

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

Muhammad Zia Mehmood*

October 17, 2025

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Abstract

Phone-based trainings are increasingly promoted as scalable tools to improve business practices and outcomes among micro-entrepreneurs in low-income settings. This paper studies the effectiveness and demand for self-paced business trainings delivered remotely through text messages (SMS-based trainings). I leverage a large-scale field experiment whereby access to an SMS-based business training was randomized across 4,700 micro-entrepreneurs in Kenya, and elicit demand using take-it-or-leave-it offers and the Becker-DeGroot-Marschak method. Three months after launch, I find positive effects on knowledge and adoption of best practices, with younger entrepreneurs experiencing stronger effects on business outcomes 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 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 additional SMS-based trainings, suggesting that they value access to the content. The results highlight sustained engagement as a key constraint to the effectiveness of remote information-based support for micro-entrepreneurs, and suggest limits to the scalability of SMS-based business training as a stand-alone intervention.

JEL Codes: C93, L26, O12

Keywords: entrepreneurship, business training, randomized control trial

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

1 Introduction

Small businesses form the economic backbone of low-income countries across the globe, employing 70 percent of the labor force world-wide and accounting for 40 percent of the GDP in emerging economies (ILO (2019); World Bank (2024)). 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 challenge¹ 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 promising way to overcome these challenges. In particular, trainings delivered through text messages (SMS-based trainings) are inexpensive, scalable, and accessible without requiring in-person attendance or even internet connectivity. They may also enable individualized learning by allowing participants to engage with the material at their own pace. These features have made SMS-based trainings increasingly popular—especially in the wake of the Covid-19 pandemic—as a low-cost tool for extending information-based support to small business owners and other populations in low-income contexts.² Yet, there is little rigorous evidence on whether remotely delivered, self-paced trainings can sustain engagement, promote learning and behavior change, or are valued by their intended beneficiaries, particularly among micro-entrepreneurs.

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 among micro-entrepreneurs in a low-income setting. I evaluate a field experiment where 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

¹The 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.

²See 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.

national economy. As of 2016, 7.4 million Micro, Small, and Medium Enterprises (MSMEs) accounted for about a third of the GDP, engaging over 90 percent of the active labor force in the country. Approximately 55 percent of these MSMEs were owned by women, and 98 percent 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 percent of micro-entrepreneurs did not advertise any of their products or services and almost 70 percent did not keep any type of business records. Furthermore, less than 10 percent accounted for prices of their competitors when setting their own. These gaps in management skills could potentially be mitigated through trainings, yet 90 percent 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 cognitively simplified 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 educational technology firm. 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 delivered through an interactive chat-bot in a fixed sequence, allowing micro-entrepreneurs to progress at their own pace. A limited number of SMS-based reminders were 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-based 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.

To assess whether the observed treatment effects diverge from existing priors in the field, I conducted a survey through the Social Science Predictions Platform (Mehmood (2023)). In this survey, social science researchers⁵ were given a description of the study and asked to predict treatment effects at Endline (12 months after launch). Comparing these predictions with observed results allows me to shed light on the extent to which the findings from this study are unexpected and informative.

I measured demand for SMS-based trainings using two incentive-compatible elicitation methods. First, after they had either completed the training or had remained inactive for two consecutive months, I offered treatment group micro-entrepreneurs the opportunity to purchase an additional SMS-based business training. The purchase price was randomized across three levels:

³Defined as businesses with less than 10 employees.

⁴The official national languages of Kenya.

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

(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 if it varies systematically with the price. Second, immediately after the Endline, I conducted an in-person willingness to pay elicitation with 103 Nairobi-based business owners drawn from both treatment and control groups, using a modified BDM method employing a multiple-price list approach.

Three months after the intervention, I find that assignment to treatment increased knowledge and adoption of best business practices by 0.27 and 0.33 standard deviations, respectively. I also find large but imprecisely estimated positive effects on business performance and survival in the overall sample, and statistically significant positive effects on business sales and survival for younger (below-median-age) micro-entrepreneurs. These stronger effects among younger entrepreneurs appear to be driven by higher engagement with the training content, as well as larger increases in time devoted to the business, and loan amounts applied for and received.

However, these gains proved short-lived. Twelve months after the intervention, there are no detectable effects on knowledge and adoption of best practices, or on business sales, profits and survival. The positive effects among younger entrepreneurs also disappear. The time trend of chat-bot activity suggests that the lack of longer-run effects is likely driven by a rapid drop-off in engagement; nearly all entrepreneurs stopped interacting with the training content within five months of launch, well before the twelve-month follow-up. Taken together, the results indicate that, despite their appeal as a scalable and low-cost tool, SMS-based trainings on their own are unlikely to generate lasting improvements in business outcomes, highlighting sustained engagement as a key constraint on their effectiveness.

Comparing these findings with expert predictions for the twelve-month treatment effects reveals that social science researchers 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 entrepreneurs are willing to pay a positive price for SMS business trainings, and the demand for SMS trainings decreases with price. In the TIOLI elicitation, 70 percent of individuals chose to accept an additional training when it was offered for free, 68 percent accepted when the price was half the marginal cost to the service provider, and about 50 percent accepted when the price was double the marginal cost. In the BDM elicitation, 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 could be explored in this context.

Lastly, I find suggestive evidence for the demand for trainings being higher among 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 three strands of literature. First, building on the literature connecting management practices and firm profitability (Bloom et al. (2010, 2013); Bloom and Van Reenen (2010); Bruhn, Karlan and Schoar (2010); McKenzie and Woodruff (2017); Bruhn, Karlan and Schoar (2018)), I contribute to the large body of evidence on the impact of business trainings on adoption of best practices, and business outcomes, with older studies finding little to no effects (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 cognitively simplified training course studied in this paper draws inspiration from nascent work on leveraging psychology-based insights to improve content internalization (Drexler, Fischer and Schoar (2014); Arráiz, Bhanot and Calero (2019); Campos et al. (2017)). However, while my short-run results are aligned with the promise these studies document, I find that the gains dissipate in the longer run.

Second, the paper contributes to the emerging evidence on the potential and limitations of technology-enabled remote delivery of information-based support. Similar to the results reported here, 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. Estefan et al. (2023) find significant effects of a mobile app-based training in Guatemala only when paired with virtual one-on-one consulting meetings, while Cole, Joshi and Schoar (2024) find weekly pre-recorded Interactive Voice Response (IVR) messages to be ineffective 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. The paper’s findings are also relevant for emerging evidence on large-language-model (LLM)-based chat-bots used for business trainings (Otis et al. (2024)), which provide richer and more interactive content but rely on the same self-paced, remote delivery model that may face comparable engagement challenges.

Third, I add to the extremely limited work on demand for business trainings among 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 among micro-entrepreneurs.

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-based business training, Section 6 compares observed treatment effects with expert predictions, 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 percent of the active labor force in the country, and contributed just above a third of the GDP in 2016. Approximately 55 percent of these MSMEs were owned by women, and 98 percent 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 percent of micro-entrepreneurs did not advertise any of their products or services in any way, and 70 percent did not keep any type of record of business transactions – not even personal notes. Furthermore, more than 90 percent 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 440⁷ in a month in 2016 (*Micro, Small and Medium Enterprises Survey* (2016)), while the average per trainee cost of business trainings in Kenya⁸ 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 percent 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.

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

⁶Defined as businesses with less than 10 employees.

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

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

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 training content was delivered in a fixed sequence, which users could progress through at their own pace by responding to the chat-bot whenever they wished to receive additional material. Completing the full course required approximately four to six hours if done continuously. Users retained access to all previously viewed messages and could revisit the material offline on their phones at any time. Those who did not initiate the training, or who became inactive for at least a week, received a weekly SMS reminder. Reminders paused as soon as the user re-engaged and resumed if inactivity persisted for another week. All reminders were discontinued after two consecutive months without any interaction.

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

3.2 Randomization Groups

Stratified by gender, the primary sample of 4,701 micro-entrepreneurs 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)

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

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

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

To assess whether the observed treatment effects diverge from expert priors, I conducted an online survey through the Social Science Prediction Platform (Mehmood (2023)). In the survey, social science researchers were provided with a description of the study and asked to predict impacts on key outcomes 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 ex ante expectations.

In addition to improving interpretation of results by credibly highlighting whether the findings are unexpected and informative, comparing research findings with expert priors 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 demand 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. 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 incentivized; 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

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

cost, respectively.

Observing buying decisions across these pricing arms allows me to confirm whether there is any positive willingness to pay for the trainings among 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 received a short overview of the SMS training content and a detailed explanation of the elicitation procedure, accompanied by hypothetical examples. The instructions emphasized that it was in their best interest to agree to purchase only at prices below their true maximum willingness to pay and to decline offers above it.

To address potential non-compliance with purchase commitments—where respondents might renege on buying at a price drawn below their stated maximum willingness to pay¹²—participants were informed in advance that payment for any potential purchase would be automatically deducted from the participation incentive to be disbursed to them at the end 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.

