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

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Abstract

SMS-based business trainings are gaining popularity as a low-cost and scalable solution for supporting micro-entrepreneurs in low-income countries. However, there is limited evidence on their effectiveness in improving business outcomes, and on their demand among targeted beneficiaries. This paper studies a field experiment whereby access to an SMS-based business training was randomized across 4,700 micro-entrepreneurs in Kenya, and documents demand for SMS trainings through take-it-or-leave-it offers and the Becker-DeGroot-Marschak method. After three months, I find positive effects of the training on knowledge and adoption of best practices, with younger entrepreneurs experiencing stronger effects on business performance, driven by higher engagement with training content, more time spent on their 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 the training content ended within the first five months of deployment. Notwithstanding low engagement and lack of longer-run effects, I find that micro-entrepreneurs are still willing to pay a small positive amount for 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 business trainings on their own are unlikely to be effective for micro-entrepreneurs in the longer run. These results highlight the importance of lack of engagement as a major challenge limiting the potential of remotely provided trainings.

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1 Introduction

Employing 70% of the labor force world-wide and accounting for 40% of the GDP in emerging economies (ILO (2019); World Bank (2024)), small businesses form the economic backbone of low-income countries across the globe. Moreover, they are crucial vehicles for female empowerment as at least one third of them are owned by women (World Bank (2020)). Research on effective strategies to support small businesses is therefore key for poverty alleviation.

Poor management practices significantly hinder 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 deliver trainings to 4-5 million entrepreneurs in low-income countries (McKenzie (2021)). However, most of these trainings are conventional in-person classroom-style trainings, which are expensive and hard to scale. Furthermore, they are typically 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 – especially in the wake of Covid-19 – as a low-cost tool for remotely extending access to information-based support across various low-income contexts.[2] However, despite the widespread use, little evidence exists on the effectiveness of SMS-based trainings, particularly for improving outcomes for micro-entrepreneurs, and their demand amongst targeted beneficiaries.

This paper seeks to address this gap by studying the impact of SMS-based business trainings on business practices and outcomes, and examining the demand for these trainings amongst micro-entrepreneurs in a low-income setting. 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 via 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. Furthermore, I measure demand for trainings through Take-It-Or-Leave-It (TIOLI) offers at different price levels, and a modified version of the Becker, Degroot and Marschak (1964) (BDM) elicitation method conducted with a subset of the study sample.

Kenya provides an ideal setting for this study as small businesses play a major role in the national economy. As of 2016, 7.4 million Micro, Small, and Medium Enterprises (MSMEs) engaged over 90% of the active labor force in the country, and accounted for about a third of

[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.

the GDP. Approximately 55% of these MSMEs were owned by women, and 98% were micro-enterprises.[3] The average education level for micro-entrepreneurs was approximately 11 years, yet adoption of basic best practices for business management was alarmingly low. Just under 80% of micro-entrepreneurs did not advertise any of their products or services and almost 70% did not keep any type of business records. Furthermore, less than 10% accounted for prices of their competitors when setting their own. These gaps in management skills could potentially be mitigated through trainings, yet 90% of micro-entrepreneurs had never received any type of business training (*Micro, Small and Medium Enterprises Survey* (2016)).

The primary intervention in this study was aimed at addressing these gaps through an SMS-based business management training course that used simply-worded content to encourage micro-entrepreneurs to adopt business practices shown to be highly correlated with profitability (Bloom and Van Reenen (2010)). This training 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)), by a local firm specializing in creation and dissemination of digital content. Available in English as well as Swahili,[4] 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 SMS-based reminders sent to those who stopped engaging at any point.

Out of the 4,700 micro-entrepreneurs recruited for the study, 2,820 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. Approximately 300 individuals were surveyed three months after the intervention (Midline), while 2,780 individuals were surveyed after another nine months (Endline) to estimate short and longer-run effects, respectively.

In order to determine if the observed treatment effects 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[5] and elicited their predictions about treatment effects at Endline. Comparing these predictions with observed results allows me to shed light on whether the findings 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 using two incentive-compatible methods. First, once treatment group micro-entrepreneurs finished the training or abandoned it for two uninterrupted months, I sent them TIOLI offers for an additional SMS business training whereby the price of the training was randomized 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 pricing arms allows me to assess if there is any positive willingness to pay for SMS trainings, and

[3] Defined as businesses with less than 10 employees.

[4] The official national languages of Kenya.

[5] Equal number of PhD students, and more advanced researchers in academia and policy circles, with 90% listing economics as their primary discipline.

if it varies systematically with the price. Second, immediately after the Endline, I approached 103 Nairobi-based business owners across treatment and control groups to conduct an in-person willingness to pay elicitation using a modified version of the BDM method that uses a multiple-price list approach.

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 imprecisely measured positive effects on business sales (12% increase), profits (15.4% increase), and survival (4.14 percentage points increase) in the overall sample, and large statistically significant positive effects on business performance and survival for younger (below-median) micro-entrepreneurs. 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.

To assess whether these findings are in line with existing priors in the field, I compare the results with predictions for the twelve-month treatment effects from social science researchers. I find that these researchers tend to overestimate the potential of SMS-based business trainings. Specifically, the predictions overstate engagement levels, and impacts on knowledge and adoption of best practices, and on subsequent business performance outcomes. The observed results on effectiveness of SMS-based trainings are thus contrary to priors.

Notwithstanding the low engagement and lack of longer run effects, I find that micro-entrepreneurs are willing to pay a positive price for SMS business trainings, and that the demand for SMS trainings decreases with price. In the TIOLI sample, 70% of individuals chose to accept the additional training when it was offered for free, 68% accepted when the price was half the marginal cost to the service provider, and about 50% accepted when the price was double the marginal cost. In the BDM sample, the average willingness to pay for SMS trainings was KSH 50 (five times the marginal cost), and almost a quarter of the respondents were willing to buy the training for KSH 100 (ten times the marginal cost). Data from both methods of measurement of demand thus reveal that micro-entrepreneurs were willing to pay a small positive amount for SMS-based business management trainings, and a substantial proportion of them were willing to pay much more than the marginal cost to service providers. This suggests that entrepreneurs value access to the content, and a market-based approach for providing SMS business trainings might be feasible in this context.

Lastly, I find correlational evidence for the demand for trainings being higher amongst individuals with more children in the household, those that recently applied for a loan, those with more knowledge of best practices, and those with higher education levels. This is in line with the intuition that those who have more dependents, and those in need of funds recently are more likely to take on a potential opportunity to increase their business profits. Also, those with more knowledge about best practices and those who are more educated recognize the importance of information about best practices, and are more likely to want to learn more.

This study contributes to four 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 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 (2021); 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 in Guatemala when complemented by virtual one-on-one consulting meetings. Cole, Joshi and Schoar (2024) find weekly pre-recorded Interactive Voice Response (IVR) messages to be ineffective for improving business outcomes for micro-entrepreneurs in India and Philippines. To the best of my knowledge, this paper presents the first rigorous evaluation of an SMS-based business training for micro-entrepreneurs.

Second, I add to the extremely limited work on demand for business trainings amongst entrepreneurs. Maffioli, McKenzie and Ubfal (2020) estimate the demand for a business training in Jamaica, however, the program they study is a conventional in-person training program rather than a remotely delivered phone-based training. Cole and Fernando (2020) estimate the willingness to pay for voice-based ICT advisory services in India, but those services are geared towards farmers. This study is the first to provide empirical evidence on demand for SMS-based business trainings amongst micro-entrepreneurs. 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 context.

Third, 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 similarly simplified content.

Fourth, I contribute to the broader literature on the potential and limitation of information communication technologies for improving socio-economic outcomes in low-income contexts (Spielman et al. (2021); United Nations Conference on Trade and Development (2012); Otis et al. (2024)). This paper highlights lack of engagement as an important limitation of remote delivery of automated information-based support in low-income contexts, pointing towards the need for further research in this direction to fully harness the potential of ICT for development.

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 results on the treatment effects of the SMS Business training, Section 7 presents results on the demand for SMS trainings, and Section 8 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) in Kenya form the backbone of the national economy. According to the nation-wide *Micro, Small and Medium Enterprises Survey* (2016), 7.4 million MSMEs engaged over 90% of the active labor force in the country, and contributed just above a third of the GDP in 2016. Approximately 55% of these MSMEs were owned by women, and 98% were micro enterprises.[6] The average education level for micro-entrepreneurs was approximately 11 years, yet adoption of basic best practices for business management was strikingly low. About 79% of micro-entrepreneurs did not advertise any of their products or services in any way, and 70% did not keep any type of record of business transactions – not even personal notes. Furthermore, more than 90% of micro-entrepreneurs did not account for prices of their competitors when setting prices for their own products and services.

These gaps in management skills may be constraining profitability, and could potentially be addressed through business management trainings. However, conventional business trainings geared towards small businesses are not affordable for small business owners. The average Kenyan micro-enterprise generated about USD 440[7] in a month in 2016 (*Micro, Small and Medium Enterprises Survey* (2016)), while the average per trainee cost of business trainings in Kenya[8] can range from USD 125 to USD 900 (Mehtha (2017)). Due to this, business training programs are typically funded by third parties, and provided to entrepreneurs free of cost at a very limited scale. Indeed, over 90% of micro-entrepreneurs had never received any type of business training in 2016 (*Micro, Small and Medium Enterprises Survey* (2016)).

Phone-based business trainings can be significantly lower-cost, and micro-entrepreneurs could theoretically afford to pay for them out of pocket. However, there is little evidence on whether and how much small business owners would be willing to pay for such trainings.

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

[6]Defined as businesses with less than 10 employees.

[7]Roughly equal to KSH 48,000 at the time of the study.

[8]E.g., International Labour Organization (2024), which is a well known training implemented in Kenya and several other countries.

3 Research Design

In this section, I describe (i) the primary intervention in the study, (ii) the randomization groups, (iii) the predictions survey, and (iv) the methods used to elicit demand for SMS trainings amongst micro-entrepreneurs.

3.1 The Intervention

The treatment consisted of an SMS-based Business Education training course, designed to be accessible on any text-enabled cell phone without the need for internet connectivity. 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 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 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 shows what engagement with the content looked like for users.[9]

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.

