columns (2), (4) and (6) show output from 2SLS regressions where the endogenous variable is whether or not the individual engaged with training content. Robust standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 25: Endline: Sales and Profits Across All Businesses

	Sales		**Profits**	
	OLS	IV	OLS	IV
Training	668.7		482.7	
	(4075.1)		(1153.7)	
Engaged		2391.6		1727.9
		(14564.1)		(4127.7)
Female	-42183.0***	-42219.9***	-11698.1***	-11723.4***
	(3951.9)	(3966.5)	(1128.2)	(1130.6)
P-value	.870	.870	.676	.676
Control Mean	64453.1	64453.1	21089.9	21089.9
Observations	2772	2772	2770	2770

Notes: This table shows the intent-to-treat and local average treatment effect estimates of SMS trainings on sales and profits across all businesses from last 30 days at Endline. Coefficients across all columns represent effects in terms of Kenyan Shillings. Columns (1), and (3) show output from OLS regressions, and Columns (2), and (4) show output from 2SLS regressions where the endogenous variable is whether or not the individual engaged with training content. Robust standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 26: Endline: Sales and Profits Across All Businesses Using Midline Sample

	Sales		**Profits**	
	OLS	IV	OLS	IV
Training	-12427.6		986.0	
	(11442.1)		(3111.7)	
Engaged		-32950.4		2614.3
		(30620.7)		(8201.6)
Female	-37827.5***	-35034.0***	-11608.2***	-11829.9***
	(9534.4)	(10050.8)	(3475.7)	(3764.6)
P-value	.279	.282	.752	.750
Control Mean	64934.5	64934.5	19560.7	19560.7
Observations	226	226	226	226

Notes: This table shows the intent-to-treat and local average treatment effect estimates of SMS trainings on sales and profits across all businesses from last 30 days at Endline, using the sample matched with Midline only. Coefficients across all columns represent effects in terms of Kenyan Shillings. Columns (1), and (3) show output from OLS regressions, and Columns (2), and (4) show output from 2SLS regressions where the endogenous variable is whether or not the individual engaged with training content. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 27: Endline: Primary Business Sales, Profits and Survival By Age

	Full			**Age >= 34**			**Age < 34**			**Diff**		
	Sales	Profits	Survival	Sales	Profits	Survival	Sales	Profits	Survival	Sales	Profits	Survival
Training	-2206.5	-220.6	-0.0159	-2217.1	2.944	-0.0178	-688.6	-259.5	-0.00680			
	(3534.1)	(1009.0)	(0.0112)	(5244.1)	(1429.6)	(0.0131)	(4680.3)	(1426.9)	(0.0184)			
Train x Age ≥ 34										-1528.5	262.4	-0.0110
										(7029.0)	(2019.8)	(0.0226)
P-value	0.532	0.827	0.154	0.673	0.998	0.174	0.883	0.856	0.712	0.828	0.897	0.627
Control Mean	59356.0	19453.4	0.915	62630.4	19478.0	0.944	55466.9	19424.2	0.882	59356.0	19453.4	0.915
Observations	2772	2770	2779	1419	1417	1425	1352	1352	1353	2771	2769	2778

Notes: This table shows the effect of treatment assignment on primary business sales in the last 30 days, primary business profits in the last 30 days, and business survival at Endline for the full sample (Columns (1), (2) and (3), respectively), the sample with median and above age (Columns (4), (5), and (6), respectively), the sample with below median age (Columns (7), (8), and (9), respectively), and the difference in treatment effects across median and above, and below median age samples (Columns (10), (11), and (12), respectively). Robust standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 28: Endline: Primary Business Sales, Profits and Survival By Age Using Midline Sample

	Full			**Age >= 34**			**Age < 34**			**Diff**		
	Sales	Profits	Survival	Sales	Profits	Survival	Sales	Profits	Survival	Sales	Profits	Survival
Training	-17305.1	-182.8	0.00879	-30631.6**	-1845.4	-0.00491	604.9	1903.7	0.0318			
	(11060.5)	(3005.2)	(0.0407)	(13859.9)	(3784.4)	(0.0498)	(17903.8)	(4890.2)	(0.0707)			
Train x Age $\geq$ 34										-31236.5	-3749.1	-0.0368
										(22628.4)	(6179.8)	(0.0865)
P-value	0.119	0.952	0.829	0.0290	0.627	0.922	0.973	0.698	0.654	0.169	0.545	0.671
Control Mean	62773.8	18878.6	0.917	67967.3	18761.2	0.939	55502.9	19042.9	0.886	62773.8	18878.6	0.917
Observations	226	226	227	126	126	127	100	100	100	226	226	227