¹²A challenge that Maffioli, McKenzie and Ubfal (2020) faced in their demand elicitation.

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 581 randomly selected leads, with random oversampling of treatment group individuals who had initiated engagement.¹³ This resulted in 307 completed surveys amounting to an overall response rate of 52.8 percent. All midline analyses account for this sampling strategy, as well as differential survey response rates by treatment assignment, engagement status, and gender by using inverse probability weights.

In addition to demographic information, the Midline survey collected data on outcomes including measures of knowledge and adoption of best practices, business sales, profits and survival in the last 30 days.¹⁴, time spent on business¹⁵ and side jobs in the last 30 days, labor hours employed in business¹⁶ in the last 30 days, loans applied for and received in the last 3 months.

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 survey response rate was slightly higher in the Endline compared to the Midline (59.1% vs 52.8%), reflecting greater follow-up effort with respondents who could not be reached in initial call attempts.

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

¹³This was done due to reporting requirements from the implementing partner.

¹⁴Only for primary business.

¹⁵For primary business as well as across all businesses

¹⁶For primary business as well as across all businesses

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 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 percent 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 percent had an active business and 40 percent 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.

¹⁷Roughly equal to USD 1 at the time.

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 percent of the respondents listed Economics as one of their main disciplines, and 7.7 percent 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 Nairobi¹⁸, (iii) the TIOLI sample includes some micro-entrepreneurs who don't have active businesses, while the BDM sample only covers business owners¹⁹, 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 percent, compared to 53 percent 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 also similar. One major difference is that while almost half the TIOLI sample is based in rural areas, only 11 percent 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.

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

¹⁹This 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 percent of the micro-entrepreneurs in the sample had an active business so this particular restriction did not meaningfully restrict the sample.

²⁰This was due to financial constraints

Nov 2021 - Dec 2021	•	Recruitment and Intervention: Study participation invitations sent over SMS; recruited individuals randomized into groups; chatbot initiated
Rolling	•	TIOLI Offers: Invitations sent to treatment individuals over SMS upon training completion or sustained 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:

$$Y_i = \beta_0 + \beta_1 treatment_i + X_i' \theta + \epsilon_i \quad (1)$$

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:

$$eng_i = \gamma_0 + \gamma_1 treatment_i + X_i' \psi + \eta_i \quad (2)$$

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

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:

$$Y_i = \beta_0 + \beta_1 treatment_i * m_i + \beta_2 treatment_i + \beta_3 m_i + X_i' \theta + [m_i * X_i]' \zeta + \epsilon_i \quad (4)$$

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 percent 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 21.5 percent of the treatment group had started engaging with the training three months after the intervention, with only 6.2 percent of treatment individuals completing at least one-fourth of the training. Conditional on starting to engage, the average percentage of training content completed was 22.3 percent, and the unconditional average percentage training content completed was 4.8 percent. 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 just under 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 0.27 SD increase in knowledge of best business practices, which is statistically significant at the 10 percent level. Conditional on engagement with any of the content, I observe a 1.24 SD effect, which is also significant at the 10 percent 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 0.33 SDs, with the effect being statistically significant at the 5 percent level. The LATE estimate is also statistically significant, with an effect of 1.5 SDs. 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 7.8 percentage points more likely to put up posters advertising their products or services on average compared to those in the control group.

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 and profits (both 15.6% higher), as well as higher survival rate (by 4.1 percentage points) in the overall sample, however these effects are not statistically significant.

Additionally, I find larger and statistically significant impacts of trainings on business sales and survival for micro-entrepreneurs of below-median age.²¹ Table B.3 shows large positive effects on business performance for younger entrepreneurs; sales increase by 87 percent and business survival rate increases by 12.5 percentage points.

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.

²¹Table A.3 shows that observable pre-intervention covariates are balanced across treatment and control, for younger as well as older entrepreneurs, which indicates that the treatment and control groups within each of these age groups are comparable.

Business performance improves 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 29.7 hours on their primary business in the last 30 days - an increase of 16.6 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 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 increased time spent on the primary business by 42 percent among those below the median age. 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 started engaging with the training content but engagement levels were low three months after launch. Despite this, the treatment micro-entrepreneurs saw significant improvements in knowledge and adoption of best practices, and imprecisely estimated positive 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 Midline²² 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 percent 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 a quarter of the treatment group had engaged with the training twelve months after deployment, with 7.2 percent covering at least a quarter of the content. Conditional on starting to engage, the average engagement was 23.3 percent, and the unconditional average engagement was 5.8 percent.

Engagement levels at Endline were thus only marginally higher than at Midline, suggesting that there was very limited 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 on 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 statistically insignificant coefficients of negligible magnitudes for the effect on primary business sales, profits and survival. Table D.3 shows the results from running the same analyses with the Midline-matched sample; the takeaway remain the same.

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.²³ Table D.4 shows that including other businesses into the equation does not change the results,

²²Out of 307 entrepreneurs surveyed in the Midline, 227 were surveyed again in the Endline.

²³Less than 10 percent of the sample.

and Table D.5 confirms that takeaways stay the same when restricting the analysis to the Midline-matched sample.

At Midline, younger entrepreneurs saw statistically significantly stronger effects on primary business performance, however, I find no heterogeneous effects by age at Endline (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 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 considerably smaller compared to the positive effects observed at Midline (9.6 hours less vs. 29.7 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 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).²⁴

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 the approximately 25 percent of the treatment group that engaged with the content during the course of the study. The figure reveals that all interactions with the SMS training platform

²⁴I observe small negative effects for above median-age entrepreneurs, but they are not robust to restricting the sample to that matched with the Midline.

ended within the first five months of the intervention, and well before the twelve month follow up. 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 any of 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. Observed treatment effects at Midline and Endline are represented by a gray rhombus and a black triangle, respectively, with error bars showing 90 percent 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 percent of the treatment group will have started engaging with the training content by Endline, with the average micro-entrepreneur in the treatment group covering approximately 40 percent of the training content. The actual engagement levels observed are much lower; 21.5 percent of the treatment group had started engaging by Midline, and only 24.5 percent had engaged at Endline. Additionally, the average micro-entrepreneur in the treatment group only covered approximately 4.8 percent of the training content by Midline, and this unconditional intensive margin engagement level only marginally increased to 5.8 percent by 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 (0.27 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 percent and 12 percent 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 percent and 15 percent, respectively. While observed effects at Midline are of similar magnitudes (about 15% increase), 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 percent.

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 percent 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 percent. 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%).²⁵

²⁵This is not surprising in light of literature on round-number bias (Lynn, Flynn and Helion (2013)).

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 percent 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 three fourths of the treatment group did not start engage 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 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 margin²⁶ as well as the intensive margin²⁷ is not lower among those who chose to buy the additional training, compared to those who chose not to. In fact, engagement rates were higher among 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.²⁸ 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 low in absolute terms.

²⁶The proportion of respondents offered the training who chose to start engaging with it.

²⁷The proportion of the training content that the average respondent engaged with.

²⁸Table 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.

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 could 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.

Table F.3 shows raw averages of individual level variables including demographic and enterprise characteristics in the TIOLI sample among those who accepted the TIOLI offer, those who rejected, and the difference between the two.²⁹ 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 among 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,³⁰ 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.

²⁹These characteristics include relevant pre-intervention covariates as well as key outcome variables considered for the earlier analyses of effectiveness of SMS trainings.

³⁰Using the price of zero (free) as the base case.

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

This paper provides experimental evidence on the effectiveness of SMS-based business trainings, and documents their demand among micro-entrepreneurs in Kenya. In a randomized field experiment involving 4,701 entrepreneurs, access to an interactive, self-paced SMS training increased knowledge and adoption of best practices after three months, with larger gains in business outcomes among younger entrepreneurs. However, these effects did not persist: twelve months after launch, there were no detectable differences in knowledge, practices, or business performance between treatment and control groups. User interaction data suggest that the lack of longer-run effects is driven by a steep decline in engagement—nearly all treated micro-entrepreneurs stopped interacting with the training chat-bot within five months of launch.

Comparing these results with expert forecasts reveals that social science researchers overestimate the potential of SMS-based trainings. Their predictions substantially overstated engagement levels and the magnitude of effects on learning, business practices, and outcomes twelve months after the intervention.

Despite the lack of longer-run effects, entrepreneurs expressed a positive willingness to pay for additional SMS trainings. Both the take-it-or-leave-it and BDM-style elicitations show that a substantial share of respondents were willing to pay several multiples of the local marginal cost of provision to access more content, indicating perceived value even in the absence of measurable performance gains. Demand was higher among individuals with more dependents, recent loan activity, greater business-knowledge scores, and higher education levels.