The training is similar in nature 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.

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

3.2 Randomization Groups

Stratified by gender, the primary sample of 4,701 micro-entrepreneurs 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 Section 3.1.[10] 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 me to evaluate the effectiveness of SMS-based business trainings.

The Treatment group was further divided into three subgroups as part of the elicitation of demand for trainings; once the treatment individuals completed the training, or if they stopped engaging for at least two uninterrupted months, they were sent Take-It-Or-Leave-It (TIOLI) offers for the option to buy an additional SMS-based business training for a price that was randomized across three levels. I present further details about this part of the design in Section 3.4.

3.3 Predictions for Treatment Effects

In order to determine whether the observed effects of the training depart from priors held by social science experts, I collect data on priors through an online survey posted on the Social Science Predictions Platform (Mehmood (2023)). In this survey, I described the study to social science researchers and elicited their predictions about how they expected key outcomes to be affected twelve months after the SMS training intervention. I then compare these predictions with treatment effects at Midline and Endline, shedding light on whether observed results are in line with unbiased expectations.

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.[11]

3.4 Demand Elicitation

I study 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 willingness to pay from a subset of the overall sample using a modified version of the method pioneered by Becker, Degroot and Marschak (1964) (BDM). Using two different methods with different samples allows for corroboration of observed trends across the exercises, and thus lends more credibility to findings.

3.4.1 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.

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

[11] See DellaVigna, Pope and Vivalt (2019) for a more detailed discussion of benefits.

The offer was sent over SMS once the users completed the first training, or if they stopped engaging for at least two uninterrupted months. 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 did not want to buy to actually report their decision instead of just not responding to the invitation to choose, so as to not overestimate the demand.

Stratified by gender, the price in these TIOLI offers was randomized across individuals over three levels; (i) 1,419 individuals (50% of Treatment group) were offered the second training for free, (ii) 697 individuals (25% of Treatment group) were offered a price of KSH 5, and (iii) 704 individuals (25% of Treatment group) were offered a price of KSH 20. The marginal cost of provision of the entire training incurred by the implementing partner was KSH 10 per person, thus the two positive price levels in the TIOLI design represented half and double the marginal cost of provision, respectively.

Observing buying decisions across these pricing arms allows me to confirm whether there is any positive willingness to pay for the trainings amongst entrepreneurs, and if it varies systematically with price.

3.4.2 The Becker-DeGroot-Marschak Method

Following the Endline Survey, I randomly selected approximately 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 the resulting prices 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 higher than their actual maximum willingness to pay for the SMS training, and to commit to buying at a price lower than their maximum willingness to pay.

To circumvent complications posed by the possibility of individuals reneging on their commitment to buy at any price drawn from the lottery which is less than or equal to the maximum willingness to pay they reported during the exercise,[12] respondents were informed upfront 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.

4 Data and Timeline

This section describes the data sources, the study sample, and the timeline of research activities.

4.1 Data Sources

There are five sources of data for the project: (i) back-end data from the SMS platform, (ii) the Midline survey, (iii) the Endline Survey, (iv) the online elicitation of predictions for treatment effects from social science researchers, and (v) the in-person BDM elicitation activity.

4.1.1 Back-end Data

The back-end data from the SMS training platform was provided by the implementing partner. This data contains information about engagement levels of each entrepreneur over the course of the study period. It also contains buying decisions of entrepreneurs from the TIOLI offers described in Section 3.4.1.

A total of 415 individuals responded to the TIOLI invitations, and 380 (91.6%) of these respondents were also covered in the Endline survey. Therefore, while analyses showing raw buying decisions will be based on data from all 415 respondents, all analyses linking buying decisions with other respondent characteristics will be based on data from the 380 respondents that overlap across the two samples.

4.1.2 Midline Survey

Conducted three months post-intervention, the Midline survey targeted approximately 700 randomly selected leads from the primary sample for phone-based data collection. This resulted in 307 completed surveys spanning treatment and control individuals.[13] 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[14] and side jobs in the last 30 days, labor hours employed in business[15] 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.[16]

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

[13] Within the treatment group, those who had started engaging with the content at the three month mark were slightly over-sampled due to reporting requirements from the implementing partner. All analyses in this paper account for this sampling strategy by using appropriate weights.

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

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

[16] Only for primary business.

4.1.3 Endline Survey

The Endline survey was 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 group, control group and the 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, the Endline survey also sought to measure 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 hours employed in the last 7 days. Compared to the Midline, the Endline thus covered more outcomes for a larger sample.

4.1.4 Predictions Survey

The predictions survey was conducted online and resulted in 70 responses. The survey elicited expectations about treatment effects at Endline on outcomes including (i) the extensive margin engagement – i.e. what proportion of those offered the SMS training will have started engaging with it, (ii) the intensive margin engagement – i.e. what proportion of the training content will the average individual in the treatment group will have engaged with, (iii) knowledge about best practices (in terms of control group standard deviations), (iv) adoption of best practices (in terms of control group standard deviations), (v) sales from primary business in the last 30 days (in terms of percentage changes), and (vi) profits from primary business in the last 30 days (in terms of percentage changes).

4.1.5 Becker-DeGroot-Marschak Elicitation

Lastly, the BDM-style demand elicitation was conducted in-person with 103 Nairobi-based business owners at the end of the Endline survey. Unlike the TIOLI offers, the targeted respondents 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.

4.2 Sample

4.2.1 Midline and Endline Surveys

The primary sample for the intervention came from a list of micro-entrepreneurs maintained by my 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.[17]. Those who accepted and signed on to the SMS platform were randomized into groups as detailed in Section 3.2. Figure A.1 shows that an overwhelming majority of businesses in the sample either fall into the category of retail or services. Figure A.2 shows that the entrepreneurs in the sample were very widely

[17] Roughly equal to USD 1 at the time.

spread out geographically across Kenya, which bolsters the external validity of the findings from this study.

No baseline survey could be conducted due to timing and logistical constraints, and the only information available for each entrepreneur at the time of the randomization 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 A.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. About 87% had an active business and 40% had an active loan at the time of the intervention deployment.

Table A.2 shows that pre-intervention covariates are largely balanced across Treatment and Control groups, for Midline as well as Endline.

4.2.2 Predictions Survey

Of the 70 respondents to the predictions survey, half were PhD student researchers, and the other half were researchers at more advanced stages in their careers (academic faculty, post-docs, and researchers at think tanks and policy organizations). About 89% of the respondents 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.

4.2.3 Demand Elicitation

The samples used for measuring demand through TIOLI offers and the BDM method differ in four ways: (i) The TIOLI sample is entirely from the treatment group, while the BDM sample spans across treatment and control groups, (ii) the BDM sample only covers respondents based in Nairobi[18], (iii) the TIOLI sample includes some micro-entrepreneurs who don't have active businesses, while the BDM sample only covers business owners[19], and (iv) the BDM sample is smaller, covering 103 respondents,[20] while the TIOLI sample contains 415 respondents.

The summary statistics presented in Table A.4 show that the two samples are somewhat similar in terms of observable individual characteristics. The proportion of female entrepreneurs is slightly lower in the TIOLI sample at 44%, compared to 53% in the BDM sample. The average education level is the same at 12 years of schooling, while the average age is about 34 and 36 years, respectively. Number of adults (2.7 vs. 2.5) and children (2.1 vs 2.0) in the household are

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

[19] 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.

[20] This was due to financial constraints

also similar. One major difference is that while almost half the TIOLI sample is based in rural areas, only 11% of the BDM sample is based in rural settings. This is expected as the scope of the BDM elicitation was restricted to business owners in the city of Nairobi due to logistical constraints.

The samples are also largely comparable in terms of business outcomes. On average, respondents fare similarly in terms of scores for knowledge (75% vs 79%) and adoption (67% vs 64%) of best business management practices. They were also similarly likely to have applied for a loan as well as to have missed a loan payment in the past 3 months. A key difference is that business sales and profits, and time spent on business, are much higher for the BDM sample. This is expected as Nairobi is the capital city of Kenya and a regional economic hub, so businesses based there are larger volume compared to the rest of the country.

4.3 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
Rolling	**TIOLI Offers Sent:** Invitation to participate in demand elicitation through TIOLI offers sent to treatment group individuals upon completion of training or two uninterrupted months of non-engagement
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
Dec 2022 - Jan 2023	**BDM-styled Demand Elicitation:** In-person BDM-style demand elicitation exercise conducted in Nairobi
Oct 2023 - Nov 2023	**Social Science Predictions Platform Survey:** Online elicitation of predictions for treatment effects from social science researchers

5 Effect of the SMS Business Training

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.

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 Local Average Treatment Effect (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 produces ITT estimates of treatment group assignment on the outcomes of interest. The following equation represents the main specification:

$$Y_i = \beta_0 + \beta_1 treatment_i + X_i'\theta + \epsilon_i \tag{1}$$

where Y_i is the outcome of interest for individual i, $treatment_i$ is the treatment indicator, X_i is a vector of controls including gender and pre-intervention covariates (if included) with θ representing the associated coefficients, ϵ_i is the error term, and β_1 is the ITT estimate.

The second estimation strategy produces LATE estimates for the effect of treatment on the outcomes of interest. The following equations represent the main specification:

$$eng_i = \gamma_0 + \gamma_1 treatment_i + X_i'\psi + \eta_i \tag{2}$$

$$Y_i = \beta_0 + \beta_1 \hat{eng}_i + X_i'\theta + \epsilon_i \tag{3}$$

where Y_i is the outcome of interest for individual i, eng_i is a binary indicator for engagement in the training, $treatment_i$ is the treatment indicator (instrument), X_i is a vector of controls including gender and pre-intervention covariates (if included) with ψ and θ representing the associated coefficients, η_i and ϵ_i 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:

$$Y_i = \beta_0 + \beta_1 treatment_i * m_i + \beta_2 treatment_i + \beta_3 m_i + X_i'\theta + [m_i * X_i]'\zeta + \epsilon_i \tag{4}$$

where Y_i is the outcome of interest for individual i, $treatment_i$ 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 (except for the heterogeneity analyses for gender, where it is accounted for by m_i) and other pre-intervention covariates (if included) with ζ representing the associated coefficients, ϵ_i 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.