Notes: This table shows the effect of treatment assignment on primary business sales in the last 30 days, primary business profits in the last 30 days, and business survival at Endline, using the sample matched with Midline only, for the full sample (Columns (1), (2) and (3), respectively), the sample with median and above age (Columns (4), (5), and (6), respectively), the sample with below median age (Columns (7), (8), and (9), respectively), and the difference in treatment effects across median and above, and below median age samples (Columns (10), (11), and (12), respectively). Robust standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 29: Endline: Sales and Profits Across All Businesses By Age

	Full		**Age >= 34**		**Age < 34**		**Diff**	
	Sales	Profits	Sales	Profits	Sales	Profits	Sales	Profits
Training	668.7	482.7	3484.0	1572.3	-484.9	-408.1		
	(4075.1)	(1153.7)	(6118.3)	(1647.0)	(5362.3)	(1633.0)		
Train x Age ≥ 34							3968.8	1980.4
							(8135.6)	(2319.3)
P-value	0.870	0.676	0.569	0.340	0.928	0.803	0.626	0.393
Control Mean	64453.1	21089.9	67194.8	20851.7	61196.7	21372.8	64453.1	21089.9
Observations	2772	2770	1419	1417	1352	1352	2771	2769

Notes: This table shows the effect of treatment assignment on sales and profits across all businesses in the last 30 days at Endline, for the full sample (Columns (1), and (2), respectively), the sample with median and above age (Columns (3), and (4), respectively), the sample with below median age (Columns (5), and (6), respectively), and the difference in treatment effects across median and above, and below median age samples (Columns (7), and (8), respectively). Robust standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 30: Endline: Sales and Profits Across All Businesses By Age Using Midline Sample

	Full		**Age >= 34**		**Age < 34**		**Diff**	
	Sales	Profits	Sales	Profits	Sales	Profits	Sales	Profits
Training	-12427.6	986.0	-26692.7*	-410.7	8250.5	3014.2		
	(11442.1)	(3111.7)	(14273.5)	(4055.5)	(18940.3)	(4952.3)		
Train x Age ≥ 34							-34943.2	-3424.9
							(23701.7)	(6397.8)
P-value	0.279	0.752	0.0640	0.919	0.664	0.544	0.142	0.593
Control Mean	64934.5	19560.7	71191.8	19634.7	56174.3	19457.1	64934.5	19560.7
Observations	226	226	126	126	100	100	226	226

Notes: This table shows the effect of treatment assignment on sales and profits across all businesses in the last 30 days at Endline, using the sample matched with Midline only, for the full sample (Columns (1), and (2), respectively), the sample with median and above age (Columns (3), and (4), respectively), the sample with below median age (Columns (5), and (6), respectively), and the difference in treatment effects across median and above, and below median age samples (Columns (7), and (8), respectively). Robust standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 31: Endline: Time Spent on Primary Business in last 30 days Using Midline Sample

	Hrs. Worked	
	OLS	IV
Training	9.672	
	(17.29)	
Engaged		25.65
		(45.96)
Female	-4.735	-6.909
	(18.98)	(20.02)
P-value	.576	.577
Control Mean	208.7	208.7
Observations	226	226

Notes: This table shows the intent-to-treat and local average treatment effect estimates of SMS trainings on time spent on primary business in the last 30 days at Endline, using the sample matched with Midline only. Coefficients represent effects in terms of hours worked. Column (1) shows output from an OLS regression, and Column (2) shows output from a 2SLS regression where the endogenous variable is whether or not the individual engaged with training content. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 32: Endline: Time Spent on All Businesses

	Hrs. in 7 days		**Hrs. in 30 days**	
	OLS	IV	OLS	IV
Training	-2.366**		-9.152**	
	(1.149)		(4.577)	
Engaged		-8.442**		-32.65**
		(4.113)		(16.38)
Female	-1.903*	-1.775	-8.249*	-7.752*
	(1.121)	(1.126)	(4.472)	(4.491)
P-value	.0396	.0401	.0457	.0462
Control Mean	55.66	55.66	223.4	223.4
Observations	2779	2779	2779	2779