Taken together, the results highlight both the promise and the limitations of digital training models for micro-entrepreneurs. Simplified, low-cost, self-paced trainings can improve business knowledge and practices in the short run, but are unlikely to generate durable impacts due to challenges in sustaining engagement.

Addressing these engagement challenges represents an important direction for future research. Ex post qualitative interviews with a small subset of disengaged treatment individuals revealed that they intended to go back to the training, but got “busy during the day with customers”, and “forgot to go back to training after getting free.” Combined with the observed positive demand, these responses suggest that behavioral biases—such as present bias and limited attention—may underlie the lack of sustained engagement. Future work could build on insights from behavioral economics, including evidence on self-control problems (Della Vigna and Malmendier (2006); Bai et al. (2021)) and attentional constraints among small-business owners (de Oliveira (2023)), to better understand the behavioral barriers to sustained engagement in remote learning settings and how they might be mitigated.

A complementary avenue for future research can be tailoring training content to individual

needs and learning trajectories. Advances in generative AI make such personalization increasingly viable. Modern large-language-model (LLM)–based chat-bots can adjust pacing, personalize examples, and adapt language in real time, potentially reducing cognitive overload and improving retention. However, recent evidence cautions that such tools can exacerbate inequalities, helping high-performers while harming low-performers (Otis et al. (2024)). Therefore, designing systems that combine adaptive content with guided support may be essential to realizing the promise of scalable, equitable, and durable remote learning.

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9 Main Tables

9.1 Midline

Table 1: Midline: Engagement

	(1)	(2)	(3)	(4)
	Engaged	Covered \geq 25%	% Covered (cond.)	% Covered (uncond.)
Training	0.215*** (0.0254)	0.0615*** (0.0120)	0.223*** (0.0226)	0.0478*** (0.00735)
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	.268* (.143)		.326** (.151)	
Engaged		1.243* (.670)		1.495** (.714)
Female	-.0343 (.131)	-.0569 (.137)	-.112 (.163)	-.142 (.174)
P-value	.0614	.0636	.0318	.0363
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	7418.6 (10665.6)		1696.3 (1572.1)		.0408 (.0375)	
Engaged		33591.8 (48071.2)		7384.6 (6803.7)		.190 (.175)
Female	-31833.7*** (11048.6)	-32478.5*** (10954.6)	-7146.5*** (1590.8)	-7301.6*** (1644.7)	-.0535 (.0346)	-.0569 (.0354)
P-value	.487	.485	.282	.278	.277	.278
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) 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 4: Midline: Intermediate Outcomes

	Hrs. worked		Lab. Hrs. employed		Loan Applied		Loan Received	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Training	29.72* (16.80)		5.339 (28.49)		-1955.7 (6196.4)		-707.7 (4755.9)	
Engaged		153.1* (88.17)		24.80 (131.6)		-9083.1 (28707.2)		-3286.8 (22006.9)
Female	-13.79 (16.92)	-16.25 (17.34)	-82.41*** (27.48)	-82.86*** (26.43)	-11737.8** (5955.1)	-11573.1* (5916.7)	-8463.4* (4766.4)	-8403.8* (4835.8)
P-value	.0781	.0826	.851	.850	.753	.752	.882	.881
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)	(2)	(3)	(4)
	Engaged	Covered $\geq 25\%$	% Covered (cond.)	% Covered (uncond.)
Training	0.247*** (0.0102)	0.0722*** (0.00599)	0.233*** (0.0116)	0.0576*** (0.00373)
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	.0301 (.0385)		-.0652 (.0401)		-.0381 (.0387)		-.0177 (.0411)	
Engaged		.122 (.156)		-.256 (.158)		-.154 (.157)		-.0696 (.162)
Female	.0126 (.0377)	.0107 (.0378)	-.288*** (.0393)	-.284*** (.0394)	-.0861** (.0383)	-.0836** (.0384)	-.0596 (.0406)	-.0585 (.0406)
P-value	.435	.434	.104	.104	.325	.325	.667	.667
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	-2005.0 (3556.4)		-134.6 (1010.1)		-.0175 (.0113)	
Engaged		-8116.3 (14397.8)		-545.5 (4091.0)		-.0706 (.0457)
Female	-34513.5*** (3397.4)	-34378.5*** (3408.5)	-9360.6*** (984.6)	-9351.9*** (985.3)	.0103 (.0112)	.0114 (.0112)
P-value	.573	.573	.894	.894	.121	.122
Control Mean	59370.5	59370.5	19469.7	19469.7	.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) 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

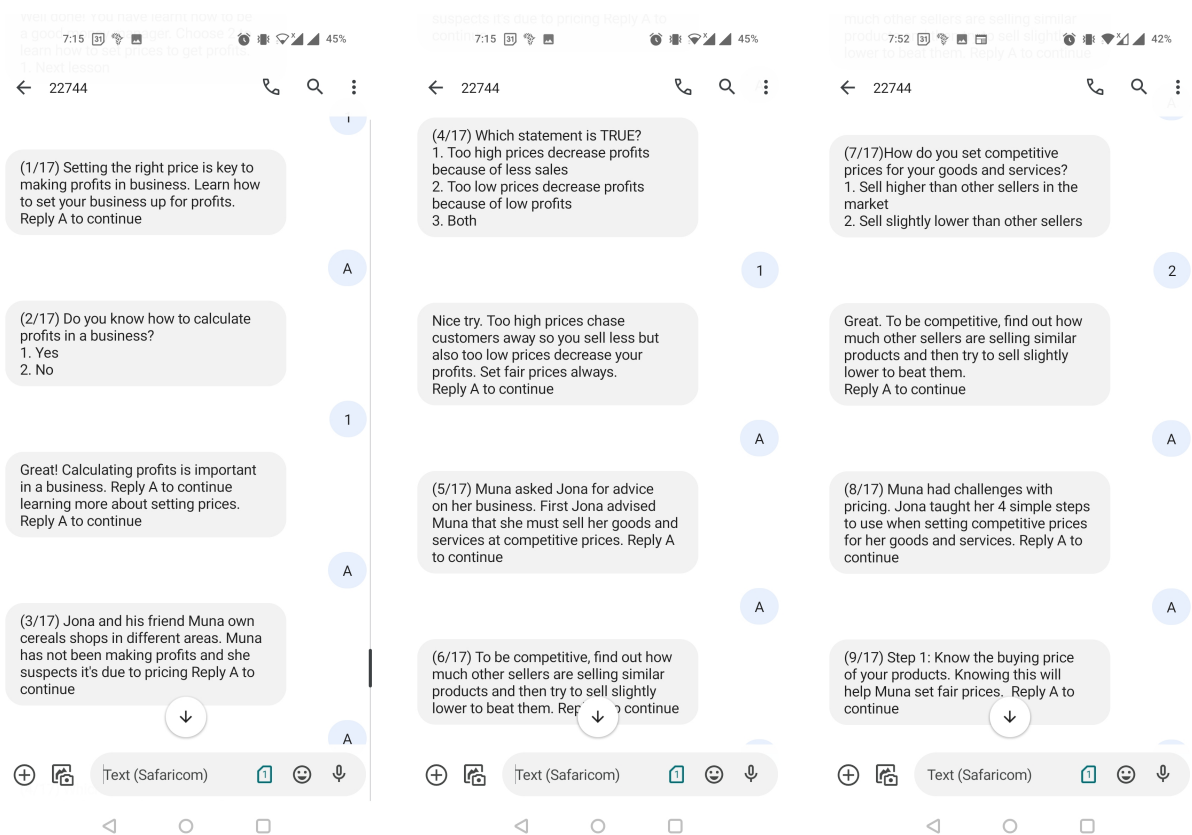
Table 8: Endline: Intermediate Outcomes

	Hrs. worked		Lab. Hrs. employed		Loan Applied		Loan Received	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Training	-9.958** (4.479)		-1.260 (6.502)		-775.6 (2354.6)		-479.4 (2098.8)	
Engaged		-40.27** (18.19)		-5.085 (26.24)		-3133.1 (9506.6)		-1936.6 (8473.5)
Female	-1.374 (4.367)	-.690 (4.393)	-67.40*** (6.330)	-67.31*** (6.396)	-7508.5*** (2254.2)	-7457.6*** (2253.2)	-5866.8*** (2002.7)	-5835.3*** (2001.8)
P-value	.0263	.0268	.846	.846	.742	.742	.819	.819
Control Mean	215.5	215.5	90.21	90.21	20534.6	20534.6	16949.8	16949.8
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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