5.2 Midline Results

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

5.2.1 Engagement at Midline

Table 1 shows the treatment effect on engagement with the training content using four different measures of engagement. Column 1 shows the effect of treatment assignment on extensive margin engagement – i.e., 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 – i.e. the proportion of training content engaged with given that the individual started engaging. Finally, Column 4 shows the treatment effect on unconditional intensive-margin engagement – i.e., the proportion of training content that the individual engaged with, including engagement of those who never engaged as zero. No controls are added to these regressions.

I find that roughly 30% of the treatment group had started engaging with the training three months after the intervention, with only 8.4% of treatment individuals completing at least one-fourth of the training. Conditional on starting to engage, the average percentage of training content completed was 23.4%, and the unconditional average percentage training content completed was 7%. 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 B.1).

5.2.2 Knowledge and Adoption at Midline

To estimate effects on knowledge and adoption, I construct means effect indices from responses to questions testing knowledge and adoption of different best business practices. Table 2 presents the OLS (Columns 1 and 3) and 2SLS (Columns 2, and 4) estimates on these means effect indices of knowledge and adoption, with coefficients showing effects in terms of control group standard deviations (SD). The endogenous variable in Columns 2 and 4 is whether or not the individual engaged with training content.

I find that assignment to treatment led to a 0.198 SD increase in knowledge of best business practices, which is statistically significant at the 10% level. Conditional on engagement with any of the content, there I observe a 0.67 SD effect, which is also significant at the 10% level.

I also see a positive 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 SD, with the effect being statistically significant at the 5% level. The LATE estimate is also statistically significant, with an effect of 1.115 SD. I find that this large and statistically significant increase in the adoption index is driven by an increase in advertising (putting up posters/flyers advertising products/services); Table B.2 shows that treatment individuals are 8.4 percentage points more likely to put up posters advertising their products or services on average compared to those in the control group. Column 6 shows that, conditional on covering the training module on advertising, the effect estimate is 81.2 percentage points and still highly statistically significant.

5.2.3 Sales, Profits, and Business Survival at Midline

I measure business performance in terms of primary business sales and profits in the last 30 days, and business survival. Three months after the intervention, I find positive but imprecisely estimated treatment effects on business performance; Table 3 shows the ITT and LATE estimates of the effect of SMS trainings on business performance, with coefficients in Columns 1 through 4 representing effects in terms of Kenyan Shillings, while those in Columns 5 and 6 representing the probability of the individual having an active business. The treatment group had higher sales (12% higher) and profits (15.4% higher), as well as higher survival rate (by 4.14 percentage points) 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 micro-entrepreneurs of below-median age. Table A.3 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 within each of these age groups are comparable. Table B.3 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 rate 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 significantly so for younger (below-median-age) micro-entrepreneurs. I examine three mechanisms to better understand these effects: (i) time spent on business, (ii) labor employed in business, and (iii) credit outcomes.

I find 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). 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 all businesses combined (to account for cases where the entrepreneur had more than one business), as well as on side jobs. Table B.4 shows a similar increase when I consider time spent on all businesses combined, while Table B.5 shows a small negative but statistically insignificant coefficient for the effect on time spent on side jobs. I therefore don't find evidence for a reallocation of time away from other income generating activities, suggesting that the additional time spent on business could be resulting from reallocation away from leisure.

Additionally, Table 4 shows that treatment assignment did not have a statistically significant impact on labor hours employed, loan amount applied for, nor loan amount received.

I further find that the increase in time spent on business is driven by younger individuals; Table B.6 shows that treatment assignment led micro-entrepreneurs below the median age to spend 67 more hours in their primary business and 70.9 more hours across all their businesses combined, in the last 30 days. There is no statistically significant difference in labor hours employed by age (Table B.7), but I find that younger entrepreneurs applied for and received significantly larger loans (Table B.8).

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 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 Results

In this section, I examine longer run effects of the SMS business training using data from the Endline survey, which was conducted twelve months after the intervention deployment, and covered a wider set of outcomes compared to the Midline.

Since the scale of the Midline Survey was considerably smaller than that of the Endline (which targeted the full study 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 argue that this is not likely the case as: (i) Table C.1 shows that within the Endline, the sample matched with the Midline[21] is very similar to the sample that is not matched with the Midline, in terms of observable pre-intervention covariates, (ii) the two samples are also very similar in terms of control group outcomes (Table C.2), and (iii) I check robustness of observed effects at Endline to restricting the analyses to the Endline sample that was also covered in the Midline, and find no meaningful difference in results.

The following subsections present the observed treatment effects at Endline, paralleling the Midline analyses.

5.3.1 Engagement at Endline

This section examines the engagement with the training content at Endline, measured twelve months after the launch of the intervention. Mirroring the format of Table 1, 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 had engaged with the training twelve months after deployment, with 8.2% covering at least a quarter of the content. Conditional on starting to engage, the average engagement was 23.3%, and the unconditional average engagement was 6.5%.

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

These results are largely the same compared to those observed at Midline, suggesting that there was little if any engagement beyond the first three months of the intervention.

5.3.2 Knowledge and Adoption at Endline

At Endline, in addition to testing knowledge and adoption of basic business practices (covered in 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 ITT and LATE estimates for the treatment effect of SMS trainings on means effect indices of basic and advanced knowledge and adoption. Results show no significant improvement in knowledge or adoption of best business practices - both for basic as well as advanced practices - twelve months after the intervention. 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 D.2).

5.3.3 Sales, Profits, and Business Survival at Endline

Table 7 shows that the training had no significant impact on business performance twelve months post-intervention. I observe very small negative coefficients that are statistically insignificant for the effect on primary business sales (3.7% decrease) and profits (1.1% decrease) in the last 30 days, as well as business survival (-1.6 percentage points decrease). Table D.3 shows the results from running the same analyses with the Midline-matched sample; I find the same takeaway of no statistically significant impact 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 cases where the individual owns more than one business.[22] Table D.4 shows that including other businesses into the equation does not change the results, and Table D.5 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; I find no effects for younger entrepreneurs (Table D.6), and this result does not change when I restrict the analysis to the Midline-matched sample (Table D.7). 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 D.8), as well as the Midline-matched sample (Table D.9).

5.3.4 Endline Mechanisms

I examine the same potential mechanisms at Endline as I did at Midline. Table 8 indicates that there was a negative and statistically significant decrease in hours worked on primary business for treatment individuals, but the magnitude is very small compared to positive effects observed at Midline (9.7 hours less vs. 29 hours more in the last 30 days). Table D.10 shows that the negative effect goes away when I restrict the analysis to the Midline-matched sample. Tables D.11 and D.12 show that the negative effect on hours worked on primary business is also not

[22] Less than 10% of the sample.

robust to aggregating time spent across all businesses, and when focusing on the Midline-matched sample for this analysis too. Taken together, I interpret these results as not showing evidence of a meaningful treatment effect on time spent on business activities twelve months after the intervention. Moreover, Tables D.13 and D.14 show that there is no significant effect on time spent on side jobs either.

Furthermore, I find that younger entrepreneurs no longer spend more time on business; whether I look at the last 30 days (Tables D.15 and D.16), or the last 7 days (Tables D.17, and D.18).[23]

Tables D.19, D.20, D.21, and D.22 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 D.23 and D.24).

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 of Results

In summary, all positive effects observed at Midline were largely short-lived; I do not observe any meaningful differences across treatment and control groups on average in terms of outcomes of interest twelve months after the intervention.

This 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 confirmed by the time trend of aggregate engagement levels measured through the SMS training platform. Figure 2 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.

6 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 3.3. In this section, I present comparisons of predicted and observed treatment effects to argue that the findings in this study are indeed unexpected and informative.

Figures 3, 4, and 5 illustrate how the predicted treatment effects for Endline compare with observed effects at Midline and Endline. In all three figures, the solid red circle shows the mean of the distribution of predictions for the twelve month treatment effect, while the red rectangle represents the inter-quartile range, with the line inside the rectangle representing the median.

[23] I observe small negative effects for above median-age entrepreneurs, but they are not robust to restricting the sample to that matched with the Midline.

Observed treatment effects at Midline and Endline are represented by a gray rhombus and a black triangle, respectively, with error bars showing 90% confidence intervals.

Figure 3 shows how extensive and intensive margin engagement at Endline compares with observed levels. Respondents from the survey predicted that 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 by the Endline. The actual engagement levels observed are much lower; only about 30% of the treatment group had started engaging by Midline, and this figure stayed at almost 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 as well by the Endline.

Figure 4 presents respondent expectations for the effect of treatment assignment on knowledge and adoption of best practices, measured in terms of control group standard deviations. Respondents predicted increases of approximately 0.3 and 0.2 standard deviations for knowledge and adoption, respectively, by the Endline. At Midline, the observed effects on knowledge (0.2 standard deviations) and adoption (0.33 standard deviations) were relatively close to these predictions. However, by Endline, these positive effects had dissipated entirely. This suggests that respondents also overestimated the longer run impact of treatment on both knowledge and adoption of best practices.

Figure 5 shows how predictions for effects on sales and profits compare to observed results. Respondents predicted a 13% and 12% increase in sales and profits in the Endline, respectively. These figures are similar to those estimated in the meta-analysis by McKenzie (2021), which finds that a typical in-person training leveraging insights from psychology to tailor content to targeted contexts, can increase sales and profits by 11% and 15%, respectively. While observed effects at Midline are of similar magnitudes (12% and 15.4%, respectively), albeit statistically insignificant, the observed effects at Endline are close to zero. I therefore find that respondents also overestimated the effect of treatment assignment on sales and profits twelve months after the intervention.

Lastly, while I find no meaningful difference between predictions given by PhD student researchers and more advanced PhD researchers, I observe that those that are more confident about their predictions overestimate treatment effects more - Figure E.1 illustrates the positive correlation between predictions for treatment effects and the confidence level in predictions reported by respondents.

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.

7 Demand for SMS Business Trainings

This section presents results from the demand elicitation for SMS trainings. Proceeding subsections cover construction of demand curves, a discussion about alternative explanations for positive demand, and analyses exploring correlates of demand.

7.1 Demand Curves

7.1.1 TIOLI Offers

About 415 individuals responded to the TIOLI invitations described in Section 3.4.1, 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 conservative acceptance rates by grouping the last category with those who explicitly chose to not buy. The overall acceptance rate in the sample was thus 65.5%.