Notes: This table shows the intent-to-treat and local average treatment effect estimates of SMS trainings on time spent across all businesses in the last 7 and 30 days at Endline. Coefficients represent effects in terms of hours worked. Columns (1) and (3) show output from an OLS regressions, and Columns (2) and (4) show output from a 2SLS regressions where the endogenous variable is whether or not the individual engaged with training content. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 33: Endline: Time Spent Across All Businesses Using Midline Sample

	Hrs. in 7 days		**Hrs. in 30 days**	
	OLS	IV	OLS	IV
Training	3.909		13.57	
	(4.487)		(17.75)	
Engaged		10.30		35.77
		(11.94)		(47.14)
Female	-3.413	-4.253	-13.21	-16.12
	(4.765)	(5.082)	(19.03)	(20.18)
P-value	.385	.388	.445	.448
Control Mean	53.26	53.26	215.0	215.0
Observations	227	227	227	227

Notes: This table shows the intent-to-treat and local average treatment effect estimates of SMS trainings on time spent across all businesses in the last 7 and 30 days at Endline, using the sample matched with Midline only. Coefficients represent effects in terms of hours worked. Columns (1) and (3) show output from an OLS regressions, and Columns (2) and (4) show output from a 2SLS regressions where the endogenous variable is whether or not the individual engaged with training content. Robust standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 34: Endline: Side Jobs in Last 30 days

	Job		**Job Hours**	
	OLS	IV	OLS	IV
Training	-.0141		-1.856	
	(.0143)		(2.411)	
Engaged		-.0503		-6.625
		(.0511)		(8.606)
Female	-.0910***	-.0902***	-17.72***	-17.62***
	(.0138)	(.0138)	(2.292)	(2.283)
P-value	.325	.325	.442	.441
Control Mean	.171	.171	23.36	23.36
Observations	2780	2780	2779	2779

Notes: This table shows the intent-to-treat and local average treatment effect estimates of SMS trainings on employment in and time spent on side jobs in the last 30 days at Endline. Coefficients in Columns (1) and (2) represent effects in terms of probability of having a side job, while those in Columns (3) and (4) represent effects in terms of hours worked. Columns (1) and (3) show output from OLS regressions, while Columns (2) and (4) show output from 2SLS regressions where the endogenous variable is whether or not the individual engaged with training content. Robust standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 35: Endline: Side Jobs in Last 30 days Using Midline Sample

	Job		**Job Hours**	
	OLS	IV	OLS	IV
Training	.0273		-1.446	
	(.0555)		(8.879)	
Engaged		.0720		-3.810
		(.145)		(23.28)
Female	-.0870	-.0928	-21.58**	-21.27**
	(.0631)	(.0641)	(8.634)	(8.986)
P-value	.623	.619	.871	.870
Control Mean	.155	.155	24.36	24.36
Observations	227	227	227	227

Notes: This table shows the intent-to-treat and local average treatment effect estimates of SMS trainings on employment in and time spent on side jobs in the last 30 days at Endline, using the sample matched with Midline only. Coefficients in Columns (1) and (2) represent effects in terms of probability of having a side job, while those in Columns (3) and (4) represent effects in terms of hours worked. Columns (1) and (3) show output from OLS regressions, while Columns (2) and (4) show output from 2SLS regressions where the endogenous variable is whether or not the individual engaged with training content. Robust standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 36: Endline: Time Spent on Business in Last 30 days by Age

	Full		**Age >= 34**		**Age < 34**		**Diff**	
	Primary	All	Primary	All	Primary	All	Primary	All
Training	-9.702**	-9.152**	-11.54*	-10.60*	-5.769	-5.859		
	(4.459)	(4.577)	(5.986)	(6.133)	(6.635)	(6.838)		
Train x Age $\geq$ 34							-5.769	-4.737
							(8.936)	(9.185)
P-value	0.0296	0.0457	0.0540	0.0840	0.385	0.392	0.519	0.606
Control Mean	215.6	223.4	223.7	230.3	205.9	215.2	215.6	223.4
Observations	2777	2779	1423	1425	1353	1353	2776	2778