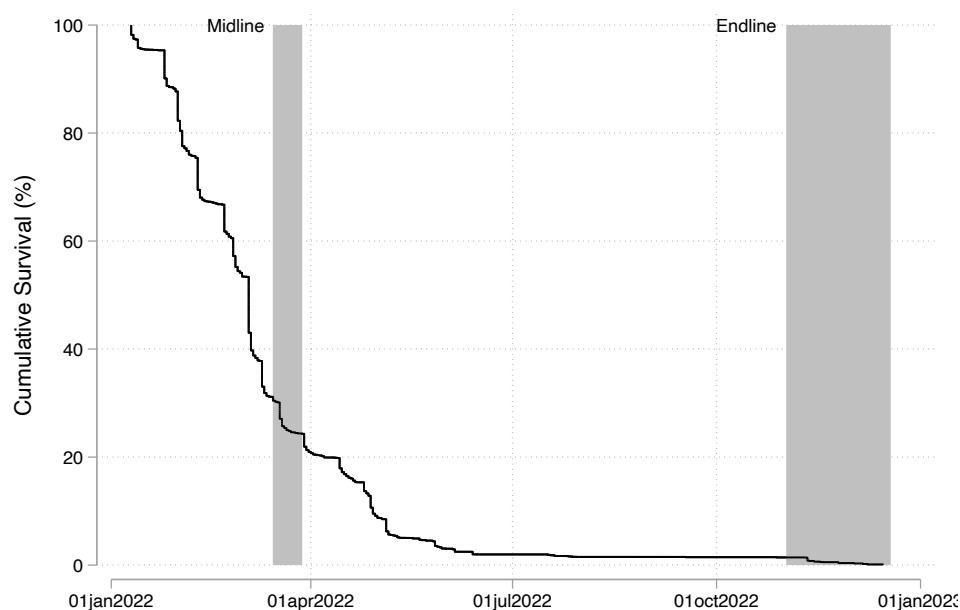
10 Main Figures

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



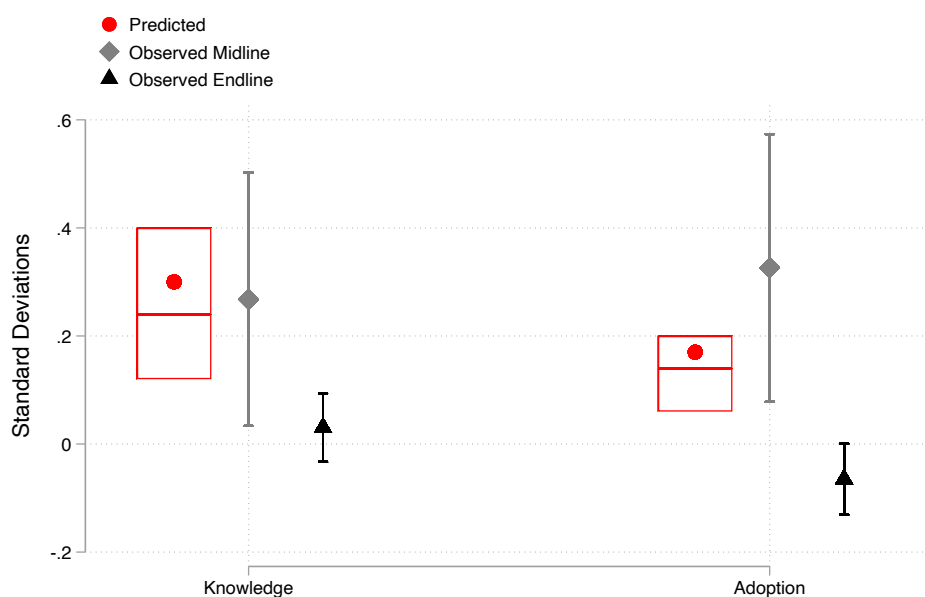
Notes: This figure illustrates how interactions with the SMS platform were distributed throughout the study period. The plot shows reverse cumulative engagement over time; for example, it shows that 80% of all the interactions with the chat-bot throughout the course of the study, had ended by 4/1/2022.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

Figure 3: Predictions vs. Observations - Engagement



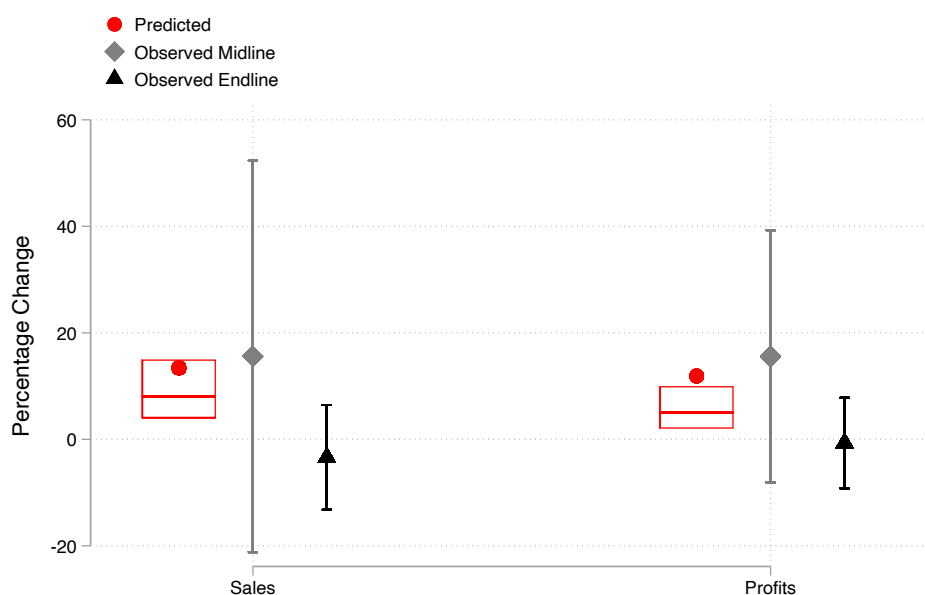
Notes: This figure shows how predicted treatment effects on extensive and intensive margin engagement for the Endline compare with observed Midline and Endline effects. Effects are in terms of percentage points. The distribution of the predicted treatment effect is illustrated in red, with the mean represented 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



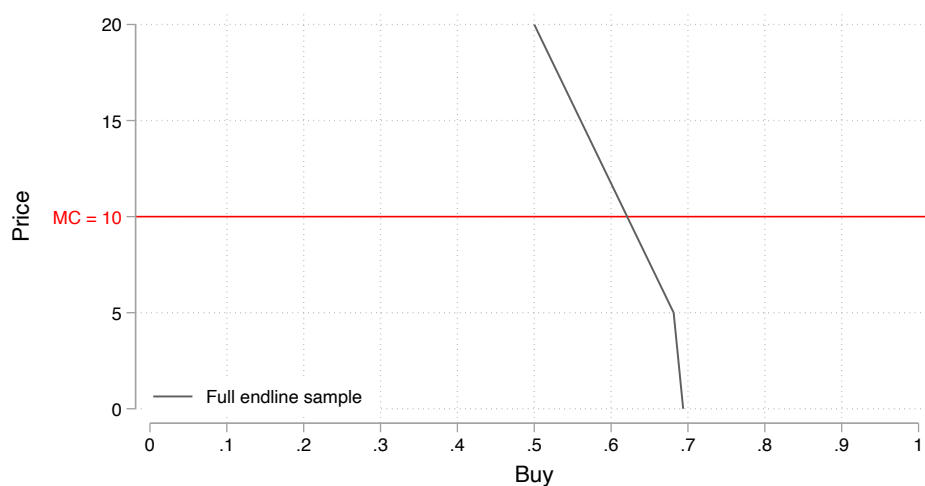
Notes: This figure shows how predicted treatment effects on knowledge and adoption of best practices for the Endline compare with observed Midline and Endline effects. Effects are in terms of control group standard deviations. The distribution of the predicted treatment effect is illustrated in red, 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



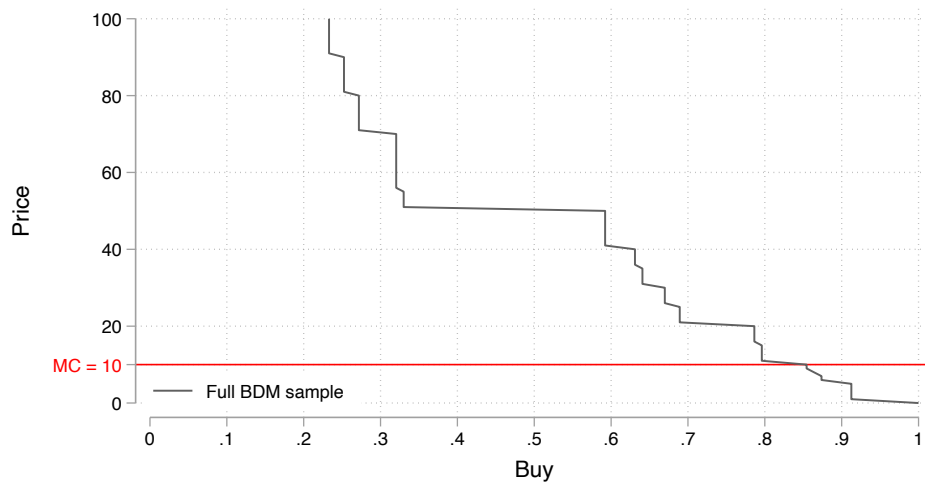
Notes: This figure shows how predicted treatment effects on business sales and profits in the last 30 days for the Endline compare with observed predicted Midline and Endline effects. Effects are in terms of percentage changes. The distribution of the predicted treatment effect is illustrated in red, 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