Figure 6 shows the (inverse) demand curve constructed using buying decisions amongst the full TIOLI sample. The horizontal red line shows the marginal cost per person faced by the service provider. I observe that about 70% of individuals chose to accept the offer when the training was offered for free. When the price was KSH 5 (half the marginal cost per user for the full training faced by the provider), acceptance rate fell slightly to approximately 68%. 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, almost half of the individuals were willing to buy the training.

7.1.2 BDM Elicitation

The average maximum willingness to pay in the BDM sample was KSH 50 (five times the marginal cost), with a standard deviation of KSH 34.9. Figure F.2 illustrates the distribution and shows bunching of responses at KSH 0 (9% of respondents), KSH 20 (10%), KSH 50 (27%), and KSH 100 (24%).[24]

I use the maximum willingness to pay for each respondent elicited using the BDM method to plot the proportion of the sample that would buy the training at each integer price level between 0 and 100 Kenyan Shillings. Figure 7 shows the resulting (inverse) demand curve. I find that the entire sample was willing to accept the SMS training when it was offered for free, while 23.3% of the sample was willing to pay KSH 100, which is ten times the marginal cost.

Both methods of elicitation thus reveal a downward sloping demand curve, and show that micro-entrepreneurs are willing to pay a small amount to get access to SMS-based business trainings. However, this positive willingness to pay might not reflect actual demand – the following subsection discusses potential alternative explanations and offers arguments ruling them out in this context.

7.2 Ruling Out Alternative Explanations

Since about 70% of the treatment group did not start engaging with the training content and no one in the control group was offered the training, the willingness to pay in the TIOLI as well as BDM elicitation could be driven by those with less or no exposure to the content. If this was the case, I would see a clear negative relationship between exposure to training content and demand. I test for this by (i) comparing engagement levels in the TIOLI sample across those who

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

chose to buy the training and those who did not, and (ii) estimating the causal effect of training on willingness to pay elicited through the BDM exercise. Table F.1 shows that engagement in the TIOLI sample at both the extension margin[25] as well as the intensive margin[26] is not lower amongst those who chose to buy the additional training, compared to those who chose not to. In fact, engagement rates were higher amongst those who chose to buy – albeit, not statistically significantly so – suggesting that those who are more exposed to the content are more likely to pay for an additional training. Furthermore, the causal effect of the SMS training on the maximum willingness to pay in the BDM sample is also non-negative – Table F.2 shows an imprecisely measured positive effect of the SMS training on willingness to pay.[27] I therefore do not find evidence for a negative relationship between exposure to content and willingness to pay for SMS-based trainings.

Another possible explanation for the observed positive willingness to pay is the influence of reciprocity (Gouldner (1960)). Respondents may have felt a sense of obligation to give back for being part of the study by agreeing to pay for the additional training. However, this concern appears minimal in this context as the entire training intervention was delivered remotely through automated text messages, with little to no direct human interaction. Although the BDM exercise involved in-person interactions with enumerators, the TIOLI elicitation was conducted entirely via SMS and was fully automated, and still resulted in positive willingness to pay. This suggests that reciprocity is unlikely to be a significant factor driving the observed demand.

Alternatively, the observed willingness to pay could just be driven entirely by a certain type of people who would say yes to anything, especially since the price is so low. However, I argue that this is also unlikely to be driving the results since I find that willingness to pay systematically decreases with price level – the demand curves are indeed 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 training content. This positive willingness to pay suggests that a market-based approach for delivery of these trainings might be feasible in this context.

7.3 Correlates of Demand

This section presents some correlational observations with regards to determinants of demand for SMS-based trainings as measured through the TIOLI offers and the BDM method.

Out of the 415 individuals who participated in the TIOLI elicitation, 65 could not be reached for the Endline survey. Therefore, I am only able to merge buying decisions of 350 out of 415 individuals with data from the Endline to shed light on correlates of demand from the TIOLI sample. Table A.5 shows that the matched sample is still jointly balanced on observables across randomized pricing arms using data from the Endline, and Figure F.1 shows that the demand curve constructed using the matched data looks very similar to that from the full sample, allaying concerns of biases due to systematic attrition.

[25]The proportion of respondents offered the training who chose to start engaging with it.

[26]The proportion of the training content that the average respondent engaged with.

[27]Table A.6 shows that the treatment and control groups for the BDM sample are balanced on observables including relevant pre-intervention covariates and outcome variables from earlier analyses on effectiveness of SMS trainings.

Table F.3 shows raw averages of individual level variables including demographic and enterprise characteristics in the TIOLI sample amongst those who accepted the TIOLI offer, those who rejected, and the difference between the two.[28] I observe that the number of children in the household, knowledge about best business practices, and likelihood of having applied for a loan in the last three months, are significantly higher amongst those that choose to buy compared to those that don't. Table F.4 shows the results from OLS and Logit regressions of the decision to buy on the price levels in the TIOLI offers,[29] and the same individual characteristics. Column 1 shows the acceptance rate at the different price levels, in line with the figures from the demand curve in the preceding section. Column 2 shows the regression output when including demographic and enterprise characteristics. I observe that the significant differences in the raw comparisons in Table F.3 survive controlling for all variables together - number of children in the household, knowledge about best practices, and having taken out a loan recently are all significantly positively related to the probability of accepting the TIOLI offer for another SMS training, controlling for other variables. The table also shows sales and profits to be statistically significantly related, but the magnitudes of the coefficients are negligible. Columns 3 and 4 show the same trend in terms of the log odds of accepting the TIOLI offer.

Table F.5 shows the relationship between willingness to pay and individual characteristics in the BDM sample using bivariate OLS regressions. I observe willingness to pay is positively correlated with education statistically significantly. The correlation with Profits in last 30 days is also statistically significant, but the magnitude of the coefficient is negligible. Table F.6 shows that the statistically significant positive association of willingness to pay with education is robust to controlling for other variables. Profits also remains statistically significant, but with a negligible coefficient.

Correlational analyses of determinants of demand for SMS-based business trainings in the TIOLI and BDM samples are thus in line with the intuition that those that have more dependents/mouths to feed at home, and those in need of funds recently are more likely to take on a potential opportunity to increase their business profits. Additionally, those with more knowledge about best business management practices and those who are more educated recognize the importance of information about best practices and are more likely to want to learn more.

8 Conclusion and Policy Implications

This paper assesses the potential of SMS-based business trainings to improve business outcomes, and their demand amongst micro-entrepreneurs via a field experiment in Kenya. Approximately 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. Data on key outcomes were collected through phone-based surveys conducted three months (Midline) and twelve months (Endline) after the intervention to estimate short and longer-run treatment effects, respectively. Additionally, I measured demand for

[28] These characteristics include relevent pre-intervention covariates as well as key outcome variables considered for the earlier analyses of effectiveness of SMS trainings.

[29] Using the price of zero (free) as the base case.

trainings using two methods; first, I analyze buying decisions of 415 individuals who were sent Take-It-Or-Leave-It (TIOLI) offers to buy an additional SMS business training, where the price was randomized across respondents over three levels: (i) free, (ii) half the marginal cost to service provider (KSH 5), and (iii) double the marginal cost (KSH 20). Second, I conducted an in-person BDM-style demand elicitation exercise aimed at measuring willingness to pay for an SMS business training among 103 entrepreneurs based in Nairobi.

Three months after the intervention, I find positive effects on knowledge and adoption of best practices, particularly for advertising, and positive but imprecisely estimated effects on business sales, profits and survival. I further find statistically 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.

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.

Furthermore, 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. In the TIOLI sample, 70% of individuals chose to accept the additional training when it was offered for free, 68% accepted when the price was KSH 5 (half the marginal cost), and about 50% accepted when the price was KSH 20 (double the marginal cost). In the BDM sample, the average willingness to pay for SMS trainings was KSH 50, and almost a quarter of the respondents were willing to buy the training for KSH 100 (ten times the marginal cost to service provider). Both methods of demand elicitation thus show that micro-entrepreneurs were willing to pay a positive amount for SMS-based business management trainings, and a substantial proportion of them were willing to pay much more than the marginal cost to the service provider. These results suggest that a market-based approach to providing SMS trainings might be feasible in this context. Additionally, I find correlational evidence showing that demand for trainings was positively associated with number of children in the household, knowledge about best business practices, education level, and having recently applied for a loan.

Taken together, the takeaways from this study direct attention towards an interesting question that can be critical for maximizing impacts of remotely provided information-based support, and should be an important research direction going forward; why was engagement low? There can be two possible non-mutually exclusive components responsible for this – (i) the content, and/or (ii) the content delivery.

If entrepreneurs judge the content to not be worth engaging with, they are unlikely to invest the required time to go through it. It is unlikely that this factor played a major role in this study as 70% of the treatment group never even started engaging with the content, and demand for SMS training was higher among those that were more exposed to it. 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[30], we still have to attend school and other classroom-type environments for acquiring knowledge and skills beyond foundational language and mathematics. Indeed, qualitative interviews with a small subset of individuals in the treatment group reveal that the reason micro-entrepreneurs did not engage with the content was that they were "busy during the day with customers" and then "forgot to engage after getting free", suggesting behavioral constraints might be playing an important role in limiting engagement. I leave a deeper dive into possible behavioral drivers in this context to future work. 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 with remotely provided content, which can greatly help unlock the full potential of digital technologies for remote learning.

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

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9 Main Tables

9.1 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.

9.2 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.