Notes: This table shows the effect of treatment assignment on hours spent working on primary business and across all businesses in the last 30 days at Endline for the full sample (Columns (1), and (2), respectively), the sample with median and above age (Columns (3), and (4), respectively), the sample with below median age (Columns (5), and (6), respectively), and the difference in treatment effects across median and above, and below median age samples (Columns (7), and (8), respectively). Robust standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 37: Endline: Time Spent on Business in Last 30 days by Age Using Midline Sample

	Full		**Age $>=$ 34**		**Age $<$ 34**		**Diff**	
	Primary	All	Primary	All	Primary	All	Primary	All
Training	9.672	13.57	-11.21	-4.813	40.41	41.62		
	(17.29)	(17.75)	(23.31)	(24.33)	(25.98)	(26.09)		
Train x Age ≥ 34							-51.62	-46.43
							(34.89)	(35.66)
P-value	0.576	0.445	0.631	0.843	0.123	0.114	0.140	0.194
Control Mean	208.7	215.0	228.5	234.9	181.0	187.1	208.7	215.0
Observations	226	227	126	127	100	100	226	227

Notes: This table shows the effect of treatment assignment on hours spent working on primary business and across all businesses in the last 30 days at Endline, using the sample matched with Midline only, for the full sample (Columns (1), and (2), respectively), the sample with median and above age (Columns (3), and (4), respectively), the sample with below median age (Columns (5), and (6), respectively), and the difference in treatment effects across median and above, and below median age samples (Columns (7), and (8), respectively). Robust standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 38: Endline: Time Spent on Business in Last 7 days by Age

	Full		**Age $>=$ 34**		**Age $<$ 34**		**Diff**	
	Primary	All	Primary	All	Primary	All	Primary	All
Training	-9.702**	-9.152**	-11.54*	-10.60*	-5.769	-5.859		
	(4.459)	(4.577)	(5.986)	(6.133)	(6.635)	(6.838)		
Train x Age ≥ 34							-5.769	-4.737
							(8.936)	(9.185)
P-value	0.0296	0.0457	0.0540	0.0840	0.385	0.392	0.519	0.606
Control Mean	215.6	223.4	223.7	230.3	205.9	215.2	215.6	223.4
Observations	2777	2779	1423	1425	1353	1353	2776	2778

Notes: This table shows the effect of treatment assignment on hours spent working on primary business and across all businesses in the last 7 days at Endline for the full sample (Columns (1), and (2), respectively), the sample with median and above age (Columns (3), and (4), respectively), the sample with below median age (Columns (5), and (6), respectively), and the difference in treatment effects across median and above, and below median age samples (Columns (7), and (8), respectively). Robust standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 39: Endline: Time Spent on Business in Last 7 by Age days Using Midline Sample

	Full		**Age >= 34**		**Age < 34**		**Diff**	
	Primary	All	Primary	All	Primary	All	Primary	All
Training	9.672	13.57	-11.21	-4.813	40.41	41.62		
	(17.29)	(17.75)	(23.31)	(24.33)	(25.98)	(26.09)		
Train x Age ≥ 34							-51.62	-46.43
							(34.89)	(35.66)
P-value	0.576	0.445	0.631	0.843	0.123	0.114	0.140	0.194
Control Mean	208.7	215.0	228.5	234.9	181.0	187.1	208.7	215.0
Observations	226	227	126	127	100	100	226	227

Notes: This table shows the effect of treatment assignment on hours spent working on primary business and across all businesses in the last 7 days at Endline, using the sample matched with Midline only, for the full sample (Columns (1), and (2), respectively), the sample with median and above age (Columns (3), and (4), respectively), the sample with below median age (Columns (5), and (6), respectively), and the difference in treatment effects across median and above, and below median age samples (Columns (7), and (8), respectively). Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 40: Endline: Labor Hours Employed in Last 30 Days

	HH Labor Hrs. - Primary		**Outside Labor Hrs. - Primary**		**HH Labor Hrs. - All**		**Outside Labor Hrs. - All**	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Training	-4.496		1.021		-5.465		2.763	
	(3.145)		(5.555)		(3.486)		(6.584)	
Engaged		-16.04		3.643		-19.50		9.859
		(11.24)		(19.80)		(12.47)		(23.47)
Female	-25.58***	-25.33***	-40.51***	-40.57***	-29.51***	-29.21***	-58.40***	-58.55***
	(2.963)	(2.994)	(5.404)	(5.432)	(3.282)	(3.318)	(6.417)	(6.446)
P-value	.153	.154	.854	.854	.117	.118	.675	.674
Control Mean	34.43	34.43	55.39	55.39	39.74	39.74	68.64	68.64
Observations	2779	2779	2778	2778	2779	2779	2779	2779