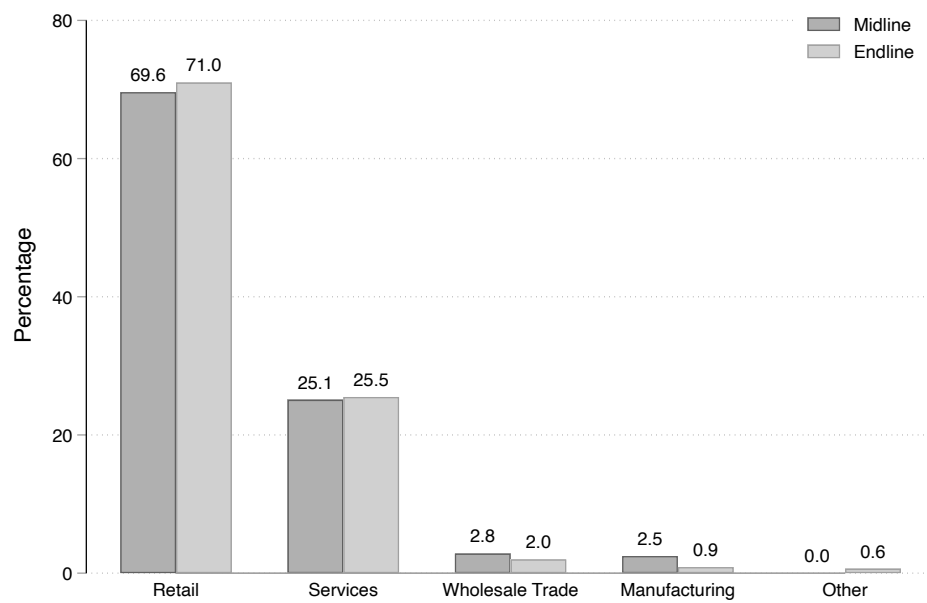


Notes: This figure shows the (inverse) demand curve based on the maximum willingness to pay elicited using the in-person elicitation using the modified BDM method. The y-axis represents the price in Kenyan Shillings, and the x-axis represents the proportion of the sample that would choose to buy at each 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

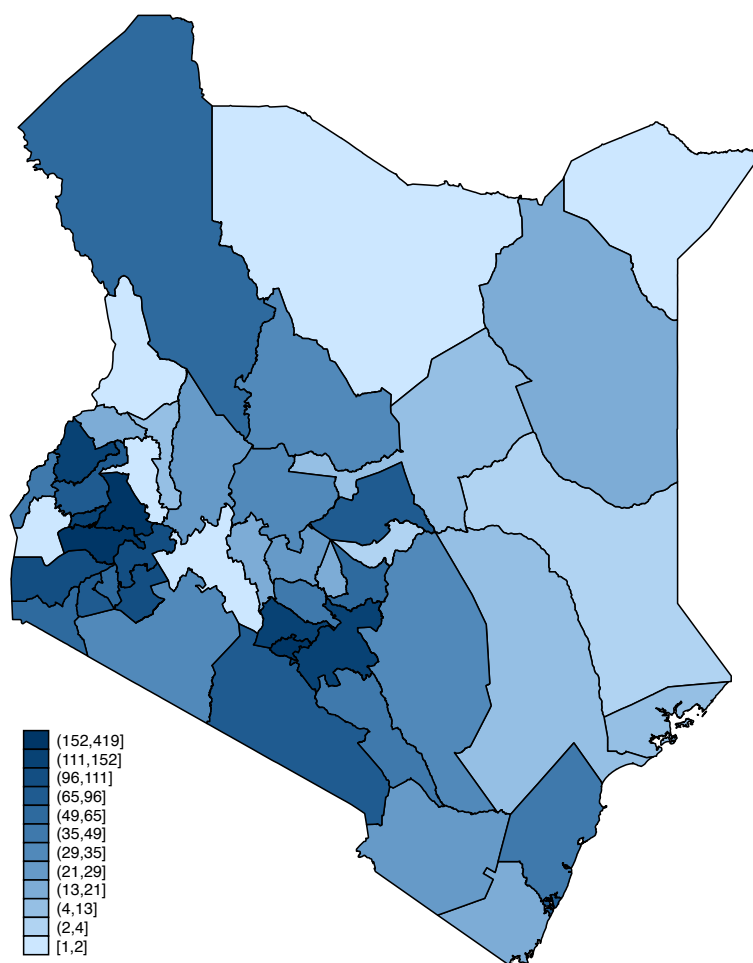
A Sample Statistics and Balance

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

Variable	<u>Midline</u>			<u>Endline</u>		
	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