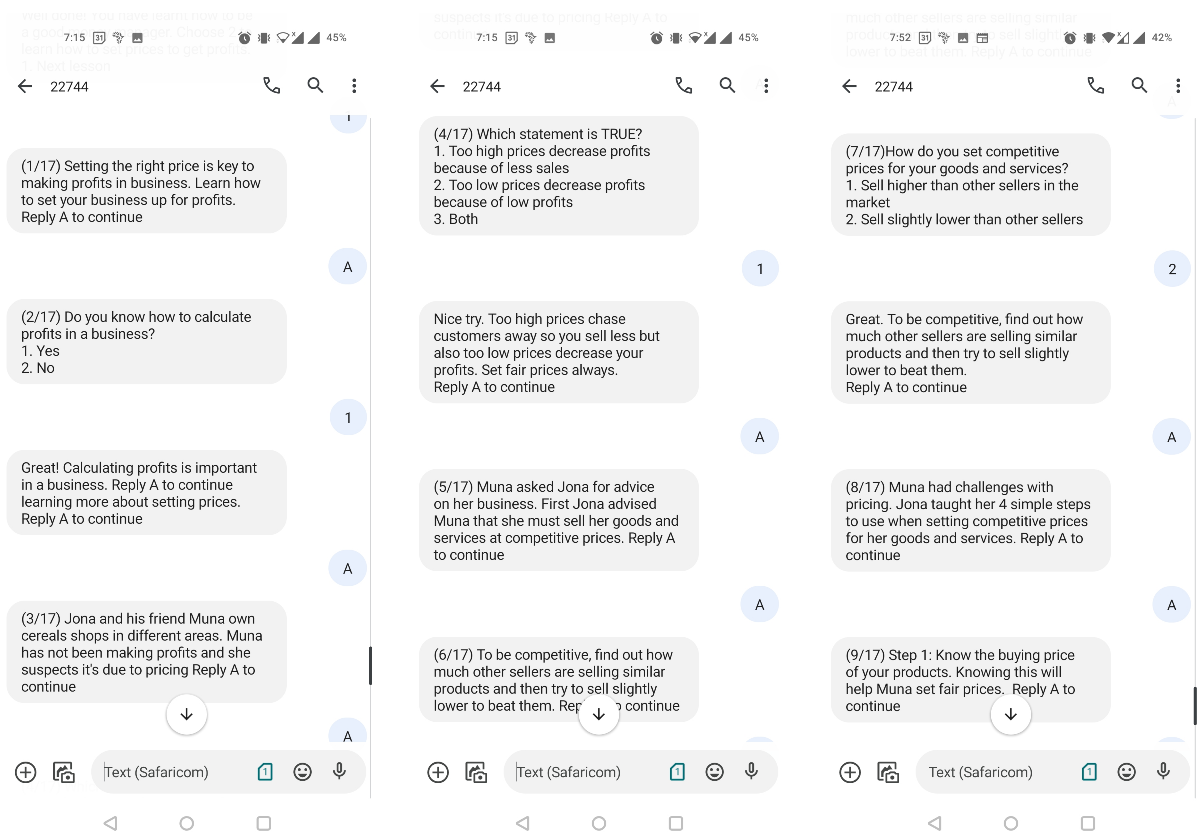
Table 8: Endline: Intermediate Outcomes

	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.

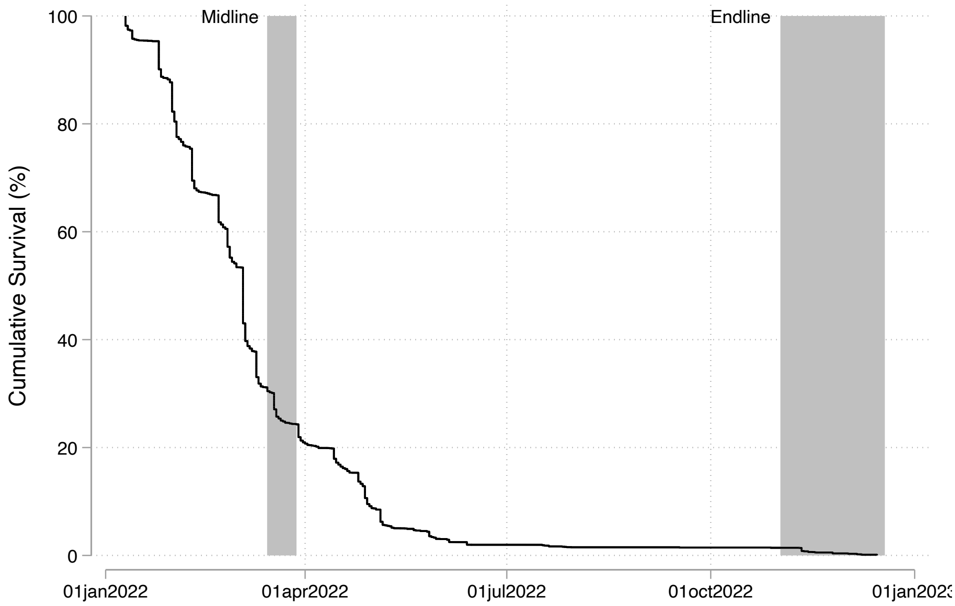
10 Main Figures

Figure 1: SMS Business Training Content



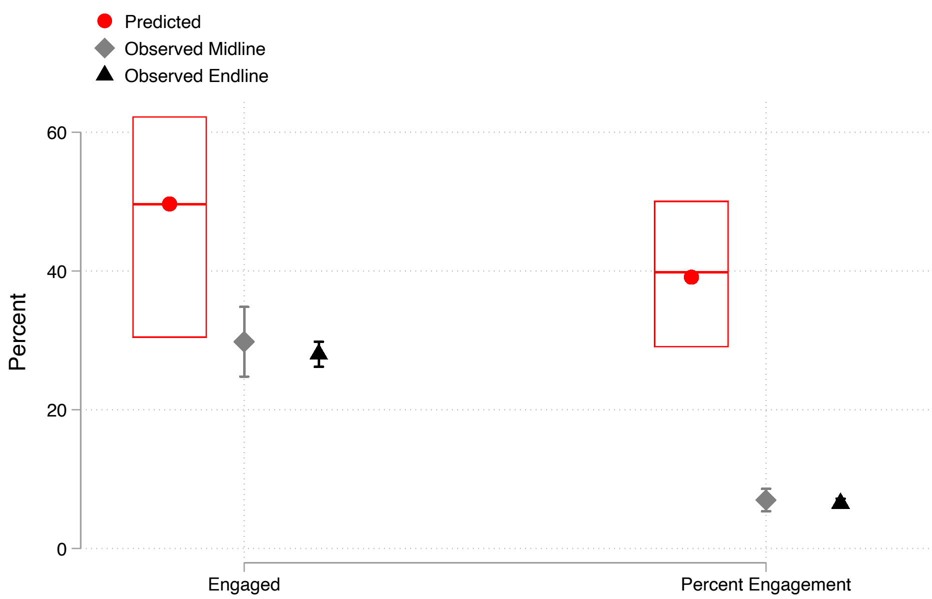
Notes: This figure shows screenshots of interactions with the SMS-based chatbot as it pushes out content to users. In this context, most micro-entrepreneurs set prices just based on their buying costs, without accounting for prices of their competitors, so the content pushes them to change their pricing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

Figure 2: Engagement Survival Curve



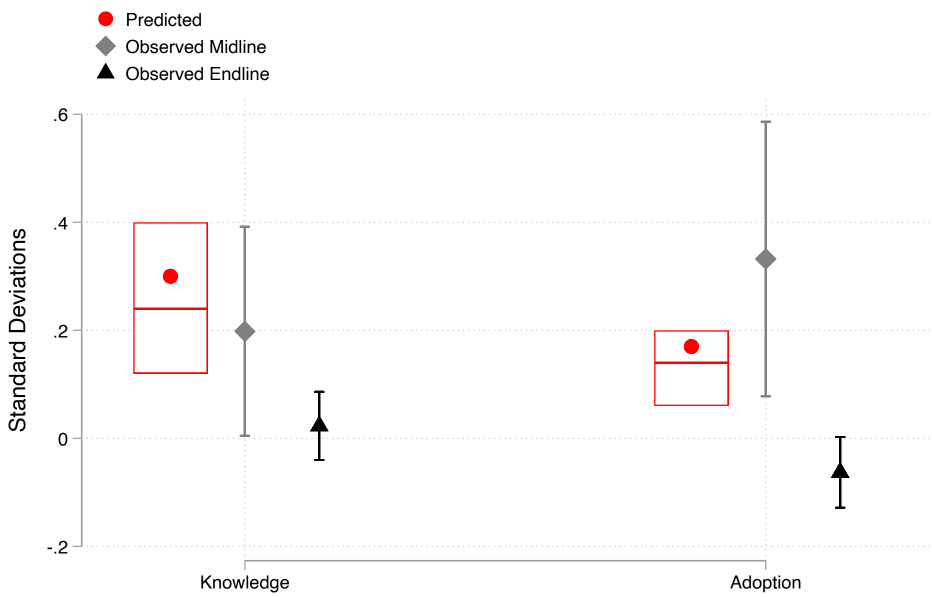
Notes: This figure illustrates how interactions with the SMS platform were distributed throughout the study period. The plot shows reverse cumulative engagement over time; for example, it shows that 80% of all the interactions with the chat-bot throughout the course of the study, had ended by 4/1/2022.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

Figure 3: Predictions vs. Observations - Engagement



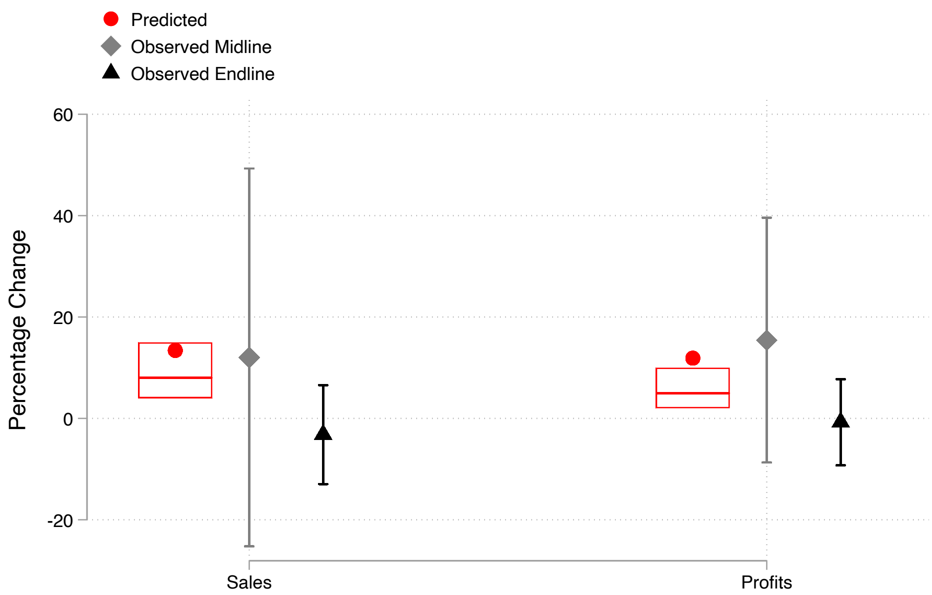
Notes: This figure shows how predicted treatment effects on extensive and intensive margin engagement for the Endline compare with observed Midline and Endline effects. Effects are in terms of percentage points. The distribution of the predicted treatment effect is illustrated in red, with the mean represented by the circle, and the rectangle representing the inter-quartile range, with the line inside the rectangle indicating the median. Observed Midline and Endline treatment effects are represented by a gray rhombus and a black triangle, respectively, with error bars representing 90% confidence intervals.