Notes: This table shows the intent-to-treat and local average treatment effect estimates of SMS trainings on household and outside labor employed in primary business and across all businesses in the last 30 days at Endline. Coefficients across all Columns represent effects in terms of labor hours employed. Columns (1), (3), (5), and (7) show output from OLS regressions, while Columns (2), (4), (6), and (8) show output from 2SLS regressions where the endogenous variable is whether or not the individual engaged with training content. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 41: Endline: Labor Hours Employed in Last 30 Days Using Midline Sample

	HH Labor Hrs. - Primary		**Outside Labor Hrs. - Primary**		**HH Labor Hrs. - All**		**Outside Labor Hrs. - All**	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Training	-4.280		-12.80		-4.110		-4.364	
	(13.09)		(19.93)		(14.75)		(23.45)	
Engaged		-11.28		-33.73		-10.83		-11.50
		(34.27)		(53.12)		(38.60)		(61.66)
Female	-25.18*	-24.26	-56.25***	-53.50**	-34.10**	-33.22*	-63.74***	-62.80**
	(14.48)	(14.82)	(19.73)	(22.33)	(16.34)	(17.13)	(24.45)	(26.97)
P-value	.744	.742	.521	.525	.781	.779	.853	.852
Control Mean	43.06	43.06	55.05	55.05	49.39	49.39	61.71	61.71
Observations	227	227	227	227	227	227	227	227

Notes: This table shows the intent-to-treat and local average treatment effect estimates of SMS trainings on household and outside labor employed in primary business and across all businesses in the last 30 days at Endline, using the sample matched with Midline only. Coefficients across all Columns represent effects in terms of labor hours employed. Columns (1), (3), (5), and (7) show output from OLS regressions, while Columns (2), (4), (6), and (8) show output from 2SLS regressions where the endogenous variable is whether or not the individual engaged with training content. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 42: Endline: Labor Hours Employed in Last 7 Days

	HH Labor Hrs. - Primary		**Outside Labor Hrs. - Primary**		**HH Labor Hrs. - All**		**Outside Labor Hrs. - All**	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Training	-.965		.221		-1.206		.617	
	(.796)		(1.352)		(.870)		(1.601)	
Engaged		-3.442		.790		-4.304		2.200
		(2.845)		(4.819)		(3.110)		(5.708)
Female	-6.367***	-6.314***	-9.912***	-9.924***	-7.247***	-7.181***	-14.28***	-14.32***
	(.750)	(.758)	(1.314)	(1.322)	(.819)	(.828)	(1.562)	(1.571)
P-value	.226	.226	.870	.870	.166	.166	.700	.700
Control Mean	8.584	8.584	13.62	13.62	9.848	9.848	16.92	16.92
Observations	2779	2779	2778	2778	2779	2779	2779	2779

Notes: This table shows the intent-to-treat and local average treatment effect estimates of SMS trainings on household and outside labor employed in primary business and across all businesses in the last 7 days at Endline. Coefficients across all Columns represent effects in terms of labor hours employed. Columns (1), (3), (5), and (7) show output from OLS regressions, while Columns (2), (4), (6), and (8) show output from 2SLS regressions where the endogenous variable is whether or not the individual engaged with training content. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 43: Endline: Labor Hours Employed in Last 7 Days

	HH Labor Hrs. - Primary		**Outside Labor Hrs. - Primary**		**HH Labor Hrs. - All**		**Outside Labor Hrs. - All**	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Training	-.785		-3.756		-.860		-1.477	
	(3.292)		(4.830)		(3.647)		(5.772)	
Engaged		-2.068		-9.898		-2.266		-3.893
		(8.611)		(12.93)		(9.536)		(15.20)
Female	-6.012	-5.843	-13.89***	-13.08**	-7.987**	-7.802*	-16.06***	-15.74**
	(3.651)	(3.738)	(4.720)	(5.389)	(4.029)	(4.209)	(6.042)	(6.696)
P-value	.812	.810	.438	.444	.814	.812	.798	.798
Control Mean	10.62	10.62	13.89	13.89	12.15	12.15	15.56	15.56
Observations	227	227	227	227	227	227	227	227