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

Variable	Age ≥ 34				Age < 34			
	Full	Treatment	Control	Diff	Full	Treatment	Control	Diff
Female	0.59 (0.49)	0.64 (0.48)	0.50 (0.50)	0.14* (0.08)	0.39 (0.49)	0.39 (0.49)	0.39 (0.49)	0.01 (0.08)
Rural	0.46 (0.50)	0.50 (0.50)	0.38 (0.49)	0.12 (0.08)	0.41 (0.49)	0.44 (0.50)	0.37 (0.49)	0.07 (0.08)
Years of education	10.85 (2.62)	10.72 (2.57)	11.12 (2.73)	-0.39 (0.44)	12.86 (1.93)	12.92 (1.73)	12.75 (2.23)	0.17 (0.33)
Num of adults in household	2.78 (1.59)	2.92 (1.77)	2.50 (1.08)	0.42 (0.27)	2.36 (1.36)	2.39 (1.48)	2.30 (1.15)	0.10 (0.23)
Num of children in household	2.50 (1.67)	2.45 (1.65)	2.60 (1.71)	-0.14 (0.28)	1.79 (1.66)	1.80 (1.81)	1.77 (1.41)	0.03 (0.28)
Job before intervention	0.19 (0.40)	0.19 (0.39)	0.21 (0.41)	-0.03 (0.07)	0.32 (0.47)	0.31 (0.47)	0.32 (0.47)	-0.00 (0.08)
Business before intervention	0.92 (0.27)	0.91 (0.29)	0.94 (0.24)	-0.03 (0.05)	0.86 (0.35)	0.88 (0.33)	0.82 (0.38)	0.05 (0.06)
Loan before intervention	0.46 (0.50)	0.49 (0.50)	0.40 (0.50)	0.09 (0.08)	0.36 (0.48)	0.33 (0.47)	0.40 (0.49)	-0.08 (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.
<i>Panel A: Baseline Covariates</i>						
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
<i>Panel B: Outcomes</i>						
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)
<i>Panel A: Baseline Covariates</i>						
Female	0.43 (0.50)	0.50 (0.50)	0.36 (0.48)	-0.06 (0.06)	0.13* (0.08)	0.07 (0.07)
Rural	0.51 (0.50)	0.48 (0.50)	0.47 (0.50)	0.03 (0.06)	0.01 (0.08)	0.04 (0.07)
Years of education	12.00 (2.59)	12.15 (2.27)	11.93 (2.42)	-0.16 (0.29)	0.22 (0.38)	0.06 (0.38)
Age	33.12 (8.33)	34.76 (9.28)	33.34 (8.05)	-1.64 (1.01)	1.42 (1.43)	-0.23 (1.23)
Num of adults in household	2.76 (1.43)	2.63 (1.52)	2.57 (1.33)	0.12 (0.17)	0.06 (0.24)	0.19 (0.21)
Num of children in household	2.21 (1.45)	2.12 (1.43)	1.93 (1.51)	0.09 (0.17)	0.19 (0.24)	0.28 (0.22)
<i>Panel B: Outcomes</i>						
Knowledge	0.74 (0.14)	0.79 (0.13)	0.75 (0.14)	-0.05*** (0.02)	0.04* (0.02)	-0.01 (0.02)
Adoption	0.67 (0.16)	0.67 (0.18)	0.68 (0.19)	-0.01 (0.02)	-0.00 (0.03)	-0.01 (0.03)
Sales in last 30 days	61449 (109417)	60733 (118607)	51741 (103972)	715.76 (13162)	8992 (18395)	9707 (16068)
Profits in last 30 days	19731 (31201)	19199 (29921)	19922 (33585)	532 (3592)	-723 (5040)	-192 (4709)
Applied for a Loan	0.52 (0.50)	0.48 (0.50)	0.50 (0.50)	0.04 (0.06)	-0.02 (0.08)	0.02 (0.07)
Loan Payment Loan Payment Missed/Late	0.19 (0.39)	0.24 (0.43)	0.14 (0.35)	-0.05 (0.05)	0.10 (0.07)	0.05 (0.06)
Hours worked on business in last 30 days	214.26 (126.40)	209.64 (112.38)	227.74 (119.86)	4.62 (14.21)	-18.10 (18.57)	-13.48 (18.55)
Hours worked on side jobs in last 30 days	26.27 (67.19)	24.04 (66.90)	12.95 (43.99)	2.24 (7.83)	11.09 (9.72)	13.32 (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 (0.50)	0.58 (0.50)	-0.07 (0.10)
Rural	0.14 (0.35)	0.05 (0.23)	0.09 (0.06)
Years of education	11.86 (2.24)	12.21 (2.41)	-0.35 (0.47)
Age	35.82 (9.74)	37.21 (8.66)	-1.40 (1.91)
Num of adults in household	2.48 (1.33)	2.39 (1.08)	0.09 (0.26)
Num of children in household	1.94 (1.45)	2.05 (1.66)	-0.12 (0.31)
Overall Knowledge	0.76 (0.14)	0.82 (0.11)	-0.06** (0.03)
Overall Adoption	0.65 (0.21)	0.62 (0.20)	0.03 (0.04)
30-day Sales from All Businesses	69729.23 (117252.40)	68397.37 (107718.30)	1331.86 (23249.43)
30-day Profits from All Businesses	24344.31 (31404.55)	23010.53 (33812.18)	1333.78 (6597.39)
Applied for a Loan	0.65 (0.48)	0.45 (0.50)	0.20** (0.10)
Loan Payment Missed/Late	0.17 (0.38)	0.21 (0.41)	-0.04 (0.08)
Hours worked on business	256.72 (104.83)	269.47 (91.06)	-12.75 (20.42)
Hours worked on side jobs	19.88 (50.94)	13.47 (41.56)	6.40 (9.74)
<i>F</i> -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	0.215*** (0.0254)	0.0478*** (0.00735)	0.167*** (0.0283)	0.0378*** (0.00886)	0.292*** (0.0495)	0.0669*** (0.0141)		
Train x Age ≥ 34							-0.126** (0.0570)	-0.0291* (0.0166)
P-value	0	0	0	0	0	0	0.0280	0.0810
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	.0900 (.0688)			.0783** (.0322)		
Engaged		.418 (.321)			.359** (.153)	
Covered advertising			1.154 (.893)			1.022** (.460)
Female	.0343 (.0686)	.0267 (.0697)	.0160 (.0721)	-.108*** (.0362)	-.115*** (.0391)	-.121*** (.0428)
P-value	.192	.193	.196	.0158	.0189	.0261
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 knowledge 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	7418.6	1696.3	0.0408	-9873.6	705.1	-0.0286	28380.9*	3145.3	0.125**			
	(10665.6)	(1572.1)	(0.0375)	(14773.4)	(1838.4)	(0.0480)	(14921.7)	(2572.7)	(0.0495)			
Train x Age ≥ 34										-38254.6*	-2440.2	-0.154**
										(20997.2)	(3161.7)	(0.0689)
P-value	0.487	0.282	0.277	0.505	0.702	0.553	0.0590	0.224	0.0120	0.0700	0.441	0.0260
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	32.87* (17.93)	
Engaged		167.7* (93.20)
Female	-21.82 (17.87)	-24.14 (18.31)
P-value	.0680	.0720
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	-.0293 (.0582)		-9.859 (12.15)	
Engaged		-.139 (.276)		-47.04 (58.08)
Female	-.0650 (.0573)	-.0620 (.0582)	-14.49 (11.34)	-13.40 (12.16)
P-value	.615	.614	.418	.418
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	29.72*	32.87*	-4.246	-3.190	62.57***	66.26**		
	(16.80)	(17.93)	(23.26)	(24.63)	(23.56)	(25.73)		
Train x Age ≥ 34							-66.82**	-69.45*
							(33.11)	(35.61)
P-value	0.0781	0.0680	0.855	0.897	0.00900	0.0110	0.0450	0.0520
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	-6.050 (13.28)		9.097 (25.26)		-16.57 (15.47)		9.618 (31.78)	
Engaged		-28.03 (61.42)		43.24 (119.5)		-76.97 (72.33)		45.72 (150.3)
Female	-34.22*** (12.65)	-33.84*** (12.88)	-44.98* (24.73)	-45.89* (23.44)	-55.83*** (14.86)	-54.44*** (15.20)	-63.36** (32.17)	-64.32** (30.30)
P-value	.649	.648	.719	.717	.285	.287	.762	.761
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	-1955.7 (6196.4)	-707.7 (4755.9)	-13737.2 (10358.6)	-9533.8 (7586.2)	11150.9 (7368.3)	8862.4 (6334.1)		
Train x Age ≥ 34							-24888.1* (12713.6)	-18396.2* (9883.5)
P-value	0.753	0.882	0.187	0.211	0.132	0.164	0.0510	0.0640
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 (0.50)	0.47 (0.50)	0.02 (0.03)
Years of education	11.91 (2.40)	11.88 (2.73)	0.03 (0.19)
Age	36.26 (9.00)	35.22 (9.17)	1.04 (0.63)
Rural	0.46 (0.50)	0.46 (0.50)	-0.00 (0.03)
Num of adults in household	2.55 (1.25)	2.63 (1.35)	-0.08 (0.09)
Num of children in household	2.11 (1.42)	2.17 (1.50)	-0.06 (0.10)
Job before intervention	0.15 (0.36)	0.18 (0.38)	-0.03 (0.03)
Business before intervention	0.85 (0.36)	0.85 (0.36)	-0.00 (0.02)
Loan before intervention	0.39 (0.49)	0.38 (0.49)	0.01 (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 (0.16)	0.73 (0.18)	0.01 (0.02)
Advanced Knowledge	0.77 (0.18)	0.79 (0.18)	-0.02 (0.02)
Overall Knowledge	0.75 (0.14)	0.76 (0.14)	-0.01 (0.02)
Basic Adoption	0.64 (0.22)	0.70 (0.21)	-0.06** (0.02)
Advanced Adoption	0.67 (0.26)	0.67 (0.22)	-0.00 (0.03)
Overall Adoption	0.66 (0.17)	0.69 (0.18)	-0.03 (0.02)
Owns Business	0.92 (0.28)	0.92 (0.28)	0.00 (0.03)
Num of Businesses Owned	0.98 (0.38)	1.01 (0.44)	-0.03 (0.05)
Business Registered	0.51 (0.50)	0.46 (0.50)	0.05 (0.06)
Num of Businesses Registered	0.55 (0.57)	0.50 (0.55)	0.05 (0.07)
7-day Sales from Primary Business	15454.17 (21356.77)	15780.95 (23449.46)	-326.79 (2644.42)
30-day Sales from Primary Business	62773.81 (93706.85)	59075.36 (90622.07)	3698.45 (10312.33)
7-day Sales from All Businesses	15993.45 (21397.30)	16975.15 (25210.13)	-981.70 (2831.15)
30-day Sales from All Businesses	64934.52 (93808.84)	64413.61 (102112.05)	520.91 (11521.62)