Figure 4: Predictions vs. Observations - Knowledge and Adoption



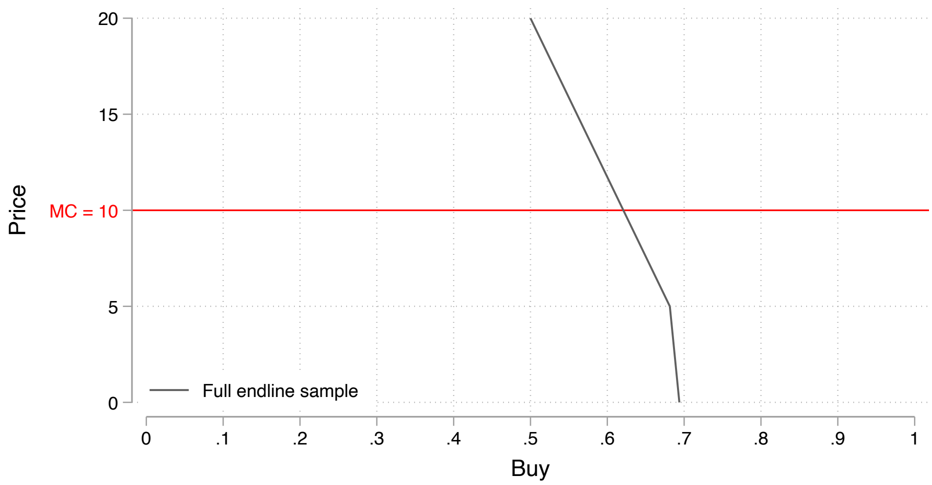
Notes: This figure shows how predicted treatment effects on knowledge and adoption of best practices for the Endline compare with observed Midline and Endline effects. Effects are in terms of control group standard deviations. The distribution of the predicted treatment effect is illustrated in red, with the mean represented by the circle, and the rectangle representing the inter-quartile range, with the line inside the rectangle indicating the median. Observed Midline and Endline treatment effects are represented by a gray rhombus and a black triangle, respectively, with error bars representing 90% confidence intervals.

Figure 5: Predictions vs. Observations - Sales and Profits



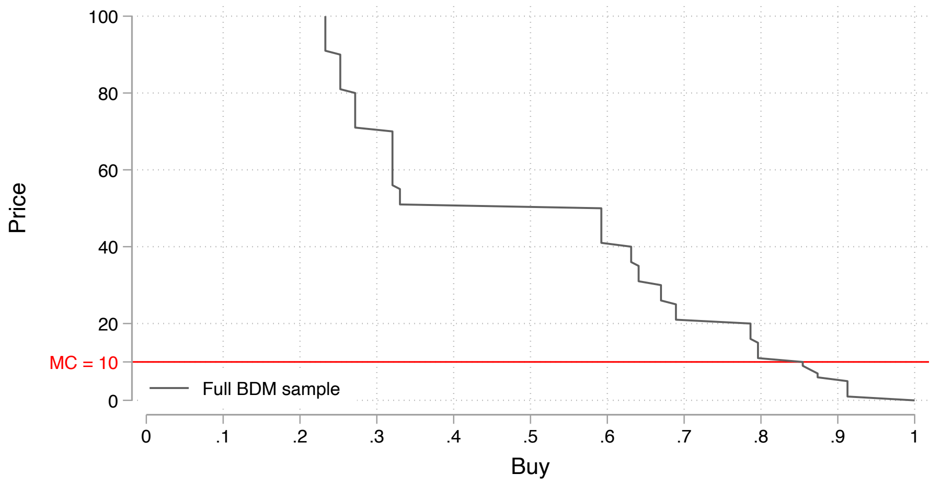
Notes: This figure shows how predicted treatment effects on business sales and profits in the last 30 days for the Endline compare with observed Midline and Endline effects. Effects are in terms of percentage changes. The distribution of the predicted treatment effect is illustrated in red, with the mean represented by the circle, and the rectangle representing the inter-quartile range, with the line inside the rectangle indicating the median. Observed Midline and Endline treatment effects are represented by a gray rhombus and a black triangle, respectively, with error bars representing 90% confidence intervals.

Figure 6: 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 y-axis represents the price in Kenyan Shillings, and the x-axis represents the proportion of the sample that chose to buy at each price level. The horizontal red line represents the per person marginal cost faced by provider for delivering the entire training.

Figure 7: Willingness to Pay - BDM

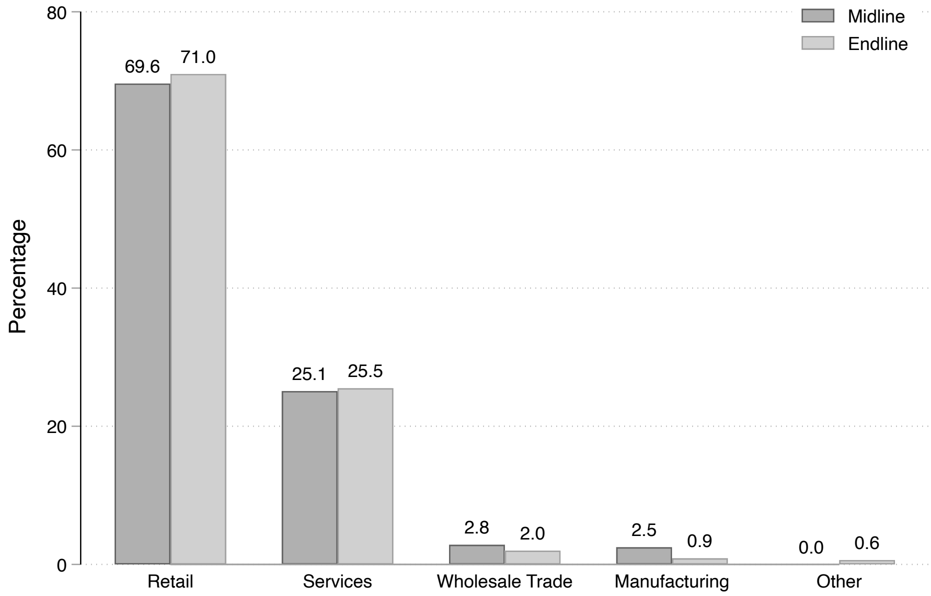


Notes: This figure shows the (inverse) demand curve based on the maximum willingness to pay elicited using the in-person elicitation using the modified BDM method. The y-axis represents the price in Kenyan Shillings, and the x-axis represents the proportion of the sample that would choose to buy at each price level, given their maximum willingness to pay. The horizontal red line represents the per person marginal cost faced by provider for delivering the entire training.

Appendix

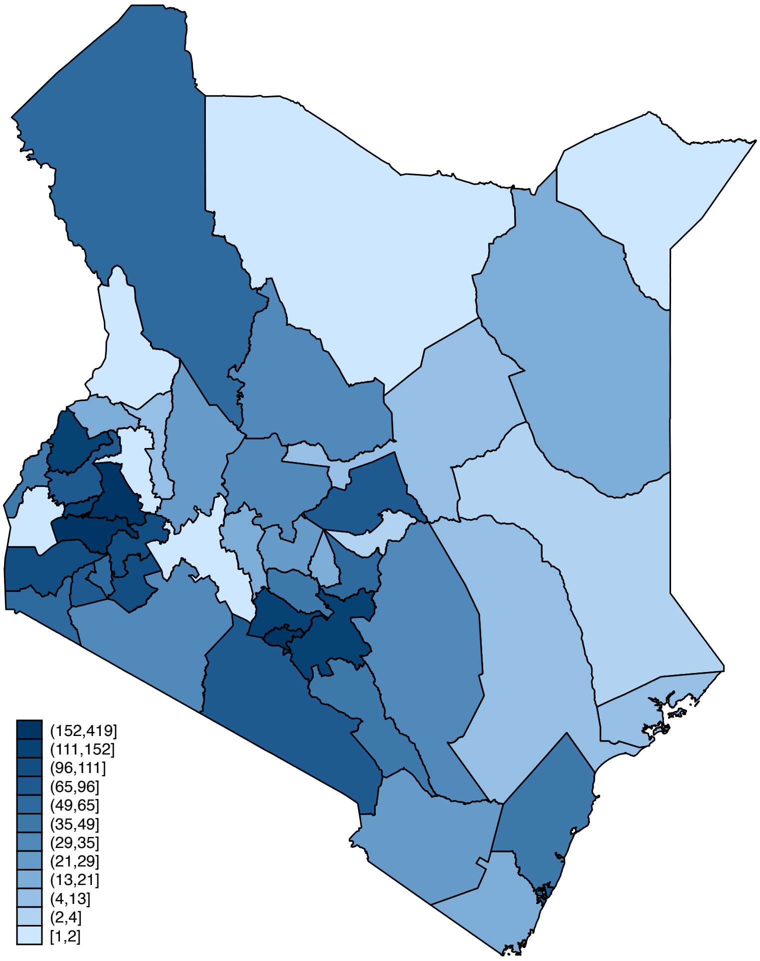
A Sample Statistics and Balance

Figure A.1: 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 A.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.

Table A.1: Summary Statistics for Midline and Endline

	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 A.2: Balance Across Treatment and Control Groups for Midline and Endline

	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 ($\beta_{diff} \neq 0$)				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.