Notes: This table shows the intent-to-treat and local average treatment effect estimates of SMS trainings on household and outside labor employed in primary business and across all businesses in the last 7 days at Endline, using the sample matched with Midline only. Coefficients across all Columns represent effects in terms of labor hours employed. Columns (1), (3), (5), and (7) show output from OLS regressions, while Columns (2), (4), (6), and (8) show output from 2SLS regressions where the endogenous variable is whether or not the individual engaged with training content. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 44: Endline: Loan Amount Applied for and Received in Last 3 months by Age

	Full		**Age >= 34**		**Age < 34**		**Diff**	
	Applied	Received	Applied	Received	Applied	Received	Applied	Received
Training	-667.9	-397.2	-2400.2	-973.9	2173.1	1156.1		
	(2321.2)	(2071.2)	(3633.6)	(3319.1)	(2660.8)	(2276.2)		
Train x Age $\geq$ 34							-4573.3	-2130.0
							(4503.7)	(4024.6)
P-value	0.774	0.848	0.509	0.769	0.414	0.612	0.310	0.597
Control Mean	20392.3	16813.0	25000	21000	15000	12000	20000	17000
Observations	2780	2780	1426	1426	1353	1353	2779	2779

Notes: This table shows the effect of treatment assignment on loan amount applied for and received in Kenyan Shillings in the last 3 months at Endline for the full sample (Columns (1), and (2), respectively), the sample with median and above age (Columns (3), and (4), respectively), the sample with below median age (Columns (5), and (6), respectively), and the difference in treatment effects across median and above, and below median age samples (Columns (7), and (8), respectively). Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 45: Endline: Loan Amount Applied for and Received in Last 3 months by Age Using Midline Sample

	Full		**Age $>=$ 34**		**Age $<$ 34**		**Diff**	
	Applied	Received	Applied	Received	Applied	Received	Applied	Received
Training	-4311.5	-2953.9	-7823.7	-5418.3	1186.8	661.6		
	(5851.4)	(5222.6)	(8891.0)	(7796.6)	(6960.9)	(6795.3)		
Train x Age $\geq$ 34							-9010.5	-6079.9
							(11294.0)	(10342.6)
P-value	0.462	0.572	0.381	0.488	0.865	0.923	0.426	0.557
Control Mean	20970.2	17396.9	24000	19000	17000	15000	21000	17000
Observations	227	227	127	127	100	100	227	227

Notes: This table shows the effect of treatment assignment on loan amount applied for and received in Kenyan Shillings in the last 3 months at Endline, using the sample matched with Midline only, for the full sample (Columns (1), and (2), respectively), the sample with median and above age (Columns (3), and (4), respectively), the sample with below median age (Columns (5), and (6), respectively), and the difference in treatment effects across median and above, and below median age samples (Columns (7), and (8), respectively). Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.5 Priors

C.6 Willingess To Pay

Table 46: Engagement Levels Across TIOLI Purchase Decisions

Variable	Accept	Reject	Diff
Engaged	0.51	0.45	0.08
	(0.50)	(0.50)	(0.06)
% Engaged	0.14	0.11	0.03
	(0.25)	(0.22)	(0.03)
Observations	272	143	415

Notes: The table shows average extensive and intensive margin engagement levels amongst those who accepted the TIOLI offer in the treatment group, those that rejected, and the difference between them. Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 47: Effect of Training on Willing to Pay - BDM

	(1) OLS	(2) IV	(3) IV
Training	2.235		
	(7.438)		
Engaged		12.90	
		(42.57)	
Engaged >= 25%			50.00
			(167.2)
Female	-7.446	-8.162	-6.420
	(6.946)	(6.880)	(8.417)
P-value	.764	.762	.765
Control Mean	48.16	48.16	48.16
Observations	103	103	103

Notes: This table shows the intent-to-treat and local average treatment effect estimates of SMS trainings on maximum willingness to pay for SMS trainings elicited via the modified BDM method. Coefficients represent effects in terms of Kenyan Shillings. Column (1) shows output from an OLS regression, Column (2) shows output from a 2SLS regression where the endogenous variable is whether or not the individual engaged with training content, and Column (3) shows output from a 2SLS regression where the endogenous variable is whether or not the individual engaged with at least 25% of the training content. Robust standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.