7-day Profits from Primary Business	4725.00 (5138.23)	4793.07 (6190.39)	-68.07 (694.35)
30-day Profits from Primary Business	18878.57 (19334.51)	19500.64 (25710.48)	-622.07 (2870.13)
7-day Profits from All Businesses	4908.93 (5180.22)	5221.90 (6997.48)	-312.97 (780.62)
30-day Profits from All Businesses	19560.71 (19391.96)	21215.50 (29073.36)	-1654.78 (3230.30)
Applied for a Loan	0.52 (0.50)	0.47 (0.50)	0.06 (0.06)
Loan Amount Applied	20970.24 (39903.22)	20345.08 (61354.25)	625.16 (6810.69)
Loan Amount Received	17396.90 (32061.82)	16765.28 (55158.15)	631.63 (6102.47)
Loan Application Success Rate	0.91 (0.29)	0.88 (0.33)	0.03 (0.05)
Loan Payment Missed/Late	0.53 (0.51)	0.56 (0.50)	-0.03 (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	0.247*** (0.0102)	0.0576*** (0.00373)	0.248*** (0.0145)	0.0537*** (0.00500)	0.247*** (0.0144)	0.0619*** (0.00560)		
Train x Age ≥ 34							0.00156 (0.0204)	-0.00822 (0.00750)
P-value	0	0	0	0	0	0	0.939	0.273
Control Mean	0	0	0	0	0	0	0	0
Observations	2780	2780	1429	1429	1350	1350	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 (.143)		.159 (.139)		-.132 (.171)		-.0128 (.137)	
Engaged		-.103 (.376)		.404 (.356)		-.347 (.453)		-.0333 (.353)
Female	.0523 (.154)	.0607 (.155)	-.114 (.139)	-.150 (.147)	-.153 (.213)	-.125 (.215)	.161 (.129)	.164 (.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 (11060.5)		-182.8 (3005.2)		.00879 (.0407)	
Engaged		-45882.8 (29928.4)		-484.7 (7915.2)		.0232 (.107)
Female	-36873.9*** (8353.9)	-32984.0*** (9411.3)	-10376.6*** (3298.1)	-10335.5*** (3571.9)	-.0380 (.0455)	-.0399 (.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	744.7 (4094.7)		557.7 (1157.2)	
Engaged		3014.5 (16563.4)		2259.6 (4685.9)
Female	-42295.3*** (3958.1)	-42345.5*** (3977.3)	-11686.0*** (1131.5)	-11722.1*** (1135.4)
P-value	.856	.856	.630	.630
Control Mean	64467.6	64467.6	21106.2	21106.2
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 (11442.1)		986.0 (3111.7)	
Engaged		-32950.4 (30620.7)		2614.3 (8201.6)
Female	-37827.5*** (9534.4)	-35034.0*** (10050.8)	-11608.2*** (3475.7)	-11829.9*** (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	-2005.0 (3556.4)	-134.6 (1010.1)	-0.0175 (0.0113)	-2252.0 (5267.7)	126.3 (1437.5)	-0.0208 (0.0133)	-184.6 (4719.2)	-198.6 (1421.7)	-0.00668 (0.0185)			
Train x Age ≥ 34										-2067.4 (7072.4)	324.9 (2021.8)	-0.0142 (0.0228)
P-value	0.573	0.894	0.121	0.669	0.930	0.117	0.969	0.889	0.719	0.770	0.872	0.535
Control Mean	59370.5	19469.7	0.915	62778.8	19512.1	0.944	55307.4	19419.1	0.881	59370.5	19469.7	0.915
Observations	2772	2770	2779	1422	1420	1428	1349	1349	1350	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 (11060.5)	-182.8 (3005.2)	0.00879 (0.0407)	-30631.6** (13859.9)	-1845.4 (3784.4)	-0.00491 (0.0498)	604.9 (17903.8)	1903.7 (4890.2)	0.0318 (0.0707)			
Train x Age ≥ 34										-31236.5 (22628.4)	-3749.1 (6179.8)	-0.0368 (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	744.7	557.7	3232.5	1673.8	-1.927	-344.6		
	(4094.7)	(1157.2)	(6138.7)	(1658.0)	(5396.8)	(1632.8)		
Train x Age ≥ 34							3234.5	2018.4
							(8173.7)	(2327.1)
P-value	0.856	0.630	0.599	0.313	1	0.833	0.692	0.386
Control Mean	64467.6	21106.2	67335.7	20883.6	61048.6	21371.6	64467.6	21106.2
Observations	2772	2770	1422	1420	1349	1349	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 (18.98)	-6.909 (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	-2.520** (1.152)		-9.578** (4.596)	
Engaged		-10.17** (4.666)		-38.66** (18.62)
Female	-1.726 (1.123)	-1.558 (1.129)	-7.668* (4.492)	-7.031 (4.517)
P-value	.0287	.0293	.0373	.0379
Control Mean	55.62	55.62	223.3	223.3
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 (4.487)		13.57 (17.75)	
Engaged		10.30 (11.94)		35.77 (47.14)
Female	-3.413 (4.765)	-4.253 (5.082)	-13.21 (19.03)	-16.12 (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	-.0132 (.0143)		-1.609 (2.422)	
Engaged		-.0535 (.0579)		-6.499 (9.781)
Female	-.0923*** (.0138)	-.0914*** (.0138)	-17.94*** (2.304)	-17.83*** (2.293)
P-value	.356	.356	.507	.506
Control Mean	.170	.170	23.22	23.22
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 (.0555)		-1.446 (8.879)	
Engaged		.0720 (.145)		-3.810 (23.28)
Female	-.0870 (.0631)	-.0928 (.0641)	-21.58** (8.634)	-21.27** (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	-9.958** (4.479)	-9.578** (4.596)	-12.47** (6.015)	-12.09** (6.159)	-5.184 (6.659)	-5.059 (6.861)		
Train x Age ≥ 34							-7.290 (8.974)	-7.033 (9.219)
P-value	0.0263	0.0373	0.0380	0.0500	0.436	0.461	0.417	0.446
Control Mean	215.5	223.3	224.2	230.8	205.1	214.3	215.5	223.3
Observations	2777	2779	1426	1428	1350	1350	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 (17.29)	13.57 (17.75)	-11.21 (23.31)	-4.813 (24.33)	40.41 (25.98)	41.62 (26.09)		
Train x Age ≥ 34							-51.62 (34.89)	-46.43 (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	-2.612** (1.119)	-2.520** (1.152)	-3.593** (1.489)	-3.476** (1.531)	-1.022 (1.677)	-1.017 (1.733)		
Train x Age ≥ 34							-2.571 (2.243)	-2.459 (2.312)
P-value	0.0196	0.0287	0.0160	0.0230	0.542	0.557	0.252	0.288
Control Mean	53.66	55.62	56.02	57.68	50.83	53.16	53.66	55.62
Observations	2777	2779	1426	1428	1350	1350	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 (4.319)	3.909 (4.487)	-2.080 (5.821)	-0.221 (6.192)	9.963 (6.475)	10.32 (6.502)		
Train x Age ≥ 34							-12.04 (8.704)	-10.54 (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	-4.442 (3.162)		1.718 (5.517)		-5.666 (3.498)		3.883 (6.499)	
Engaged		-17.93 (12.79)		6.934 (22.25)		-22.87 (14.16)		15.68 (26.21)
Female	-25.63*** (2.979)	-25.33*** (3.015)	-40.00*** (5.377)	-40.12*** (5.422)	-29.55*** (3.289)	-29.17*** (3.330)	-58.15*** (6.343)	-58.41*** (6.395)
P-value	.160	.161	.756	.755	.105	.106	.550	.550
Control Mean	34.43	34.43	54.52	54.52	39.74	39.74	67.56	67.56
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 (13.09)		-12.80 (19.93)		-4.110 (14.75)		-4.364 (23.45)	
Engaged		-11.28 (34.27)		-33.73 (53.12)		-10.83 (38.60)		-11.50 (61.66)
Female	-25.18* (14.48)	-24.26 (14.82)	-56.25*** (19.73)	-53.50** (22.33)	-34.10** (16.34)	-33.22* (17.13)	-63.74*** (24.45)	-62.80** (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	-.950 (.800)		.417 (1.349)		-1.254 (.872)		.918 (1.590)	
Engaged		-3.836 (3.232)		1.685 (5.440)		-5.061 (3.528)		3.705 (6.414)
Female	-6.414*** (.753)	-6.350*** (.762)	-9.844*** (1.313)	-9.872*** (1.326)	-7.291*** (.819)	-7.207*** (.830)	-14.30*** (1.553)	-14.37*** (1.568)
P-value	.235	.235	.757	.757	.151	.151	.564	.564
Control Mean	8.584	8.584	13.42	13.42	9.848	9.848	16.68	16.68
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 (3.292)		-3.756 (4.830)		-.860 (3.647)		-1.477 (5.772)	
Engaged		-2.068 (8.611)		-9.898 (12.93)		-2.266 (9.536)		-3.893 (15.20)
Female	-6.012 (3.651)	-5.843 (3.738)	-13.89*** (4.720)	-13.08** (5.389)	-7.987** (4.029)	-7.802* (4.209)	-16.06*** (6.042)	-15.74** (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	-775.6 (2354.6)	-479.4 (2098.8)	-2741.2 (3684.1)	-1165.8 (3374.0)	2332.6 (2693.9)	1215.0 (2285.1)		
Train x Age ≥ 34							-5073.7 (4564.0)	-2380.8 (4075.0)
P-value	0.742	0.819	0.457	0.730	0.387	0.595	0.266	0.559
Control Mean	20534.6	16949.8	25000	21000	15000	12000	21000	17000
Observations	2780	2780	1429	1429	1350	1350	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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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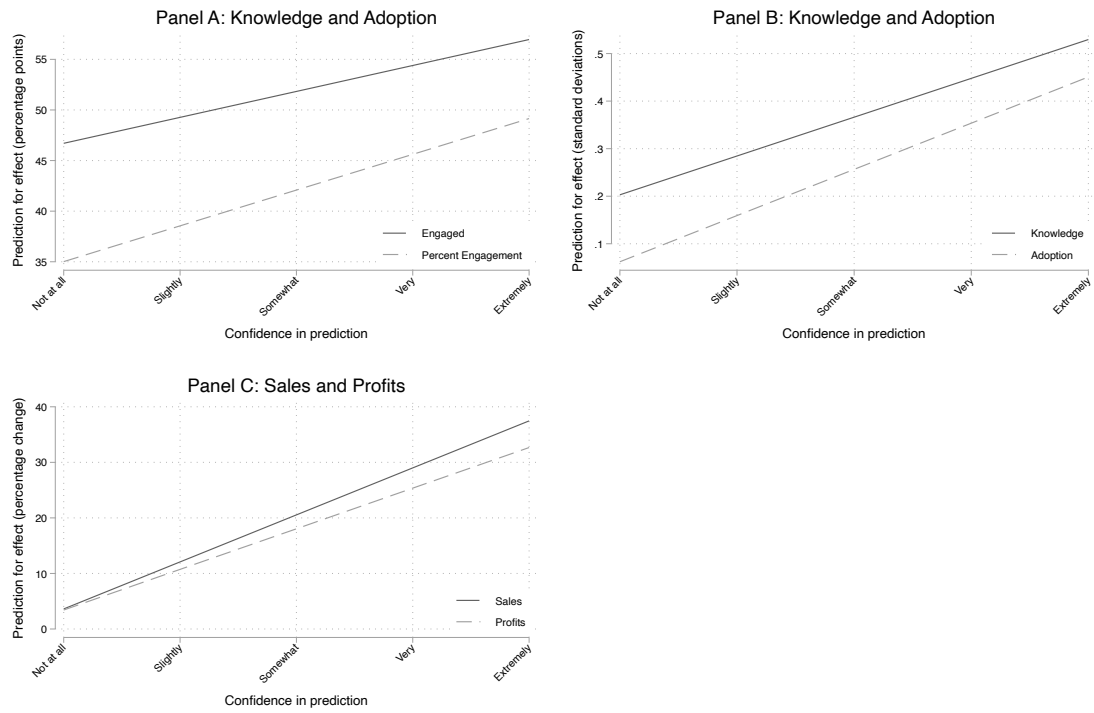
Table D.24: Endline: Loan Amount Applied for and Received in Last 3 months by Age Using Midline Sample