Table A.3: 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 A.4: Summary Statistics for TIOLI and BDM Samples

	TIOLI			**BDM**		
	Mean	SD	Obs.	Mean	SD	Obs.
Panel A: Baseline Covariates						
Female	0.44	0.50	380	0.53	0.50	103
Rural	0.49	0.50	380	0.11	0.31	103
Years of education	12.0	2.47	380	12.0	2.30	103
Age	33.6	8.59	380	36.3	9.34	103
Num of adults	2.69	1.44	379	2.45	1.24	102
Num of children	2.14	1.45	379	1.98	1.52	102
Panel B: Outcomes						
Knowledge	0.75	0.14	380	0.79	0.13	103
Adoption	0.67	0.17	351	0.64	0.21	103
Sales in last 30 days	59,754	111,199	380	69,238	113,295	103
Profits in last 30 days	19,602	31,122	380	23,852	32,155	103
Applied for loan	0.50	0.50	380	0.57	0.50	103
Missed loan payment	0.20	0.40	380	0.18	0.39	103
Hours worked on business	214.9	121.2	380	261.4	99.7	103
Hours worked on side jobs	23.6	64.1	380	17.5	47.6	103

Notes: This table shows the the mean, standard deviation and number of observations for pre-intervention covariates, and outcomes studied in the evaluation of the SMS-based training intervention. The summary statistics are presented separately for the Take-It-Or-Leave-It and Becker-DeGroot-Marschak demand elicitation samples.

Table A.5: Balance Across TIOLI Pricing Arms

Variable	P_1	P_2	P_3	Diff (P_1, P_2)	Diff (P_2, P_3)	Diff (P_1, P_3)
Panel A: Baseline Covariates						
Female	0.43	0.50	0.36	-0.06	0.13*	0.07
	(0.50)	(0.50)	(0.48)	(0.06)	(0.08)	(0.07)
Rural	0.51	0.48	0.47	0.03	0.01	0.04
	(0.50)	(0.50)	(0.50)	(0.06)	(0.08)	(0.07)
Years of education	12.00	12.15	11.93	-0.16	0.22	0.06
	(2.59)	(2.27)	(2.42)	(0.29)	(0.38)	(0.38)
Age	33.12	34.76	33.34	-1.64	1.42	-0.23
	(8.33)	(9.28)	(8.05)	(1.01)	(1.43)	(1.23)
Num of adults in household	2.76	2.63	2.57	0.12	0.06	0.19
	(1.43)	(1.52)	(1.33)	(0.17)	(0.24)	(0.21)
Num of children in household	2.21	2.12	1.93	0.09	0.19	0.28
	(1.45)	(1.43)	(1.51)	(0.17)	(0.24)	(0.22)
Panel B: Outcomes						
Knowledge	0.74	0.79	0.75	-0.05***	0.04*	-0.01
	(0.14)	(0.13)	(0.14)	(0.02)	(0.02)	(0.02)
Adoption	0.67	0.67	0.68	-0.01	-0.00	-0.01
	(0.16)	(0.18)	(0.19)	(0.02)	(0.03)	(0.03)
Sales in last 30 days	61449	60733	51741	715.76	8992	9707
	(109417)	(118607)	(103972)	(13162)	(18395)	(16068)
Profits in last 30 days	19731	19199	19922	532	-723	-192
	(31201)	(29921)	(33585)	(3592)	(5040)	(4709)
Applied for a Loan	0.52	0.48	0.50	0.04	-0.02	0.02
	(0.50)	(0.50)	(0.50)	(0.06)	(0.08)	(0.07)
Loan Payment Loan Payment Missed/Late	0.19	0.24	0.14	-0.05	0.10	0.05
	(0.39)	(0.43)	(0.35)	(0.05)	(0.07)	(0.06)
Hours worked on business in last 30 days	214.26	209.64	227.74	4.62	-18.10	-13.48
	(126.40)	(112.38)	(119.86)	(14.21)	(18.57)	(18.55)
Hours worked on side jobs in last 30 days	26.27	24.04	12.95	2.24	11.09	13.32
	(67.19)	(66.90)	(43.99)	(7.83)	(9.72)	(9.34)
Wald Chi-Sq. Test P-value = 0.26						

Notes: This table shows the balance of pre-intervention covariates across TIOLI pricing arms for the TIOLI sample overlapping with the Endline data. The reported p-value at the bottom is from a test of joint orthogonality across all randomization groups. Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A.6: Balance Across Treatment and Control in BDM Sample

Variable	Treatment	Control	Difference
Female	0.51	0.58	-0.07
	(0.50)	(0.50)	(0.10)
Rural	0.14	0.05	0.09
	(0.35)	(0.23)	(0.06)
Years of education	11.86	12.21	-0.35
	(2.24)	(2.41)	(0.47)
Age	35.82	37.21	-1.40
	(9.74)	(8.66)	(1.91)
Num of adults in household	2.48	2.39	0.09
	(1.33)	(1.08)	(0.26)
Num of children in household	1.94	2.05	-0.12
	(1.45)	(1.66)	(0.31)
Overall Knowledge	0.76	0.82	-0.06**
	(0.14)	(0.11)	(0.03)
Overall Adoption	0.65	0.62	0.03
	(0.21)	(0.20)	(0.04)
30-day Sales from All Businesses	69729.23	68397.37	1331.86
	(117252.40)	(107718.30)	(23249.43)
30-day Profits from All Businesses	24344.31	23010.53	1333.78
	(31404.55)	(33812.18)	(6597.39)
Applied for a Loan	0.65	0.45	0.20**
	(0.48)	(0.50)	(0.10)
Loan Payment Missed/Late	0.17	0.21	-0.04
	(0.38)	(0.41)	(0.08)
Hours worked on business	256.72	269.47	-12.75
	(104.83)	(91.06)	(20.42)
Hours worked on side jobs	19.88	13.47	6.40
	(50.94)	(41.56)	(9.74)
F-test p-value ($\beta_{diff} \neq 0$)			0.13

Notes: This table shows the balance of pre-intervention covariates across TIOLI pricing arms for the TIOLI sample overlapping with the Endline data. The reported p-value at the bottom is from a test of joint orthogonality across all randomization groups. Standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

B Additional Results for Midline

Table B.1: 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 B.2: 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 B.3: 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 B.4: 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 B.5: 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 B.6: 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 B.7: 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 B.8: 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 Endline Vs Midline Sample Comparison

Table C.1: Endline Sample – Matched VS Unmatched with Midline: 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 ($\beta_{diff} \neq 0$)			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 C.2: Endline Sample – Matched VS Unmatched with Midline: 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 ($\beta_{diff} \neq 0$)			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.

D Additional Results for Endline

Table D.1: 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 $\geq$ 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 D.2: 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 D.3: 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 D.4: 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 D.5: 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 D.6: 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 $\geq$ 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 D.7: 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 D.8: 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 D.9: 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 D.10: 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 D.11: 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 D.12: 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 D.13: 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 D.14: 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 D.15: 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 ≥ 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 D.16: 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 D.17: 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	-2.534**	-2.366**	-3.414**	-3.125**	-1.065	-1.079		
	(1.113)	(1.149)	(1.482)	(1.529)	(1.667)	(1.729)		
Train x Age ≥ 34							-2.349	-2.046
							(2.231)	(2.308)
P-value	0.0229	0.0396	0.0210	0.0410	0.523	0.533	0.292	0.375
Control Mean	53.68	55.66	55.96	57.64	50.97	53.31	53.68	55.66
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 D.18: 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	2.781	3.909	-2.080	-0.221	9.963	10.32		
	(4.319)	(4.487)	(5.821)	(6.192)	(6.475)	(6.502)		
Train x Age ≥ 34							-12.04	-10.54
							(8.704)	(8.976)
P-value	0.520	0.385	0.721	0.972	0.127	0.116	0.168	0.242
Control Mean	51.60	53.26	56.47	58.22	44.77	46.31	51.59	53.26
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 D.19: 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 D.20: 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 D.21: 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 D.22: 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 D.23: 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 ≥ 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.

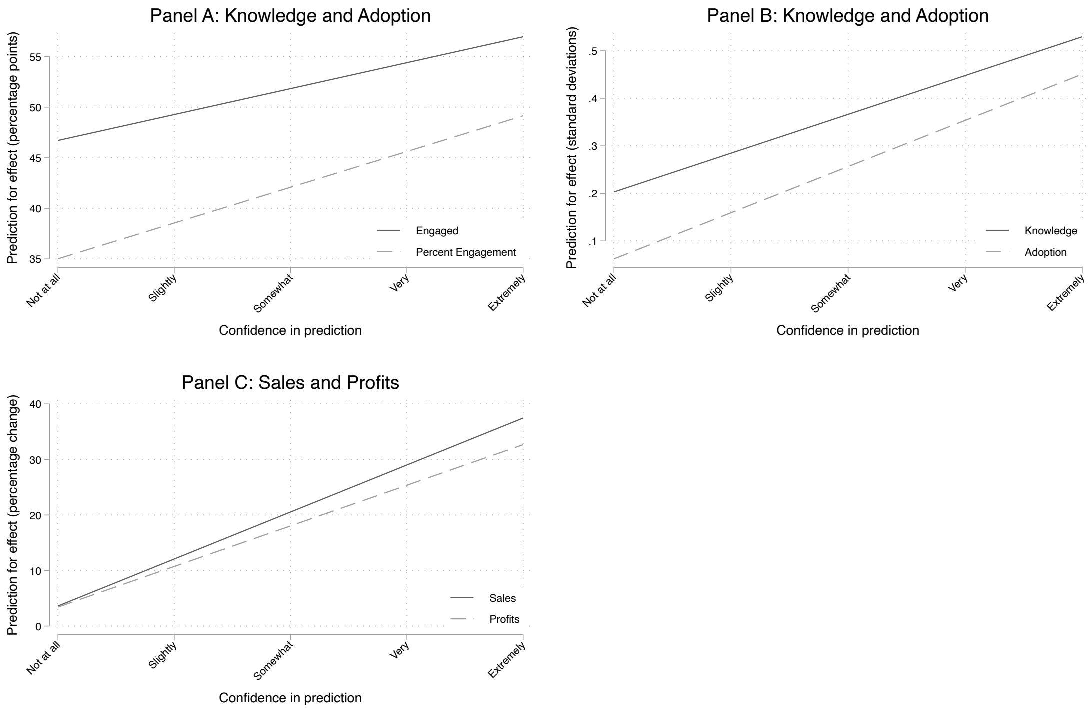
Table D.24: Endline: Loan Amount Applied for and Received in Last 3 months by Age Using Midline Sample

	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 ≥ 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.