	Full		Age ≥ 34		Age < 34		Diff	
	Applied	Received	Applied	Received	Applied	Received	Applied	Received
Training	-4311.5 (5851.4)	-2953.9 (5222.6)	-7823.7 (8891.0)	-5418.3 (7796.6)	1186.8 (6960.9)	661.6 (6795.3)		
Train x Age ≥ 34							-9010.5 (11294.0)	-6079.9 (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

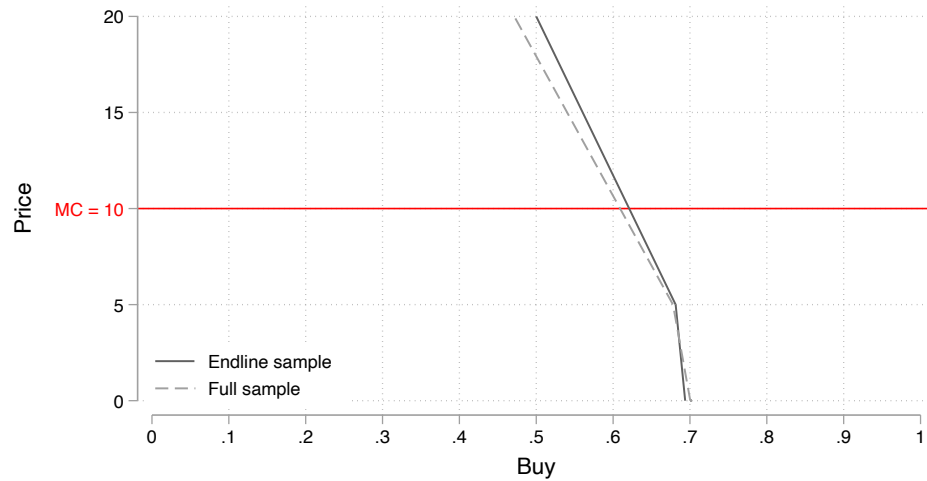
Figure E.1: Predictions and Confidence behind Predictions



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.

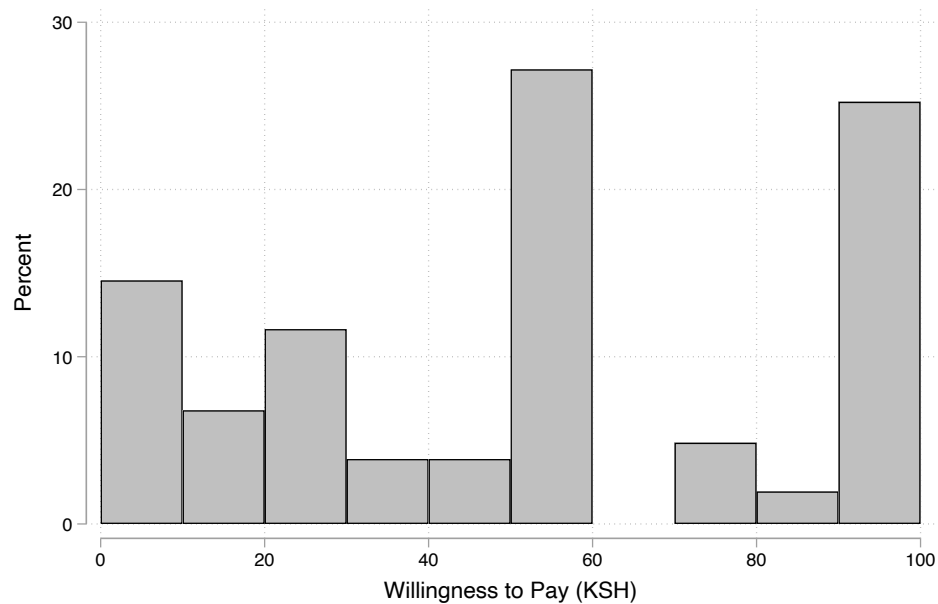
F Additional Results for Demand Elicitation

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 (0.50)	0.45 (0.50)	0.08 (0.06)
% Engaged	0.14 (0.25)	0.11 (0.22)	0.03 (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 $\geq 25\%$			50.00 (167.2)
Female	-7.446 (6.946)	-8.162 (6.880)	-6.420 (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 (0.50)	0.41 (0.49)	0.04 (0.05)
Rural	0.51 (0.50)	0.46 (0.50)	0.05 (0.05)
Years of education	12.00 (2.48)	12.13 (2.46)	-0.14 (0.27)
Age	33.81 (8.36)	33.41 (9.01)	0.40 (0.93)
Num of adults in household	2.72 (1.36)	2.64 (1.58)	0.07 (0.16)
Num of children in household	2.32 (1.44)	1.81 (1.41)	0.52*** (0.15)
Overall Knowledge	0.77 (0.14)	0.73 (0.14)	0.04** (0.02)
Overall Adoption	0.67 (0.17)	0.67 (0.16)	0.00 (0.02)
30-day Sales from All Businesses	64326.42 (119199.66)	50740.97 (93513.92)	13585.45 (12043.19)
30-day Profits from All Businesses	19554.49 (30843.84)	19674.42 (31778.75)	-119.93 (3376.04)
Applied for a Loan	0.54 (0.50)	0.44 (0.50)	0.10* (0.05)
Loan Payment Missed/Late	0.22 (0.41)	0.16 (0.37)	0.05 (0.04)
Hours worked on business	222.00 (125.89)	202.29 (109.27)	19.72 (13.06)
Hours worked on side jobs	21.77 (60.90)	27.08 (70.11)	-5.30 (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 (0.0529)	-0.0180 (0.0561)	-0.105 (0.245)	-0.0678 (0.279)
Price = KSH 20	-0.229*** (0.0672)	-0.145* (0.0791)	-0.964*** (0.280)	-0.638* (0.349)
Female		0.0343 (0.0535)		0.141 (0.262)
Rural		-0.0091 (0.0525)		-0.0429 (0.251)
Years of education		0.00108 (0.0105)		0.000145 (0.0534)
Age		-0.00128 (0.00312)		-0.00727 (0.0147)
Num of adults in household		-0.0101 (0.0189)		-0.0549 (0.0902)
Num of children in household		0.0654*** (0.0186)		0.328*** (0.0982)
Knowledge		0.371** (0.181)		1.888** (0.861)
Adoption		0.0141 (0.153)		-0.0259 (0.739)
Sales in last 30 days		0.0000009*** (0.000000336)		0.00000636** (0.00000315)
Profits in last 30 days		-0.00000315** (0.00000128)		-0.0000205** (0.00000891)
Applied for a loan		0.090* (0.0506)		0.463* (0.249)
Loan payment missed/late		0.0633 (0.0628)		0.336 (0.333)
Hours worked on business in last 30 days		0.000148 (0.000230)		0.000646 (0.00117)
Hours worked on side jobs in last 30 days		-0.000116 (0.000492)		-0.000573 (0.00234)
Intercept	0.70*** (0.0305)	0.227 (0.247)	0.849*** (0.145)	-1.294 (1.228)
<i>N</i>	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)
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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.