E Additional Results for Predictions

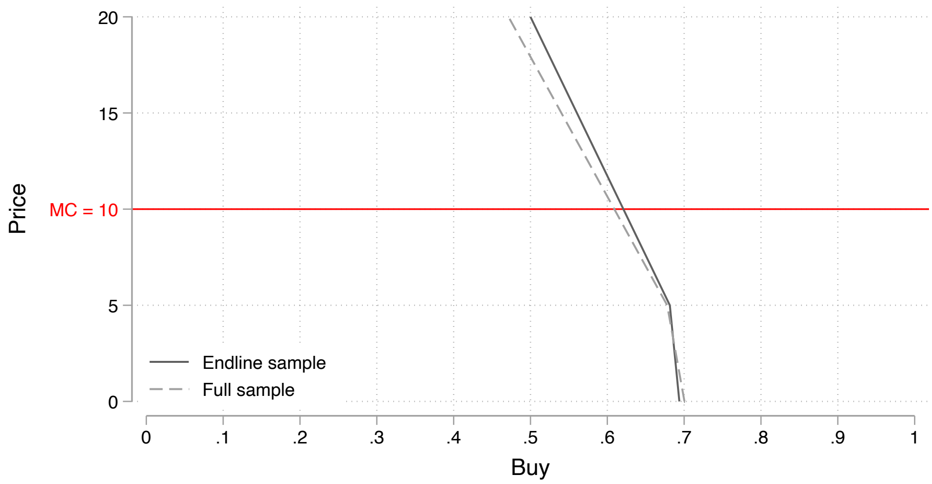
Figure E.1: Predictions and Confidence behind Predictions



Notes: This figure shows the best-fit line representing the correlation between predictions of treatment effects and how confident the respondents reported to be in their predictions, ranging from not at all confident, to extremely confident.

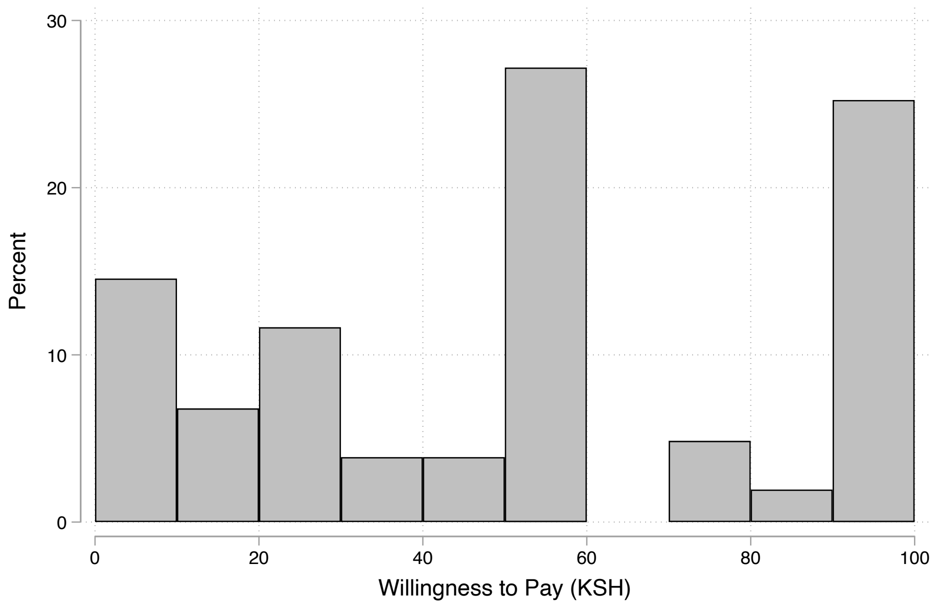
F Additional Results for Demand Elicitation

Figure F.1: TIOLI Demand Curve - Full Sample vs. Endline Sample



Notes: This figure shows the (inverse) demand curves based on buying decisions from randomized TIOLI offers sent to treatment individuals in the full TIOLI sample and that overlapping with the Endline sample. The y-axis represents the price in Kenyan Shillings, and the x-axis represents the proportion of the sample that chose to buy at each price level. The horizontal red line represents the per person marginal cost faced by the service provider for delivering the entire training.

Figure F.2: BDM Willingness to Pay Distribution



Notes: This figure shows the distribution of maximum willingness to pay (in Kenyan Shillings) measured through the in-person BDM elicitation exercise.

Table F.1: 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. Robust standard errors in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table F.2: 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.

Table F.3: TIOLI - Differences Between Buyers and Non-buyers

Variable	Accept	Reject	Diff
Female	0.45	0.41	0.04
	(0.50)	(0.49)	(0.05)
Rural	0.51	0.46	0.05
	(0.50)	(0.50)	(0.05)
Years of education	11.98	12.13	-0.15
	(2.48)	(2.46)	(0.27)
Age	33.76	33.41	0.35
	(8.38)	(9.01)	(0.93)
Num of adults in household	2.72	2.64	0.07
	(1.36)	(1.58)	(0.16)
Num of children in household	2.32	1.81	0.51***
	(1.44)	(1.41)	(0.16)
Knowledge	0.77	0.73	0.04**
	(0.14)	(0.14)	(0.02)
Adoption	0.67	0.67	0.00
	(0.17)	(0.16)	(0.02)
30-day Sales from All Businesses	64386.18	50740.97	13645.21
	(119183.62)	(93513.92)	(12041.96)
30-day Profits from All Businesses	19564.45	19674.42	-109.97
	(30842.64)	(31778.75)	(3375.95)
Applied for a Loan	0.53	0.44	0.09*
	(0.50)	(0.50)	(0.05)
Loan Payment Missed/Late	0.71	0.60	0.11
	(0.46)	(0.50)	(0.10)
Hours worked on business	221.45	202.29	19.16
	(126.64)	(109.27)	(13.11)
Hours worked on side jobs	21.77	27.08	-5.30
	(60.90)	(70.11)	(6.95)

Notes: This table shows the averages of listed variables amongst those who accepted the TIOLI offer for a second SMS training, those who rejected, and the difference between them. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table F.4: TIOLI - Determinants of Decision to Buy

	OLS		**Logit**	
	(1)	(2)	(3)	(4)
Price = KSH 5	-0.0225	-0.0180	-0.105	-0.0678
	(0.0529)	(0.0561)	(0.245)	(0.279)
Price = KSH 20	-0.229***	-0.145*	-0.964***	-0.638*
	(0.0672)	(0.0791)	(0.280)	(0.349)
Female		0.0343		0.141
		(0.0535)		(0.262)
Rural		-0.0091		-0.0429
		(0.0525)		(0.251)
Years of education		0.00108		0.000145
		(0.0105)		(0.0534)
Age		-0.00128		-0.00727
		(0.00312)		(0.0147)
Num of adults in household		-0.0101		-0.0549
		(0.0189)		(0.0902)
Num of children in household		0.0654***		0.328***
		(0.0186)		(0.0982)
Knowledge		0.371**		1.888**
		(0.181)		(0.861)
Adoption		0.0141		-0.0259
		(0.153)		(0.739)
Sales in last 30 days		0.0000009***		0.00000636**
		(0.000000336)		(0.00000315)
Profits in last 30 days		-0.00000315**		-0.0000205**
		(0.00000128)		(0.00000891)
Applied for a loan		0.090*		0.463*
		(0.0506)		(0.249)
Loan payment missed/late		0.0633		0.336
		(0.0628)		(0.333)
Hours worked on business in last 30 days		0.000148		0.000646
		(0.000230)		(0.00117)
Hours worked on side jobs in last 30 days		-0.000116		-0.000573
		(0.000492)		(0.00234)
Intercept	0.70***	0.227	0.849***	-1.294
	(0.0305)	(0.247)	(0.145)	(1.228)
N	415	350	415	350

Notes: This table shows OLS and Logit regressions of the decision to accept the TIOLI offer for another SMS training, on the listed variables. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table F.5: BDM - Bivariate Analyses for Willingness to Pay

	Coefficient	Standard Error	Observations
Female	-7.595	(6.828)	103
Rural	7.233	(11.97)	103
Years of education	3.592*	(1.503)	103
Age	-0.226	(0.357)	103
Num of adults in household	-0.171	(2.896)	102
Num of children in household	0.260	(2.502)	102
Knowledge	14.77	(23.05)	103
Adoption	-9.340	(17.30)	103
Sales in last 30 days	0.0000325	(0.0000320)	103
Profits in last 30 days	0.000204*	(0.0000967)	103
Applied for a loan	-1.558	(7.005)	103
Loan payment missed/late	-11.95	(8.956)	103
Hours worked on business in last 30 days	0.0348	(0.0335)	103
Hours worked on side jobs in last 30 days	-0.0433	(0.0650)	103

Notes: This table shows results from bivariate OLS regressions of the maximum willingness to pay for an SMS training, on the listed variables. Each row represents a separate regression. Intercepts are included in the regression but not showed in the table for clarity. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table F.6: BDM - Determinants of Willingness to Pay

	max_wtp
Female	-4.040
	(7.704)
Rural	9.901
	(15.01)
Years of education	3.673*
	(1.851)
Age	-.464
	(.372)
Num of adults in household	1.771
	(2.918)
Num of children in household	1.575
	(2.442)
Overall Knowledge	13.33
	(26.85)
Overall Adoption	-26.96
	(17.66)
30-day Sales from All Businesses	-.0000252
	(.0000407)
30-day Profits from All Businesses	.000219*
	(.000124)
Applied for a Loan	.675
	(7.146)
Loan Payment Missed/Late	-11.73
	(9.496)
Hours worked on business	.00416
	(.0429)
Hours worked on side jobs	-.0971
	(.0687)
Constant	21.97
	(30.38)
Control Mean	48.16
Observations	102

Notes: This table shows OLS regression of the maximum willingness to pay for an SMS training, on the listed variables. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.